La chaîne de blocs et les technologies avancées au service de la décentralisation et l'automatisation du réseau électrique : le modèle des stations autonomes décentralisées

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AVANT-PROPOS

Cette thèse de doctorat rentre dans le cadre du programme de doctorat en ingénierie en vue de l’obtention du grade de Philosophiae doctor (Ph.D). Elle vise à explorer la possibilité de transformer le réseau électrique traditionnel en un réseau intelligent, autonome et décentralisé. À l'ère de la numérisation et de la transition énergétique, il est impératif de repenser les infrastructures électriques pour répondre aux défis croissants de la gestion de l'énergie, de la fiabilité et de la durabilité. Pour ce faire, nous nous appuyons principalement sur la technologie de chaîne de blocs (*blockchain*), mais aussi sur d’autres technologies avancées comme l'intelligence artificielle (IA) et l'internet des objets (IdO).

En effet, les entreprises d'énergie d'aujourd'hui sont confrontées à des niveaux de perturbation, sans précédent, dans la chaîne de valeur de l'énergie en raison de l'ère numérique. En plus, les technologies énergétiques matures, comme les panneaux photovoltaïques, les systèmes de stockage et les véhicules électriques remettent en cause la relation des entreprises énergétiques avec les clients, donnant naissance au prosommateur qui est à la fois micro-fournisseur et consommateur. En parallèle, la chaîne de blocs offre des solutions prometteuses en matière de sécurité, de transparence et de décentralisation des transactions énergétiques. En combinant cette technologie avec les capacités prédictives et analytiques de l'intelligence artificielle, nous pouvons améliorer la gestion et la distribution de l'énergie en temps réel.

Cette recherche a pour objectif de proposer un cadre théorique et pratique pour la mise en œuvre de ces technologies au sein des réseaux électriques pour le transformer en un réseau intelligent, autonome et décentralisé afin de pousser les réseaux électriques vers la nouvelle ère d’Énergie 4.0, défini comme un réseau décentralisé, numérisé et décarboné.

RÉSUMÉ

Le secteur énergétique est en pleine mutation, porté par de nouvelles réglementations climatiques et une tendance politique à la sortie du nucléaire, visant à atteindre la neutralité carbone pour la production d'électricité et une efficacité accrue des réseaux électriques. Au cours de la dernière décennie, cette transformation a été motivée par une forte tendance à encourager une plus grande intégration des ressources énergétiques distribuées et une plus grande électrification du secteur de transport. Cependant, la pénétration rapide des technologies de production décentralisée telles que le photovoltaïque, l'éolien et l'hydraulique, combinée aux contraintes du réseau électrique, nécessite l'exploration de différentes configurations du système énergétique. L'une des caractéristiques de cette reconfiguration est la nécessité d'équilibrer la production et la demande aux niveaux local et national afin de faire face à la pénétration croissante des énergies renouvelables intermittentes dans le réseau. Ces générateurs d'énergie renouvelables intermittents sont généralement situés aux extrémités du réseau, ce qui crée des problèmes de connexion au réseau et d'équilibrage de charge, et nécessite des coûts de mise à niveau des infrastructures importants.

Ainsi, ce qui est censé être une solution aux défis et barrières du réseau électrique s'est avéré au fil des années être lui-même à la base d'une série de nouveaux défis et de nouvelles barrières qui nécessitent d'être ciblés. Par conséquent, le passage à un système électrique décentralisé, numérisé et décarboné ne consiste pas seulement à changer de carburant pour produire de l'énergie de manière plus durable, mais plus important encore, il s'agit de changer la façon dont l'énergie est consommée, produite, gérée et commercialisée, permettant ainsi une plus grande efficacité et une meilleure durabilité dans l'utilisation des ressources. Par conséquent, l'une des priorités devrait être de mettre en œuvre un changement de paradigme fondamental dans les marchés de l'énergie et la manière dont les systèmes électriques sont gérés. Néanmoins, le principal problème qui se pose est que le système électrique n'a jamais

été conçu avec le concept de décentralisation à l'esprit. Le marché de l'électricité repose sur des transactions unidirectionnelles et dans le meilleur des cas, bidirectionnels. Néanmoins, il est certain que des modifications doivent être mises en place afin de s'adapter au nouveau contexte d'innovation, de durabilité et d'urgence de la transition énergétique exigé par la société. Les approches de gouvernance traditionnelles, basées sur des techniques de prise de décision centralisées, devraient être remplacées par une approche décentralisée plus collaborative qui accorde aux parties prenantes, localisées aux extrémités, un plus grand rôle dans la gérance du réseau. C'est là que la transformation numérique, et plus particulièrement la technologie de la chaîne de blocs, peut apporter une contribution décisive à l'atteinte de l'objectif de décarbonation et au renforcement de la décentralisation du système électrique.

La chaîne de blocs (*blockchain*), en tant que plateforme de transaction transparente, sécurisée et décentralisée, a suscité l'intérêt des entreprises et des industries du monde entier, débloquant de nouveaux modèles commerciaux et promettant de nouvelles sources de revenus. Cette promesse est particulièrement puissante dans le secteur de l'énergie, lorsqu'elle est déployée à la périphérie du réseau, où une implication et une transparence accrues des consommateurs sont requises. Les programmes de gestion de la demande d'énergie basés sur la chaîne de blocs ou les modèles d'échange d'énergie de poste-à-poste sont des solutions typiques à envisager.

L'objectif général de la thèse est de proposer un modèle d'un réseau électrique intelligent , autonome et décentralisé tout en s'inspirant de la technologie de chaîne de blocs et en identifiant des applications possibles basées sur cette technologie dans le secteur électrique, tout en prenant en compte les implications techniques, sociologiques, environnementales et économiques sur les différentes parties prenantes (société de production d'électricité, société de services publics, société de distribution et utilisateurs finaux). La principale méthodologie de recherche est basée sur l'exploration de plusieurs solutions énergétiques basées sur la technologie de chaîne de blocs tout au long de la chaîne de valeur électrique, de la production, à la transmission jusqu'à la distribution, ainsi que sur l'évaluation des impacts économiques, sociaux et techniques de ces applications sur le marché. Ce projet est méthodologiquement innovant dans la manière dont on s'inspire d'une technologie qui a révolutionné les bases de données pour proposer un modèle révolutionnaire pour les réseaux électriques.

Cette thèse fournit une preuve validée qu'une chaîne d'approvisionnement énergétique décentralisée, décrite comme Énergie 4.0, présente un nouvel écosystème énergétique axé sur le consommateur qui offre de nouveaux modèles commerciaux énergétiques qui peuvent être plus avantageux pour les parties prenantes que les modèles existants conventionnels, ainsi que libérer de nouveaux potentiels pour une meilleure intégration et gestion des ressources énergétiques distribuées.

Mots clés : Énergie, chaîne de blocs, réseau autonome décentralisé, contrat intelligent, P2P, ressources énergétiques distribuées, énergie renouvelable, prosommateur, réseau intelligent

TABLE DES MATIÈRES

LISTE DES TABLEAUX

LISTE DES FIGURES

LISTE DES ABRÉVIATIONS, DES SIGLES ET DES ACRONYMES

API	Application Programming Interface
AMI	Advanced Metering Infrastructure
BFT	Byzantine Fault Tolerance
CCC	Centre de Contrôle Centralisé
CPE	Contrat de Performance Énergétique
CPS	Cyber-physical System
CO2	Dioxyde de carbone
C&T	Cap and Trade
dAPP	Decentralized Application
DeFi	Decentralized Finance
DLT	Distributed Ledger Technology
DoS	Denial of Service
DSM	Demand Side Management
ECDSA	Elliptic Curve Digital Signature Algorithm
EE	Efficacité Énergétique
EMS	Energy Management System
ER	Énergie Renouvelable

ESCO	Energy Service Company
EU	États-Unis
EVM	Ethereum Virtual Machine
FiT	Feed-in-Tariff
GES	Gaz à effet de serre
HAN	Home Area Network
HTTP	Hypertext Transfer Protocol
HTML	Hypertext Markup Language
IA	Intelligence Artificielle
ICI	Interface Cérébrale Informatique
ICP	Indicateur Clé de Performance
IdO	Internet des Objets
IO	Input-Output
LCoE	Levelized Cost of Energy
MCE	Mesure de Conservation de l'énergie
MILP	Mixed-Integer Linear Programming
M&V	Mesure et Verification
M2M	Machine à Machine
NAN	Neighberhood Area Network
NEM	Net Metering

NIST	National Institute of Standards and Technology
OAD	Organisation Autonome Décentralisée
OWL	Ontology Web Language
PAD	Poste Autonome Décentralisé
PBFT	Practical Byzantine Fault Tolerance
PED	Production d'Électricité Distribuée
PET	Privacy-Enhancing Technology
PoD	Point of Delivery
PoN	Proof of Need
PONDCOA	Proof of Need Dynamic Charging Optimization Algorithm
PoS	Proof of Stake
PoW	Proof of Work
P2P	Pair à Pair
RA	Réalité Augmentée
RDF	Resource Description Framework
RED	Resource Energétique Distribuée
RV	Réalité Virtuelle
SER	Source d'Énergie Renouvelable
SSE	Système de Stockage d'Énergie
SHA	Secure Hash Algorithm

SOC State of Charge

SPOF Single Point of Failure

SWIFT Society for Worldwide Interbank Financial Telecommunication

TIC Technologie de l'Information et des Communications

VE Véhicule Électrique

VPP Virtual Power Plant

WAN Wide Area Network

WWW World Wide Web

XAI eXplainable Artificial Intelligence

ZKP Zero Knowledge Proof

CHAPITRE 1
INTRODUCTION GÉNÉRALE

1.1 CONTEXTE

Le secteur de l'énergie connaît actuellement une transition fondamentale. Sous l'impulsion de l'idée d'atténuation du changement climatique et des discussions politiques sur la sortie du nucléaire, le secteur a connu une évolution prononcée vers la production d'électricité neutre en CO_2 et l'efficacité énergétique [1]. Ainsi, les réseaux électriques mondiaux subissent des transformations pour l'intégration de technologies propres à la suite de politiques qui encouragent l'utilisation de ressources renouvelables et distribuées et augmentent la participation des consommateurs d'électricité à la gestion et à la production d'énergie. Parallèlement à cette évolution technologique, des tentatives ont été faites pour libéraliser partiellement les marchés de l'électricité. Ces transitions mettent au défi les compagnies d'électricité, qui ont l'habitude de fonctionner dans un environnement commercial assez stable. En outre, les prix des sources énergétiques ont considérablement augmenté après 2010, ce qui a encore accentué la pression sur les modèles économiques traditionnels des compagnies dans le secteur de l'énergie [2]. Les compagnies d'électricité mondiales sont confrontées à des crises électriques graves et récurrentes causées par une combinaison de problèmes liés à l'offre, notamment les difficultés d'approvisionnement en carburant, les exigences de maintenance et les pannes imprévues, et une augmentation continue de la demande d'énergie, due à la croissance démographique mondiale, à l'électrification du secteur des transports et à l'augmentation des besoins de chauffage et de refroidissement. En plus, le secteur énergétique est actuellement sous une pression croissante en raison des politiques strictes qui exigent sa décarbonation. Ces politiques sont mises en place pour lutter contre le changement climatique en réduisant les émissions de gaz à effet de serre. Les gouvernements, les organisations internationales et les institutions régulatrices imposent des normes environnementales rigoureuses, des objectifs de réduction des émissions et des incitations pour adopter des sources d'énergie renouvelable. En conséquence, les entreprises du secteur énergétique doivent transformer leurs modèles d'affaires, investir massivement dans les technologies vertes telles que l'énergie solaire, éolienne et les solutions de stockage d'énergie, tout en se détournant des combustibles fossiles traditionnels comme le charbon, le pétrole et le gaz naturel. Cette transition vers une énergie plus propre et durable représente non seulement un défi financier et technologique, mais aussi une opportunité de redéfinir le futur énergétique mondial de manière plus écologique et résiliente. Néanmoins, la pénétration rapide des technologies de production d'énergie propre telles que le photovoltaïque, l'éolien et l'hydroélectricité, de nature intermittente et généralement situées aux extrémités du réseau, pose des problèmes de connexion au réseau et d'équilibrage des charges, et nécessite des coûts importants de mise à niveau des infrastructures [3]. Ceci nécessite l'exploration de différentes configurations du système énergétique.

D'autre part, la transformation numérique est une tendance globale qui touche tous les secteurs, redéfinissant la manière dont les entreprises et les industries fonctionnent. Grâce aux avancées technologiques telles que l'intelligence artificielle, l'internet des objets (IdO), les mégadonnées et la chaîne de blocs (*blockchain*), les entreprises peuvent améliorer leur efficacité opérationnelle, innover dans leurs produits et services et offrir une expérience client supérieure. Cette transition numérique permet une automatisation accrue, des processus décisionnels basés sur des données et une meilleure connectivité. Ces nouvelles technologies émergentes ont le potentiel de perturber fortement le secteur de l'énergie et de le faire passer d'une chaîne d'approvisionnement centrale et hiérarchique à une plateforme intelligente décentralisée, numérisée et décarbonée. Les fournisseurs d'énergie sont en quête permanente d'une plus grande productivité et d'une meilleure résilience. La numérisation du secteur de l'énergie peut améliorer la résilience du réseau, accroître la productivité et réduire les coûts. La numérisation est essentielle pour intégrer les ressources énergétiques distribuées (REDs), pour débloquer la flexibilité de la charge, pour augmenter la variabilité du système, pour permettre aux gens de participer à la gestion de leur approvisionnement en énergie, ou pour les aider à devenir des participants actifs du système énergétique avec leurs propres projets, avec leurs propres ressources. Du point de vue des services publics, la numérisation leur permet de surveiller le système, de détecter les défaillances et de se procurer les services et les solutions dont ils ont besoin pour maintenir le système en fonctionnement [4]. En outre, le contrôle et la supervision en temps réel jouent un rôle important dans la gestion des réseaux énergétiques intelligents. En raison de la croissance rapide du déploiement des ressources énergétiques distribuées, les problèmes de gestion des réseaux intelligents ne peuvent plus être traités efficacement par des approches centralisées. Par conséquent, le besoin d'approches et d'architectures décentralisées visionnaires est largement reconnu. La technologie de la chaîne de blocs pourrait faciliter la mise en place d'un système énergétique entièrement décentralisé [5].

Une chaîne de blocs est un registre chronologique distribué qui est partagé, mis à jour et validé par plusieurs nœuds pairs, plutôt que par une seule autorité centralisée. En éliminant l'autorité centrale et en disposant d'enregistrements de transactions immuables qui sont validés par plusieurs pairs, la chaîne de blocs promet d’augmenter la simplicité, la rapidité et la transparence des transactions entre des pairs. Un exemple de la mise en œuvre de la chaîne de blocs est la cryptomonnaie Bitcoin. Alors que les transactions internationales, à travers le réseau Society for Worldwide Interbank Financial Telecommunication (SWIFT), nécessitent la validation de plusieurs banques intermédiaires et prennent du temps, la chaîne de blocs ne nécessite pas de validation centrale et les transactions entre deux parties se font immédiatement [6]. Comme la chaîne de blocs est une plateforme d'échange sécurisée de pair-à-pair (P2P), elle a suscité l'intérêt des entreprises et des industries. La chaîne de blocs promet une plateforme transactionnelle rapide, hautement sécurisée, présentant moins d'incidents d'erreurs et pouvant souvent réduire les besoins en capitaux [7]. Elle permet aux entreprises d'automatiser davantage leurs processus d’affaire, tout en traitant de plus grands volumes de données avec moins de personnes, à moindre coût et à moindre risque. Les entreprises de distribution d'énergie doivent faire face à des exigences accrues en matière de gestion des données, de transparence et de sécurité des données, ce qui augmente les coûts et les besoins en personnel et en ressources. La technologie de chaîne de blocs apporte des solutions à ces défis. Le secteur de l'énergie est l'une des industries où la chaîne de blocs peut avoir un impact substantiel [8]. Les modèles transactionnels traditionnels sont basés sur une structure centralisée. Les transactions entre les nœuds du réseau se font uniquement par le biais d'un tiers intermédiaire. L'implication d'un intermédiaire est souvent nécessaire, car elle crée la confiance lorsque les partenaires de la transaction ne se connaissent pas. Les intermédiaires facturent généralement des frais pour leurs services. L'implication d'intermédiaires augmente le temps de traitement nécessaire aux transactions. Étant donné que toutes les transactions sont liées et stockées sur un serveur ou une infrastructure centrale, les structures centralisées présentent l'inconvénient d'un point de défaillance unique. En revanche, les systèmes décentralisés, tels que celui proposé par la chaîne de blocs, comportent différents nœuds de réseau qui peuvent interagir directement les uns avec les autres sans intermédiaire. Avec une technologie de registre distribué P2P sécurisé, la plupart des problèmes associés aux structures centralisées peuvent être résolus ou atténués [9].

Par conséquent, la technologie de chaîne de blocs a le potentiel de fournir une plateforme de transaction plus efficace, transparente et en temps quasi réel qui débloquera de nouveaux modèles commerciaux. Dans le secteur de l'énergie, cette promesse est particulièrement convaincante lorsqu'elle est appliquée à la périphérie du réseau, car on recherche une plus grande participation au marché et une plus grande transparence, tout en transformant le modèle bidirectionnel de flux d'énergie en un modèle multidirectionnel. La chaîne de blocs permet d'enregistrer toutes les transactions et les flux d'énergie de manière décentralisée et immuable, ce qui réduit le risque de fraude et d'erreurs tout en améliorant la confiance entre les différents acteurs du réseau. De plus, cette technologie facilite l'intégration des REDs en permettant une gestion plus efficace des échanges d'énergie entre les producteurs et les consommateurs. Grâce à des contrats intelligents (*smart contracts*), les transactions d'énergie peuvent être automatisées et exécutées de manière transparente et sans intermédiaire, réduisant ainsi les coûts et les délais de traitement. En somme, la chaîne de blocs est particulièrement adaptée à la gestion des réseaux électriques modernes, car elle soutient un modèle plus résilient, flexible et équitable, capable de répondre aux exigences croissantes en matière de durabilité et d'innovation énergétique.

1.2 PROBLÉMATIQUE

La nécessité de décarboner le réseau électrique est devenue une priorité mondiale en raison des enjeux environnementaux et climatiques actuels. Les émissions de gaz à effet de serre (GES), principalement dues à la combustion de combustibles fossiles pour la production d'électricité, sont l'un des principaux contributeurs au réchauffement climatique. Les gouvernements, les organisations internationales et les entreprises prennent conscience de l'importance cruciale de réduire ces émissions pour limiter les impacts catastrophiques du changement climatique sur notre planète. Pour atteindre cet objectif, il est impératif de transformer notre infrastructure énergétique en un réseau électrique propre et durable, une transition qui nécessite l'abandon des sources d'énergie fossiles au profit de ressources énergétiques renouvelables et distribuées. Les REDs sont des éléments clés de cette transition. Contrairement aux centrales électriques traditionnelles, généralement de grande taille et centralisées, les REDs sont souvent de plus petite taille et géographiquement dispersées. Cette décentralisation offre plusieurs avantages, notamment une réduction des pertes de transmission, une augmentation de la résilience du réseau et une meilleure intégration des énergies renouvelables. Par conséquent, l'une des priorités devrait être de mettre en œuvre un changement fondamental de paradigme sur les marchés de l'énergie et dans la façon dont les systèmes électriques sont gérés. Néanmoins, le principal problème qui se pose est que le système électrique n'a jamais été conçu en tenant compte du concept de décentralisation. Le marché de l'électricité est basé sur des transactions à sens unique ou bidirectionnel, qui devront certainement être modifiées pour s'adapter au nouveau contexte d'innovation, de durabilité et d'urgence de la transition énergétique exigée par la société. Les approches traditionnelles de la gouvernance, fondées sur des techniques centralisées de prise de décision, doivent être bouleversées au profit d'une approche décentralisée plus collaborative qui accorde aux parties prenantes périphériques un rôle plus important dans la gouvernance. Subséquemment, la gestion efficace de ces ressources distribuées pose des défis uniques qui nécessitent une approche novatrice et sophistiquée. La numérisation du réseau électrique moderne est essentielle pour répondre aux défis posés par la complexité géographique, la diversité des ressources énergétiques et la nature intermittente des énergies renouvelables. Avec l'essor des REDs, souvent situées dans des zones éloignées ou dispersées, une gestion en temps réel est indispensable pour coordonner efficacement la production et la consommation à travers différentes régions. La variabilité des sources d'énergie, comme l'éolien et le solaire, nécessite des outils numériques avancés pour prévoir leur disponibilité et adapter le fonctionnement du réseau en conséquence. De plus, la diversité des acteurs, allant des prosommateurs aux grandes installations industrielles, impose une approche collaborative et flexible. La numérisation permet ainsi d'intégrer des technologies intelligentes, telles que les compteurs avancés, les systèmes de gestion de données et les plateformes d'automatisation, pour optimiser le fonctionnement du réseau, réduire les pertes et garantir une alimentation électrique fiable, durable et résiliente. Ainsi, pour maximiser le potentiel des REDs, il est essentiel de numériser le réseau électrique. La numérisation implique l'utilisation de technologies avancées telles que la chaine de blocs [10], les capteurs intelligents, l'IdO, l'IA et les systèmes de gestion de l'énergie (EMS) pour surveiller, contrôler et optimiser en temps réel la production, la distribution et la consommation d'énergie. Ce passage à un réseau intelligent (*smart grid*) permet de gérer de manière plus efficace et dynamique les flux d'électricité, de répondre rapidement aux variations de la demande et de l'offre, et de garantir une stabilité et une fiabilité accrues du réseau.

L'un des principaux avantages de la numérisation est la capacité à collecter et à analyser des données en temps réel. Les capteurs intelligents installés sur les équipements de production, de distribution et de consommation d'énergie permettent de recueillir des informations détaillées sur l'état du réseau. Ces données sont ensuite traitées par des algorithmes d'IA pour prévoir les fluctuations de la demande et de la production, optimiser les flux d'énergie et détecter rapidement les anomalies ou les pannes. Par exemple, les prévisions météorologiques peuvent être intégrées pour anticiper la production d'énergie solaire ou éolienne, permettant ainsi une meilleure planification et gestion des ressources disponibles. La numérisation est aussi fondamentale pour la gestion en temps réel des ressources renouvelables afin de minimiser les pertes d'énergie et réduire les coûts de production et de distribution. De plus, les systèmes numériques d'optimisation seront nécessaires pour une meilleure intégration des véhicules électriques (VE) et des systèmes de stockage d'énergie, en offrant une gestion flexible de la demande et une utilisation plus efficace des excédents de production. Par exemple, les VE peuvent être chargés pendant les périodes de faible demande ou de forte production renouvelable, et leurs batteries peuvent être utilisées comme sources d'énergie de secours pendant les périodes de pointe, contribuant ainsi à l'équilibrage du réseau. Un autre aspect crucial de la numérisation est l'amélioration de la résilience et de la sécurité du réseau.

Néanmoins, la transition vers un réseau électrique décentralisé et numérique s'accompagne de nombreuses problématiques complexes, qui touchent à la fois les aspects techniques, économiques, réglementaires et sociaux. Ces problématiques nécessitent une analyse approfondie pour garantir une transformation réussie. Le réseau électrique actuel, qualifié d'Énergie 3.0 (Figure 1), est confronté aux défis majeurs suivants :

Sécurité : Les réseaux électriques traditionnels, conçus autour d'une structure centralisée, présentent une vulnérabilité accrue face aux pannes et aux cyberattaques. Leur dépendance à des systèmes de contrôle souvent obsolètes limite leur capacité à détecter et à répondre rapidement aux défaillances, qu'elles soient d'origine technique ou intentionnelle. Une panne à un point critique du réseau peut entraîner des effets en cascade, provoquant des coupures de courant sur une vaste zone. Par ailleurs, l'absence de technologies modernes de cybersécurité expose ces réseaux à des intrusions potentielles, mettant en péril l'intégrité des données et le fonctionnement global du système. Ces faiblesses sont exacerbées par la complexité croissante des interactions entre les producteurs, les consommateurs, et les nouvelles ressources énergétiques décentralisées. La modernisation des infrastructures, notamment par la mise en place de systèmes de contrôle numériques et résilients, devient essentielle pour renforcer la sécurité et la fiabilité des réseaux électriques face aux menaces actuelles.

Défis techniques : La gestion des REDs présente des défis techniques considérables en raison de leur nature décentralisée et variée. L'un des principaux défis réside dans la coordination et l'optimisation des flux d'énergie provenant de multiples sources renouvelables, souvent fluctuantes et réparties sur une vaste zone géographique. Pour gérer efficacement ces ressources et assurer un approvisionnement énergétique stable et fiable, il est nécessaire de disposer d'un système de gestion des données capable de s’adapter à la nature décentralisée du réseau. Ce système doit être aussi capable de traiter des milliers de transactions multidirectionnelles en temps réel, en tenant compte des différentes contraintes et besoins des producteurs, des consommateurs et des prosommateurs. La compatibilité avec la structure décentralisée de la nouvelle topologie du réseau électrique est cruciale. Un tel système permettrait non seulement de gérer les transactions énergétiques de manière transparente et sécurisée, mais aussi d'optimiser l'utilisation des REDs, de réduire les pertes d'énergie et d'améliorer la résilience du réseau. Les systèmes existants de gestion des réseaux électriques, conçue pour une architecture plus centralisée, ne répondent pas à ces défis. Cependant, la décarbonation n'est pas le seul incitatif pour un passage à un réseau électrique décentralisé. Les compagnies d’électricité au monde sont confrontées à des crises électriques aiguës et répétitives dues à la combinaison de problèmes liés à l'offre, notamment la pénurie de carburant, les besoins de maintenance et les pannes non planifiées, et d'une augmentation continue de la demande d'énergie, en particulier d'électricité [11]. Historiquement, les réseaux électriques conventionnels étaient conçus avec de grandes centrales de production centralisées où la production suivait la demande d'électricité, ce qui permettait d'atteindre un certain équilibre. Bien que les micro-réseaux fournissent une plateforme pour mettre en œuvre des REDs plus rentables, leur développement est confronté à de nombreux défis techniques, économiques et d'infrastructure associés à la capacité et à la stabilité du réseau, ce qui entrave la large intégration des ressources d'énergie renouvelable (ER) et de la production d'électricité distribuée (PED). En outre, le déséquilibre entre la production et la charge ainsi que les demandes de pointe sont devenus deux problèmes critiques dans le fonctionnement d'un réseau électrique qui peuvent affecter de manière significative la fiabilité et la qualité de l'énergie.

Demande accrue : En plus, la croissance de l'économie mondiale, l'explosion démographique, la numérisation, la mobilité accrue et une plus grande demande de chauffage et de refroidissement en raison du changement climatique dans différentes régions du monde sont les principaux moteurs de l'augmentation de la demande d'énergie [12]. L'augmentation de la demande d'énergie est à l'origine de défis économiques pour les compagnies d'électricité, ainsi que de plusieurs problèmes socio-économiques dans les communautés, tels que la pauvreté énergétique, qui se définit comme la couverture insuffisante des besoins énergétiques [13], en particulier dans le secteur résidentiel. Pour répondre à cette demande accrue, deux stratégies principales sont définies. La première stratégie se concentre sur de nouveaux modes de production d'énergie durables et respectueux de l'environnement, tels que les REDs, avec un faible coût moyen de l'énergie. La deuxième stratégie est axée sur la demande plutôt que sur l'offre. Les programmes de gestion de la charge, de réponse à la demande et d'efficacité énergétique entrent dans cette catégorie [14]. À ce niveau-là, les consommateurs d'électricité peuvent jouer un rôle important dans le fonctionnement du système électrique en réduisant leur consommation d'électricité pendant les heures de pointe et en retour gagner de l'argent grâce au programme de réponse à la demande [15]. Néanmoins, lorsque des stratégies de consommation d'énergie telles que les programmes de gestion de la charge et de réponse à la demande sont envisagées, le problème économique du parasitisme se pose [16]. On parle de parasitisme (*free-ride*) lorsqu'une personne bénéficie de certains biens ou services sans faire d'effort ni payer. En d'autres termes, les resquilleurs sont ceux qui utilisent des biens sans contribuer leur juste part et finissent même par consommer excessivement. Dans les programmes de gestion de la demande, le parasitisme se produit lorsque les consommateurs reçoivent des incitations sans vraiment réduire leur charge. En général, les gens profitent de la consommation d'énergie, mais paient rarement pour celle-ci comme pour d'autres biens publics, ce qui peut conduire à la destruction de ce bien ou service public [17]. D'autre part, un obstacle important à surmonter lorsqu'on considère l'impact souhaité et conçu pour les projets d'efficacité énergétique à long terme est ce qu'on appelle l'effet rebond. En économie de la conservation et de l'énergie, l'effet de rebond, ou effet de reprise, est la réduction des gains attendus des nouvelles technologies qui augmentent l'efficacité de l'utilisation des ressources, en raison de réactions comportementales ou autres réactions systémiques [18]. Il s'agit d'un résultat important de l'efficacité énergétique, qui est souvent sous-estimé. Il caractérise la relation négative entre la technologie et la consommation [19]. Il est donc essentiel de développer des programmes de gestion de la demande qui puisse atteindre les objectifs ultimes de réduction de la demande énergétique globale et de réduction de la charge de pointe tout en évitant les effets de parasitisme et de rebond.

Défis de facturation : D'autre part, les systèmes actuels de facturation de l'énergie ne sont pas conçus pour un marché de l'énergie bidirectionnel dans lequel les clients produisent et consomment de l'énergie en même temps. Par exemple, des factures individuelles sont encore émises pour chaque point de livraison (PoD), au lieu d'une facture globale par client, qui peut être propriétaire de plusieurs appartements, ce qui montre que ces systèmes n'appliquent pas une hiérarchie de système centrée sur l'utilisateur. Par conséquent, les détaillants ne disposent d'aucune information sur les clients qui possèdent plusieurs logements, et ne sont donc pas en mesure de proposer des produits personnalisés. En outre, la facturation représente une bonne portion des frais fixes payés par le client. Cela s'explique par le fait que le secteur s'appuie toujours sur des logiciels anciens coûteux et obsolètes, dont les coûts d'installation et de maintenance sont élevés, sans offrir les fonctionnalités nécessaires pour être compétitif sur un marché de l'énergie davantage axé sur le client. En outre, les processus actuels de collecte, de traitement et de règlement financier des données sont très inefficaces et sujets aux erreurs, ce qui entraîne des retards importants dans le règlement des valeurs et la nécessité de processus de réconciliation coûteux [20]. D'où la nécessité de développer un système de facturation de l'énergie automatique et décentralisé, capable de collecter automatiquement la consommation d'énergie, d'offrir une approche centrée sur l'utilisateur et d'assurer la simplicité des transactions énergétiques de manière multidirectionnelle. C'est là que la chaîne de blocs, l'IdO et l'IA peuvent révolutionner les modèles d'affaires actuels, en offrant aux entreprises énergétiques la possibilité d'intégrer des milliers de points de données par jour et par compteur intelligent, ce qui leur permet de proposer aux clients une variété de tarifs, de services et de produits innovants et dynamiques, tout en fonctionnant sur un système de facturation efficace et entièrement automatisé.

Manque d'incitation : De plus, les marchés émergents des REDs ont besoin d'un environnement favorable qui permette aux réseaux d'augmenter leur adoption et d'améliorer leur gestion des technologies hors réseau. Les systèmes d'incitation existants, tels que le comptage net (*Net Metering*) et les tarifs de rachat garantis (FIT), ne reflètent pas toujours le coût de l'électricité au moment de l'injection dans le réseau et peuvent fausser le marché si la quantité injectée est importante. Afin de tirer parti de ces systèmes, les prosommateurs doivent soit injecter de l'énergie pendant les périodes où les tarifs de compensation sont élevés, soit maximiser l'autoconsommation ou stocker l'énergie lorsque les tarifs sont bas. En outre, dans ces systèmes, la compagnie d'électricité est le seul acheteur d'électricité auprès des prosommateurs et elle contrôle généralement les tarifs auxquels l'électricité est achetée. En l'absence d'un marché concurrentiel, le résultat sera toujours en faveur de la compagnie d'électricité. Le commerce de l'énergie de P2P donne naissance à un écosystème énergétique qui a le potentiel d'offrir des incitations économiques uniques au consommateur plutôt qu'à la compagnie d'électricité ou au gestionnaire de réseau. La nature fragmentée du marché des REDs augmente la concurrence, ce qui profite aux consommateurs. Cette concurrence accrue a déjà amorcé la transition énergétique en faisant passer le marché de la production d'électricité des combustibles fossiles aux énergies renouvelables. L'avantage de cette transition du marché n'est pas seulement écologique, mais aussi financier, car les actifs de production d'énergie renouvelable ont un coût d'énergie actualisé (*Levelized Cost of Energy*, LCoE) plus faible. Alors que les tarifs fixes sur la consommation d'énergie ont quelque peu protégé les consommateurs de la volatilité des prix de l'énergie, et que le comptage net ou le FIT ont réussi à encourager l'adoption de la production d'énergie renouvelable domestique pour aider le réseau [21], un marché plus libre basé sur l'offre et la demande peut contribuer à équilibrer les charges sur le réseau. Aussi un tel marché incite les propriétaires à soutenir le réseau par des services auxiliaires tels que les batteries domestiques et aider le consommateur final à réduire sa facture d'énergie. Un tel modèle soutient également l'évolution vers un réseau énergétique connecté et décentralisé.

Défis de gestion et d’optimisation des VPPs : Compte tenu de la nature diversifiée et décentralisée des REDs, les centrales électriques virtuelles (Virtual Power Plant, VPP) s'avèrent être une solution prometteuse pour un avenir durable, les énergies renouvelables alimentant la centrale. La VPP est un regroupement de ressources distribuées mises en commun. La mise en œuvre des VPP dans les réseaux électriques offre la possibilité de convertir l'énergie des centrales stochastiques en énergie sécurisée en la mélangeant avec des portions d'énergie provenant de sources déterministes. Les fournisseurs d'électricité peuvent utiliser la capacité agrégée pour optimiser le programme d'électricité et minimiser les coûts de déséquilibre ou pour échanger sur le marché des services auxiliaires. L'intégration des REDs dans un concept des VPPs a été rendue possible par les progrès récents dans le domaine des technologies de l'information et des communications (TIC) et par les problèmes des systèmes électriques modernes [22]. Néanmoins, cette solution n'est pas exempte de défis et de limites. Les relations multiformes entre les parties prenantes, impliquées dans une centrale virtuelle, nécessitent un processus administratif complexe qui induit des coûts opérationnels élevés, des frais de transaction et des problèmes de confiance entre les parties.

Résilience : Les systèmes modernes d'approvisionnement en énergie électrique sont régis par trois critères essentiels : la quantité, la qualité et la fiabilité. La quantité implique le maintien d'un équilibre entre la production et la demande d'électricité, tandis que la qualité garantit que l'électricité fournie est conforme à des caractéristiques prédéfinies telles que la tension, la fréquence, les harmoniques, etc. La fiabilité, un aspect crucial, est définie comme la fourniture constante d'électricité sans interruption ou fluctuations importantes, ce qui nécessite un flux stable, une production d'électricité répondant à la demande et des perturbations minimales dues à divers facteurs. La résilience du réseau est un élément fondamental pour garantir la fiabilité des réseaux électriques. Elle se caractérise par la capacité du réseau à supporter et à récupérer de diverses perturbations ou événements imprévus, tels que les catastrophes naturelles, les cyberattaques ou les pannes d'équipement [23]. Cette résilience englobe la capacité du réseau à absorber les chocs, à s'adapter aux conditions dynamiques et à rétablir rapidement le courant après une panne. Les stratégies visant à améliorer la résilience du réseau consistent souvent à exploiter diverses sources d'énergie, à mettre en place une infrastructure robuste et à appliquer des mécanismes de réaction rapide. En revanche, la fiabilité vise principalement à prévenir les perturbations et à maintenir une alimentation électrique ininterrompue. Cependant, au sujet de la résilience des réseaux, un discours et une analyse continus tournent autour des avantages et des inconvénients des approches centralisées et décentralisées. Les approches centralisées de la résilience des réseaux adoptent une architecture de contrôle centralisée, dans laquelle les décisions et les actions sont coordonnées et exécutées par une autorité ou un opérateur central. Cette approche offre une contrôlabilité et une prévisibilité supérieures, facilitant une gestion efficace des ressources et une réponse aux perturbations. Néanmoins, les réseaux centralisés présentent un inconvénient notable connu sous le nom de « point de défaillance unique » (SPOF). Il s'agit d'un élément spécifique du réseau, tel qu'un centre de contrôle, une centrale électrique ou une ligne de transmission, dont la défaillance peut perturber de manière significative ou potentiellement effondrer la fonctionnalité de l'ensemble du réseau. Il s'agit essentiellement d'une vulnérabilité qui, si elle est compromise, peut entraîner des coupures de courant ou des perturbations généralisées. Aussi, le manque de modularité des réseaux centralisés peut nuire à leur flexibilité face aux changements rapides de la charge et à leur adaptation aux impacts des conditions météorologiques extrêmes et des perturbations techniques.

En conclusion, la problématique abordée dans cette thèse met en évidence les défis complexes et multidimensionnels associés à la transformation du réseau électrique vers un modèle décentralisé et durable. La nécessité de décarboner le secteur énergétique est impérative pour répondre aux enjeux climatiques mondiaux, mais elle s'accompagne de défis techniques, économiques et sociaux considérables. La gestion efficace d’un réseau électrique décentralisé requiert des innovations technologiques et organisationnelles, notamment à travers la numérisation et l'adoption de systèmes de gestion décentralisés et intelligents. En explorant ces défis et en proposant des solutions viables, cette thèse vise à contribuer à l’avancement de la science pour la construction de réseaux électriques plus résilients, flexibles et capables de répondre aux exigences d'un avenir énergétique durable.

1.3 OBJECTIF

Il y a près de 140 ans, le monde a assisté à l'émergence des premiers réseaux électriques. Au début, les réseaux électriques étaient localisés, décentralisés et non réglementés. Cependant, au cours des cinq décennies suivantes, sous l'effet de la demande accrue d'électricité, induite par la seconde révolution industrielle, et d'un besoin pressant de réguler les marchés de l'énergie, les réseaux électriques se sont métamorphosés en grands réseaux électriques centralisés. Les premiers réseaux décentralisés primitifs ont constitué la première ère des réseaux électriques, ou ce que nous définissons comme l'énergie 1.0, suivie par l'architecture centralisée qui a constitué la deuxième ère, ou l'énergie 2.0 (voir Figure 1). Cependant, avec les réseaux Énergie 1.0 et Énergie 2.0, le consommateur était entièrement dépendant de la compagnie d'électricité et le flux d'énergie était unidirectionnel (voir Figure 2), du réseau à l'utilisateur final. Parallèlement, les entreprises de services publics du monde entier étaient soumises à la pression constante d'équilibrer leurs capacités de production d'électricité avec la demande croissante, en plus d'un marché de l'approvisionnement en combustibles en constante fluctuation, de contraintes environnementales et d'attentes croissantes de la part des utilisateurs finaux [24]. Néanmoins, les réseaux électriques centralisés sont restés une solution substantielle pour le marché de l'électricité jusqu'à la fin du vingtième siècle, lorsque l'image a commencé à changer à nouveau.

Limité par de nouvelles considérations mondiales telles que le changement climatique et de nouvelles tendances du marché telles que la sécurité énergétique [25], les énergies renouvelables (ER) et l'efficacité énergétique (EE), le réseau électrique s'est transformé en une architecture décentralisée basée sur des micro-réseaux de REDs. Les progrès technologiques et la commercialisation de solutions basées sur les énergies renouvelables ont permis un large déploiement de stratégies à l'échelle des services publics et de projets REDs à petite échelle. Ce changement a conduit à une nouvelle restructuration fondamentale de l'architecture du réseau électrique qui ne repose plus sur des centrales de production d'énergie centralisées, mais dépend des ressources de l'offre et de la demande principalement situées à la périphérie du réseau, du côté des consommateurs. Le nouveau réseau électrique est donc devenu un réseau décentralisé qui encourage un flux d'énergie bidirectionnel, du réseau à l'utilisateur final et vice versa, défini dans cet article comme l'énergie 3.0 (voir Figure 1). En outre, au cœur de ce nouveau cadre de l'énergie 3.0, le consommateur est devenu une partie prenante fondamentale, un membre proactif et engagé dans la gestion du réseau énergétique [26]. Les consommateurs actifs sont devenus des prosommateurs grâce à leurs investissements dans les énergies propres et à leur participation à la production d'électricité et à la gestion de la demande [27]. De plus, la progression des systèmes de stockage de l'énergie a ouvert la voie aux micro-réseaux hors réseau [28] et, pour la première fois, les utilisateurs finaux n'étaient plus dépendants du réseau de distribution, mais avaient la possibilité d'être indépendants (voir Figure 2).

Par conséquent, en réponse à la nécessité d'une plus grande numérisation et d'un système énergétique plus centré sur l'utilisateur, le marché de l'énergie est une fois de plus propulsé vers un nouveau modèle, défini comme l'énergie 4.0 (voir Figure 1), basé sur l'échange d'énergie P2P et une interdépendance accrue entre les prosommateurs, les consommateurs et le réseau lui-même (voir Figure 2). Contrairement au réseau traditionnel, où l'énergie circule de manière unidirectionnelle des centrales centralisées vers des consommateurs passifs, ou de manière bidirectionnelle entre les prosommateurs et le réseau, ce nouveau modèle repose sur des systèmes décentralisés et collaboratifs. Les prosommateurs, grâce à leurs REDs, produisent leur propre énergie et peuvent échanger leurs surplus directement avec d’autres utilisateurs via des plateformes P2P, tout en restant connectés au réseau. Ce système interdépendant permet une circulation dynamique de l’énergie, intégrant les capacités de production locale, les besoins de consommation et les infrastructures du réseau. L’Énergie 4.0, soutenue par des technologies comme la chaîne de blocs et les compteurs intelligents, promet une optimisation de l’efficacité énergétique, réduction des coûts, renforcement de la résilience du réseau et accélération de l’adoption des énergies renouvelables. Ce modèle transforme le réseau électrique en un écosystème intégré, durable et participatif.

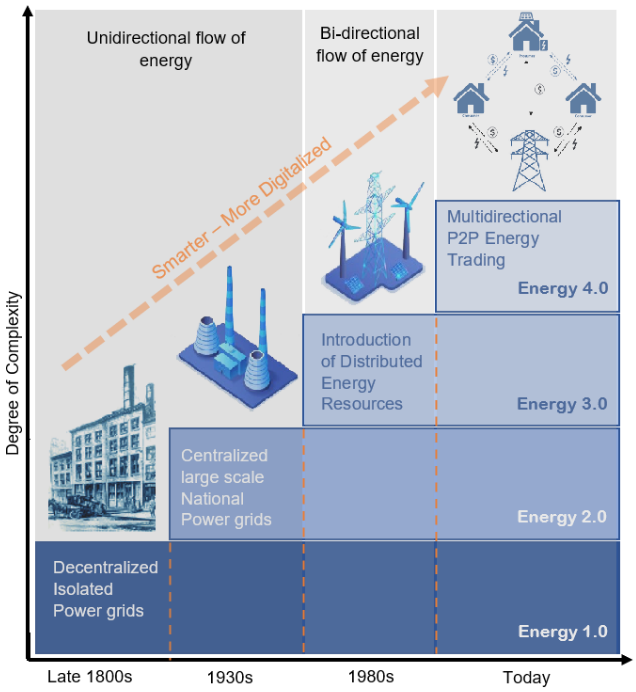

Figure 1. Évolution historique du réseau électrique.

Le commerce d'énergie P2P offre un nouveau modèle décentralisé multidirectionnel pour la vente et l'achat d'énergie. Contrairement au modèle existant précédemment, le modèle d'échange d'énergie P2P est considéré comme un modèle interdépendant (Figure 2), dans lequel l'échange d'énergie n'est pas monopolisé par l'opérateur du réseau ou la société de services publics, mais offre aux ménages, aux entreprises ou même aux communautés la possibilité d'être à la fois consommateurs et producteurs d'énergie tout en échangeant de l'énergie les uns avec les autres. Toutefois, ce concept nécessite une plateforme numérique capable de connecter des nœuds homologues sans intermédiaire, de sécuriser et de gérer les transactions en temps réel tout en tirant parti de la transparence, de l'immuabilité et de l'anonymat. La technologie de chaîne de blocs répond parfaitement à ce besoin. La technologie de chaîne de blocs est une union de plusieurs technologies, telles que les bases de données numériques, les réseaux P2P et la cryptographie [29]. Cette combinaison de technologies peut apporter des changements profonds à la numérisation du secteur de l'énergie.

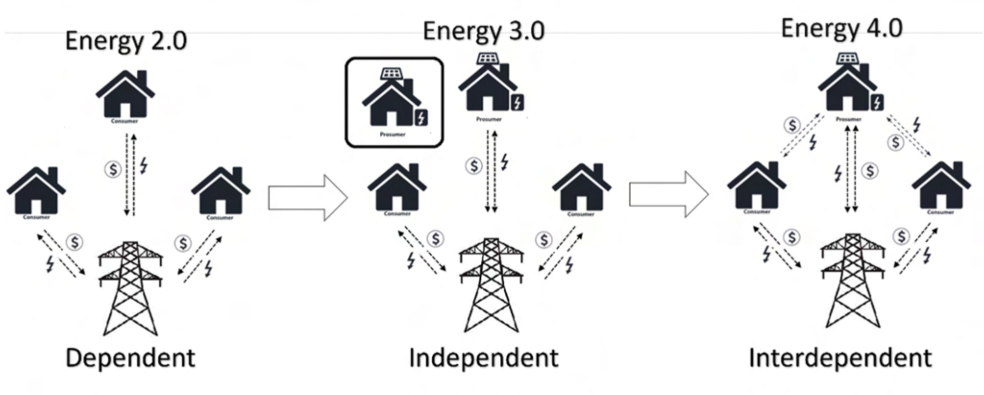

Figure 2. Marchés de l'énergie dépendants, indépendants et interdépendants.

La chaîne de blocs a la capacité de transformer le secteur de l'énergie en harmonie avec les lois naturelles de la croissance. Elle offre une approche incrémentielle, séquentielle et hautement intégrée du développement de l'efficacité et de l'efficience du secteur énergétique. Cette nouvelle technologie peut faire passer progressivement le marché de l'énergie d'un marché dépendant à un marché indépendant, puis à un marché interdépendant. Le marché existant est un marché entièrement dépendant où les consommateurs dépendent totalement des entreprises de services publics et des fournisseurs de services. Avec le développement des technologies REDs, le marché peut évoluer vers un marché indépendant où les micro-réseaux isolés hors réseau ont la capacité de survivre. Mais avec l'intégration de la chaîne de blocs, le secteur de l'énergie va se métamorphoser en un marché interdépendant régi par le paradigme du "nous pouvons le faire", où les gens peuvent coopérer et combiner leurs efforts, leurs capacités et leurs ressources afin de créer ensemble quelque chose de plus grand.

Alors que la transformation numérique de la chaîne de valeur électrique continue de gagner en intérêt et que la pénétration des REDs dans le mix énergétique continue d'augmenter (voir Figure 3), les données générées par la chaîne de valeur électrique continueront également de croître de manière exponentielle, entraînant ainsi de nouvelles tendances, de nouveaux concepts, de nouveaux défis en matière de sécurité et d'énormes difficultés en termes de stockage, d'analyse et de gestion des données. C'est pourquoi il est impératif de développer des réseaux électriques plus intelligents, plus résistants et plus efficaces, capables de fonctionner dans des conditions défavorables et de fournir les services requis en dépit de plusieurs défis.

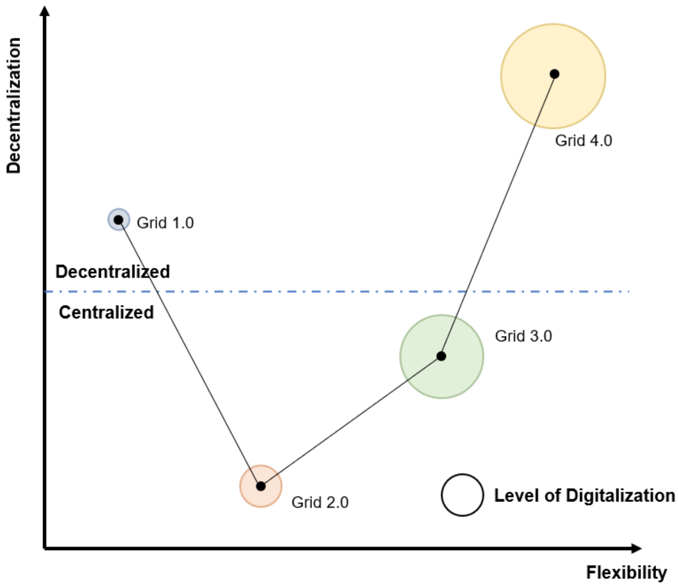

Figure 3. Évolution de la décentralisation et la numérisation des réseaux électriques.

Bien que l'intégration des REDs dans les réseaux électriques puisse être considérée comme la première étape vers une architecture décentralisée, le processus décisionnel et le contrôle des réseaux électriques restent centralisés. Il est donc essentiel de décentraliser les couches de communication, de contrôle et de données du réseau électrique pour compléter la décentralisation de l'infrastructure physique du réseau et atteindre en même temps une flexibilité, une résilience et une sécurité accrues. L'approche traditionnelle de la gestion centralisée des données ne répond pas aux exigences de sécurité et d'efficacité du stockage des données énergétiques en raison d'une protection insuffisante de la sécurité des données, d'un manque de cohérence, d'une traçabilité médiocre et d'une surveillance inadéquate des processus de partage des données [30]. Les réseaux de communication décentralisés améliorent la fiabilité du réseau en réduisant le risque de points de défaillance uniques et en permettant un échange de données plus robuste entre les composants du réseau. Les systèmes de contrôle décentralisés favorisent la prise de décision au niveau local, ce qui permet de réagir plus rapidement et plus efficacement aux modifications des conditions du réseau et d'en améliorer la stabilité globale. En outre, une couche de gestion décentralisée des données permet de collecter et d'analyser des données provenant de nombreuses sources, ce qui facilite la surveillance et l'optimisation en temps réel des opérations du réseau. Cette décentralisation multicouche garantit que le réseau peut s'adapter à la complexité et à la variabilité croissantes des systèmes énergétiques modernes, ce qui permet d'améliorer la résilience, l'efficacité et la durabilité.

L'objectif de cette thèse est de proposer un modèle qui permet une décentralisation complète du réseau électrique à partir de l'infrastructure jusqu'à la gestion des données et en passant par les modes de communication. Un réseau électrique interdépendant qu'on définit comme Énergie 4.0, basé sur un flux multidirectionnel d'énergie et de données. Cette thèse propose un nouveau concept inspiré de la chaîne de blocs et plus spécifiquement des organisations autonomes décentralisées (OADs). Contrairement aux organisations centralisées, les OADs n'ont pas d'autorité centrale et tous les membres participent à la prise de décision. Elles sont souvent alimentées par la technologie de chaîne de blocs et ont un niveau de sécurité relativement élevé [30,31]. Ainsi, le modèle proposé, dans cette thèse, est basé sur le concept de poste autonome décentralisée (PAD), où les sous-stations servent en tant que nœuds vitaux à la fois pour la transmission et la distribution de l'électricité dans un réseau électrique. Ils constituent des éléments d'infrastructure importants qui permettent un fonctionnement fiable, efficace et sûr des réseaux électriques. En explorant des applications et des mécanismes basés sur la technologie de chaîne de blocs et d'autres technologies avancées comme l'IA et l'IdO, le modèle proposé vise à accroître la flexibilité du système énergétique, de fournir des services complémentaires et d'augmenter la fiabilité et la sécurité du réseau. Cet objectif est atteint par la validation et le développement du modèle proposé en identifiant des applications possibles de la technologie de chaîne de blocs dans le secteur de l'énergie, simulant ces applications dans des scenarios différents, et analysant leurs implications techniques, environnementales et économiques sur les différentes parties prenantes (entreprise d'électricité, société de services publics, société de distribution et utilisateurs finaux). Plus précisément, cette thèse vise à atteindre les objectifs spécifiques suivants :

1. Répondre au défi de la gestion numérique complexe et de l'optimisation des REDs dans les réseaux électriques à travers un modèle de réseau Énergie 4.0 décentralisé intelligent et autonome, basé sur le concept de postes autonomes décentralisés.

2. Améliorer la résilience des réseaux électriques contre les pannes, cyberattaques, événements climatiques

3. Créer un écosystème ouvert d'offre et demande avec des prix négociables, basé sur le P2P pour combattre contre la volatilité des prix d'énergie.

4. Optimiser le choix des REDs pour réduire les prix, les pertes techniques et les émissions des GES.

5. Trouver un modèle de gestion de la demande qui permet de lutter contre l'effet rebond et l'effet du *free-rider* et limiter la croissance de la demande énergétique à long terme.

6. Contrôler et limiter la demande de pointe résultante de la charge non coordonnée des VEs.

1.4 MÉTHODOLOGIE ET PORTÉE DE LA RECHERCHE

La méthodologie scientifique adoptée dans la thèse vise à proposer et valider une architecture innovante pour le réseau électrique basée sur l'intégration de sous-stations autonomes décentralisées. Cette approche s'articule autour de plusieurs étapes complémentaires. Dans un premier temps, une analyse critique des architectures existantes a été réalisée pour identifier les limitations actuelles en termes de résilience, flexibilité, rentabilité et gestion décentralisée des flux énergétiques. Cette phase a permis de cadrer les enjeux techniques et économiques et de définir les objectifs spécifiques de la nouvelle architecture (sous-objectif 1 – Figure 2).

Dans un second temps, le cœur de la méthodologie repose sur l'introduction du modèle des postes autonomes décentralisées, ces fonctionnalités, ces avantages, ainsi que ces limitations (sous-objectif 2 – Figure 2).

En troisième lieu, le modèle proposé sera validé en testant plusieurs de ces fonctionnalités à travers des modèles numériques de simulation. Ces modèles ont été conçus pour simuler les modalités opérationnelles et les fonctionnalités des sous-stations autonomes décentralisées. La méthode de validation adoptée s'articule autour de trois axes stratégiques du réseau électrique: la résilience et la sécurité, l'optimisation de la production d'électricité, et la gestion efficace de la charge (sous-objectif 3 – Figure 2). Ces axes sont explorés de manière intégrée, en tenant compte des interactions complexes entre les dimensions économiques, énergétiques et environnementales. L'objectif est de proposer des solutions innovantes qui renforcent la capacité des réseaux à résister et à s'adapter aux perturbations, maximisent l'efficacité et la durabilité de la production d'énergie, et équilibrent l'offre et la demande en temps réel, tout en minimisant les impacts environnementaux et en favorisant une viabilité économique à long terme. Les modèles intègrent des scénarios réalistes de fonctionnement, tenant compte des contraintes telles que les variations de charge, les interruptions de service, et les cyber-risques, pour évaluer leur robustesse et leur adaptabilité.

Par ailleurs, des outils d'analyse quantitative ont été mobilisés pour mesurer les performances de plusieurs algorithmes de fonctionnement et d'optimisation de ces sous-stations en termes de résilience, de stabilité, d'efficacité énergétique et de réduction des coûts d'exploitation. Ces évaluations ont été confrontées à des normes de références issus de la littérature scientifique et à des simulations sur des réseaux de test standardisés pour valider les gains apportés par cette nouvelle architecture. Des méthodes qualitatives, telles que des études comparatives et des consultations avec des experts du domaine, ont également été employées pour enrichir l’analyse.

Enfin, la méthodologie inclut une réflexion systémique sur les impacts économiques et sociétaux de l’intégration de cette architecture. L’objectif final est de démontrer que l’adoption des sous-stations autonomes décentralisées peut contribuer de manière significative à relever les défis actuels des réseaux électriques, tels que l’intégration accrue des énergies renouvelables, la gestion de la demande en temps réel et l'amélioration de la résilience face aux événements extrêmes.

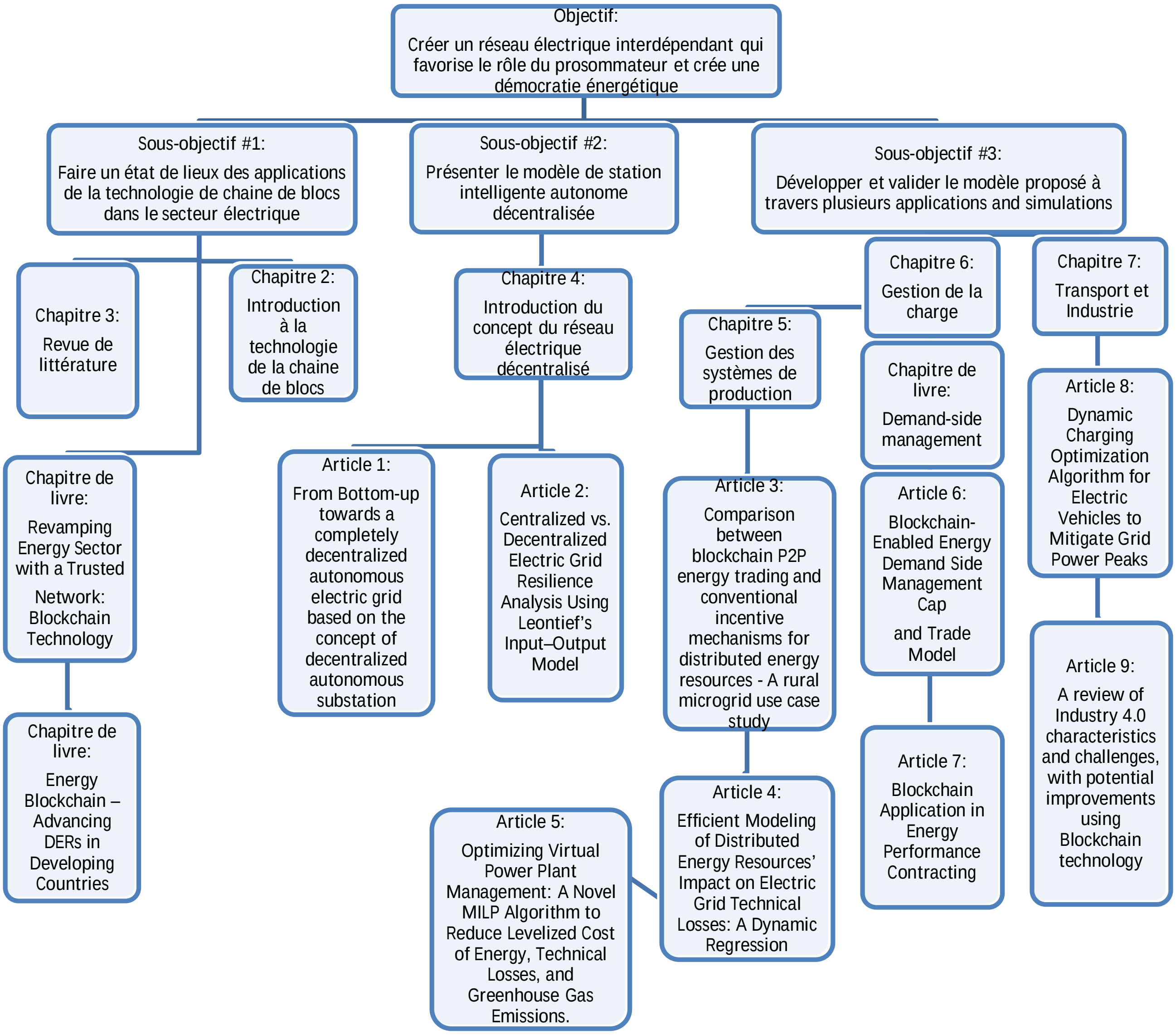

Figure 4. Structure de la thèse.

La structure de cette thèse est organisée en plusieurs chapitres, chacun visant à explorer une dimension clé de la problématique étudiée, en partant des fondements théoriques jusqu'aux résultats expérimentaux et aux perspectives.

Le chapitre 2 de la thèse présente les notions clés de la technologie de la chaine de blocs en commençant par une définition et un bref historique, suivis d'une explication du fonctionnement et de ses principales fonctionnalités. Il explore ensuite les architectures possibles, ainsi que les algorithmes de consensus distribué utilisés pour valider les transactions. Le concept de contrat intelligent est également abordé, avant de conclure par un aperçu des principales étapes du développement de cette technologie.

Le chapitre 3 explore l'application de la chaîne de blocs dans le secteur électrique, en commençant par une revue de la littérature synthétisant les recherches existantes. Il présente ensuite un chapitre de livre intitulé « *Revamping Energy Sector with a Trusted Network: Blockchain Technology* », qui examine l'application de la chaîne de blocs dans les réseaux électriques intelligents, en mettant en lumière les innovations technologiques, les avantages et les défis de son intégration. La deuxième partie de ce chapitre est un article intitulé « *Energy Blockchain – Advancing DERs in Developing Countries* » examine l'évolution des réseaux électriques vers des systèmes intelligents et bidirectionnels grâce aux REDs, tout en soulignant que dans les pays en développement, des obstacles économiques et sociaux freinent leur adoption. L'hypothèse de cet article est que l'intégration de la chaîne de blocs et des marchés P2P pourrait encourager les communautés à développer les REDs pour répondre à la demande d'énergie propre.

Le chapitre 4 traite de la transition vers un réseau électrique autonome décentralisé basé sur des sous-stations autonomes. Le premier article, intitulé « *From Bottom-Up Towards a Completely Decentralized Autonomous Electric Grid Based on the Concept of Decentralized Autonomous Substation* », explore l'intégration des REDs et propose un réseau entièrement décentralisé, utilisant la chaîne de blocs pour la gestion des données, pour une meilleure résilience et durabilité. Le second article, intitulé « *Centralized vs Decentralized Electric Grid Resilience Analysis Using Leontief's Input-Output Model* », compare la résilience des réseaux centralisés et décentralisés face aux perturbations. Les conclusions de l'article vont dans le sens que la décentralisation améliore la résilience et la sécurité des réseaux électriques.

Le chapitre 5 examine l'application de la chaîne de blocs et la décentralisation dans la production d'énergie électrique. Le premier article, intitulé « *Comparison Between*

Blockchain P2P Energy Trading and Conventional Incentive Mechanisms », compare le commerce d'énergie P2P basé sur la chaîne de blocs avec des mécanismes traditionnels comme le Net Metering, en montrant que la chaîne de blocs offre plus de flexibilité et de transparence dans les micro-réseaux ruraux. Le second article, intitulé « *Efficient Modeling of Distributed Energy Resources' Impact on Electrical Grid Technical Losses* », utilise un modèle de régression pour démontrer comment les REDs peuvent réduire les pertes techniques des réseaux électriques, offrant ainsi une gestion plus efficace des infrastructures.

Le chapitre 6 examine les applications et impacts de la chaîne de blocs et de la décentralisation dans la gestion de la charge énergétique. La première publication de ce chapitre, un chapitre de livre intitulé « *Demand Side Management* », aborde les défis de l'équilibre entre l'offre et la demande dans les réseaux électriques et compare différentes approches, notamment les systèmes de stockage et la gestion de la demande pour réduire la charge de pointe. La deuxième publication, intitulé « *Blockchain-Enabled Energy Demand Side Management Cap and Trade Model* », propose un modèle DSM basé sur la chaîne de blocs qui encourage les consommateurs à réduire leur consommation d'énergie en échange de crédits énergétiques échangeables via des transactions P2P. La troisième publication de ce chapitre, un article intitulé « *Blockchain Application in Energy Performance Contracting* », explore comment la chaîne de blocs et les contrats intelligents peuvent simplifier les CPE, réduire les coûts de transaction, et améliorer la confiance entre les parties, facilitant ainsi l'accès à ce mécanisme pour de plus petites entreprises et organisations.

Le chapitre 7 explore le rôle de la chaîne de blocs dans l'électrification du transport et de l'industrie. Le premier article, intitulé « *Dynamic Charging Optimization Algorithm for Electric Vehicles to Mitigate Grid Power Peaks* », se concentre sur les défis que pose la recharge non coordonnée des véhicules électriques (VE) pour le réseau électrique. Il propose un algorithme d'optimisation dynamique qui coordonne la recharge des VE pour réduire les pics de puissance du réseau tout en maintenant les temps de recharge optimaux. Le deuxième article, intitulé « *A Review of Industry 4.0 Characteristics and Challenges with Potential Improvement Using Blockchain Technology* », examine les similitudes entre l'Industrie 4.0

et la chaîne de blocs, en mettant en avant comment la chaîne de blocs peut améliorer la gestion des données, la connectivité et l'automatisation dans les usines intelligentes, où les systèmes autonomes et interconnectés sont au coeur de la prise de décision sans intervention humaine.

Les chapitres 7 et 8 comprenent respectivement les perspectives et la conclusion. Cette étape finale vise à synthétiser les résultats obtenus au cours des recherches et des analyses précédentes, en évaluant leur portée et leurs implications pratiques sur le réseau électrique. Les perspectives de la thèse mettront en lumière les opportunités futures pour l'intégration de notre modèle de réseau décentralisé autonome basé sur la technologie de chaîne de blocs, en identifiant les domaines nécessitant des recherches supplémentaires et les innovations potentielles. La conclusion résumera les principaux apports de la thèse, réaffirmant l'importance du modèle proposé pour améliorer l'efficacité énergétique, la résilience, la sécurité et la gestion des ressources du secteur électrique.

1.5 CONTRIBUTIONS

Les travaux menés, dans cette thèse, apportent de nouvelles connaissances et des solutions innovantes pour améliorer l'efficacité énergétique, la résilience et la sécurité du réseau électrique, ainsi que de nouvelles méthodologies pour optimiser la gestion des ressources, et réduire les coûts et les émissions de carbone. En détaillant ces contributions, cette section souligne l'impact potentiel de la recherche sur les pratiques industrielles et les politiques énergétiques, ouvrant la voie à une adoption plus large de systèmes énergétiques décentralisés, autonomes et intelligents. Les principaux domaines de contribution sont les suivants :

- Du point de vue théorique, cette étude propose un nouveau concept et une nouvelle conception pour la structure des réseaux électriques décentralisés qui permet au réseau de fonctionner dans des conditions défavorables et de fournir les services requis en dépit de plusieurs défis. Elle offre une nouvelle perspective aux chercheurs dans le domaine de la décentralisation et de la surveillance, du contrôle et de l'optimisation autonomes des futurs réseaux électriques et ouvre différentes directions de recherche vers le remodelage et le développement d'un nouveau concept de réseau électrique décentralisé inspiré par les DAO et basé sur les postes décentralisés autonomes qui servent de composants d'infrastructure importants qui permettent un fonctionnement fiable, efficace et sûr des réseaux électriques.

- Cette étude explore l'impact de la décentralisation des réseaux électriques du point de vue de la résilience. Le modèle mathématique proposé, basé sur le modèle entrée-sortie d'inopérabilité de Leontief, pour calculer la résilience du réseau électrique, offre une méthode relativement plus simple, plus rapide et plus facile à mettre en œuvre que les techniques conventionnelles.
- Cette thèse propose un nouveau mécanisme de facturation pour les REDs en utilisant un modèle d'échange d'énergie P2P basé sur la chaîne de blocs. La principale contribution de ce travail est qu'il offre une comparaison directe entre le mécanisme d'échange d'énergie P2P, NEM et FiT en termes de rentabilité pour les prosommateurs en utilisant différents indicateurs de performance clés (ICP) tels que la quantité totale d'énergie excédentaire non rémunérée et les revenus financiers provenant de l'énergie échangée.
- Cette thèse propose un nouveau programme de gestion de la demande basé sur la technologie de chaîne de blocs, le commerce d'énergie P2P et le concept de plafonnement et d'échange, couramment désigné par l'expression anglaise « *Cap and Trade* », précédemment appliqué au marché des émissions de carbone. Le modèle présenté, testé et validé, minimise les effets de parasitisme et de rebond auxquels sont généralement confrontés les programmes conventionnels de DSM. Il est fondamentalement basé sur l'intégration des consommateurs en tant que principales parties prenantes dans le processus d'approvisionnement et de fourniture d'énergie. Il récompense les consommateurs efficaces et pénalise les gros consommateurs. En outre, il crée un marché ouvert pour le commerce de l'énergie basé sur le commerce

de l'énergie P2P. Les prix ne sont pas contrôlés par une entité centrale, mais sont plutôt régis par les règles générales d'une offre et d'une demande déréglementées.

- Cette étude introduit une équation de régression polynomiale dynamique avec des coefficients variables pour évaluer l'impact de l'intégration des REDs en différents points du réseau électrique, sur les pertes techniques du réseau en tenant en compte la puissance des REDs, la charge connectée et l'impédance totale au point concerné. Ce modèle de régression dynamique offre une approche rapide et directe de l'évaluation de ces réductions, en remplacement des méthodologies traditionnelles.
- Cette thèse apporte une contribution significative en présentant un algorithme dynamique d'optimisation de la charge des véhicules électriques, conçu pour éviter les nouvelles pointes de charge causées par la recharge non coordonnée simultanée. L'algorithme proposé ajuste en temps réel les plages horaires de recharge en fonction des prévisions de la demande énergétique et de la capacité du réseau, tout en prenant en compte les préférences des utilisateurs et les caractéristiques des véhicules. En répartissant de manière intelligente les cycles de charge, cet algorithme réduit les risques de surcharge du réseau et améliore la stabilité globale du système électrique. Cette approche innovante favorise une utilisation plus efficace des ressources énergétiques existantes, minimisant ainsi la nécessité d'investissements coûteux dans l'infrastructure de réseau et contribuant à une gestion plus durable de l'énergie.
- Cette thèse vise à ouvrir de nouveaux horizons sur le potentiel de la technologie de chaine de blocs en tant qu'outil d'automatisation pour la 4e industrie en examinant les fondamentaux de l'industrie 4.0, ses défis, ses obstacles et ses limites, ainsi qu'en explorant les domaines où la technologie de la chaîne de blocs peut apporter de nouvelles fonctionnalités et ajouter de la valeur au déploiement de l'industrie 4.0.
- Cette thèse présente un prototype de contrat de performance énergétique (CPE) basé sur la chaîne de blocs. La méthodologie est basée sur l'intégration de la chaîne de blocs et des contrats intelligents dans le processus CPE en collectant les données des mesures d'économie d'énergie mises en œuvre, en calculant les économies d'énergie, en gérant les paiements et en imposant des pénalités. Une fois que les processus de

mesure et vérification (M&V) sont terminés et que les exigences du contrat sont satisfaites, le contrat intelligent libère automatiquement le paiement du portefeuille électronique de l'hôte à la société de services énergétiques.

CHAPITRE 2
LA TECHNOLOGIE DE CHAÎNES DE BLOCS

2.1 INTRODUCTION

La chaîne de blocs (*blockchain*), est une technologie révolutionnaire qui promet de transformer de nombreux secteurs en offrant une méthode sécurisée, transparente et décentralisée, de stocker et de transférer des données. Ce chapitre explore les fondements de la chaîne de blocs, son fonctionnement, ses types, ses applications, ses avantages et ses inconvénients, ainsi que les enjeux de sécurité et de réglementation.

La technologie de la chaîne de blocs a été popularisée en 2008 comme la technologie sous-jacente du Bitcoin, la première monnaie cryptographique, et depuis, elle a évolué pour trouver des applications dans de nombreux autres domaines, allant des finances aux chaînes d'approvisionnement, en passant par la santé et le secteur public. Cette technologie repose sur un registre distribué, partagé parmi tous les participants d'un réseau, qui enregistre toutes les transactions de manière sécurisée et immuable [32]. Le Bitcoin est une monnaie numérique décentralisée qui utilise un réseau pair-à-pair (P2P) pour réaliser des transactions de jetons entre les participants sans l'intervention d'intermédiaires tiers ou d'institutions financières. En règle générale, un tel intermédiaire serait nécessaire pour garantir l'intégrité du contenu du réseau et veiller à ce que les jetons ne soient pas dépensés plus d'une fois [33]. Par conséquent, le Bitcoin résout les problèmes de double dépense et le problème dit des généraux byzantins (maintenir le système fiable même en cas de défaillance d'un certain nombre de ses composants). Il parvient ainsi à remplacer l'intermédiaire par une preuve cryptographique [34]. Cependant, le livre blanc de Satoshi Nakamoto publié en 2008 [35] et introduisant le réseau de Bitcoin, ne cite pas textuellement le mot *blockchain*, mais fait référence à des expressions pertinentes telles que « les blocs sont enchaînés » (*blocks are chained*) ou « chaîne de blocs » (*chain of blocks*). D’autre part, l'idée générale de la vérification des données par horodatage est liée au document de 1991 "How to Time-Stamp a Digital Document" [36]. Le terme "*blockchain*" remonte même à 1976, cité dans le document de brevet d'IBM "Message verification and transmission error detection by block chaining" [37].

Cependant, la chaine de blocs ne peut exister sans un réseau d'internet fiable, distribué, et utilisé par un grand nombre de personnes. À ses débuts, dans les années 1960, l'internet était un réseau simple et relativement petit, principalement utilisé par les chercheurs universitaires et le gouvernement américain pour partager des informations sous forme numérique. Au fil du temps, les pionniers de l'internet ont rendu le système plus utilisable. Les impacts les plus importants sont venus du développement de Transmission Control Protocol/Internet Protocol (TCP/IP), qui a établi une norme de communication, de Hypertext Transfer Protocol (HTTP), qui a permis la navigation sur le web, et de Simple Mail Transfer Protocol (SMTP), qui a permis la distribution du courrier électronique. Ces protocoles ont rendu l'internet accessible non seulement aux chercheurs, mais à tout le monde, et sur un nombre croissant d'appareils, y compris les ordinateurs et, plus tard, les tablettes et les smartphones. L'évolution de l'internet a changé la vie pour toujours : des quantités incroyables d'informations et de services sont désormais disponibles aux utilisateurs. Cependant, l'utilisation de la plupart des produits ou services en ligne nécessite qu'une personne ou une entité, appelée « tiers », joue le rôle de gardien de confiance. Ces systèmes requièrent deux types de confiance : La confiance intermédiaire, un tiers est chargé de prendre des décisions rationnelles et équitables, et la confiance dans l'émission, on compte sur un tiers pour garantir la sûreté et la sécurité d'une valeur.

Les transactions financières sont l'un des principaux domaines où l'on se fie à cette confiance, puisque la plupart des échanges monétaires sont devenues numériques. Pour diverses raisons, l'utilisation de la monnaie fiduciaire, ou de l'argent liquide sont en déclin. Les gens utilisent aujourd'hui plus que jamais des outils financiers électroniques tels que les cartes de débit et de crédit. Dans les pays développés, les systèmes de paiement sont presque entièrement électroniques, la plupart des clients utilisant des smartphones et des cartes aux points de vente. Si, pour les consommateurs, le passage d'interfaces de paiement physiques à des interfaces numériques est une tendance relativement récente, les systèmes qui alimentent cette comptabilité sont depuis longtemps électroniques. Bien que la plupart des gens puissent encore se procurer de l'argent liquide, l'argent est passé du papier et des pièces de monnaie à de simples chiffres dans un système informatique. Lorsque la valeur passe d'un objet physique à une base de données, il doit y avoir un élément de confiance entre les différentes parties concernées. D'énormes sociétés de paiement ont été créées dans le monde entier sur la base de l'idée que les personnes qui stockent de la valeur numériquement peuvent faire confiance à ces marques. Cependant, la confiance n'a pas toujours été un facteur fiable dans la finance. En fait, la crise financière de 2008 a fait réfléchir les gens, et beaucoup ont commencé à penser que la confiance aveugle et la foi dans les institutions financières n'étaient peut-être pas ce qu'elles étaient censées être [38].

La chaine de blocs vise à créer une confiance numérique, basée sur des modèles et algorithmes mathématiques [39]. Elle utilise la technologie, en particulier la cryptographie, pour automatiser et renforcer la confiance entre les pairs sans besoin d’un tiers. Bitcoin a été le premier système fonctionnel à utiliser une chaine de blocs. Mais avant que Bitcoin n'existe, plusieurs prédécesseurs ont essayé et échoué de créer des concepts similaires. L'une des principales raisons de leur échec était l'incapacité à mettre en place un système véritablement distribué sur l'internet. L'internet d'aujourd'hui est un mélange d'applications centralisées et distribuées, bien qu'il ait été conçu comme une technologie distribuée. Plutôt que de construire une structure centralisée avec un seul point de défaillance, les premiers architectes de l'internet voulaient créer un système plus résistant. L'idée d'un internet distribué est née de l'objectif (inspiré par les militaires) de s'assurer que si une partie du système était attaquée, elle pourrait toujours fonctionner si elle était correctement distribuée [40]. Le premier internet, nommé APRANET, tel qu'il a été conçu il y a plusieurs décennies, était distribué de manière à protéger le réseau de tout type de perturbation, et ce système a fait ses preuves jusqu'à aujourd'hui. Plus récemment, des entreprises centralisées telles que Google, Facebook, Apple et Amazon ont fini par dominer largement l'internet. Certains espèrent que la nature distribuée de la technologie de chaine de blocs pourrait contribuer à atténuer la domination du web par ces quelques entreprises puissantes en donnant plus de contrôle aux utilisateurs individuels.

Dans le domaine de l'informatique, un système distribué est un système dans lequel le traitement n'est pas effectué uniquement sur un seul ordinateur. Au contraire, les calculs sont partagés entre plusieurs ressources informatiques. Ces systèmes communiquent entre eux à l'aide d'une certaine forme de messagerie. La Figure 5 illustre les trois modèles principaux de réseaux. Un système distribué présente des caractéristiques de décentralisation, en ce sens que la défaillance d'une seule entité (ou nœud) n'entraîne pas la défaillance de l'ensemble du réseau. L'objectif commun est d'utiliser la puissance de traitement pour accomplir collectivement une tâche en répartissant les responsabilités entre de nombreux ordinateurs ou nœuds. Dans un système entièrement décentralisé, un nœud donné ne collabore pas nécessairement avec tous les autres nœuds pour atteindre son objectif, et la prise de décision se fait par le biais d'une forme de consensus plutôt que de laisser cette responsabilité entre les mains d'une seule entité.

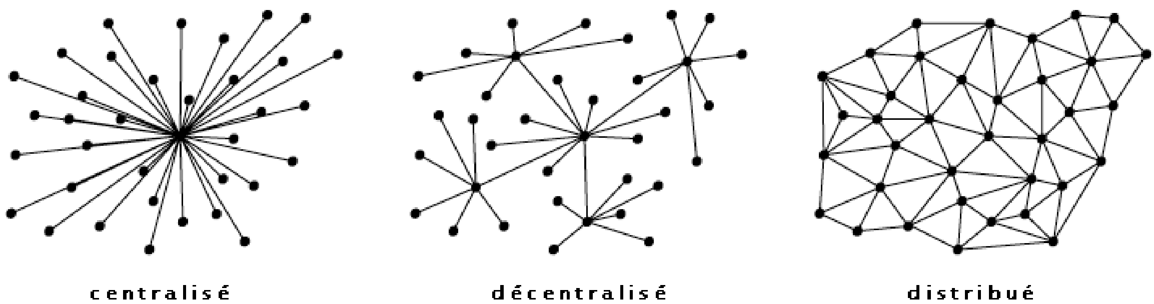

Figure 5. Les trois types de réseaux

Le monde de la technologie est en perpétuelle évolution et le découplage de l'évolution de la chaîne de blocs de l'évolution de l'internet est presque impossible. En effet, la chaîne de blocs a émergé comme une technologie clé parallèlement à ces évolutions, influençant et étant influencée par les différentes phases de développement du web. L'émergence de la technologie de chaine de blocs a propulsé le Web 3.0 à un autre niveau. Bien qu'elle soit souvent considérée à tort comme un synonyme du Web 3.0, la chaine de blocs est la technologie fondamentale qui facilite le web décentralisé, mieux connu sous le nom de Web 3.0, et qui modifie la dynamique de base de la version actuelle du web.

2.2 DÉFINITION ET HISTORIQUE

2.2.1 L'Évolution de l'Internet : Du Web 1.0 au Web 3.0

L'évolution de l'internet, depuis ses débuts jusqu'à nos jours, a connu trois grandes phases que l'on peut résumer par les termes Web 1.0, Web 2.0 et Web 3.0 [41]. Chaque phase a apporté des changements fondamentaux dans la manière dont les utilisateurs interagissent avec le web, créant de nouvelles opportunités et des défis uniques.

• Web 1.0 : Les Origines de l'Internet (1991-2004)

Le Web 1.0, souvent appelé le web statique, a marqué les débuts de l'internet. Cette phase, qui s'étend des années 1990 au début des années 2000, se caractérise par des pages web statiques, essentiellement constituées de texte et d'images, avec très peu d'interaction utilisateur. Les pages étaient principalement des documents Hypertext Markup Language (HTML) simples, souvent reliés entre eux par des hyperliens [42].

Les utilisateurs consommaient principalement des informations sans possibilité d'interagir ou de modifier le contenu. D’autre part, les entreprises et les particuliers créaient des sites pour partager des informations, souvent sous forme de pages à propos, de descriptions de produits et de contacts. Tandis que les moteurs de recherche étaient basiques et souvent manuels, avec des annuaires comme Yahoo! Directory permettant de trouver des sites web pertinents. Le web 1.0 reposait sur des technologies comme HTML, HTTP et des navigateurs web rudimentaires tels que Netscape Navigator et les premières versions d’Internet Explorer.

• Web 2.0 : L'Internet Social et Interactif (2004-présent)

L'avènement du Web 2.0 au milieu des années 2000 a transformé l'internet en une plateforme interactive et sociale. Ce changement a été impulsé par des technologies permettant aux utilisateurs de créer, partager et interagir avec du contenu en ligne de manière beaucoup plus dynamique et participative. Avec le Web 2.0, les utilisateurs ne se contentent plus de consommer du contenu ; ils en créent également. Les blogues, les forums, et plus tard, les réseaux sociaux deviennent des espaces où chacun peut publier et échanger [43]. L'usage massif de technologies telles qu'AJAX, JavaScript, et les bases de données dynamiques permettent des interactions en temps réel sans recharger la page. En plus les plateformes comme Facebook, Twitter, et YouTube ont explosé, offrant des moyens nouveaux et puissants pour les gens de se connecter et de partager des expériences. En outre, le Web 2.0 a facilité l'économie de partage et le Crowdsourcing [44]. Des services comme Wikipedia, Uber, et Airbnb montrent comment des informations et des ressources peuvent être partagées et optimisées collectivement et avec l'essor des smartphones et des applications mobiles, l'accès à l'internet devient omniprésent, permettant une connexion constante et une interaction fluide à tout moment et en tout lieu.

Le Web 2.0 a transformé la manière dont nous communiquons, collaborons et faisons des affaires. Il a permis la création de nouvelles formes d'expression et de communautés en ligne, tout en changeant les dynamiques économiques à travers des modèles comme le freemium et la publicité en ligne. La démocratisation de la publication et de la consommation de contenu a également mis en lumière des questions de confidentialité, de sécurité et de gestion des données.

• Web 3.0 : L'Internet intelligent et Décentralisé (en développement)

Le Web 3.0, souvent désigné comme le web sémantique ou le web décentralisé [45], est la prochaine évolution prévue de l'internet. Cette évolution vise à rendre le web plus intelligent et plus interconnecté, grâce à l'utilisation de technologies avancées comme l'IA, la î et l'IdO. Le web 3.0 utilise des technologies pour comprendre le sens et le contexte des données, permettant une recherche et une interaction plus intelligente. Cela inclut des standards comme Resource Description Framework (RDF), Ontology Web Language (OWL) et SPARQL pour structurer les données. L'IA et l'apprentissage automatique permettent des expériences personnalisées et des services automatisés, offrant des recommandations et des interactions beaucoup plus sophistiquées. De son côté, l'utilisation de la chaîne de blocs permet de créer des applications décentralisées (dApps) et des transactions sécurisées sans besoin d'intermédiaires, promettant plus de transparence et de contrôle pour les utilisateurs. En plus, l'intégration des appareils connectés à l'internet, connu sous l'IdO, permet une communication et une coordination sans précédent entre les objets physiques et le web, créant un écosystème numérique intégré.

Le web 3.0 favorise l'interopérabilité entre différents systèmes et plateformes, ainsi que la distribution des données à travers des réseaux P2P, réduisant la dépendance aux serveurs centraux [46]. Le Web 3.0 promet une plus grande autonomie pour les utilisateurs, avec des services plus intelligents et personnalisés. Les avantages incluent une sécurité accrue, une confidentialité améliorée et une diminution des monopoles technologiques. Cependant, cette évolution soulève également des défis, notamment en termes de scalabilité des technologies de chaîne de blocs, de gouvernance décentralisée et d'intégration des normes sémantiques à grande échelle.

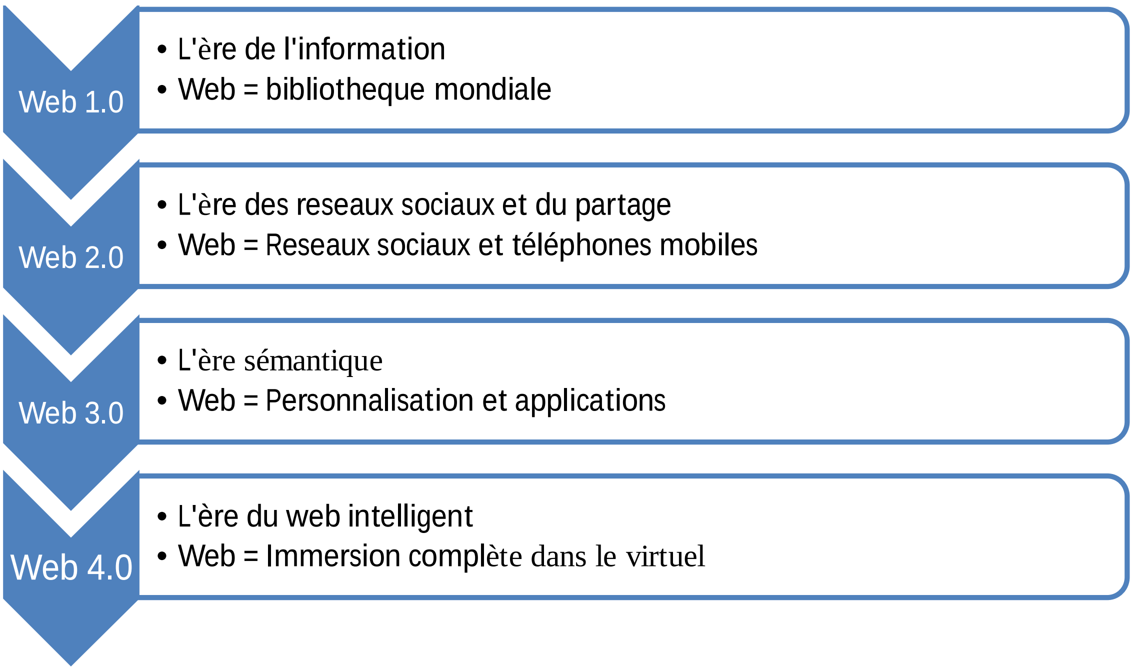

Figure 6. L'évolution de l'internet du Web 1.0 au Web 4.0

Aujourd'hui on commence de parler de la quatrième génération de l'internet, le Web 4.0. Le Web 4.0, souvent appelé "Web symbiotique" ou "Web intelligent" [47], représente une vision futuriste de l'internet où les interactions entre les utilisateurs et les machines deviennent plus fluides et intégrées. Tandis que le Web 3.0 se concentre sur l'intelligence artificielle, le web sémantique et la décentralisation, le Web 4.0 promet d'aller encore plus loin en intégrant les avancées technologiques de manière symbiotique dans notre quotidien. Le Web 4.0 exploitera des IAs extrêmement avancées qui ne se contenteront pas seulement de répondre aux demandes des utilisateurs, mais pourront anticiper leurs besoins et comportements. Les IAs du Web 4.0 seront capables de comprendre des contextes complexes, des émotions et des intentions, offrant des interactions quasi humaines. L'IdO deviendra omniprésent, où tous les appareils, des réfrigérateurs aux voitures, seront connectés et communicants, permettant une automatisation complète et une interaction transparente entre les objets et les utilisateurs. Les interfaces utilisateur deviendront plus intuitives et naturelles, incluant la réalité augmentée (RA), la réalité virtuelle (RV) et les interfaces cérébrales informatiques (ICI) [48]. Les utilisateurs pourront interagir avec le web et les machines par la pensée, la voix et les gestes, rendant l'expérience plus immersive. Le Web 4.0 sera capable de détecter et de répondre aux émotions humaines, ajustant ses réponses en fonction de l'état émotionnel de l'utilisateur, permettant des interactions plus personnalisées et empathiques. Les services web seront ultra-personnalisés grâce à l'analyse de grandes quantités de données et à l'apprentissage profond, offrant des expériences adaptées aux préférences et aux besoins individuels. La sécurité des données et la confidentialité seront renforcées avec des technologies avancées de cryptage et de gestion des identités, permettant aux utilisateurs de contrôler leurs données. L'interopérabilité et l'intégration globale des systèmes et des plateformes faciliteront des écosystèmes numériques où les données et les services circulent librement et efficacement. Toutefois, cette vision comporte des défis significatifs, notamment en matière d'éthique, de régulation, de dépendance technologique, d'inégalités numériques et de protection des données. Le Web 4.0 représente l'avenir de l'internet, où les technologies deviendront intégrées de manière symbiotique dans nos vies, transformant radicalement notre manière de vivre et d'interagir avec la technologie.

2.2.2 DÉFINITION DE LA CHAINE DE BLOCS

La chaîne de blocs est une technologie de stockage et de transmission d'informations de manière sécurisée et transparente, fonctionnant sans entité centrale de contrôle. Elle se compose de blocs de données liés et sécurisés par cryptographie, chaque bloc contenant un enregistrement des transactions effectuées. La décentralisation et l'immutabilité sont des caractéristiques clés de la chaîne de blocs, permettant aux utilisateurs de vérifier et de valider les informations sans avoir besoin d'intermédiaires. Cette technologie trouve des applications dans divers domaines, notamment les crypto-monnaies, la finance décentralisée (Decentralized Finance, DeFi), la gestion des chaînes d'approvisionnement et la sécurité des données.

Cette technologie est souvent décrite comme une infrastructure sous-jacente qui existe en parallèle du World Wide Web sur l'internet. Contrairement aux sites web et aux services traditionnels du Web 2.0 qui reposent sur une architecture centralisée avec des serveurs contrôlés par des entités spécifiques, la chaine de blocs fonctionne sur un réseau décentralisé où chaque nœud participe à la validation et au maintien des données. Cette technologie repose sur des protocoles cryptographiques avancés pour sécuriser les transactions et les enregistrements, formant ainsi une structure résistante à la censure et à la manipulation. En intégrant la transparence, l'immuabilité et la confiance au sein de ses principes fondamentaux, la chaîne de blocs offre une alternative novatrice à l'infrastructure centralisée du Web 2.0, ouvrant la voie à de nouvelles applications telles que les crypto-monnaies, les contrats intelligents et la gestion sécurisée des données sensibles.

Dans le paysage dynamique des technologies numériques, la chaine de blocs et la *Distributed Ledger Technology* (DLT) émergent comme des piliers essentiels de l'innovation. La chaîne de blocs, en particulier, se distingue comme une forme spécifique de DLT qui utilise une structure de chaîne de blocs pour sécuriser et enregistrer de manière chronologique les transactions. Chaque bloc dans une chaîne de blocs contient des données et un hachage cryptographique du bloc précédent, garantissant l'intégrité et la traçabilité des informations.

Donc la chaine de blocs est un registre distribué de données qui ressemble à un livre et chaque bloc est considéré comme une page de ce livre. Chaque page (ou bloc) dans ce livre contient plusieurs entrées, qui sont comme des transactions. Chaque transaction représente une inscription spécifique dans le livre. Par exemple, une transaction pourrait être l'enregistrement d'un achat en ligne, indiquant qui a acheté quoi et à quel prix. Chaque page (bloc) est ajoutée au livre (*blockchain*) de manière chronologique et est liée à la page précédente par une référence cryptographique, un peu comme une numérotation continue de pages dans un livre. Chaque fois qu'une nouvelle transaction est effectuée, elle est ajoutée comme une nouvelle entrée sur la page actuelle du livre (bloc), créant ainsi une trace chronologique immuable de toutes les transactions qui ont eu lieu. De cette manière, la chaîne de blocs agit comme un registre comptable numérique, garantissant la transparence, la sécurité et l'intégrité des données enregistrées. Cette technologie trouve des applications dans divers secteurs, de la finance décentralisée aux systèmes de traçabilité et de gouvernance numérique.

En revanche, la DLT, dans son ensemble, englobe une gamme plus large de technologies de registres distribués qui ne sont pas limitées à l'utilisation de blocs. Elle peut utiliser diverses structures de données pour enregistrer et valider les transactions. La DLT peut inclure des technologies comme les registres distribués basés sur les graphes, les bases de données distribuées sans chaînes de blocs, et d'autres systèmes de gestion de données distribuées, offrant une flexibilité pour répondre aux besoins spécifiques de gestion des données dans des contextes variés comme la gestion de la chaîne d'approvisionnement et les registres de propriété. Donc, la chaine de blocs se concentre sur la sécurité et la transparence grâce à une structure de blocs, tandis que la DLT explore des approches diversifiées pour sécuriser et synchroniser les informations à travers des réseaux décentralisés, propulsant ainsi l'innovation dans la manière dont nous enregistrons, partageons et gérons les données à l'ère numérique.

Historiquement, les bases de données permettaient des échanges d'informations, permettant la diffusion rapide de données à travers le monde. Cependant, avec l'avènement de la chaine de blocs, cette dynamique évolue vers la gestion et le transfert sécurisé d'actifs numériques. Grâce à des protocoles cryptographiques avancés, la chaîne de blocs permet de tokeniser des actifs physiques et numériques, qu'il s'agisse de crypto-monnaies, de titres financiers, de propriétés intellectuelles ou de biens immobiliers. Ces actifs tokenisés peuvent être échangés de manière sécurisée et transparente sans nécessiter d'intermédiaires traditionnels, réduisant ainsi les coûts et les délais associés aux transactions. En fournissant une trace immuable et vérifiable de la propriété et des transferts, la chaine de blocs renforce la confiance et l'efficacité dans les transactions économiques. Cette transformation permet de créer un nouvel écosystème où la valeur, sous diverses formes, peut circuler aussi librement et rapidement que l'information, redéfinissant ainsi les fondamentaux économiques et ouvrant la voie à de nouvelles opportunités et modèles commerciaux dans le monde numérique.

La tokenisation consiste à représenter un actif, qu'il soit tangible (comme un bien immobilier ou une œuvre d'art) ou intangible (comme des actions ou des droits de propriété intellectuelle), sous forme de jetons numériques sur une chaîne de blocs. Elle offre de nombreux avantages, notamment une liquidité accrue, une transparence améliorée, et une accessibilité élargie, tout en assurant la sécurité et l'efficacité des transactions grâce à la technologie de la chaîne de blocs. La tokenisation permet de diviser un actif en parts plus petites, rendant ainsi possible la possession fractionnée. Par exemple, un bien immobilier d'une valeur élevée peut être fractionné en plusieurs jetons, permettant à plusieurs personnes d'en posséder une part. Les jetons peuvent être échangés plus facilement que les actifs traditionnels, augmentant ainsi la liquidité. Les transactions de jetons sont souvent plus rapides et moins coûteuses que les transactions traditionnelles, car elles éliminent le besoin d'intermédiaires.

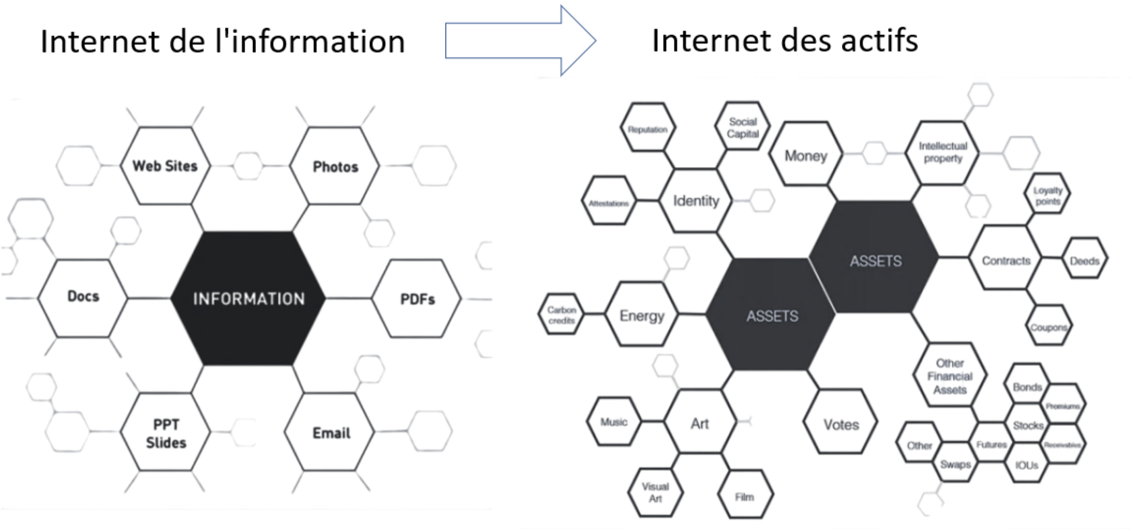

Figure 7. Internet de l’information vs Internet des actifs

2.2.3 LES PRÉDÉCESSEURS DE LA CHAINE DE BLOCS

La chaine de blocs est en réalité un assemblage de plusieurs technologies préexistantes. Satoshi Nakamoto n'a pas inventé des ingrédients, mais plutôt préparé une recette. La chaîne de blocs n’est pas donc une invention, mais une innovation en sorte. Cette technologie repose sur des concepts antérieurs tels que la cryptographie, les bases de données distribuées et les réseaux P2P. Ce qui rend la chaîne de blocs novatrice, c'est sa combinaison ingénieuse de ces éléments pour créer un système décentralisé, sécurisé et transparent. Nakamoto, l'auteur du célèbre article sur Bitcoin, a introduit un cadre technologique permettant de résoudre le problème de la double dépense sans avoir besoin d'une autorité centrale de confiance. Ainsi, la chaine de blocs est à la fois un héritage des innovations passées et une avancée significative dans la manière dont les transactions et les données peuvent être gérées numériquement, sans intermédiaires et avec une confiance renforcée.

La proposition de Bitcoin comportait un certain nombre d'idées tirées des systèmes qui l'ont précédée. Il s'agit notamment de :

• Contrats intelligents : Les contrats intelligents, un concept révolutionnaire en cryptographie et en informatique, ont été introduits par le cryptographe et informaticien Nick Szabo dans les années 1990. Ces contrats, également connus sous le nom de « *smart contracts* », visent à automatiser et à sécuriser les transactions en ligne sans nécessiter d'intermédiaires [49].

• Réseaux P2P : Les réseaux P2P ont vu leur première apparition significative avec le développement du protocole Napster à la fin des années 1990. Conçu par Shawn Fanning, Napster était une plateforme révolutionnaire permettant aux utilisateurs de partager des fichiers musicaux directement entre eux, sans passer par des serveurs centraux. Ce modèle décentralisé a ouvert la voie à une nouvelle ère de partage de contenu en ligne, inaugurant une approche où chaque utilisateur agit à la fois comme consommateur et fournisseur de contenu [50].

• L'utilisation de la cryptographie pour sécuriser les transactions, comme dans DigiCash : Digicash est l'une des premières entreprises à avoir développé et mis en œuvre une monnaie numérique utilisant des techniques cryptographiques pour sécuriser les transactions. Fondée par le cryptographe David Chaum en 1989, Digicash visait à offrir un moyen de paiement électronique anonyme et sécurisé [51].

• La possibilité théorique d'envoyer de petites quantités de valeur sécurisée, comme l'a fait E-gold. E-Gold était une monnaie électronique basée sur l'or, créée en 1996 par Douglas Jackson et Barry Downey. C'était l'une des premières formes de monnaie numérique, permettant aux utilisateurs d'effectuer des transactions en ligne en utilisant l'or comme valeur sous-jacente [52].

• La création d'argent en dehors des systèmes gouvernementaux, comme l'a proposé B-Money : B-Money est un concept de monnaie numérique décentralisée proposé par le cryptographe Wei Dai en 1998. Bien que B-Money n'ait jamais été implémenté, il est reconnu pour avoir posé les bases conceptuelles de ce qui deviendrait plus tard Bitcoin et d'autres cryptomonnaies. Wei Dai a imaginé une monnaie électronique qui permettrait des transactions anonymes sans avoir besoin d'une autorité centrale. Les participants au réseau B-Money utiliseraient des pseudonymes pour effectuer des transactions, garantissant ainsi la confidentialité des utilisateurs. B-Money proposait une base de données distribuée où chaque participant maintiendrait un registre des soldes des comptes. Ce concept est similaire à la chaîne de blocs utilisée dans Bitcoin, où chaque nœud du réseau maintient une copie du grand livre des transactions [53].

• L'utilisation de la preuve de travail : La preuve de travail (Proof of Work, PoW) est un concept fondamental en cryptographie et en informatique, largement reconnu pour son rôle central dans les cryptomonnaies comme Bitcoin. Cependant, ses origines remontent bien avant l'avènement des cryptomonnaies. Le concept de preuve de travail a été introduit pour la première fois par Cynthia Dwork et Moni Naor dans un article publié en 1993 intitulé "Pricing via Processing or Combatting Junk Mail" [54]. Dans cet article, Dwork et Naor proposaient d'utiliser des calculs informatiques comme une forme de "caution" pour contrer le spam et les abus de services en ligne. L'idée était que les utilisateurs devaient résoudre un problème mathématique difficile, mais faisable avant d'envoyer un courriel, rendant ainsi coûteux l'envoi de courriels massifs indésirables. En 1997, Adam Back a développé le système Hashcash, qui est l'une des premières implémentations pratiques de la preuve de travail [55]. Hashcash était conçu pour lutter contre le spam en obligeant les expéditeurs de courriels à effectuer un calcul qui prouve qu'ils ont consacré une certaine quantité de puissance de calcul. Ce calcul impliquait de trouver un hash (résultat d'une fonction de hachage cryptographique) qui répondait à certains critères, un concept qui deviendrait crucial dans les cryptomonnaies.

• Hachage : Une sortie de longueur fixe est produite afin que des données de tailles et de séquences différentes puissent être organisées. Une fonction de hachage cryptographique est un algorithme qui prend une quantité arbitraire de données en entrée et produit en sortie un texte chiffré de taille fixe appelé valeur de hachage, ou simplement "hachage". L'algorithme de hachage cryptographique a été conceptualisé dans les années 1970 avec la montée des préoccupations concernant la sécurité des données numériques. Le hachage cryptographique permet de transformer des données de longueur variable en une empreinte (ou "digest") de longueur fixe, qui est unique à chaque ensemble de données. Cela signifie que toute modification des données entraînera une empreinte complètement différente, ce qui est crucial pour détecter les altérations. En 1993, le National Institute of Standards and Technology (NIST) a publié le Secure Hash Algorithm (SHA), connu sous le nom de SHA-0. Cependant, en raison de vulnérabilités découvertes peu après sa publication, il a été rapidement remplacé par SHA-1 en 1995 [56]. Les algorithmes de la famille SHA ont été continuellement développés et améliorés, avec des versions plus sécurisées comme SHA-2 (publié en 2001) et SHA-3 (publié en 2015). Le SHA 256, utilisé dans la majorité des chaines de blocs, a été publié par le NIST en 2001 [57]. Il est l'un des algorithmes de hachage les plus largement utilisés aujourd'hui, offrant un niveau de sécurité élevé pour de nombreuses applications.

Le livre blanc du Bitcoin présentait également plusieurs concepts nouveaux et solutions, notamment :

• La double dépense : La double dépense est un problème potentiel pour toute monnaie numérique : elle se produit lorsqu'une unité de monnaie est dépensée plus d'une fois. Bitcoin, en tant que première cryptomonnaie décentralisée, a été spécifiquement conçu pour résoudre ce problème, grâce à un mécanisme ingénieux basé sur la technologie de la chaîne de blocs et la preuve de travail. La double dépense se produit lorsqu'un utilisateur essaie de dépenser la même unité de monnaie numérique dans deux transactions distinctes. Dans un système de monnaie numérique centralisé, une autorité centrale (comme une banque) vérifie chaque transaction pour éviter ce problème. Cependant, dans un système décentralisé comme Bitcoin, il n'y a pas d'autorité centrale pour vérifier les transactions, ce qui rend la prévention de la double dépense plus complexe. Bitcoin résout le problème de la double dépense en utilisant un registre public et distribué de toutes les transactions. Chaque transaction est enregistrée dans un bloc, et chaque bloc est lié au bloc précédent, formant une chaîne de blocs. Cette chaîne de blocs est maintenue par un réseau de nœuds (ordinateurs) décentralisés.

• Nonces : Un nombre aléatoire est utilisé pour s'assurer qu'une communication particulière ne peut être utilisée qu'une seule fois. Un "nonce" (contraction de "number once", soit "nombre utilisé une seule fois") est un élément crucial dans le domaine de la cryptographie et des technologies de chaîne de blocs. Elle joue un rôle essentiel dans la sécurisation des communications et la validation des transactions dans les réseaux décentralisés comme Bitcoin. Un nonce est un nombre arbitraire qui est utilisé une seule fois dans un protocole de communication cryptographique. Elle est souvent employée dans des processus nécessitant des éléments uniques et imprévisibles, comme les algorithmes de hachage dans la chaîne de blocs. Dans le contexte de la chaîne de blocs, en particulier avec Bitcoin, un nonce est utilisé dans le processus de minage. Les mineurs doivent trouver une valeur de nonce spécifique qui, lorsqu'elle est combinée avec les données du bloc (comme les transactions), produit un hachage satisfaisant les conditions de difficulté du réseau.

2.3 OPÉRATION ET FONCTIONNALITÉS

2.3.1 PROCESSUS DE CRÉATION D’UN BLOC

Une transaction dans une chaîne de blocs commence lorsque deux parties décident de transférer des actifs numériques ou des données. Chaque transaction est vérifiée par les participants du réseau d’une chaîne de blocs pour s'assurer de son authenticité et de sa validité. Une fois vérifiée, la transaction est regroupée avec d'autres transactions en attente pour former un nouveau bloc. La création d'un bloc commence par la collecte des transactions validées. Un mineur ou un valideur regroupe ces transactions dans un bloc candidat. Ensuite, le mineur résout un problème mathématique complexe, souvent en utilisant un algorithme de preuve de travail ou de preuve d'enjeu, pour trouver une solution valide. Cette solution est appelée "nonce" et est incluse dans le bloc pour prouver que le travail a été effectué. Une fois que la solution est trouvée, le bloc est diffusé à travers le réseau pour que les autres nœuds le valident. Lorsqu'une majorité de nœuds confirme la validité du bloc et accepte la solution de preuve de travail, le bloc est ajouté à la chaîne de blocs existante de manière permanente et immuable. Ce processus garantit la sécurité et l'intégrité des transactions en éliminant le risque de double dépense et en permettant un consensus décentralisé sur l'état de la chaîne de blocs.

Les transactions Bitcoin suivent un type de comptabilité unique appelé UTXO, qui signifie Unspent Transaction Output (sortie de transaction non dépensée). Une transaction est essentiellement constituée d'une liste d'entrées et d'une liste de sorties. Chaque entrée identifie une adresse Bitcoin qui sert de source de fonds, ainsi qu'une transaction non dépensée que cette adresse a reçue par le passé. Elle contient également une signature numérique prouvant que le propriétaire de cette adresse a autorisé la transaction. Chaque sortie identifie l'adresse Bitcoin qui recevra les fonds et le montant qu'elle recevra.

Le processus complet de transaction et de création de blocs dans une chaîne de blocs est détaillé ci-après :

• Initiation de la Transaction : Une transaction est initiée lorsque deux parties décident d'échanger des actifs numériques (comme des cryptomonnaies) ou des données (comme des contrats intelligents). Chaque transaction comprend des informations telles que l'expéditeur, le destinataire, le montant de l'actif, et d'autres métadonnées pertinentes.

• Validation de la Transaction : Avant d'être incluse dans un bloc, chaque transaction doit être vérifiée pour s'assurer qu'elle est valide et légitime. Les vérifications typiques incluent la vérification de la signature numérique de l'expéditeur pour prouver son autorisation, la vérification des fonds disponibles pour éviter la double dépense, et la conformité aux règles de la chaîne de blocs spécifique (comme les frais de transaction minimaux).

• Regroupement des Transactions : Une fois validée, la transaction est propagée à travers le réseau de chaîne de blocs où elle est temporairement stockée dans une file d'attente appelée "mempool". Les mineurs ou valideurs collectent ensuite plusieurs transactions de la mempool pour les regrouper dans un bloc.

• Création d'un Bloc Candidat : Pour créer un nouveau bloc, un mineur ou un valideur assemble un groupe de transactions valides dans un ordre spécifique. Ensuite, il calcule un hachage cryptographique pour ce bloc, qui inclut également le hachage du bloc précédent dans la chaîne.

• Résolution de la Preuve de Travail : Le processus de preuve de travail implique de résoudre un problème mathématique complexe qui nécessite une puissance de calcul considérable. Ce problème est généralement une fonction de hachage cryptographique dont la difficulté est ajustée par le réseau pour maintenir un rythme de création de blocs stable (par exemple, toutes les 10 minutes pour Bitcoin).

• Trouver la Nonce : Le mineur tente de trouver une "nonce" valide, un nombre aléatoire inclus dans le bloc, qui, lorsqu'il est combiné avec les données du bloc et le hachage du bloc précédent, produit un résultat de hachage satisfaisant les critères de difficulté fixés par le réseau.

• Validation et Diffusion du Bloc : Une fois que le mineur a trouvé une nonce valide et résolu le problème de preuve de travail, il diffuse le bloc proposé aux autres nœuds du réseau. Les autres nœuds vérifient la validité du bloc en recalculant le hachage et en s'assurant que toutes les transactions incluses respectent les règles du protocole.

• Consensus et Ajout à la chaîne de blocs : Si une majorité des nœuds valide le bloc proposé, il est accepté et ajouté à la chaîne de blocs existante de manière permanente. Chaque nouveau bloc contient un hachage du bloc précédent, formant ainsi une chaîne de blocs continue et immuable.

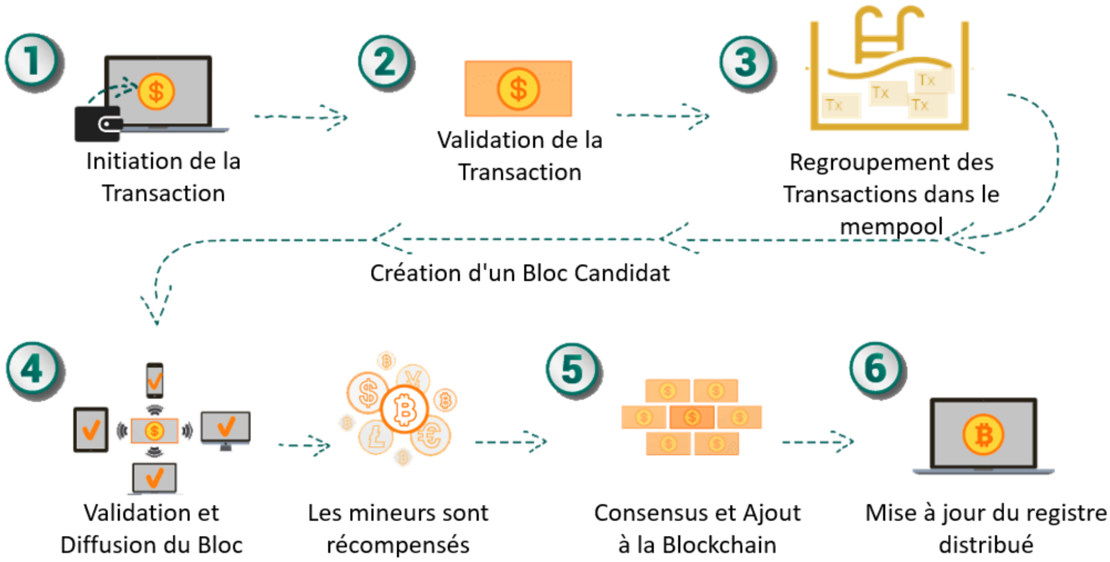

Figure 8. Processus de création d'un bloc

2.3.2 LA SÉCURITÉ DE LA TECHNOLOGIE CHAINE DE BLOCS

2.3.2.1 TRANSPARENCE VS CONFIDENTIALITÉ

La transparence est une qualité essentielle de la technologie de la chaîne de blocs. Toutefois, la coexistence entre la transparence et la confidentialité peut être mystifiante. La protection de la vie privée des utilisateurs est un défi pour les modèles d'affaires des entreprises modernes, notamment ceux qui cherchent à numériser leurs services. Par définition, la confidentialité est le droit de protéger les données, les attributs et les actifs d'une entité contre l'observation par des parties non consentantes. La confidentialité des données garantit que seules les parties autorisées peuvent y avoir accès. Dans les systèmes conventionnels, les données des utilisateurs risquent toujours d'être manipulées à mauvais escient. Dans le cas des géants des médias sociaux par exemple, une grande quantité d'informations personnelles, comme la localisation, l'historique des recherches, les applications utilisées, etc., sont stockées à l'insu des utilisateurs finaux ou sans qu'ils en aient conscience et sans leur permission. Ces données sont principalement utilisées par ces entreprises pour vendre des publicités ciblées, ce qui représente leur principale source de revenus. De plus, l'architecture actuelle pour les réseaux est basée sur la centralisation du stockage des données et des millions de dollars sont investis pour garantir la sécurité des informations stockées. Cependant, les attaques de piratage informatiques qui ont réussi à franchir toutes les mesures de sécurité du contrôle d'accès et de voler les données des utilisateurs sont de plus en plus fréquentes. Le droit à l'oubli est né du désir des individus de "déterminer le développement de leur vie de manière autonome, sans être perpétuellement ou périodiquement stigmatisés en conséquence d'une action spécifique réalisée dans le passé". Ce concept, qui a pour but de protéger les informations privées potentiellement préjudiciables concernant les individus, a été mis en place dans l'Union européenne et en Argentine [58]. Les données personnelles des utilisateurs doivent être effacées immédiatement lorsque les données ne sont plus nécessaires à la finalité initiale du traitement ou que la personne concernée a retiré son consentement. On parle parfois de droit à l'effacement.

La technologie de la chaîne de blocs a pour mission de favoriser la transparence de l'information. La transparence de la chaîne de blocs dépend du fait que toutes les transactions numériques sur une chaîne de blocs sont enregistrées sur un registre distribué infalsifiable. Ce registre peut être partagé entre différentes parties et peut être privé, public ou semi-privé. Dans une plateforme publique, comme Bitcoin, chaque nœud participant possède sa propre copie du registre enregistré sur son ordinateur. Le registre fournit l'heure de la transaction, le hachage du bloc, le numéro du bloc, l'adresse de l'expéditeur, l'adresse du destinataire, la valeur de la transaction et les frais. Il est important de noter que ce ne sont pas les informations contenues dans le bloc qui sont stockées dans le registre distribué et qui sont transparentes pour tous les nœuds, mais plutôt le hachage du bloc. Les blocs sont généralement hachés en collaboration avec les données originales stockées en dehors de la chaîne. Afin de mieux comprendre ce phénomène, on peut comparer ce phénomène aux empreintes digitales du corps humain. Les empreintes numériques sont hachées dans la chaîne de blocs, tandis que le corps principal de l'information peut être stocké hors ligne.

La chaîne de blocs offre aux utilisateurs la possibilité de consulter l'historique de toutes les transactions. Cependant, la transparence de la chaîne de blocs n'est ni exclusive ni inconditionnelle. Les différents types de plateformes de chaîne de blocs permettent de trouver divers degrés de transparence. En utilisant une chaîne de blocs sans permission, comme le bitcoin, les données des transactions sont partagées publiquement. En ce qui concerne une chaîne de blocs avec permission, où un participant doit obtenir une permission pour rejoindre le réseau, les données des transactions restent confidentielles et ne sont visibles que par les participants authentifiés.

Les problèmes de confidentialité typiques d'une chaîne de blocs découlent de la caractéristique de transparence des réseaux, mais celles-ci sont atténués par le cryptage asymétrique. En outre, et afin de se conformer aux dernières exigences du marché en matière de protection de la vie privée, des recherches approfondies basées sur la preuve de zero-knowledge proof (ZKP) et l'algorithme de cryptage homomorphique sont menées. Les concepts de ZKP peuvent constituer la prochaine étape des transactions privées. Dans une chaîne de blocs publique, le mode par défaut pour la visibilité de toute transaction est l'ouverture et la transparence. Cela signifie que tout le monde peut retracer le parcours d'une transaction, y compris la valeur qu'elle détient et ses adresses d'origine et de destination. Cependant, il est désormais possible d'assurer la confidentialité des transactions en chiffrant les valeurs, et il est également possible de dissimuler les identités grâce à des systèmes de ZKP. Les protocoles de ZKP permettent de vérifier des données sans les révéler. Ils ont donc le potentiel de révolutionner la manière dont les données sont collectées, utilisées et échangées. D'autre part, le chiffrement homomorphe est une méthode de chiffrement qui permet d'effectuer des opérations utiles, ou des calculs, sur des valeurs chiffrées sans les déchiffrer. Les résultats de ces calculs restent sous forme cryptée et ne peuvent être décryptés que par le détenteur de la clé de sécurité ou, dans le cas de la chaîne de blocs, de la clé privée. Il existe aujourd'hui plusieurs implémentations open-source de schémas de chiffrement homomorphique [59], mais elles sont encore considérées comme étant en phase de recherche.

2.3.2.2 CRYPTOGRAPHIE À CLÉ PUBLIQUE/PRIVÉE

Bitcoin utilise la cryptographie à clé publique/privée pour prouver la validité d'une transaction. Les clés privées de Bitcoin sont utilisées pour signer numériquement les transactions en bitcoins, ce qui permet au propriétaire d'une adresse bitcoin de prouver au réseau qu'il est le propriétaire légitime de cette adresse. Les clés privées autorisent une transaction. Elles sont gardées secrètes, tout comme les mots de passe. Les clés publiques de Bitcoin ne sont utilisées que pour générer une adresse Bitcoin. L'adresse est essentiellement une version compressée de la clé publique, ce qui la rend plus facile à lire. Une adresse Bitcoin est une valeur qui peut être partagée publiquement avec n'importe qui, généralement lorsqu'on demande à quelqu'un d'envoyer des bitcoins. En ce sens, elle est un peu comme une adresse électronique ou une adresse courriel.

Une clé privée est un nombre de 256 bits choisi au hasard. Les clés privées sont presque toujours présentées au format hexadécimal. La clé privée est générée par un ordinateur. La plupart des langages de programmation disposent d'une fonction permettant de générer un nombre au hasard. Une clé privée peut être associée à une clé publique pour effectuer des transactions sur le réseau Bitcoin. Sans clé privée, il est, de par sa conception, presque impossible de le faire. En cryptographie, une clé publique peut être générée en faisant passer la clé privée par une fonction secp256k1 de l'algorithme de signature numérique à courbe elliptique (Elliptic Curve Digital Signature Algorithm, ECDSA). Un hachage de la clé publique est ensuite généré en faisant passer la clé publique par les fonctions cryptographiques SHA256 et RIPEMD160. L'adresse Bitcoin est générée en ajoutant d'abord 00 au hachage de la clé publique, puis en soumettant cette valeur à une fonction Base58Check.

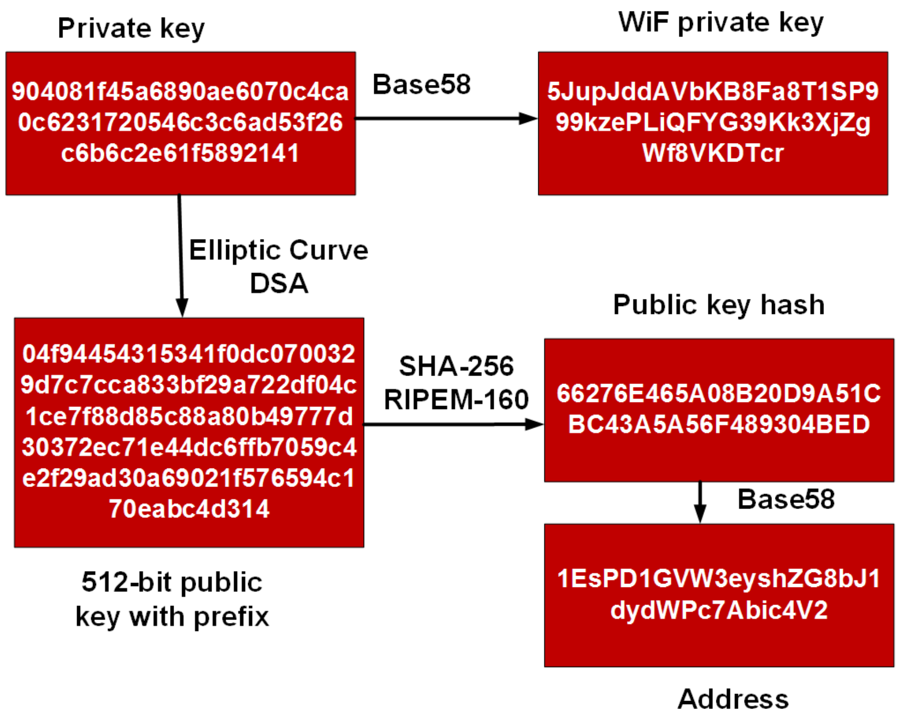

Figure 9. Processus de cryptage de clé privée et clé publique

2.3.2.3 IMMUABILITÉ AUX CYBER-ATTAQUES

Le concept de "chaîne la plus longue" (ou "chaîne la plus difficile") est fondamental dans le fonctionnement des chaînes de blocs basées sur la preuve de travail, telles que Bitcoin. Il est étroitement lié à la puissance de hachage, qui représente la capacité de calcul totale dédiée par les mineurs ou les nœuds du réseau pour sécuriser et valider les transactions. Dans une chaîne de blocs, chaque nouveau bloc ajouté contient un hachage qui référence le bloc précédent. Ainsi, les blocs sont liés en une séquence chronologique, formant une chaîne de blocs. Lorsqu'un mineur trouve une solution valide à un problème de preuve de travail et crée un nouveau bloc, ce bloc est diffusé à travers le réseau. Les autres nœuds vérifient sa validité et l'ajoutent à leur copie locale de la chaîne de blocs s'il est conforme aux règles du protocole.

Le concept de la "chaîne la plus longue" émerge lorsque plusieurs mineurs trouvent simultanément des solutions valides et proposent différents blocs candidats presque en même temps. Dans ce cas, les nœuds du réseau commencent à travailler sur l'extension de la chaîne en ajoutant des blocs supplémentaires à partir du dernier bloc accepté. La chaîne qui devient la "plus longue" (c'est-à-dire celle qui a le plus grand nombre de blocs valides attachés en séquence) est généralement acceptée par le réseau comme la version canonique de la chaîne de blocs. La puissance de hachage représente la capacité de calcul globale et la performance du réseau de chaîne de blocs. Elle est mesurée en termes de la quantité de calculs par seconde que le réseau peut effectuer pour résoudre des problèmes de preuve de travail. Plus la puissance de hachage est élevée, plus il est difficile pour un attaquant de prendre le contrôle de la chaîne de blocs en produisant une chaîne alternative plus longue plus rapidement que le reste du réseau. La sécurité d'une chaîne de blocs comme Bitcoin repose sur l'hypothèse que la majorité de la puissance de hachage est contrôlée par des nœuds honnêtes. Cela garantit que la chaîne la plus longue est également la version qui représente le consensus du réseau. Ainsi, même si des mineurs malveillants existent, il leur serait extrêmement coûteux de surpasser la puissance de hachage collective du réseau pour invalider des transactions passées ou réécrire l'historique de la chaîne de blocs.

Ainsi, la "chaîne la plus longue" et la puissance de hachage sont des concepts essentiels qui assurent la sécurité, la résilience et la confiance dans les chaînes de blocs décentralisées en permettant un consensus distribué et en dissuadant les attaques potentielles par leur coût prohibitif.

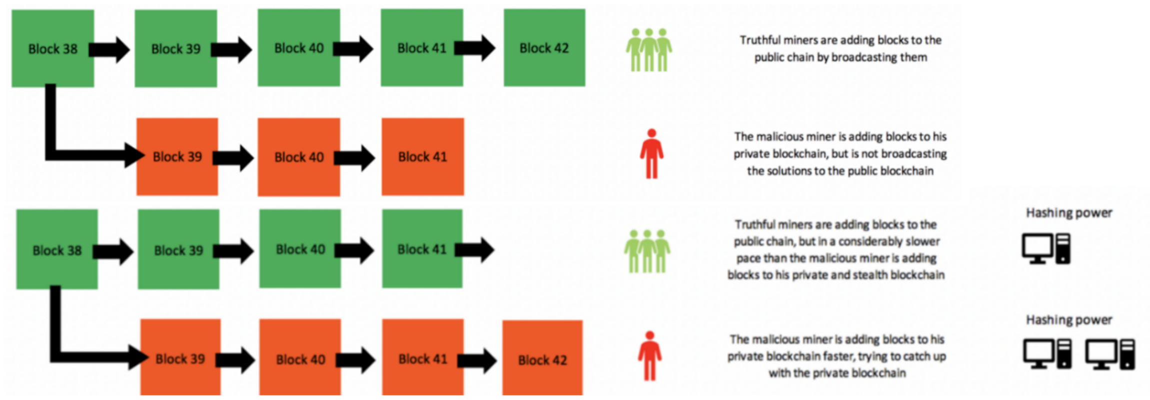

Figure 10. Concept de la chaine la plus longue

2.3.2.4 ANONYMITÉ

La technologie de la chaîne de blocs offre un certain degré de pseudonymat plutôt qu'un anonymat complet. Les transactions de la chaîne de blocs sont enregistrées dans un registre public à l'aide d'adresses cryptographiques plutôt que d'identités réelles. Les utilisateurs sont représentés par ces adresses, qui sont des pseudonymes. Si les adresses elles-mêmes ne révèlent pas d'informations personnelles, toutes les transactions associées à ces adresses sont visibles sur la chaîne de blocs. Les transactions sur une chaîne de blocs sont transparentes et traçables. N'importe qui peut consulter l'historique complet des transactions d'une adresse donnée, y compris les montants envoyés et reçus. Cette transparence renforce la responsabilité, mais réduit l'anonymat.

Malgré l'utilisation de pseudonymes, les transactions de la chaîne de blocs peuvent être reliées entre elles pour créer un historique des transactions. Les techniques d'analyse avancée ou d'analyse en chaîne peuvent parfois relier plusieurs adresses à une seule entité, révélant potentiellement l'identité du propriétaire. Bien que les transactions de la chaîne de blocs soient elles-mêmes pseudonymes, les informations hors chaîne, telles que les adresses IP, les métadonnées des transactions ou les interactions avec les échanges centralisés, peuvent potentiellement relier les activités de la chaîne de blocs à des identités réelles. Certains projets de chaîne de blocs intègrent des technologies d'amélioration de la confidentialité (Privacy-Enhancing Technology, PET) telles que les algorithmes ZKP ou les signatures en anneau pour améliorer la confidentialité. Ces technologies masquent les détails des transactions tout en garantissant leur validité.

En résumé, même si la chaîne de blocs offre un pseudonymat et améliore la protection de la vie privée par rapport aux systèmes financiers traditionnels, l'obtention d'un anonymat total nécessite des mesures supplémentaires et une compréhension des moyens potentiels par lesquels les données peuvent être liées ou analysées à la fois sur la chaîne et en dehors de la chaîne.

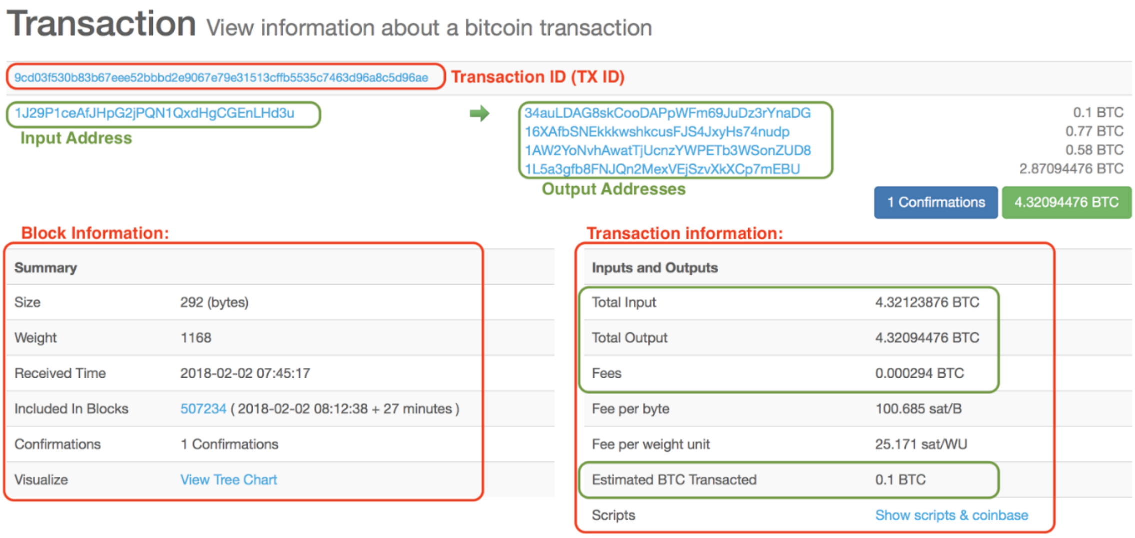

Figure 11. Un modèle de transaction sur la plateforme Bitcoin

2.4 ARCHITECTURES DES CHAINES DE BLOCS

En fonction de l'objectif de développement et du cas d'utilisation des systèmes de chaîne de blocs, une variété d'architectures de système peut être suivie. Les architectures de chaîne de blocs peuvent être classées en fonction des droits d'accès qu'elles accordent (public et privé) et de leurs règles de gouvernance (*open-source* et *closed-source*) [60].

2.4.1 BLOCKCHAINS AVEC OU SANS PERMISSION

Les chaînes de blocs peuvent être divisées en avec permission (*permissioned*) et sans permission (*permissionless* ou non-permissioned) en fonction de leur ouverture. Alors que toutes les chaînes de blocs étaient sans permission (ouvertes) à leur état initial, le type avec permission (fermé) a évolué par la suite et a constitué un cas d'utilisation supérieur pour les processus et applications commerciaux internes dans un contexte d'entreprise [61].

La plupart des monnaies numériques utilisent le type de chaîne de blocs sans permission. Ce type de chaîne de blocs permet à quiconque d'entrer dans le réseau et d'interagir avec lui sans l'approbation préalable d'une entité ou de tiers [62]. Les participants, en fonction de la puissance de calcul qu'ils souhaitent engager, peuvent choisir soit de simplement faire fonctionner un nœud au sein du réseau et d'effectuer différentes actions (par exemple, les "nœuds complets" confirment les transactions dans le Bitcoin), soit de valider des blocs (par exemple, les "nœuds miniers" dans le cas du Bitcoin).

Les chaînes de blocs à autorisation peuvent garantir un environnement plus contrôlé pour l'opérateur du réseau. Pour ce faire, les utilisateurs ne peuvent rejoindre le réseau qu'après vérification de leur identité [63]. Pour exécuter différentes fonctions au sein du réseau (par exemple, initier des transactions, valider des blocs), les participants doivent également obtenir des autorisations spéciales de l'opérateur du réseau. Il s'agit notamment de l'autorisation de :

- Lire (accéder au grand livre et à l'historique des transactions)
- Écrire (initier des transactions)
- Commit (valider les blocs et mettre à jour l'état du registre distribué).

2.4.2 BLOCKCHAINS PUBLIQUES, PRIVÉES ET DE CONSORTIUM

Les chaînes de blocs peuvent être séparées en public, privé ou consortium en fonction de leur contrôle d'accès. Les réseaux Bitcoin et Ethereum sont à la fois publics et sans permission, ce qui signifie qu'ils peuvent être rejoints par n'importe qui sans qu'aucune permission ne soit requise [64]. Grâce à la politique de libre accès, les réseaux publics sont décentralisés et les nœuds qui participent au réseau sont chargés de fournir de la puissance de calcul et de vérifier les nouvelles données (blocs, transactions). En raison de la nature coûteuse du consensus dans les réseaux publics de chaîne de blocs, des mécanismes d'incitation sont prévus pour les nœuds de validation [65]. Dans la plupart des cas, les membres d'une chaîne de blocs publique et sans permission ne sont représentés que par un identifiant aléatoire, et aucune information personnelle n'est communiquée au reste du réseau.

En revanche, les réseaux de chaîne de blocs privés ne sont ouverts à l'adhésion ou à l'apport de puissance de calcul qu'après avoir reçu une autorisation spéciale de l'organe directeur. Les données personnelles des participants sont également connues de l'organe directeur [66].

Les chaînes de blocs de consortium sont des grands registres hybrides qui présentent à la fois des caractéristiques publiques et privées, mais sont principalement considérées comme semi-privées, car seuls les utilisateurs vérifiés sont autorisés à participer à la validation des blocs. Leur organe directeur est généralement un groupe d'entreprises et ils offrent une série d'incitations pour la mise en œuvre sur le marché de l'énergie, à savoir : la confidentialité, l'évolutivité et la performance [67].

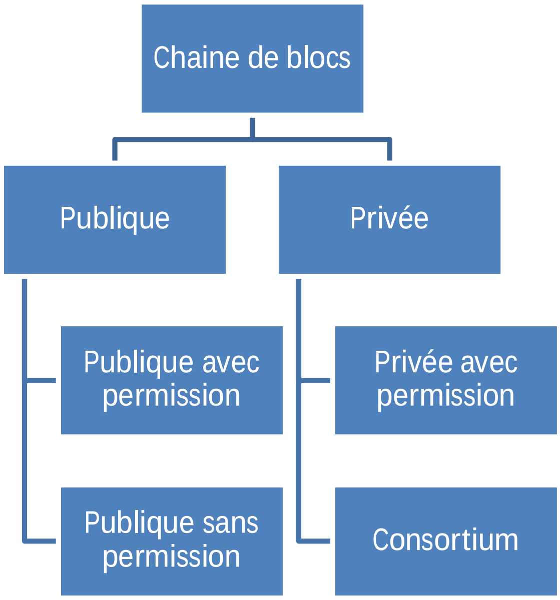

Figure 12. Les différents types de chaîne de blocs

D'une part, les chaînes de blocs privées offrent de meilleures performances globales et des attributs tels que les processus d'authentification des utilisateurs. D'autre part, les chaînes de blocs privées offrent une meilleure performance globale et des attributs tels que les processus d'authentification des utilisateurs, ce qui offre une confidentialité optimale, qui correspond mieux aux exigences du monde de l'entreprise et en particulier aux industries hautement réglementées telles que celle de l'énergie.

D'autre part, les chaînes de blocs publiques sont naturellement accessibles à un public plus large, ce qui peut favoriser l'innovation et la productivité. De plus, elles sont moins vulnérables aux attaques grâce à leur nature décentralisée, contrairement aux réseaux privés qui ont une autorité centrale et, par conséquent, un point de défaillance unique. Le Tableau 1 définit les caractéristiques et les propriétés de chaque type de chaine de blocs.

Tableau 1. Caractéristiques et propriétés des différents types de chaîne de blocs

		Lecture	Écriture	Engagement	Caractéristiques	Propriétés
Publique	Publique sans permission	Ouverte à tous	Ouverte à tous	Participation volontaire de tous	Décent. élevée, transparence totale, problèmes de scalabilité	Immuabilité +++ Transparence ++ Performance + Rentabilité +
Publique	Publique avec permission	Ouverte à tous	Restreinte	Participation des membres approuvés	Transparence publique avec contrôle sur les participants qui peuvent écrire	Immuabilité ++ Transparence ++ Performance ++ Rentabilité ++
Privée	Privée avec permission	Restreinte	Restreinte	Participation des membres approuvés et contrôlés	Plus rapide, scalable, contrôle centralisé, moins décentralisée	Immuabilité + Transparence + Performance +++ Rentabilité +++
Privée	Consortium (Fédérée)	Restreinte	Restreinte	Participation des organisations membres	Équilibre entre décentration et contrôle, collaboration entre organisations	Immuabilité ++ Transparence + Performance ++ Rentabilité ++

2.4.3 CHAÎNE DE BLOCS À SOURCE OUVERTE ET À SOURCE FERMÉE

Les architectures de la chaîne de blocs peuvent être classées selon leur statut de gouvernance en deux catégories : les chaînes de blocs source ouverte et les chaînes de blocs à source fermée. Les chaînes de blocs à source ouverte sont accessibles à tous les membres du réseau pour examen et prise de décision par la communauté (par exemple, décisions sur des questions d'améliorations techniques, sélection de logiciels, etc.) [68]. Les projets de chaîne de blocs à code source ouvert les plus connus sont Bitcoin et Ethereum.

En comparaison, toute modification de la gouvernance ou des règles de fonctionnement du système est décidée en privé dans les chaînes de blocs à source fermée, tandis que leur code source est géré par une organisation ou un consortium d'institutions et n'est pas partagé publiquement [69]. Ripple est une plateforme de chaîne de blocs à source fermée bien connue, utilisée principalement par les institutions financières pour faciliter les paiements transfrontaliers.

2.5 ALGORITHMES DE CONSENSUS DISTRIBUÉ

Un mécanisme de consensus est une méthode utilisée pour parvenir à un accord, à la confiance et à la sécurité au sein d'un réseau informatique décentralisé. Le consensus dans une chaîne de blocs est le processus par lequel les participants du réseau (nœuds) s'accordent sur un ensemble unique de données et valident les transactions. Cela permet de garantir que toutes les copies de la chaîne de blocs contiennent les mêmes informations et sont synchronisées [70, 71]. Ce mécanisme est considéré comme l'élément central d'un réseau de chaîne de blocs, car la sécurité de l'ensemble du système et l'intégrité des transactions dépendent de cette couche [72].

Lorsque les ordinateurs et les réseaux ont commencé à gagner en popularité dans les années 1980 et 1990, des bases de données partagées ont été créées afin que plusieurs utilisateurs puissent accéder aux informations stockées. La plupart des systèmes disposaient d'une base de données centralisée avec des autorisations auxquelles les utilisateurs accédaient à partir de différents postes de travail. Cette configuration a évolué vers des réseaux centralisés avec des administrateurs qui accordaient des droits aux utilisateurs et maintenaient l'intégrité des données. Certaines de ces bases de données partagées ont évolué vers des programmes qui distribuaient la puissance de stockage et de traitement à travers un réseau de dispositifs de stockage situés à différents endroits. L'un des problèmes les plus importants à résoudre était celui de la prévention de la falsification des données et de l'accès non autorisé, qu'il soit malveillant ou non. Une méthode d'automatisation de la gestion des bases de données distribuées était nécessaire pour garantir que les données ne soient pas modifiées. Ce besoin a conduit à la création du consensus autonome distribué, dans lequel les programmes d'un réseau s'accordent sur l'état d'une base de données à l'aide de techniques cryptographiques. L'accord a été conçu pour être obtenu à l'aide d'algorithmes de cryptage afin de créer un hachage formé de longues chaînes de nombres alphanumériques qui sont ensuite vérifiées par les programmes fonctionnant sur le réseau. Un hachage ne change que si les informations entrées dans l'algorithme de hachage sont modifiées. Les programmes ont donc été conçus pour comparer les hachages afin de s'assurer qu'ils correspondent.

Les principales approches des mécanismes de consensus comprennent le consensus de Nakamoto et les variations de l'algorithme de tolérance aux fautes byzantines (*Byzantine Fault Tolerance*, BFT). Dans le cas du consensus de Nakamoto, un protocole basé sur la loterie, les principales règles suivies sont celles de la chaîne la plus longue et de la preuve de travail (PoW) [73]. La majorité des chaînes de blocs publiques utilisent le consensus de Nakamoto, la plus connue étant le réseau Bitcoin. Les protocoles de consensus basés sur le BFT suivent le concept de maintien du bon fonctionnement d'un réseau informatique distribué, malgré un éventuel dysfonctionnement des processus du système ou une action malveillante à son encontre. Un point commun des deux mécanismes de consensus est qu'ils ont tous deux pour objectif de garantir qu'il existe un accord entre les participants sur l'historique des blocs [74].

D'un point de vue économique, les algorithmes de consensus ont un impact direct sur les coûts de calcul et le montant global de l'investissement dans un système de chaîne de blocs. Du côté technique de l'équation, ils déterminent de nombreuses caractéristiques de performance du réseau, telles que la sécurité, l'évolutivité et la vitesse de transaction [75]. Par conséquent, si une solution de chaîne de blocs doit être intégrée dans le monde de l'entreprise, les différents aspects de chaque algorithme doivent être pris en compte. Cela peut aider les entreprises à mettre en œuvre l'algorithme de consensus optimal pour le cas d'utilisation qu'elles envisagent.

Il existe de nombreuses variantes de modèles de consensus appliqués dans différentes plateformes de chaîne de blocs, les plus connues étant : preuve de travail (Proof of Work, PoW), preuve d'enjeu (*Proof of Stake*, PoS) et *Practical Byzantine Fault Tolerance* (PBFT).

2.5.1 PREUVE DE TRAVAIL (POW)

Initialement utilisée par le réseau Bitcoin, la preuve de travail est un mécanisme de consensus qui repose sur la validation de nœuds (appelés "mineurs"), qui s'affrontent pour résoudre un problème mathématique cryptographique [76]. La solution à ce problème est appelée "hash". Les nœuds de minage testent des nombres aléatoires, également connus sous le nom de "nonce", par le biais d'un processus d'essais et d'erreurs jusqu'à ce qu'ils produisent un nonce qui délivre la valeur de hachage demandée. Le mineur qui le trouve en premier remporte la manche et associe un nouveau bloc à la base de données aux blocs existants devant lui [77]. Ils reçoivent également des récompenses définies par la structure incitative du réseau pour leur utilisation informatique.

Grâce à sa conception, le PoW est résistant à une série de cyberattaques, notamment les attaques type *Denial of Service* (DoS), qui surchargent les serveurs d'un réseau et le rendent indisponible pour ses utilisateurs [78]. En outre, il s'agit d'un mécanisme qui peut être mis à l'échelle et prendre en charge un grand nombre d'utilisateurs.

L'inconvénient le plus important du PoW est que le processus de minage nécessite d'immenses quantités d'énergie et de dépenses informatiques et qu'il souffre de vitesses de transaction plus lentes par rapport à d'autres mécanismes de consensus. En outre, il peut être sujet à des attaques de 51 %, c'est-à-dire qu'une seule entité (ou un groupe d'entités) acquiert la majorité de la puissance de calcul - "minage" - du réseau et l'utilise pour monopoliser le minage des blocs ou modifier l'ordre des blocs, ce qui entraîne un problème de double dépense [79].

2.5.2 PREUVE D'ENJEU (POS)

La preuve d'enjeu est un mécanisme de consensus qui remplace la nécessité de miner des blocs par un système de vote qui dépend de la richesse du valideur. Ainsi, la probabilité pour un nœud validant d'ajouter un bloc à la chaîne est directement liée à la possession par le nœud du jeton natif du réseau (par exemple l'éther dans le cas du réseau Ethereum) [80].

Le PoS est considéré comme une alternative plus rapide et plus rentable que le PoW pour les chaînes de blocs publiques. En outre, son mécanisme de vote dépendant des enjeux peut être utilisé comme un moyen de prévenir les attaques de centralisation et de 51 %, car les participants ne sont pas incités à accumuler une puissance de calcul importante ou à former des pools miniers. Ethereum est le réseau de chaîne de blocs le plus connu qui envisage de passer de solutions PoW à PoS [81].

Bien que le PoS soit moins vulnérable aux attaques de 51 %, un problème connu sous le nom de "rien en jeu" est prédominant dans les réseaux PoS [82]. En outre, ses capacités et ses vulnérabilités n'ont pas été largement exposées, car elles ont été moins mises en œuvre que la PoW [83].

2.5.3 TOLÉRANCE BYZANTINE PRATIQUE (PBFT)

PBFT est l'un des protocoles de consensus basés sur BFT les plus connus. Le PBFT convient mieux aux chaînes de blocs avec permission qu'aux chaînes de blocs publiques sans permission [84]. Cela est dû au fait que le PBFT est un algorithme de consensus basé sur le vote, dans lequel un nœud leader est choisi par le réseau uniquement s'il a été approuvé par au moins 2/3 de tous les nœuds, et que chaque participant doit donc être connu du reste du réseau. Le leader est chargé de sélectionner les blocs qui seront ajoutés au réseau et est remplacé à chaque tour du processus [85]. L'un des principaux avantages du protocole PBFT est que, par rapport au PoW, il est nettement moins gourmand en calculs, ce qui se traduit par une réduction de la consommation d'énergie électrique. Un autre avantage important du mécanisme de consensus particulier est son temps de latence plus faible (le temps nécessaire pour valider un bloc et l'ajouter dans la chaîne) par rapport au PoW [86]. Parmi les inconvénients du PBFT figure sa capacité à ne prendre en charge qu'un petit nombre de participants et sa vulnérabilité aux attaques Sybil en raison de son algorithme basé sur le vote [87].

2.6 CONTRAT INTELLIGENT

Le terme "contrat intelligent", comme déjà mentionné, a été décrit en 1997 par Nick Szabo comme une combinaison de protocoles avec des interfaces utilisateur dans le but de formaliser et de sécuriser les relations dans les réseaux informatiques et de sécuriser les relations dans les réseaux informatiques. Les objectifs et les principes de conception de ces systèmes devaient être basés sur des principes juridiques, des théories économiques et la théorie des protocoles crédibles et sécurisés.

Les contrats intelligents reposent sur des conditions prédéfinies codées qui déclenchent automatiquement des actions spécifiques lorsque ces conditions sont remplies. Par exemple, un contrat intelligent pour la location d'un appartement pourrait stipuler que lorsque le locataire paie le loyer, une clé numérique est délivrée pour permettre l'accès à l'appartement. Cette automatisation élimine le besoin de faire appel à des tiers de confiance comme les avocats ou les notaires, réduisant ainsi les coûts et les délais.

La structure d'un contrat intelligent peut être décomposée en plusieurs composantes clés :

• Conditions et Clauses : Les termes du contrat, définis de manière claire et précise, incluant les conditions à remplir pour exécuter le contrat.

• Entrées : Les données d'entrée nécessaires pour vérifier si les conditions du contrat sont remplies. Ces données peuvent provenir de diverses sources, y compris des capteurs IdO, des *Application Programming Interface* (API) externes, ou des entrées manuelles.

• Exécution Automatique : Une fois que les conditions spécifiées sont remplies, le contrat s'exécute automatiquement. Cela peut inclure le transfert de fonds, l'émission de licences numériques, ou la mise à jour de registres.

• Immutabilité : Les contrats intelligents sont stockés sur la chaîne de blocs, garantissant que les termes et l'exécution du contrat ne peuvent pas être modifiés une fois qu'ils sont enregistrés.

• Auditabilité : Étant donné que toutes les transactions et exécutions sont enregistrées sur la chaîne de blocs, il est possible de vérifier l'intégrité et l'exactitude du contrat à tout moment.

Les contrats intelligents s'exécutent automatiquement lorsque les conditions sont remplies, réduisant ainsi la nécessité d'interventions humaines et minimisant les erreurs. Étant donné que les termes du contrat sont inscrits dans le code et enregistrés sur la chaîne de blocs, toutes les parties peuvent vérifier les termes et l'exécution du contrat. Au niveau de la sécurité, les contrats intelligents utilisent la cryptographie pour garantir que les transactions sont sécurisées et que les données ne peuvent pas être altérées. En outre, en éliminant les intermédiaires, les contrats intelligents réduisent les coûts et accélèrent les processus contractuels. Les contrats intelligents sont exécutés exactement comme codé, sans possibilité de manipulation, ce qui renforce la confiance entre les parties.

Ethereum est la plateforme la plus populaire pour la création et l'exécution de contrats intelligents. Elle utilise une machine virtuelle (Ethereum Virtual Machine, EVM) pour exécuter les contrats intelligents. Les développeurs écrivent des contrats intelligents en utilisant des langages de programmation comme Solidity et Vyper. Une fois déployés, ces contrats sont immuables et autonomes, exécutant automatiquement les termes du contrat lorsque les conditions sont remplies.

Hyperledger Fabric est une autre plateforme populaire, souvent utilisée par les entreprises pour ses fonctionnalités de confidentialité et de permission. Contrairement à Ethereum, Hyperledger Fabric permet des contrôles d'accès granulaires, ce qui est crucial pour les entreprises qui doivent protéger des données sensibles. Les contrats intelligents, appelés "chaincodes" dans Fabric, peuvent être écrits en Go, JavaScript, ou Java.

Cardano propose une approche différente avec son langage de contrat intelligent Plutus, basé sur Haskell. Cardano se concentre sur la sécurité et la scalabilité, cherchant à corriger les faiblesses perçues d'autres plateformes de contrats intelligents.

Cependant, plusieurs défis et limites font face aux Contrats Intelligents. La rédaction de contrats intelligents nécessite des compétences en programmation, ce qui peut être un obstacle pour les non-techniciens. Aussi, bien que l'immutabilité soit un avantage en termes de sécurité, elle peut aussi être un inconvénient si des erreurs sont présentes dans le code, car elles ne peuvent pas être corrigées facilement. Au niveau juridique, les cadres juridiques actuels ne sont pas toujours adaptés aux contrats intelligents, ce qui peut poser des défis juridiques et réglementaires.

Les contrats intelligents existent dans le monde virtuel. Ils permettent l'exécution automatique des accords et transactions sans nécessiter d'intermédiaires. Cependant, pour que ces contrats intelligents puissent fonctionner efficacement et de manière fiable, ils doivent être connectés au monde réel, ce qui nécessite l'utilisation d'oracles. Les oracles servent de pont entre la chaîne de blocs et les sources de données externes, fournissant les informations nécessaires pour déclencher l'exécution des contrats intelligents lorsque les conditions spécifiées sont remplies. Sans oracles, les contrats intelligents seraient limités à des données statiques, ne pouvant pas réagir aux événements du monde réel comme les changements de prix, les conditions météorologiques ou les résultats d'événements sportifs. Ainsi, les oracles jouent un rôle crucial en intégrant les contrats intelligents dans un écosystème plus large, leur permettant de réaliser leur plein potentiel et d'apporter une véritable valeur ajoutée dans divers secteurs, allant de la finance à la chaîne d'approvisionnement en passant par l'assurance.

Techniquement parlant, les oracles sont des services ou des dispositifs qui permettent aux chaînes de blocs d'interagir avec des sources de données externes, facilitant ainsi l'intégration d'informations du monde réel dans les contrats intelligents. Les chaînes de blocs, par leur nature, ne peuvent accéder qu'aux données internes et ne peuvent pas directement se connecter à des systèmes externes pour obtenir des informations nécessaires à l'exécution des contrats intelligents.

Les oracles recueillent des informations à partir de sources de données externes, telles que des API, des capteurs IdO, des bases de données, ou des sites web. Ensuite elles transmettent ces données aux contrats intelligents sur la chaîne de blocs. Cette transmission peut se faire de manière unidirectionnelle (de l'externe vers la chaîne de blocs) ou bidirectionnelle (interactions entre la chaîne de blocs et les systèmes externes). Pour garantir la fiabilité des données, certains oracles utilisent des mécanismes de vérification et des protocoles de consensus décentralisés. Par exemple, plusieurs sources peuvent être agrégées pour réduire les risques d'erreurs ou de manipulations.

Il existe différents types d'oracles en fonction de leur fonctionnement et de leurs sources de données :

- Oracles Entrants (Inbound Oracles) : Ils fournissent des données externes à la chaîne de blocs, comme les prix des actifs, les résultats sportifs, ou les conditions météorologiques.

- Oracles Sortants (Outbound Oracles) : Ils permettent aux contrats intelligents d'envoyer des commandes vers des systèmes externes, comme déclencher un paiement ou envoyer une notification.

- Oracles Centralisés : Contrôlés par une seule entité, ces oracles peuvent être plus rapides et plus simples à mettre en place, mais ils présentent des risques de centralisation et de points de défaillance uniques.

- Oracles Décentralisés : Ils utilisent plusieurs sources de données et des mécanismes de consensus pour garantir la fiabilité et la sécurité des informations fournies. Chainlink est un exemple d'oracle décentralisé largement utilisé.

Plusieurs réseaux et plateformes existent aujourd’hui sur le marché, offrant des services de base de données basés sur les oracles :

- Chainlink : Un réseau décentralisé d'oracles qui permet aux contrats intelligents d'accéder de manière sécurisée à des données externes. Chainlink agrège les données de multiples sources pour assurer leur fiabilité.
- Band Protocol : Une plateforme d'oracles décentralisés qui collecte et fournit des données externes à des chaînes de blocs, avec un accent sur la sécurité et la scalabilité.
- Oraclize (Provable) : Un service d'oracle qui vérifie les données externes à l'aide de preuves cryptographiques et permet aux contrats intelligents d'accéder à des API web.

Les oracles sont essentiels pour débloquer le potentiel des contrats intelligents en leur permettant de réagir aux événements et aux données du monde réel. Ils étendent les applications possibles des chaînes de blocs au-delà des transactions purement internes, permettant des cas d'utilisation dans la finance, l'assurance, la chaîne d'approvisionnement, les jeux, et bien d'autres domaines. Toutefois, l'intégration des oracles doit être réalisée avec soin pour garantir la sécurité, la précision et la fiabilité des données, car des données erronées ou manipulées peuvent compromettre l'intégrité des contrats intelligents et des systèmes de chaîne de blocs.

Les contrats intelligents représentent une avancée majeure dans la façon dont les transactions et les accords sont gérés. En automatisant l'exécution des termes du contrat, ils offrent une efficacité, une sécurité et une transparence accrues. Cependant, leur adoption à grande échelle nécessite de surmonter plusieurs défis techniques et réglementaires. À mesure que la technologie continue de progresser, les contrats intelligents pourraient devenir une composante essentielle de nombreux secteurs, transformant non seulement les transactions financières, mais aussi la façon dont nous interagissons avec les systèmes numériques dans notre vie quotidienne.

2.7 LES ÉTAPES DU DÉVELOPPEMENT DE LA TECHNOLOGIE CHAÎNE DE BLOCS

Depuis sa conception en 2009, un certain nombre de nouvelles caractéristiques et capacités ont été ajoutées à la technologie de chaîne de blocs. Il est donc possible de la classer en trois étapes, chacune ayant un objectif de développement différent, en fonction de son degré de complexité :

- Étape I - "Blockchain 1.0" : Le premier stade de développement de la chaîne de blocs est lié aux crypto-monnaies et aux réseaux qui les soutiennent. Cela est dû au bitcoin, qui a été le premier cas d'utilisation de la technologie pour résoudre un problème pratique : l'exécution de transactions sécurisées dans un environnement non fiable et anonyme, sans avoir besoin d'un intermédiaire tiers de confiance [88].

- Étape II - "Blockchain 2.0" : La deuxième phase du développement de la chaîne de blocs représente les contrats intelligents, une forme de contrats numériques pratiquement dérivés de la généralisation des "paiements sans confiance" de la première étape. Le réseau Ethereum a été la première plateforme à réaliser le développement et le déploiement de contrats intelligents en 2015 [89].

- Phase III - "Blockchain 3.0" : La mise en œuvre de la technologie chaîne de blocs dans différentes industries constitue la troisième et dernière phase de développement de la chaîne de blocs. Pour l'instant, les applications pertinentes à grande échelle sont limitées. À l'avenir et une fois que l'environnement logiciel se sera développé, la chaîne de blocs pourra permettre de nouveaux modèles commerciaux et fournir des solutions pour automatiser et accélérer les processus dans plusieurs industries, y compris l'énergie [90]

- Phase IV – " Blockchain 4.0 " : La chaîne de blocs 4.0 représente la prochaine évolution des technologies de la chaîne de blocs, visant à intégrer pleinement cette technologie dans les industries et les infrastructures existantes pour créer des systèmes plus efficaces, sécurisés et automatisés [91]. Contrairement à ses prédécesseurs, Blockchain 4.0 se concentre sur l'interopérabilité et la scalabilité, permettant une intégration transparente avec l'IdO, l'IA et les systèmes de mégadonnées. Cette version avancée de la chaîne de blocs propose des solutions pour les défis liés à la vitesse des transactions, à la consommation d'énergie et à la complexité des contrats intelligents, tout en offrant une meilleure confidentialité et une gouvernance décentralisée. En facilitant l'automatisation des processus industriels et la gestion des chaînes d'approvisionnement avec des contrats intelligents plus sophistiqués et des consensus plus rapides, Blockchain 4.0 ouvre la voie à une adoption massive de la technologie de chaîne de blocs dans des secteurs variés tels que la santé, la finance, l'énergie, et la logistique.

CHAPITRE 3
LA CHAINE DE BLOCS AU SERVICE DU SECTEUR ÉLECTRIQUE

3.1 REVUE DE LITERATURE

La technologie de la chaîne de blocs a émergé comme une innovation révolutionnaire, offrant des solutions pour améliorer la sécurité, la transparence, et l'efficacité dans divers secteurs. Ce chapitre présente une revue de littérature approfondie des travaux de recherches axés sur les applications de la technologie de chaine de blocs tout au long de la chaine d'approvisionnement du réseau électrique, ainsi qu'un article et un chapitre de livre qui explorent les applications de la technologie de la chaîne de blocs dans le secteur énergétique, avec un accent particulier sur les réseaux électriques intelligents et décentralisés. La revue met en lumière les contributions, les méthodologies, les résultats, et les implications des travaux de recherches et les applications, qui existent dans ce domaine, offrant un cadre pour comprendre l'impact et les perspectives de l'intégration de la chaîne de blocs dans le secteur énergétique.

Au cours des dernières années, on a constaté une augmentation de l'intérêt académique pour la technologie de chaîne de blocs, et il est devenu plus évident pour les chercheurs que la chaîne de blocs jouera un rôle intégral dans le changement de la façon dont nous faisons des affaires. De nombreuses études récentes se sont concentrées sur la technologie de chaîne de blocs et la transformation numérique du secteur de l'énergie à un niveau distinct. Le travail effectué dans [92] explore plus que 622 articles scientifiques sur les tendances, enjeux, défis et opportunités de la technologie de chaine de blocs dans le secteur de l'énergie. Les travaux menés dans [93] fournissent une revue systématique des opportunités et des défis de la technologie de chaîne de blocs dans le secteur de l'énergie en examinant diverses sources académiques et industrielles. A l'issue de leur travail, les auteurs de l'article ont conclu que le marché de l'énergie, dans ses différents secteurs : opérations, marché et consommateurs, peut clairement bénéficier des caractéristiques de désintermédiation, de transparence et d'immuabilité offertes par la technologie de chaîne de blocs. De même, dans les articles [94-

97], les opportunités, les défis potentiels et les limites d'un certain nombre de cas d'utilisation, de l'application de la chaîne de blocs dans le secteur de l'énergie, sont discutés, allant des échanges d'énergie émergents en P2P et des applications de l'IdO, aux places de marché décentralisées, à la recharge des VEs et à l'e-mobilité. Dans l'article [98], la procédure de fonctionnement de la technologie de chaîne de blocs, y compris plusieurs applications dans les réseaux intelligents, est discutée. De même, le travail présenté dans l'article [99] présente l'état actuel du développement et la recherche sur l'application de la technologie de chaîne de blocs dans l'industrie de l'énergie en Chine sous les aspects de la réponse à la demande, de la transaction point à point et des ressources énergétiques distribuées. Avec le développement rapide des technologies d'énergie durable et des technologies de réseau, le travail dans [100] offre une vue d'ensemble de l'application de la technologie de chaîne de blocs dans les systèmes d'énergie durable tout en introduisant la recherche de compatibilité de la technologie de chaîne de blocs et de l'Internet de l'énergie (Nouvelle énergie + Internet), prouvant que l'application de la technologie de chaîne de blocs à l'Internet de l'énergie fournit une bonne opportunité pour son développement, puisque la chaîne de blocs peut résoudre de nombreux problèmes qui entravent le développement de l'Internet de l'énergie, tels que le contrôle et la gestion des formes d'énergie durable distribuées.

Néanmoins, la majorité des documents et des articles publiés, relatifs à l'intégration de la chaîne de blocs dans le secteur de l'énergie, se concentrent sur le commerce de l'énergie en P2P. Les travaux menés dans [101] comparent les systèmes d'échange d'énergie existants avec les nouveaux modèles d'échange d'énergie basés sur la chaîne de blocs, tout en fournissant un aperçu des différents modèles d'échange d'énergie basés sur la chaîne de blocs en étudiant les méthodologies pour les transactions énergétiques. Dans l'article [102], un nouveau modèle basé sur la chaîne de blocs et les contrats intelligents pour mettre en œuvre un marché hybride efficace d'échange d'énergie tout en réduisant le coût et le ratio pic/moyen de l'électricité est proposé. Les auteurs de l'article [103] ont utilisé la chaîne de blocs dans le marché d'échange d'énergie P2P à petite échelle. Dans l'article [104], les auteurs proposent un système qui permet de construire un marché de l'énergie ouvert pour une communauté d'utilisateurs basé sur la technologie IoT dans le but de surmonter le besoin d'une entité de contrôle centrale tout en gardant une trace des transactions énergétiques distribuées. D'autre part, dans [105], un modèle basé sur la chaîne de blocs est proposé pour gérer les problèmes techniques dans un micro-réseau. En plus des aspects économiques du marché, le modèle proposé est utilisé pour prendre les décisions techniques pour les opérations distribuées du marché. Avec une approche plus spécifique, le travail présenté dans [106], un modèle de chaîne de blocs énergétique est introduit pour exploiter et programmer les VPPs avec l'objectif de résoudre les problèmes et les défis existants associés aux VPP. Et dans l'article [107] propose un nouveau cadre hiérarchique pour la gestion de la demande d'énergie par l'échange d'informations et d'énergie entre pairs sur le marché en temps réel en utilisant des contrats intelligents.

Néanmoins, le marché de l'énergie d'aujourd'hui est motivé par des besoins plus importants et des attentes plus élevées [108]. Des besoins et des attentes qui ne peuvent plus être satisfaits par les modèles de financement traditionnels. Il est donc nécessaire de mettre en place un nouveau modèle de facturation capable d'assurer une plus grande contribution des clients, non seulement à la production d'électricité, mais aussi à la gestion du réseau en général et au contrôle précis des prix. C'est là que le modèle d'échange d'énergie P2P entre en jeu. Inversement, il y a plus d'une décennie, un nouveau modèle d'échange d'énergie a fait son apparition. L'émergence du commerce P2P de l'énergie remonte au début des années 2010. Le concept a pris de l'ampleur à mesure que les progrès technologiques, en particulier la chaîne de blocs et les contrats intelligents, offraient de nouvelles possibilités de transactions énergétiques décentralisées. Toutefois, c'est entre le milieu et la fin des années 2010 que le commerce P2P de l'énergie a été largement reconnu et a fait l'objet d'une mise en œuvre pratique [109, 110]. Le commerce d'énergie P2P est apparu comme un paradigme prometteur dans la transition vers des systèmes énergétiques décentralisés et durables. L'évolution de ce concept est en cours et sa trajectoire est influencée par les progrès technologiques, les évolutions réglementaires et la prise de conscience croissante de la nécessité d'adopter des pratiques énergétiques plus durables. Le mécanisme d'échange d'énergie P2P permet l'échange direct d'énergie électrique entre les prosommateurs et les consommateurs à un prix négocié par les deux parties sans vendre cette énergie à l'opérateur de réseau au préalable. Par conséquent, les modèles d'échange d'énergie P2P éliminent la nécessité pour les entreprises de services publics ou les opérateurs de réseau d'intervenir en tant qu'intermédiaires. Les modèles d'échange d'énergie P2P utilisent fréquemment des approches fondées sur la théorie des jeux [111], des procédures basées sur les enchères [112], des méthodes d'optimisation [113, 114] et la technologie basée sur la chaîne de blocs. De nombreuses études ont exploré les aspects techniques des échanges d'énergie P2P, notamment les protocoles de communication [115], les mécanismes de marché et l'intégration au réseau. Les contrats intelligents basés sur la technologie de chaîne de blocs sont couramment utilisés pour automatiser les transactions et garantir la confiance et la transparence entre les participants. D'autres approches utilisent des réseaux P2P ou des plateformes centralisées pour le commerce de l'énergie. Les modèles économiques jouent un rôle crucial dans les systèmes d'échange d'énergie P2P, car ils déterminent les mécanismes de tarification, la répartition des coûts et les incitations pour les participants [116]. La tarification dynamique basée sur l'offre et la demande, les tarifs en fonction du temps d'utilisation et les systèmes incitatifs sont couramment utilisés pour optimiser l'utilisation des ressources et encourager la production d'énergie renouvelable. Cependant, grâce à la technologie de chaîne de blocs et aux contrats intelligents, les systèmes d'échange d'énergie P2P ont été rendus possibles et faciles à mettre en œuvre [117]. Ce concept vise à créer un écosystème énergétique plus efficace et plus durable en donnant directement aux individus les moyens de participer à la production, à la consommation et aux transactions d'énergie, favorisant ainsi les communautés énergétiques locales. Néanmoins, malgré ses avantages potentiels, le commerce P2P de l'énergie est confronté à plusieurs défis, notamment des obstacles réglementaires, des complexités techniques, des problèmes de conception du marché et des préoccupations en matière de protection de la vie privée. L'évolutivité, l'interopérabilité et la stabilité du réseau sont des défis importants qui doivent être relevés pour l'adoption généralisée des modèles d'échange P2P. Les défis et les limites du commerce P2P de l'énergie sont détaillés dans [118].

En outre, la chaîne de blocs est apparue récemment comme une nouvelle technologie qui peut jouer un rôle important dans les réseaux intelligents et plus particulièrement dans la gestion avancée de la demande. Comme présenté dans [119], la technologie de chaîne de blocs, en particulier lorsqu'elle est associée à une infrastructure de mesure avancée (Advanced Metering Infrastructure, AMI), peut offrir une flexibilité énergétique transparente, sûre, fiable et opportune pour adapter les profils de charge des consommateurs aux capacités des acteurs de la chaîne de valeur de l'énergie. Les travaux menés dans [120] suggèrent un modèle DSM basé sur la chaîne de blocs utilisant la plateforme Ethereum qui fait correspondre la demande et la production d'énergie au niveau d'un réseau intelligent pour valider ce concept. Le modèle améliore le retour d'information des consommateurs inscrits au DR et agrège et prévoit les charges DR disponibles tout en réduisant la quantité de flexibilité énergétique nécessaire à la convergence. De même, l'article [121] utilise un micro-réseau avec différents profils de charge résidentielle pour tester un mécanisme de gestion de la demande amélioré par la chaîne de blocs qui réduit le ratio pic-moyenne et lisse les creux dans le profil de charge causés par les contraintes d'approvisionnement. En outre, le modèle proposé optimise les gains du fournisseur d'énergie et du consommateur. De même, l'article [122] introduit une gestion distribuée de la demande interconnectant, à l'aide d'un réseau de compteurs intelligents IoT, plusieurs ménages équipés de sources d'énergie renouvelable dans un micro-réseau unique. Le système proposé minimise le coût individuel de l'électricité pour chaque ménage et le coût total de la consommation d'énergie pour l'ensemble du micro-réseau. Les consommateurs cherchent à optimiser leur consommation quotidienne d'énergie en plus de leur source d'énergie : énergie autoproduite à partir de sources d'énergie renouvelable, énergie partagée sur le micro-réseau communautaire et énergie fournie par la compagnie d'électricité. Chaque participant applique la meilleure stratégie qui minimise son coût de consommation d'énergie tout en préservant la confidentialité de sa consommation d'énergie. Par ailleurs, l'application de la technologie de chaîne de blocs à la gestion de la demande ne se limite pas à la relation entre le fournisseur de services énergétiques et le consommateur, mais peut couvrir l'interaction machine-machine (M2M) dans le contexte de la réponse à la demande. Le travail présenté dans [123] fournit un exemple d'interaction M2M où un système de gestion de l'énergie et un générateur coopéreront pour ajuster la production d'énergie par le biais de la chaîne de blocs. Mais là encore, la gestion de la demande ne se limite pas aux programmes de réponse à la demande et comprend également des mécanismes d'efficacité énergétique. Même à ce niveau, la chaîne de blocs peut jouer un rôle majeur dans l'avancement des mesures de conservation de l'énergie, comme le montre l'article [124].

Sur la base des travaux susmentionnés, il est évident que différents mécanismes de chaîne de blocs ont été introduits sur le marché de l'énergie. En plus, l'exploration des différentes études sur l'application de la technologie de la chaîne de blocs dans le réseau électrique révèle un potentiel significatif pour transformer et moderniser le secteur énergétique. Les recherches ont démontré que la chaîne de blocs peut faciliter une gestion plus efficace et sécurisée des ressources énergétiques distribuées, permettre des transactions P2P plus transparentes et automatisées, et renforcer la résilience et la sécurité des infrastructures énergétiques. Ainsi, la chaîne de blocs pourrait non seulement répondre aux exigences actuelles de la transition énergétique, mais aussi poser les bases d'un réseau électrique plus décentralisé, transparent et durable pour les générations futures. Néanmoins, la grande majorité de ces travaux ne présente que la partie technique du mécanisme sans cibler les impacts économiques et sociaux de ces solutions à la fois au niveau macro des fournisseurs de services énergétiques et au niveau micro des consommateurs d'énergie. En plus, notre travail est le premier à s'inspirer du mode de fonctionnement et de la topologie de la chaine de blocs, pour proposer une décentralisation totale du réseau électrique à tous les niveaux : infrastructure, contrôle et gestion des données. Ce concept sera plus détaillé dans le chapitre 3.

3.2 Chapitre de Livre: Revamping Energy Sector with a Trusted NETWORK: Blockchain Technology

Ce chapitre, intitulé « *Revamping Energy Sector with a Trusted Network : Blockchain Technology* », a été accepté pour publication dans sa version finale en 2022 par les éditeurs de la maison d'édition *WILEY SCRIVENER PUBLISHING* dans leur livre intitulé : « *Blockchain Technology in Corporate Governance: Transforming Business Industries* ».

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En tant que premier auteur, j'ai contribué au développement de l'idée générale, à l'essentiel de la recherche sur l'état de la question et au développement de la méthode, à la collecte et l'analyse des données et à la rédaction du manuscrit. Les professeurs Mazen Ghandour, Adrian Ilinca et Hussein Ibrahim en tant que co-auteurs, ont participé à la supervision du travail, ainsi qu'à la révision de l'article et à la revue de la littérature.

Résumé : Le secteur de l'énergie est en pleine mutation, sous l'impulsion de nouvelles réglementations climatiques et d'une tendance politique à la sortie du nucléaire, visant à réduire les émissions de gaz à effet de serre et une tendance politique à la sortie du nucléaire, visant à atteindre la neutralité carbone pour la production d'électricité et une efficacité accrue dans la production d'électricité et l'amélioration de l'efficacité des réseaux électriques. En conséquence, la plupart des réseaux électriques encouragent une plus grande intégration des ressources énergétiques distribuées et une plus grande implication des consommateurs dans la gestion de l'énergie, grâce à une application considérable des technologies intelligentes, telles que la chaîne de blocs, l'intelligence artificielle, les technologies de l'information et de la communication. Cette transformation numérique au cœur du secteur de l'énergie promet de lourdes perturbations, le faisant passer d'une chaîne d'approvisionnement centralisée et séparée à une plateforme intelligente interconnectée, décarbonée, décentralisée et numérisée.

La chaîne de blocs, en tant que plateforme commerciale transparente, sécurisée et décentralisée, a suscité l'intérêt des entreprises et des industries du monde entier, débloquant de nouveaux modèles et promettant de nouvelles sources de revenus. Cette promesse est particulièrement dans le secteur de l'énergie, lorsqu'elle est déployée à la périphérie du réseau, où l'implication et la transparence des consommateurs sont requises. L'énergie basée sur gestion de la demande ou des modèles d'échange d'énergie de pair-à-pair sont des solutions typiques à envisager. Dans ce chapitre, les applications de la chaîne de blocs dans le secteur de l'énergie, ainsi que leurs impacts sociaux, économiques et environnementaux.

Contexte et Objectifs : Ce chapitre se concentre sur l'application de la chaîne de blocs dans les réseaux électriques intelligents (*smart grids*). L'objectif principal de l'étude est de fournir une vue d'ensemble des innovations technologiques, des avantages potentiels, et des défis associés à l'intégration de la chaîne de blocs dans les réseaux intelligents.

Méthodologie : Une analyse thématique a été menée pour extraire les principaux thèmes et sous-thèmes de la littérature. Ces thèmes ont été organisés en catégories telles que la sécurité, l'efficacité énergétique, la gestion des REDs, la gestion de charge, etc. La méthodologie adoptée dans cette étude combine une revue exhaustive de la littérature et des études de cas détaillées. Cette approche multi-dimensionnelle permet de fournir une vue d'ensemble complète et équilibrée des innovations technologiques, des avantages potentiels et des défis associés à l'intégration de la chaîne de blocs dans les réseaux électriques intelligents.

Résultats et Contributions : Cette étude permet de contextualiser les recherches en cours, d'identifier les tendances émergentes et de mettre en lumière les lacunes et les controverses dans la littérature existante. Les résultats de cette étude ont servi comme guide dans cette thèse pour exploiter les bénéfices de la chaîne de blocs, définir l'étendue des travaux et des domaines et de proposer des solutions qui n'ont pas encore été explorées, tout en surmontant les obstacles pour une transition énergétique réussie.

8

Revamping Energy Sector with a Trusted Network: Blockchain Technology

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Abstract
The energy sector is in the midst of a major transformation, driven by new climate regulations and a political tendency towards a nuclear phase-out, aiming to achieve carbon neutrality for power generation and increased efficiency in electric grids. As a result, most power grids are encouraging higher integration of distributed energy resources and greater involvement of consumers in the energy management of the grid, served by a considerable application of smart technologies such as blockchain, artificial intelligence, big data, cloud computing, etc. This digital transformation at the core of the energy sector promises heavy disruptions, changing it from a centralized, segregated supply chain to a decarbonized, decentralized, and digitalized interconnected smart platform.

Blockchain as a transparent, secure, and decentralized trading platform, has gained the interest of businesses and industries worldwide unlocking new business models and promising new revenue streams. This promise is particularly potent, in the energy industry, when deployed at the grid edge, where increased consumer involvement and transparency are required. Blockchain based energy demand side management programs or energy peer-to-peer trading models, are typical solutions to be considered. In this chapter, blockchain applications in the energy sector are addressed along with their social, economic, and environmental impacts.

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***Keywords*:** Energy, blockchain, smart contract, P2P, distributed energy resources, renewable energy, prosumer, smart grid

8.1 Introduction

Global megatrends, such as globalization, urbanization, demographic growth, climate change, and digitalization, are shaping world economy in profound ways. These megatrends promise to reform the different economic sectors by disrupting existing and established business models, presenting new enterprise and value chain architectures, and offering new revenue streams. And particularly, the energy sector is not exempt from the direct impact of these trends. From the use of wood as dominant fuel, to the mastering of hydropower, to the adoption of coal and more recently oil and gas and finally to the integration of renewable energy resources, the global energy landscape has gone through fundamental transformations and will continue to do so in the future. However, failing to acknowledge these driving trends would have detrimental outcomes on the development of the sector. On the other hand, energy represents an exceptional commodity to be carefully addressed, since all economic sectors involve some sort of an energy form as a basic source, as well as being considered concurrently a key driver and an indicator of economic growth.

Driven by the need to achieve carbon neutrality and meet new climate regulations, as well as attending to new consumer behaviors and expectations, energy companies worldwide are encouraging higher integration of distributed energy resources (DERs) and greater involvement of the consumers in the management of the energy supply chain, enabled by a considerable application of smart technologies such as blockchain, artificial intelligence (AI), big data, cloud computing, etc. Yet, these new changes challenge energy companies, which are not used to operating in such a rapidly varying decentralized business environment. For instance, oil and gas companies face price volatilities and new patterns of demand. Similarly, electric utility companies and independent system operators (ISOs) have to deal with the complex and intermittent nature of distributed energy resources, as well as the evolving nature of consumers' expectations. Moreover, the rising integration of DERs such as photovoltaic, wind turbines, electric vehicles and demand management, merged with the limitations of the existing electricity grids, necessitates the development and implementation of new innovative energy management systems. One of the main reasons for a fundamental reconfiguration at the core of existing electricity grids, compelling an architecture change from a centralized network to a decentralized form, is the need to deal with the distributed nature of DERs that are located at the grid edges, while overcoming the resulting grid connection and load balancing challenges, as well as the incurring significant infrastructure upgrade investments, with an ultimate target of maintaining a balance between supply and demand [1].

For the electrical grid, the balance between the supply and demand is a fundamental element of a good grid operation. Power generation arrangements and load management are governed by a rule that equilibrium between power generation and power demand should be maintained at all time. Power companies worldwide are challenged by recurring power crisis as a result of supply side problems, such as fuel supply shortage, maintenance requirements, and natural disasters, combined with a continuous growth in energy demand [2]. Historically, electric grids started as decentralized isolated small generators feeding power to small towns and cities. But with the emergence of the first industrial revolution and the discovery of alternating current (AC), that allowed power transmission over long distances, power grids shifted into the form of large centralized generation plants capable of satisfying the needs of continuously increasing energy demand. And today, following the wide adoption of DERs, the electric grid is once again shifting to a decentralized yet smarter architecture. Though smart decentralized microgrids provide a platform to implement more cost effective DERs, their development faces numerous technical, economic and infrastructure challenges associated with grid capacity and stability hindering the wide integration of renewable energy (RE) resources and distributed power generation. Power imbalance and peak load have emerged as two major concerns in the operation of an electrical grid, both of which can have a considerable impact on power reliability and quality. Furthermore, the surge in energy consumption is being driven by global economic growth, demographic expansion, digitization, increasing mobility, and growing demand for heating and cooling owing to climate change in various parts of the world. The growing in energy demand is the basis of economic challenges for power companies alongside several socio-economic concerns in communities such as energy poverty and energy democracy. Two key strategies have been identified to address the increasing energy demand dilemma. The first strategy focuses on new sustainable and eco-friendly modes of power generation such as renewable energy resources and distributed energy resources (DERs). The second strategy is demand side oriented rather than supply side. Demand side management, demand response and energy efficiency programs fall under this category.

On the other hand, energy suppliers are in a continuous quest to reap greater productivity, lower costs, and improved safety. A quest that can be achieved by digitalizing the energy sector. Digitalization is essential to attend to the distributed nature of DERs, manage the complexity of smart grids while unlocking load flexibility, increase diversity in the system, create an interconnected supply chain that can respond to fast changes in demands, and encourage higher consumers' engagement by allowing them to control their energy supply and resources. From a utility's perspective, digitalization of the energy value chain allows better monitoring of the assets and thus enabling early fault detection, minimizing downtimes, increasing equipment lifespan, and improving efficiency by controlling wasted energy.

Nevertheless, what is supposed to be a solution to the electric grid challenges and barriers has proved over the years that itself is a generator of a series of new challenges and barriers that require to be targeted. Hence, the shift towards a decentralized, digitalized and decarbonized (3Ds) electric system is not simply a matter of using a cleaner fuel or source for power generation, but more importantly it is a matter of altering energy consumption habits, as well as energy production, management and trading means in order to achieve higher resource efficiency and sustainability. Consequently, there is a need to introduce a fundamental paradigm shift in energy markets and energy management. Traditional management methodologies, based on centralized decision-making techniques, should be replaced with a decentralized, collaborative strategy that grants all stakeholders and specifically edge users a bigger say in governance.

Thus, there is a widespread recognition of the necessity for imaginative decentralized systems and designs. In this context, it comes as no surprise that blockchain technology is one of the main drivers of the digital transformation across various industries and can play an important role in delivering a completely decentralized energy grid [3]. Blockchain represents a technological breakthrough that can redefine the way transactions are conducted. Additionally, blockchain can serve as a platform for data transfer, management, and storage for other disruptive technologies such as Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML). For the energy sector, this can be translated in shifting the grid from a unidirectional or bidirectional energy trading grid into a multi-directional system where consumers can transact not only with the grid but also among themselves, thus making the consumer an integral part of the new energy transition. Similarly, the implementation of blockchain technology in the energy sector can unlock new ways to deal with consumers' metering data without jeopardizing their privacy. Utilities' access to real-time metering data allows new demand side management programs to be designed and offers in depth insights on energy consumption patterns. Blockchain's potential in the energy sector is reflected the growing number of start-ups as well as research and Proof-of-Concept (PoC) projects. A survey conducted by the German Energy Agency (Deutsche Energie-Agentur GmbH - DENA) [4], showed that 80% of energy executives believe that blockchain is a game changer. Moreover, according to reports prepared by Deloitte [5] and PwC [6], energy commodities tokenization, enabled by blockchain technology, has the potential to change the way energy products are traded, making the process more interoperable.

This chapter sheds the light on the importance of digitalization in the energy sector and more specifically on the potentials and challenges of blockchain integration in the newly digitalized energy outlook. Through real life applications and conceptual models, this work aims to underline the different possibilities for new blockchain based energy business frameworks and revenue streams as well as their economic, environmental, and social impacts.

8.2 Energy Digital Transformation

Without a doubt, the energy sector is undergoing a substantial shift, and digitalization is one of the key facilitators in ensuring that this transition is accomplished. As a matter of fact, today's energy sector as well as its complete value chain is strongly driven by the new digital revolution. The tendency to have a higher integration of DERs in modern grids combined with the necessity to transform the conventional energy grid into a smart energy grid that meets both utilities and consumers' expectations and helps to overcome new market challenges such as the high volatility of energy prices and new patterns of demand, make from the adoption of new digital technologies at the core of the energy sector an inevitability. In this sense, digital technologies, such as AI, IoT and blockchain, comes into play as new game changers that offer the means to monitor and control the currently reshaped decentralized energy value chain. New energy management softwares, based on emerging digital technologies, allow not only to manage but also to optimize the energy supply chain, thus increasing its efficiency and productivity, while unlocking innovative business models and creating new revenue streams that couldn't be reachable without a fundamental digital transformation.

The transitioning from analogue energy meters to digital meters and later on to smart meters began more than half a century ago. However, until now, digital technologies have only been used to improve the energy management process; this will change if these technologies are used to transform the way energy is produced and distributed.

8.2.1 Digitalization, Decarbonization, and Decentralization of the Energy Sector

During the past decade global economy has been fundamentally reshaped as a result of recurring financial crisis, raising environmental concerns and new geopolitical apprehensions. This change can be summarized by the newly established triple bottom line: energy, environment, and economy. World Bank expects the world population to increase by 1 billion by the end of the decade. This growth can mean two things: the increase in world population will exhaust the remaining carbon credits and will lead to a definite increase in energy demand. This is why the decarbonization of the energy sector is no longer just an image improving choice but rather a must. By definition, decarbonization is the reduction of carbon dioxide emissions through the use of low carbon sources, achieving a lower output of greenhouse gasses into the atmosphere. In the electricity sector this means a decrease in the specific amount of carbon (or CO_2) emitted per unit of primary energy consumed. Additionally, electricity supply is the single most important emissions source sector, accounting for around 40% of global energy-related CO2 emissions.

At COP21 in Paris, the international community has agreed to limit global warming to well below 2°C, and to reach net greenhouse gas (GHG) emissions neutrality in the second half of the twenty-first century. Nevertheless, this can only be achieved by implementing serious measures that lead to a considerable decarbonization of the energy sector. These measures can be grouped into five main categories:

- Employ energy efficiency: Increasing energy efficiency will lead to a reduction in energy consumption which can counter-effect the increase in the energy demanding resulting from the growth of world's population
- Zero carbon electricity: This point can be achieved by decarbonizing the energy reply through a shift towards more sustainable and renewable sources of energy
- Economy wide electrification: Pushing clean electrification into energy consuming sectors, such as the transportation sector, can play a major role in shaving a larger amount of GHG emissions

- Zero carbon fuels: The use of zero carbon fuels can be very beneficial, especially for sectors where clean electrification cannot be integrated
- Carbon capture and removal: Carbon removal mechanisms can be implemented for areas where fossil fuels are still used in order to achieve negative emissions

However, the above detailed energy sector decarbonization measures will be hard to be employed in a conventional centralized and unidirectional energy supply chain. The integration of some of these measures, such as zero carbon electricity, employment of energy efficiency and economy wide electrification, necessitates a complete restructuring of the current energy grids and a shift towards a decentralized architecture that can be more adequate for a larger integration of DERs. Changing the energy system over from fossil energy carriers and nuclear energy to renewable energies and DERs opens up a range of new options for providing energy in a decentralized manner in the form of smaller plants.

Though, it is very important not to confuse decentralization with self-sufficiency. The concept of self-sufficiency is associated with economic independence, autonomy, and control over one's own energy supply. But decentralized energy is energy that is generated off the main grid and produced close to where it will be used rather than at a large plant. So, in other words, energy sector decentralization is the transformation of the "one-way street" of energy into a multi-directional, multi-lane highway. A decentralized energy supply offers individuals the possibility of playing an active part in shaping the energy transition, where every prosumer is an energy company. Such transition promises new deregulated energy markets that not only offer prosumers new revenue streams and earnings but also a role to contribute in the management of the energy grid via their resources and load flexibility. Such a prosumer-driven energy market might be beneficial to all stakeholders. Prosumers will not only benefit from direct earnings resulting from reduced energy bills but can as well contribute to the reduction of the energy cost for the system at large. In this case, utility companies can, at their end, benefit from this reduction to increase their profits, as well as beneficiating from the avoided investments costs to enlarge the grid, in order to accommodate new energy demands. Moreover, the decentralization of the energy supply chain will contribute to the decrease of technical and non-technical losses of the grid and thus adding more benefits to the utility companies.

Yet, the decentralization of the energy sector does not come without challenges. Today's decentralized energy model is complex and will be more so in the future. The integration of DERs at the edges of the grid as well as the intermittent nature of most renewable energy generators renders the management of the energy grid a difficult task. Moreover, the increased number of DERs added to the electric grid, leads to vast amounts of data being produced throughout the energy chain. Thus, the only way to respond to these challenges is to take the energy sector one step further and implement a fundamental digital transformation at the core of the energy value chain. Digitalization can serve as a lever in the energy sector to battle climate change and optimize power generation operations in order to reduce emissions and achieve the goals of decarbonization. Moreover, data is the key driver for optimized energy management. Digital technologies are set to make energy systems around the world more connected, intelligent, efficient, reliable, and sustainable. Without advanced technologies such as IoT, AI, blockchain, big data ...etc., it would be impossible to manage a decarbonized and decentralized energy system. Digitalization is a must for today's energy management systems and is set to transform the global energy system with profound impacts on both energy demand and supply. Digitalization can improve energy efficiency through technologies that gather and analyze data to effect real-world changes to energy use.

In summary, an energy transition is required in order to achieve energy security, supply and demand balance, economic growth, increase access to energy and guarantee sustainability while mitigating climate change. This transition is only possible through a strong correlation between the 3D variables: decarbonization, decentralization, and digitalization. The decarbonization of the energy sector is a main piece of the sustainability puzzle of this planet and decentralization is the mean to reach this goal. However, the decarbonization of the energy sector and its decentralization are not feasible without digitalization. The digitalization of the energy sector has an important part to play in the management of the new energy fabric and the synchronization of all its elements.

8.2.2 Blockchain: A Disruptive Technology of the Energy Value Chain

The energy sector is rapidly evolving from a highly centralized analog world of fossil fuel-based production and transmission system to a new paradigm of decarbonization, decentralization, and digitization. This transition is only possible if the available technology allows it and at this level blockchain might be the solution being a digital decentralized network formed of distributed computers connected to a platform. In fact, just by looking at the main features of modern energy networks, we find many similarities with blockchain technology. The key drivers of the new energy supply chain are management of big data, digital connectivity, decentralization, and security. All these drivers are common features with blockchain networks.

Blockchain has gained its reputation as a secure, transparent, fast, and low-cost peer-to-peer (P2P) transactional platform. For energy companies this can be translated into higher automation capabilities and greater data processing abilities with less human intervention at a lower cost and risk. The new energy revolution has caused market companies to deal with an increasing necessity for reporting, transparency, storage, and security of data, which incurs higher processing costs and a draining exploitation of personnel and resources. Blockchain technology can offer solutions for those challenges and have a significant impact on the entire energy value chain. Current energy transaction models are based on unidirectional and centralized structures. Energy transaction occurs only from energy companies to consumers with a need for third party intermediaries, such as brokers and aggregators, in most cases. However, the integration of DERs in the energy mix of modern energy grids has forced the conventional energy transaction model to change into a bidirectional system where energy can be traded from the grid to the consumer and vice versa. Nevertheless, the still imposing need for third party intermediaries to bridge the trust gap between consumers and energy companies imposes additional charges to consumers' bills, as well as increasing the processing time for transactions. Additionally, the existing energy transaction structure has a centralized architecture that induces a single point of failure risk. In case the connection to the energy service provider's central energy management server is lost, the complete network is jeopardized. Alternatively, a blockchain network allow to mitigate the single point of failure risk, since it has different connected nodes that interact with each other and a copy of the ledger containing all transactions is shared among all nodes. Thus, even when a single node or multiple nodes disconnect from the network, the system's operation and integrity are maintained.

Therefore, blockchain technology has the potential to unlock new business models and create new revenue streams for both energy companies and consumers, especially when applied to grid edges, as greater market participation and transparency are thought. Additionally, the balance between power generation and power demand is the foundation of any energy management process. The application of blockchain technology in the form of energy demand profiles management or energy peer-to-peer trading to create a transparent, secure and near real-time energy model is something to consider, as we will see throughout the next sections of this chapter.

8.2.3 Blockchain Advancing DERs

As elaborated in the previous paragraph, the fast growth of distributed energy resources is pushing the power system into a decentralized bidirectional power flow system where blockchain technology can play a major role in optimizing DERs' integration to the grid, minimizing costs, managing load profiles and increasing grid's flexibility. By definition, the term "Distributed Energy Resource" (DER), refers to the following (Figure 8.1):

- Distributed Generation: Power generation units that produces power on the consumer's side of the meter
- Distributed Power: Any technology that produces power or stores power (i.e., batteries and electric vehicles)
- Demand Side Management

Though microgrids provide a platform to implement more cost effective DERs, their development faces numerous technical and non-technical challenges. On a technical level, infrastructure barriers associated with grid capacity, synchronization, and stability are considered a major limitation that confronts a wider integration of renewable energy (RE) resources and distributed power generation. Another barrier to the development of RE resources is the adequacy of existing transmission lines to transmit energy from the points of generation to the points of consumption. Furthermore, the lack of skilled utility workers in some regional markets limits the implementation and development of DERs. Another barrier is the lack of awareness and knowledge of personnel about the availability and performance of renewable energy.

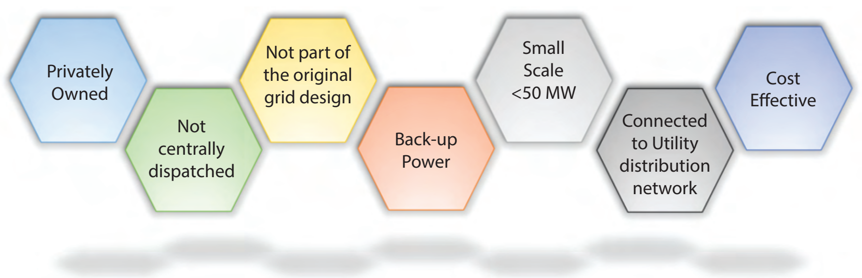

Figure 8.1 DER characteristics.

On the other hand, the economic challenges that hinder the development of microgrids which use renewable energy sources include market and financial barriers. Identified market barriers include the following:

- Inconsistent pricing structures that disadvantage renewables, especially those in long term power purchase agreements.
- Subsidies for fossil fuels. Subsidized fossil fuel-generated electricity makes it difficult for RE resources to compete.
- Failure to include social and environmental costs in the overall costing procedure

Financial barriers include lack of adequate funding and financing for renewable energy. The commercialization of DERs heavily depend on reducing the production costs of RE, storage technologies and energy management systems.

To minimize their reliance on fossil fuels and increase their energy security, many industrialized and developing countries are adopting and promoting renewable energy resources and distributed energy resources as part of their overall energy mix. These countries have adopted a slew of laws, directives, and regulations, as well as setting targets to endorse distributed generation, renewable energy, and microgrid development. Nevertheless, the issue is not a lack of regulation, but rather its flaws and ambiguities. Some regulations are undefined or not clearly stated. Additionally, lengthy administrative procedures and policy instabilities play an important role in hindering efforts to deploy renewables and expand microgrid markets.

Blockchain technology can help to overcome some of the challenges associated with a wide integration of DERs in electric grids, especially in developing countries where in most cases a solid infrastructure and a trusted public framework are lacking. Blockchain technology has the potential to transform the entire contractual life cycle of energy trading by minimizing the need for human intervention from the time of trade execution to the time of payment. Also, blockchain technology's integration in the DER market has the potential to improve market efficiency and disrupt energy markets by creating unforeseen opportunities, as well as providing incentives for DER development, particularly in developing countries, and creating new revenue streams that can render the investments in DERs economically appealing. Among the conceivable applications, that can advance DER implementations, are blockchain based smart meters, energy backed digital currencies, P2P energy trading and blockchain enabled new demand side management programs.

Blockchain and Smart Meters: Using blockchain and cryptocurrencies for monetary transactions is an achievable application of blockchain technology in the energy sector. Blockchain eliminates the need for a third party in money transfer transactions and reduces transfer costs by eliminating administrative fees, bank fees, and commissions. Savings from using the blockchain's platform can be re-invested. An application of the blockchain in the energy sector is through the installation of smart prepaid electric meters that provide power to the end-user once money is transferred from the end-user's account to the utility account. This application improves end-users' payment discipline and reduces the cost of reading meters, billing and collections. In most developing countries, the utility company suffers from low billings and collections. Prepaid electric meters offer a solution which decreases utility company losses, leads to lower energy rates, and avoids increases in electricity prices. Another application of blockchain for energy sector money transfers is demonstrated by the South African company Bankymoon who uses Bitcoin to perform remote payment transactions with compatible smart meters. The application works as follows: assume a donor wants to support a school in a developing country; the donor can send cryptocurrency directly to the school's smart meter, enabling electricity from the grid to be supplied to the school.

Analogously, today's energy billing systems are not designed for a bi-directional energy market in which customers produce and consume energy at the same time. For example, individual bills are still issued for every PoD (Point of Delivery), rather than one aggregate bill per customer, who might own several apartments, illustrating that these systems do not apply a user-centric system hierarchy. As a result, retailers do not have any information about customers who own multiple locations, and therefore are unable to offer personalized products. Moreover, billing constitutes between 5% and 15% of retailers' total operating costs. This results from the fact that the industry still relies on expensive and outdated legacy softwares that have high setup and maintenance costs, without providing the necessary functionalities that are needed in order to compete in a more customer centric energy market. Moreover, the current data collection, processing and financial settlement processes are highly inefficient and error-prone, resulting in significant time delays in value settlement and the need for costly reconciliation processes [7]. Thus, the need to develop an automatic decentralized energy trading system that can automatically collect energy consumption, offer a user-centric approach and ensures a simple settlement for energy transactions in a bidirectional way. This is where blockchain technology combined with IoT and AI can revolutionize the current energy trading models by providing energy companies with the possibility to incorporate thousands of data points per day per smart meter, enabling them to offer customers a variety of innovative, dynamic tariffs, services and products, while running on an efficient, fully automated and process assured billing system.

Energy Backed Currencies: The lack of financial incentives or funds is the main barrier facing the development of distributed energy resources. This challenge applies to both developed and developing countries. In 2016, approximately a third of Germany's electricity consumption was generated using renewables. Recently, the central government reduced financial incentives for new RE installations, particularly solar photovoltaic [8]. An energy-backed currency might be the type of incentive needed to improve the economic feasibility of renewable energy-based power generation. The concept of an energy-backed currency is similar to the gold reserves that are used to stabilize national currencies. An application of this concept is offered by the SolarCoin Foundation, a nonprofit organization. They focus on promoting solar energy generation by providing SolarCoin to solar energy producers. Nick Gogerty and Joseph Zitoli, two founders of the SolarCoin Foundation, had an idea for an energy- backed currency called DeKo in 2011 [9]. In 2014, the DeKo was transformed by the SolarCoin Foundation into a digital asset reward program for RE installations based on a new cryptocurrency, called SolarCoin. SolarCoin is a digital currency backed by solar-generated electricity, electronically representing a verified 1 MWh of solar-generated electricity. The main purpose of this initiative was to provide an incentive to produce solar energy by rewarding SolarCoin to producers of solar electricity. SolarCoin is active in 17 countries and is intended for worldwide circulation. SolarCoin can be exchanged for other cryptocurrencies or conventional currencies. Holders can user their SolarCoin to pay for products and services from participating merchants and service providers.

The Jouliette is another energy-backed currency named after the joule, an SI energy measurement unit. The Jouliette is backed by physical energy production. In September 2017, Spectral and Alliander launched the Jouliette token at De Ceuvel, a city playground for innovation and creativity in Amsterdam and a showcase for sustainable urban development [10]. A private smart grid made the Jouliette model feasible for the De Ceuvel community. With the Jouliette token, the De Ceuvel community members can transact using a secure blockchain platform, without the need of any bank or a trusted third party. Transaction histories can be shared with all community members enabling automatic verification. The De Ceuvel community is exploring further applications for the Jouliette tokens such as using it to trade for goods and services within the community [11].

Energy-backed currencies using blockchain might provide incentives for communities in developing countries, especially if combined with smart contracts and P2P energy trading within community micro-grids.

8.3 Energy Trading Mechanisms

With an aim to incentivize consumers' investments in DER projects, energy utility companies have developed various incentive programs. Some of the most common incentive programs are Net Metering, Feed-In Tariff, and Power Purchase Agreements (PPA). Usually net metering and feed-in tariff financing mechanisms are applied to small scale projects while PPAs are applied to medium and large-scale power generation projects.

Net Metering: Net metering (NM) is a billing mechanism that allows prosumers to inject any surplus of generated energy to the grid and retrieve it back whenever needed. For example, if during the day a solar system is producing more energy than what the house is consuming, the extra energy would be exported to the utility grid, and the consumer would be able to use this energy at night, at a time where the solar system is not producing any energy. This eliminates the need for battery energy storage systems that are considered an expensive and high maintenance component. Net metering is concretely implemented by using an electric meter that would operate in two directions: the meter would be able to run backwards whenever the renewable energy system is injected back to the grid. However, the main drawback of NM is that by the end of the year, if the amount of energy injected to the grid exceeds the yearly consumed energy, the excess energy will not be remunerated by the utility company. This feature would limit the capacity of the renewable energy installed and would increase the payback period of the system.

Feed-in Tariff: Feed-in tariff (FIT) is a billing mechanism that also encourages investment in renewable energy systems. They are long-term contracts (15–25 years) that would specify a cost per kWh for energy supplied to the grid for each type of technology. The tariff is set to reflect the cost of the system. Consequently, the tariff may vary based on the technology used, the size of the system, the region where it is implemented and the type of installation whether it is a rooftop or ground-mount project. The FIT program includes a tariff degression. FIT mechanism provides a security to the renewable energy installers due to its fixed tariff over the contract period (with percentage degression). However, these renewable energy technologies have a fast development and evolution, which results in a fast drop in market cost as well. The FIT tariff scheme is very sensitive to these changes, hence the set tariff along with the degression percentage, defined for a 25-year period, could eventually result in an overcompensation or under compensation for the investor [12]. Currently, the FIT rate is lower than the retail electricity rate. In fact, Germany is one of the most relevant examples who had first implemented the FIT scheme; it first started with providing a high tariff for electricity from renewable energy sources, with a modest degression, in order to scale up generation. From 2009 to 2011, with the fast decrease of solar PV prices, Germany had to adjust the PV FIT in a way to manage the quantity of domestic PV installations. As of 2012, with constant decline in renewable energy costs, a reduction of FIT payments was applied in a way that it became lower than traditional energy prices. Unlike Net Metering, the FIT system requires two meters, one that would measure the outflow of energy to the grid, and the other one that measures the inflow of energy to the load. This would allow having different rates for both imported and exported energy.

Power Purchase Agreement: A Power Purchase Agreement (PPA) is a contract between an electricity producer and a purchaser. Usually, the producer is a private entity while the purchaser is a governmental or state associated entity. The agreement is a long-term contract, 20 to 25 years in the case of renewable energy sources, where a tariff for selling the electricity is fixed over that period. There are also several conditions that would be agreed upon, such as the minimum energy to be produced and sometimes a maximum amount of production would be specified; if the producer does not meet the range set, some penalties would apply. PPA contracts are done for the export of the total energy produced and are usually applicable for medium to large-scale capacity. While the renewable energy market and technologies are rapidly changing, a fixed tariff over a long period could be unfavorable to either the purchaser or the producer in case of market price fluctuations.

8.3.1 Blockchain P2P Energy Trading: A New Financing Mechanism

Another way to incentivize the surplus of energy without having a sole purchaser or entity to trade with is the Peer-to-Peer energy trading. With PPA, NM, and FIT, the trade of energy is always between the producer and the grid utility retailer or state-owned authority, which decides on the price of this surplus. However, Peer-to-Peer energy trading provides the option to buy and sell electricity between peers directly. Peers could be any entity, prosumers, consumers, and energy producers that are interconnected through a grid and can exchange power between each other without the intermediary of a conventional power authority. Peer-to-Peer (P2P) energy trading is a new financing mechanism that can be adopted to incentivize the development of distributed energy resources (DERs), by promoting the selling of excess energy to other peers on the network at a negotiated rate. Current incentive programs, such as Net Metering (NEM) and Feed-in-Tariff (FIT), operate according to a centralized policy framework, where energy is only traded with the utility, the state-owned grid authority, service provider or power generation/distribution company, that also have the upper hand in deciding on the rates for buying the excess energy. P2P energy trading has the potential to present a solution for both prosumers and consumers to decide on the amount of energy to be traded, the time of the transaction, as well as on the rates in an open decentralized, deregulated market model. Nevertheless, in order to make the P2P energy trading feasible, executable in real time, irreversible, immutable, and cost effective, a certain trading platform, with specific requirements that can only be shaped by relying on the blockchain technology, is essential.

The growing adoption of DER solutions has introduced a number of new variables to the energy trading economics and load balancing equation. And on the other side, DERs emerging markets need an enabling environment that allows grids to increase their uptake and improve their management of off-grid technology. Existing incentive-based schemes such as Net Metering and Feed-in-Tariff (FIT) are not always reflective of the cost of electricity at the moment of injection into the grid and might distort the market if the quantity injected is significant. In order to take advantages of such schemes, prosumers should either inject energy in periods when the compensation tariffs are high or maximize self-consumption or store energy when the tariffs are low. Also, in such schemes, the utility is the single buyer of electricity from prosumers and they usually control the tariffs at which electricity is bought. In the absence of a competitive market, the result will be always in favor of the utility company. Peer to Peer (P2P) energy trading creates a completely new energy framework with unique fair economic incentives for all stakeholders. The deregulated nature of the blockchain P2P energy trading system helps to create an open market that favors innovation and increases competition which can lead to a reduction of the overall market energy prices. In fact, the open market competition was a main driver for the energy market transition from fossil fuel-based generation to renewable energy, since the benefit is not only ecological but also financial as renewable energy-based power generation systems have a lower levelized cost of energy (LCoE). While fixed energy tariffs have helped to safeguard consumers from fluctuating energy prices, Net Metering or FIT has succeeded to incentivize the private sector's investment in renewable energy solutions, especially at a small scale, and thus transforming the conventional energy consumer into an active prosumer that contributes to the grid's power generation mix. However, a freer, P2P deregulated energy market, based on supply and demand, has the potential to further reduce energy prices and transform small scale renewable energy power generation systems from independent systems to interdependent and thus extending their contribution to the connected and decentralized grid through ancillary services.

For P2P energy trading to be applicable through blockchain technology, smart contracts, and smart oracles are required. A typical P2P energy trading smart contract would contain the amount and price of energy, the timeframe for transfer, the legally binding conditions including payment terms, conflict resolution, actions in case the agreed upon energy is not met, etc. After setting the smart contract agreement and trading terms, it is very important to establish a connection between the digital world of blockchain and the physical world of energy. Smart oracles are used for this purpose. Smart oracles would be the bridge between the smart contracts and the tangible equipment; they are a digital medium that would take the required data from the equipment, verify them, and send them to the smart code in order for it to take action.

To better understand how a blockchain based P2P energy trading system works, let's consider the following example. A prosumer signs a smart contract with a certain consumer to sell him/her 10kWh on the following day between 10h and 14h. The conditions of the contract state that Consumer shall pay in advance, based on a pre-agreed price, in order for the smart contract to be activated. However, the money remains in the smart contract escrow account and gets transferred to the prosumer's e-wallet once the correct amount of energy has been exchanged. In case the prosumer fails to provide the required amount of energy to the consumer, the smart contract will calculate the difference in energy terms and will pay the prosumer the exact amount for the traded energy while returning the remaining amount to the consumer's e-wallet.

The oracles needed for such transaction to take place are:

- Smart meter oracles to activate the corresponding meters and log the energy sent from the prosumer's meter to the consumer's meter
- Time oracle to provide information about the current time to the smart contract in order for it to initiate and terminate the transfer

- Utility availability oracle to provide the blockchain with a binary value that represent whether the utility is available or not so that the energy transfer takes place

Similarly, various interconnected smart contracts are required as well:

- A smart contract to collect the data from oracles: time, energy sent, energy received, utility availability
- A smart contract to compare the energy transferred to the energy set in the agreement within the set timeframe
- A smart contract to calculate the difference between money received and the money equivalent to the energy transferred, and would re-distribute the money accordingly

The smart contracts work in real-time, which enables P2P energy trading participants to sell or buy energy whenever it is available and/or needed. The fact that no intermediary is involved to validate the transaction makes the smart contract fast and cheap. It is important to note that although the ledger containing all the information about the contract and records about the transaction is distributed among all the nodes of the blockchain, only authorized users, which are the parties involved in that contract, have access to the information in the blocks. Moreover, the most important part of the whole system is the platform that would allow human interface, through which, users would be able to manage their transactions and have access to their information in the corresponding blocks.

Although the blockchain use for P2P energy trading is relatively new, various applications have already been implemented. One of them is the Grid+; a blockchain-based solution that works in a deregulated market. The Grid+ has a software and a hardware facet. The hardware equipment would be programed to automatically buy and sell electricity from the most beneficial source of energy, existing in the P2P network, and execute payments in real time. It would also communicate with internet connected smart equipment in the house in order to manage the loads.

So, in summary, direct energy trading in a micro-grid between peers, known as Peer-to-Peer energy trading, is a new way to incentivize DER projects. Blockchain based P2P energy trading allows prosumers to produce or store energy and sell it in a free market while satisfying their needs and increasing their profitability, as well as those of the buyers. Nevertheless, aside from the financial benefits, P2P energy trading actually presents technical challenges that should be respected in order to keep a strong electrical grid, problems could result from nodal overvoltage, energy losses, and frequency instability.

8.3.2 Blockchain-Based Virtual Power Plant (VPP) Model

In the previous paragraph, P2P energy trading, for small scale DER applications, was explored. Nonetheless, P2P energy trading can also be applied on a larger scale via blockchain based virtual power plants (VPPs). VPPs were conceived to tackle the techno-economic complications resulting from the increasing share of renewable energy sources in the energy grids. A VPP is a platform to monitor, manage, and optimize the operation of thousands of distributed power generation systems, aggregating their capacities to create a homogeneous power generation system. Hence, a VPP is not a true power plant, but rather an aggregation of several heterogeneous DERs, including PV systems, wind turbines, micro-gas turbines, electric vehicles, battery energy storage systems, as well as load management. When integrated into a VPP, the power and flexibility of the aggregated assets are traded collectively via an aggregator. The integration of VPPs in electric grids allows avoiding large investments in new centralized power plants and infrastructure expansions in addition to the benefit of generating electricity at the edges of the grid where energy is actually consumed, thus reducing technical losses resulting from long transmission lines. Moreover, since renewable energy power generation solutions have a low LCoE, the VPP approach allows reducing the overall energy cost and making it more competitive, as compared with fossil-based energy generators. Nevertheless, this solution does not come without its own challenges and limitations. The architecture of VPPs involves several stakeholders: the energy supplier/producer, the electric grid operator, the aggregator, the prosumers, and can involve several financial institutes as well. The extensive administrative process, required by these multifaced relationships, results in high operational expenses, transaction fees, and issues of trust among the stakeholders.

Blockchain's decentralized architecture not only is convenient for the energy management of DERs, by providing a real-time communication system for bidding, settling, and payment, but also helps to eliminate the need for an aggregator, which reduces process costs. Blockchain's P2P communication combined with smart contracts enables the automation of the complete energy trading process, while maintaining a balance between consumer's privacy and the transparency of the process. A blockchain based VPP model will give users the flexibility to trade between each other or with the grid as well as choosing to contribute to the energy grid by aggregating their ancillary services through the VPP. Blockchain based VPPs promise to provide the necessary capabilities to maximize DERs output while also ensuring reliability.

8.3.3 Blockchain Technology for Electric Vehicle (EV) Charging and Discharging

The transportation sector electrification is seen as a solution to worldwide challenges such as global warming, sustainability, and geopolitical concerns on the availability of fossil fuels. Yet, besides their major environmental and geopolitical contributions, the electric vehicles can also have a major contribution in the development of smart grids and will be considered in the near future as a key component of all residential micro-grids. Nevertheless, as EVs will become more and more used, new challenges for the electric grid will immerge. Utility companies will have to deal with issues such as peak loads resulting from simultaneous charging, increased energy demand and higher end-user's electricity bills. Smart grid technologies, using smart metering and advanced communication protocols, are already being developed by utility companies to better manage loads while increasing grids efficiency and resilience and cutting GHG emissions. EVs can play an important role in the smart grid framework. EVs should not only be considered uniquely as an electric load but rather as a mean of energy storage. With advanced techniques such as Vehicle-to-Grid (V2G), energy can be stored in EV's battery in off peak periods and then use the stored energy to shave peak time loads. Additionally, the EV's stored energy can potentially be used to compensate for the intermittent nature of renewable energy sources such as solar and wind.

However, the wide adoption of EVs remains challenged by the availability of charging stations at large scale. Yet in order to incentivize private sectors investments in EV charging stations, especially the ones owned by private entities such as EV stations installed in shopping malls or a public parking, the concerns of simplicity, security and privacy of charging stations, should be addressed. Blockchain technology can offer the perfect platform for a simple and secure billing model for EV charging and hence incentivize a wider development of public charging stations. Widespread use of electric vehicles (EV) becomes more feasible when drivers can universally access charging stations. A typical blockchain based EV charging system will offer EV drivers the possibility to park their vehicle at any blockchain compatible charging station while the vehicle autonomously connects to the charging station and recharges automatically. Once the vehicle leaves the parking space, the charging station automatically bills the driver for the energy received. Furthermore, a blockchain based EV charging/discharging model can take into consideration the bidirectionality flow of energy from and to the vehicle, thus considering the EV as both a load and an energy storage device. Such EV charging/discharging configuration can help attend to several grid challenges such as peak load shaving and reducing the impact of uncoordinated simultaneous EV charging. Since EVs are potential energy storage systems, the excess energy stored in their batteries can be fed back to the network and the owner earning money. The concept is based on the smart plug, which can be used as a normal electrical outlet plug but is linked with an identification code. Users install an app on their smartphones to authorize the EV charging process. It connects to the blockchain platform which negotiates the price, records the charging data, and manages the payment process (Figure 8.2). The application of blockchain technology for charging EVs represents a change in how private businesses interface with their customers. This model is ideal for small businesses, shopping malls, office buildings, and car parks who offer customers renewable energy charging for their plug-in electric vehicles.

A blockchain based EV charging/discharging system will basically have three main components:

- The Smart Plug: The smart plug can be considered as the digital identity of all peers using the platform. The Smart Plug enables users and devices to authenticate themselves to other network participants. Each EV Charging Station will hold a computer chip connected to the blockchain network and linked with an identification code to control the accessibility to the system by verifying the identity of the user connected to the charging station
- The mobile application: allows the customer to check the offered price, sign the smart contract and visualize the charging process on a smartphone
- The blockchain platform manages and records all payment and charging data. All charging processes will be completed using blockchain smart contracts between the EV vehicle owner and the EV charging station owner.

The system uses blockchain smart contracts to verify user identities anonymously and create a trusted contract between the EV vehicle owner and the EV charging station owner to manage the charging of the electric vehicle and manage payments between parties. Additionally, the smartphone application can notify the EV driver of the closest charging stations

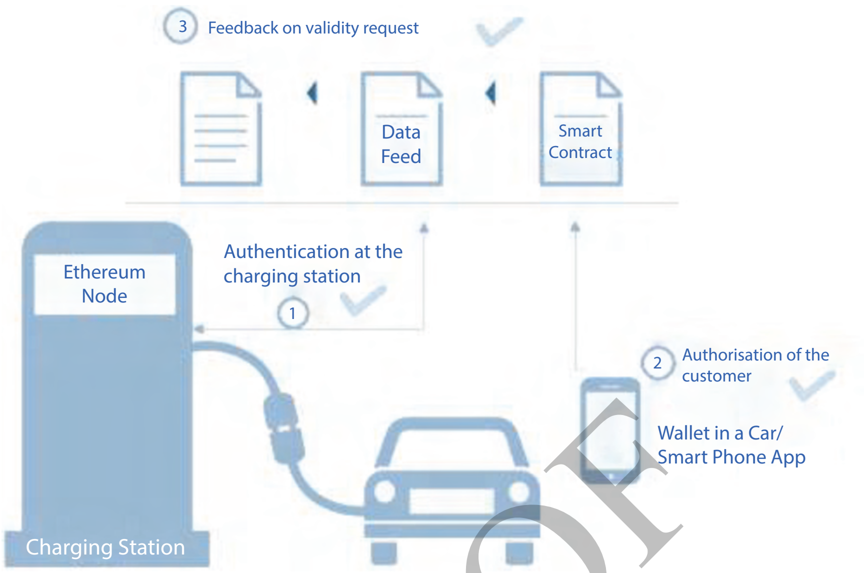

Figure 8.2 Blockchain based EV charging model.

along with the offered energy prices. Also, it will notify users of the preferable times to charge their vehicles in order to avoid uncoordinated EVs charging, offering them credits as incentives to charge their vehicles during off-peak periods thus contributing the valley filling in the utility profile. On the other side, during peak times, the EVs owners can be notified of Demand Response (DR) requests, thus injecting the energy stored, in the batteries of their EVs, onto the grid in order to respond to the peak load. By participating in these DR programs, users can also earn credits and they can use those credits to pay for their EVs charging.

Blockchain based EV charging and discharging model can help mitigate risks associated with the heavy electrification of the light duty transportation sector as well as bringing DER energy management up to a new level.

8.4 Blockchain Unlocking New Demand Side Management Models

Demand Side Management (DSM) first emerged as a response to rising costs of energy sources during the energy crisis of the 1970s, and it incorporates programs that help consumers manage their energy use, such as appliance rebates, energy-efficient lighting programs, as well as programs that reward customers for shifting their load during times of peak energy use. Demand Side Management is the term used to describe these programs developed by utilities to influence the electricity usage patterns of their customers and, in return, the achieved energy savings allow utilities to avoid or delay new investments in supply side generation, transmission lines, or even distribution networks. DSM is a crucial component of any smart grid energy management system. Basically, Demand Side Management, or sometimes called Energy Demand Management, is a set of interconnected programs that aim to encourage the end user to be more energy efficient. A DSM portfolio may include a variety of measures used to improve the consumer's load profile. Depending on the methodology used, the time of application, on-peak or off-peak, and the defined target, DSM mechanisms can be grouped into 4 main categories: demand response, energy efficiency, virtual power plants and spinning reserve.

Traditional transactional models are based on a centralized structure. Transactions between network nodes occur only through an intermediary third party who maintains the ledgers. Involvement of an intermediary is often necessary because it creates trust when transaction partners are unacquainted. Intermediaries usually charge fees for their services. The involvement of intermediaries increases the processing time required for transactions. Since all transactions are linked and stored on a central server or infrastructure, centralized structures have the disadvantage of a single point of failure. Alternatively, decentralized systems, such as the one offered by Blockchain, have different network nodes that can interact directly with each another without an intermediary. There are many ways that transaction ledgers can be maintained. With a secure P2P distributed ledger technology, problems with associated with centralized structures can be resolved.

So, blockchain technology has the potential to deliver more efficient, transparent and near real time transaction platforms that will unlock new business models. In the energy industry, this promise is particularly compelling when applied at the grid edge, as greater market participation and transparency are sought. An interesting feature of DSM projects is that multiple parties can benefit simultaneously from a single action. The forecasting of power generations and power demands is the essential premise for generation arrangement and power management. The use of blockchain technology for delivering a transparent, secure, reliable, and near real time energy model, under the form of energy demand profiles management, is something to look at. Such a model can be based on a blockchain enabled distributed tamperproof ledger where the energy prosumption data, collected from smart meters, is stored while self-enforcing smart contracts programmatically define the expected energy flexibility at the level of each prosumer, the associated rewards or penalties, and the rules for balancing the energy demand with the energy production at grid level. Another potential use case is the model of a DSM aggregator, as a key player in managing the demand during the peak hours by acting as an energy manager between the utility and the consumer.

8.4.1 Blockchain in the Energy Efficiency Market

Energy efficiency is an important pillar of utility companies' DSM strategies that can counterbalance the continuously increasing demand for energy. On the end-user's side, the development of new technologies, that allow consumers to monitor in real time their energy consumption, check their energy profiles and compare them to benchmarks, combined with an increase in electricity tariffs, has raised the interest in energy efficiency.

However, the process of collecting the correct data required to make the best judgments about building energy efficiency, can be very challenging. The energy consumption, operating cost, and asset value of a building are rarely publicly shared. Building energy efficiency data is generally siloed in original equipment manufacturers' (OEMs) hardware and software packages, making it hard and costly to access. Without easy access to energy consumption related data, building owners would struggle to assess the performance of their buildings as well as to quantify the impact of implemented energy conservation measures (ECMs) on their energy performance. The use of blockchain technology offers a means to extract and share buildings' binned data without jeopardizing neither the privacy of owners nor the security and integrity of data. Blockchain presents an open-access, transparent and yet confidential and secure platform that promotes simple and safe data sharing in order to create an accurate benchmark for building's energy performance and unlocks new energy efficiency opportunities in buildings.

Blockchain technology can simplify the energy efficiency service market. Instead of having a separate hardware and software for each OEM, the energy efficiency market can benefit from a publicly shared open access energy efficiency data platform. Data owners can be rewarded for their contribution to the platform with tokens that can be used to buy equipment or benefit from other services. And on the other hand, building owners and OEMs will have to pay with tokens in order to get access to the data. Building owners can benefit from the data to benchmark the performance of their own buildings and OEMs can use the data to assess the performance of their equipment and improve their performance.

In fact, the data sharing process for equipment or building performance assessment can be complimented by the blockchain based digital twin technology. As a result of their capabilities to simulate any process under different scenarios and provide performance insights, digital twins have emerged as an important instrument of Industry 4.0. Nevertheless, in the energy efficiency and energy management framework, digital twins can combine the semantically rich building information models with real time streaming data coming from building sensors in order to optimize the energy performance and the operation and maintenance of these physical assets. This data-driven model can play a major role in enabling advanced energy management applications.

8.4.2 New Blockchain-Enabled Demand Response (DR) Models

Demand response (DR) is a term used for programs designed to encourage end-users to make short-term reductions in energy demand in response to a price signal. DR programs pursues the temporary reduction of electricity consumption by the consumer, for a short period and in peak demand periods in exchange of economic incentives. However, the implementation of DR programs is faced with several challenges and limitations. The first challenge is the complexity of the management process. Due to the fact that a DR program can include thousands of participants, the registration, implementation, communication, and management processes are not considered easy tasks. The implementation of a DR program can induce a high overhead cost resulting from the management of participating entities, settlement of payments, market organization, data management …etc. This high cost can render some DR programs economically less appealing. Additionally, the collection, management, storage, and security of the large amount of data resulting from DR programs can be a real hustle and bustle for utility companies. Furthermore, DR programs are most of the time based on a bidding process. The disclosure risk of important data such as bidding data can generate a trust issue that challenges the integrity of the integrity and fairness of the bidding process and thus weakening the interest of participants.

The integration of blockchain technology in DR programs allows targeting most of the challenges faced by DR programs. Blockchain based DR programs offer the possibility to simplify and automate the registration, management and settlement processes by relying on smart contracts, especially that the decentralized structure of blockchain is perfectly suited for this type of applications. The use of smart contracts allows reducing DR programs costs and increasing utility profits. Moreover, blockchain improves the authenticity of DR programs by making DR related data traceable, transparent, and immutable. At the end-user's side, blockchain enables participants to tokenize their energy reductions and get compensate it for that in an automated manner. Additionally, it may also offer end-users to trade their energy reduction tokens with other peers and not necessarily just with the utility.

8.4.3 Blockchain-Based Energy Performance Contracting

Energy performance contracting (EPC) is an important concept for financing EE. It is based on an energy services company (ESCO) implementing an investment to reduce a host's energy cost, and accepting the financial and technical risks for a specified contract term. The host uses the project's future avoided costs to amortize the invested capital. These funds may be supplied by the ESCO or a third party. At the end of the performance contract term and after the investment has been amortized, the host often continues to benefit from lower energy costs. When the capital is sourced from the ESCO, the financing mechanism is the energy performance contract and the collection mechanism is through invoices and payments.

Performance contracting financial structures are tailored for each specific host and application. A typical structure would follow these stages:

- A preliminary analysis is undertaken to determine the host's energy consumption and costs and identify ways to maximize energy savings.
- A detailed energy analysis (known as an investment grade audit) is performed to determine energy savings and costs associated with the improvement measures.
- Improvements are selected for implementation.
- Facility improvements are implemented and the new equipment associated with the project is installed.
- Periodic measurement and verification (M&V) of savings determines the savings that is achieved.

Energy performance contracts are helpful in situations when funding sources are elusive, maintenance is lacking, or new equipment and technology is needed and requires unique skills. Energy performance contractors use future energy savings to finance present improvement measures and generally guarantee the savings to lower the risks of the host.

Despite the advantages of EPC projects, their providers and customers face legislative, administrative, and financial barriers. When compared with traditional methods of delivering EE projects (e.g., fixed-fee for services, or design-bid-build), EPC projects accept long-term performance and financial risks. EPC procedures seem comparatively complex. For both public and private institutions, disadvantages of EPC include the need for a more sophisticated contract and the calculation of the energy consumption baseline. Mills *et al.* identified the threats associated with EE projects and classified them as economic, contextual, technological, operations and M&V risks.

The payments in EPC projects are linked to verifiable energy savings achieved by the ESCO during the performance period. Defining a suitable payment arrangement is important for the ESCO to maintain a stable cash flow during the project term. Often fixed payment schedules are adopted in EPC contracts. The ESCO receives the fixed amount of payment from the host when the actual savings are determined to be equal to or greater than the guaranteed amount in each M&V period. Deductions are applied when performance shortfalls occur. M&V performance reporting periods could be monthly, quarterly or annually. It is not uncommon for the host to dispute the energy savings achieved by the ESCO, which may result in possible payment defaults by the host. Also, a payment default may occur from the host's inability to fulfill its payment responsibilities. In a worst-case scenario, the host might go out of business before full contract payment. Additionally, the multifaceted relationships between involved parties in an EPC contract induce operational risk associated with the complex project administrative process. Such risk causes higher operational costs and transaction fees and reduces the trust among the different parties. The existing EPC models rely heavily on traditional payment methods that necessitate trusted third-party intermediaries. The problems with the third-party intermediaries are that they charge considerable transaction and commission fees, and fail to offer real time payment processing. Plus, the forced bureaucratic process can be complicated and time consuming.

Blockchain technology can help improve EPCs by tackling barriers and risks are related to trust between parties, payment defaults, human errors, process complexity, delays and high processing cost, A blockchain based energy performance contracting would typically include four elements:

- Agreement on the baseline model: Stakeholders agree on the proposed predictive model, define frequency of data collection, outline the accepted accuracy, and set the energy data and mode of payment.
- Programming of the corresponding smart contract: The conditions defined in the first phase are hard coded inside different smart contracts.

- Deployment on the blockchain: A unique address is generated for each stakeholder and hard coded inside the smart contract to allow controlled access to the smart contracts. Then the smart contracts are deployed to the blockchain and their corresponding unique addresses are generated.
- Execution inside the blockchain: At this phase, the smart contracts are executed and called through their addresses.

Figure 8.3 shows a blockchain-based EPC model for a cooling energy conservation measure. Three oracles would measure the daily temperature, energy consumption and the time, whereas three smart contracts are responsible for data logging, implementing baseline adjustments, and calculating the energy savings.

ESCOs are continuously seeking new methodologies to reduce the complexity of EPCs. Blockchain technology and smart contracts can render the EPC process an autonomous process, thus reducing the time and costs associated with setting up and administering EPC projects. The reduction of manpower, processing cost and time will allow ESCOs to undertake a larger number of projects simultaneously thus increasing their profits and as a result a larger number of energy savings can be achieved. Moreover, the automation of the M&V process helps to lower the human risk and to eliminate the need for human auditors to carry out measurements of baseline and actual consumption data. Human errors in the M&V process can directly affect the monthly calculated savings and thus jeopardizing the profitability of the EPC project. So, not only blockchain helps to reduce

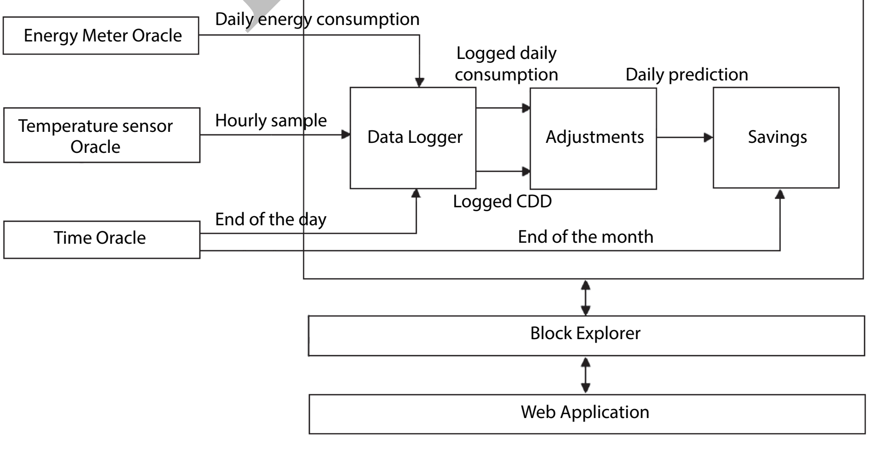

Figure 8.3 Blockchain based EPC model.

risks associated with the M&V process but also provides the added value of having data collected and monitored in real time as well as continuously calculating energy savings which can give early indications to ESCOs on the performance of the EPC project. On the other hand, blockchain and smart contracts also minimize the risk of payment defaults, since in a blockchain based EPC projects, a smart contract autonomously handles payments between parties at the end of each reporting period. Additionally, this feature allows speeding up the payment settlement process which can be a crucial payment for ESCOs, especially when the EPC project is funded via a bank loan and monthly payments are due at the beginning of each month. And finally, blockchain technology has the potential to render the data sharing process in an EPC project more secure and more transparent. The application of a distributed ledger technology (DLT) will help to create an auditable trail of energy savings and payments that is completely transparent to all involved stakeholders.

8.5 Energy Blockchain's Social and Environmental Impacts

Blockchain implementation in the energy sector can contribute to more than just solving the technical challenges and limitations detailed in the previous sections. Energy blockchain also impacts the social and environmental aspects of the energy sector. As previously discussed, blockchain applications in the energy sector improve the energy efficiency of buildings and systems, incentivize clean energy sources and help to reduce energy consumption. All those outcomes lead to a reduction in GHG emissions. But also, blockchain can contribute to the enhancement carbon tracking and trading process, Renewable Energy Certificates trading as well as providing means to fight energy poverty and establish energy democracy.

8.5.1 Blockchain Market for Carbon Credits and RECs

In response to global trends and expending environmental legislations, many energy and utility companies have implemented serious measures to reduce their carbon emissions and improve their green image. According to regulations, companies that are required to cut down their carbon emissions are requested to annually report their carbon footprint. However, the process of tracking and reporting carbon emissions proved to be a complicated one, due to the complexity of the measurement and reporting practices. The calculation and reporting of carbon emissions is based on manual data entry into spreadsheets which may lead to erroneous results. Afterwards, these spreadsheets are compiled and submitted to an auditor or a regulatory body. And in case any calculation or measurement error is detected, the company will be fined. For that reason, most companies have large teams involved in the carbon emissions measurement and reporting process. And despite that, most carbon emission reports tend to be conservative, by reporting lower carbon savings, in order to avoid any future penalties. Such practices lead to missed remediation credits and inaccurate carbon output data that most regulatory bodies and scientists rely on in developing policies and strategies. Therefore, companies and organizations need to adopt a new method of tracking carbon emissions in order to maximize their carbon credits and provide an accurate and more realistic image of carbon outputs. Additionally, the complexity of the carbon emissions tracking process may result from other factors such as:

- The multiplicity of data sources throughout the complete supply chain
- Regulations and reporting standard that may vary from one region to another
- The diversity of calculation methods and simulation models implemented to measure carbon emissions

Blockchain and IoT technologies can fundamentally transform the carbon emissions market. IoT devices and sensors allow having accurate and real-time data collection from the different carbon emissions sources. Thus, IoT technology can help reduce the risk that may result from manual data collection and entry. Similarly, the implementation of digital twin models, fed with real time data provided by IoT sensors, offer a real time simulation model that is capable of offering unprecedented insights into real time carbon emissions for each building or piece of machinery. With hourly outcomes from digital models, companies can improve their abilities to project their emissions levels and keep track of the efficiency of their carbon reduction implemented measures. Along with, blockchain technology provides the perfect platform to permanently and immutably record carbon emission's data that can be audited at any time. Blockchain's shared carbon emissions ledger offers auditors a proof that shared data is accurate and authentic. Moreover, using blockchain allows companies to overcome the regulatory confusion that results from operating in different areas of the world, as the time and location data can be encoded in the emissions transaction data, thus avoiding any confusion that may arise during an audit. And finally, once carbon savings are reported and validated, earned carbon credits can be tokenized and traded using blockchain.

However, carbon credits are not the only attributes that can be tracked and traded using blockchain. Renewable Energy Certificates (RECs) can similarly benefit from the features offered by the blockchain technology to make the certification and trading process more transparent, private, secured, and at a lower cost. RECs are market instruments that prove that the holder of those certificates owns 1 MWh of energy generated from renewable energy resources. Blockchain based REC trading platforms improve REC's traceability where any REC can be traced from where it has been generated to its final holder.

8.5.2 Fighting Energy Poverty

Energy poverty is a term that generally refers to a state where people cannot access to or secure basic energy services. In most cases, low household income, high energy tariffs or lack of infrastructure are correlated with energy poverty. In order to measure energy poverty several metrics can be used including, energy bills ration to household income, thermal comfort (access to heating and cooling), connection to the utility grid and access to utility services and finally occurrence of utility disconnection.

Energy policymakers worldwide are in a continuous quest to fight energy poverty. Nevertheless, this isn't an easy mission since energy poverty may affect households with diverse income ranges and people living in different places which makes it very hard to identify affected categories and design a unique solution that fits all.

Blockchain based P2P energy trading systems offer people the chance to contribute to the management of the electric grid and to influence market energy rates, thus lowering the overall cost of energy and increasing other people's access to energy. The same applies to energy backed cryptocurrencies, EV charging and discharging, DSM, and other previously discussed blockchain enabled mechanisms that enable end-users to improve their uptakes from their electric systems. Furthermore, blockchain technology promotes energy democracy by opening the door to new market players and business models that can disrupt the entire energy market, in addition to empowering end-users; converting them from just passive acceptors to a proactive engaged prosumer that plays an integral role in the new energy transition. Energy democracy is a political, economic, social, and cultural concept that merges the technological energy transition with a strengthening of democracy and public participation. The concept is connected with an ongoing decentralization of energy systems with energy efficiency and renewable energy being used also for a strengthened local energy ownership.

8.6 Conclusion

Blockchain is being recognized as a game changer in most economic sectors, but its potentials in the energy sector have not been fully realized yet. It took nearly a decade to transform the energy supply chain from its original centralized form into a decentralized architecture. Yet, this transition was only possible as a result of the emergence of low-cost renewable energy power generation systems and enforcement of new climate regulations that requires energy companies to reduce their carbon emissions. Hence, the energy grid moved from a dependent unidirectional mode of operation into a bidirectional independent mode of operation where off-grid micro grids can subsist. And now blockchain technology offers the chance to shift the energy sector into a multidirectional interdependent mode of operation where users can transact between each other and with the grid. Nevertheless, blockchain market infiltration will be met with resistance because it represents an extreme change to the present ways of doing business, especially since it eliminates the need for trusted third party intermediaries and disturbs current business models.

Nonetheless, blockchain longevity in energy markets has not been determined yet, particularly since it has not demonstrated yet long scale commercial benefits for the users. For blockchain technology to be embraced by the energy sector, it is necessary to overcome the shortcoming and limitation resulting from the fact that current blockchain platforms that use a Proof-of-Work (PoW) consensus mechanism consume an enormous amount of energy which might neutralize any positive effect that the technology can have on the energy sector practices. Additionally, challenges such as technological maturity and scalability as well as the need for a clear regulatory framework, should also be taken into account.

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3.3 ARTICLE: ENERGY BLOCKCHAIN – ADVANCING DERS IN DEVELOPING COUNTRIES

Une version abrégée de cet article, intitulée *« Energy Blockchain – Advancing DERs in Developing Countries »,* a été acceptée en tant qu'article-conférence dans la conférence « Association of Energy Engineers World Energy Conference à Charlotte. (É.-U.) en octobre 2018. L'article a été publié dans le journal « International Journal of Strategic Energy & Environmental Planning ». En plus, cet article a été transformé en un chapitre de livre et a été publié dans sa version finale en 2020 par les éditeurs de la maison d'édition *Taylor & Francis* dans leur livre intitulé : *« Fundamentals of Microgrids ».*

Référence: Aoun, Alain G. "Energy Blockchain—Advancing DERs in Developing Countries." Fundamentals of Microgrids. CRC Press, 2020. 189-200, eBook ISBN : 9781003082408

En tant que premier auteur, j'ai contribué au développement de l'idée générale, à l'essentiel de la recherche sur l'état de la question et au développement de la méthode, à la collecte et l'analyse des données et à la rédaction du manuscrit.

Résumé : Les réseaux électriques mondiaux subissent des transformations pour appliquer des technologies intelligentes à la suite de politiques qui encouragent l'utilisation de RED et augmentent l'implication des consommateurs d'électricité dans la gestion et la production d'énergie. Le système énergétique centralisé unidirectionnel du réseau évolue vers un réseau dynamique bidirectionnel qui dépend de plus en plus des REDs. Dans les pays sous-développés, les REDs se heurtent à des défis et à des obstacles économiques, sociaux et environnementaux. Il s'agit notamment de la culture communautaire, de l'insatisfaction à l'égard de l'infrastructure existante, du manque d'incitations et de l'absence de législation habilitante. Dans les communautés où la pénétration des REDs est faible et où la demande d'énergie propre est élevée, l'intégration de la chaîne de blocs et des marchés énergétiques P2P pourrait inciter les résidents de la communauté à développer les REDs.

Contexte et Objectifs : Dans ce chapitre, nous soulignons les principaux défis et obstacles auxquels est confrontée la mise en œuvre des REDs dans les pays en développement. Nous identifions également comment l'application de la chaîne de blocs dans le secteur de l'énergie peut introduire de nouvelles incitations à développer les REDs dans les pays en développement, en se basant sur les startups commerciales mondiales. Les applications de la chaîne de blocs dans le secteur électrique présentent souvent plus de chances de succès dans les pays en développement par rapport aux pays développés pour plusieurs raisons clés. Premièrement, les infrastructures existantes dans de nombreux pays en développement peuvent être moins développées et plus flexibles, permettant une adoption plus rapide de nouvelles technologies sans les contraintes des systèmes établis et parfois rigides des pays développés. Deuxièmement, les défis énergétiques et les besoins en infrastructure dans les pays en développement créent une opportunité pour des solutions innovantes comme la chaîne de blocs, qui peut améliorer la transparence, la gestion des actifs et la résilience des réseaux électriques. Troisièmement, les gouvernements et les acteurs du secteur dans les pays en développement sont souvent plus ouverts à l'expérimentation et aux partenariats public-privé pour moderniser leurs infrastructures énergétiques, créant ainsi un environnement propice à l'innovation technologique.

Méthodologie : Ce travail s’est basé sur une recherche approfondie des publications académiques, des rapports industriels et des études de cas sur les défis actuels du secteur électrique dans les pays en développement. Cela inclut l'analyse des politiques énergétiques, des infrastructures existantes, et des problématiques telles que la décarbonation, la gestion de la demande, et la stabilité du réseau. En plus un examen des cas d'utilisation existants des technologies basées sur la chaîne de blocs dans le secteur électrique à travers le monde, a été effectué, tout en incluant l'étude de projets pilotes, de collaborations entre entreprises et gouvernements, et des résultats obtenus en termes d'efficacité opérationnelle, de transparence et de réduction des coûts.

Résultats et Contributions : Les résultats et les contributions de ce chapitre mettent en lumière plusieurs aspects cruciaux concernant les défis du réseau électrique dans les pays en développement ainsi que les opportunités offertes par les applications basées sur la chaîne de blocs. L'étude identifie de manière approfondie les défis spécifiques auxquels ces pays font face, tels que l'instabilité du réseau, les obstacles réglementaires existants, l'absence de financement adéquat et les difficultés d'accès à l'électricité pour les populations rurales. En explorant les cas d'utilisation des technologies de la chaîne de blocs, l'article démontre leur potentiel à améliorer la transparence, l'efficacité opérationnelle et la gouvernance du secteur électrique.

Peer Reviewed Article

Energy Blockchain— Opportunities and Challenges in Advancing Distributed Energy Resources

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ABSTRACT

Blockchain has developed a reputation as a secure peer-to-peer trading platform that has gained the interest of the world's new businesses and industries. In a future in which consumers are encouraged to become producers and everyone is encouraged to become entrepreneurs, energy blockchains have an important role in smart grid frameworks. Blockchain has the potential to change people's digital life by changing the ways transactions are processed. By eliminating the roles of third parties in transactions, blockchain can make our systems more efficient, thus reducing cost and improving reliability. As a result of the development of the renewable energy sector, the energy market is shifting towards smart de-centralization. Nevertheless, in developing countries, the development of distributed energy generation faces economic and financial barriers. Therefore, in countries lacking distributed energy resources (DER), the integration of blockchain and peer-to-peer energy trading can create incentives for end-users to invest in DERs and microgrids. When blockchain is integrated within electrical power networks, it enables the tracking of energy generated by DERs, documents the reporting of savings from energy conservation measures and facilitates the trading CO_2 credits.

How can the blockchain be modified to serve the energy market and create opportunities for energy producers and consumers? This article answers this question by providing an overview of the blockchain mode of operation, highlighting the potential of the blockchain in the energy trading business, and identifying the challenges and barriers confronting the development of the energy blockchain.

INTRODUCTION

Recently, the *World Energy Issues Monitor* published a report by the World Energy Council that offered an annual survey of key challenges and opportunities faced by energy leaders in managing robust energy transitions [1]. Blockchain was identified as one of the most critical uncertainties within the digitalization elements and was perceived by global energy leaders to be an issue of relatively high impact and uncertainty [1]. Blockchain has the ability to change the way we manage, organize, record and verify transactions. According to Don Tapscott, Tapscott Group (dontapscott.com), the blockchain technology that underpins cryptocurrency could revolutionize the world's economies. Its model provides an opportunity to shift from a centralized transaction structure (exchanges, trading platforms, energy companies) to a decentralized system based on peer-to-peer (P2P) trading.

The world's electric grids are undergoing transformations to apply intelligent technologies as a result of policies that encourage the use of renewable and distributed energy resources (DERs) and increase the involvement of electricity consumers in managing and producing energy. Improving the reliability of today's energy supply system is hindered by the existing infrastructure of the centralized power supply system called the *grid*. The grid's unidirectional centralized energy system, supplying electricity to passive customers using traditional sources of energy is shifting to a dynamic, bi-directional network which is increasingly dependent upon DERs (e.g., intermittent renewable energy, electric vehicles and energy storage systems). The diversity of the technology, sources of energy, and power purchase agreements (net metering and feed-in tariffs) have important roles in adopting and advancing the use of DERs. In underdeveloped countries, DERs face economic, social and environmental challenges and barriers. These include community culture, dissatisfaction with the existing infrastructure, scant financial incentives and lack of enabling legislation.

In communities that have low DER penetration and a high demand for clean energy, the integration of blockchain and P2P energy markets could be an incentive for community residents to develop DERs.

In this article, the key challenges and barriers facing the implementation of DERs in developing countries are considered. Ways that the application of blockchain in the energy sector can introduce new incentives to develop DERs in developing countries are identified.

BLOCKCHAIN OPPORTUNITIES FOR ENERGY TRADING

A blockchain is a distributed chronological ledger that is hosted, updated, and validated by several peer nodes, rather than by a single centralized authority. By eliminating the central authority and having immutable transaction records that are validated by several peers, the blockchain increases the simplicity, speed, and transparency of transactions between two peers. An example of the implementation of blockchain is the cryptocurrency Bitcoin. While credit card transactions require validation from a bank and require time, blockchain doesn't require central validation and two-party transactions happen immediately [2].

Since blockchain is a secure peer-to-peer trading platform, it has gained the interest of businesses and industries in energy markets. The blockchain promises a transactional platform that is fast, highly secure, has lower incidents of error, and can often reduce capital requirements [3]. It allows companies to automate more while processing greater volumes of data with fewer people at lower cost and risk. Companies that market energy are dealing with greater requirements for reporting, transparency and security of data, which increases energy trading process costs and the need for personnel and resources. Energy blockchain provides solutions for these challenges. The energy sector is one of the industries where blockchain can have substantial impact.

Traditional transactional models are based on a centralized structure. Transactions between network nodes occur only through an intermediary third party. Involvement of an intermediary is often necessary because it creates trust when transaction partners are unacquainted. Intermediaries usually charge fees for their services and their involvement increases the processing time required for transactions. Since all transactions are linked and stored on a central server or infrastructure, centralized structures have the disadvantage of a single point of failure. Alternatively, decentralized systems, such as Blockchain, have different network nodes that interact directly with each other without an intermediary. With a secure P2P distributed led-

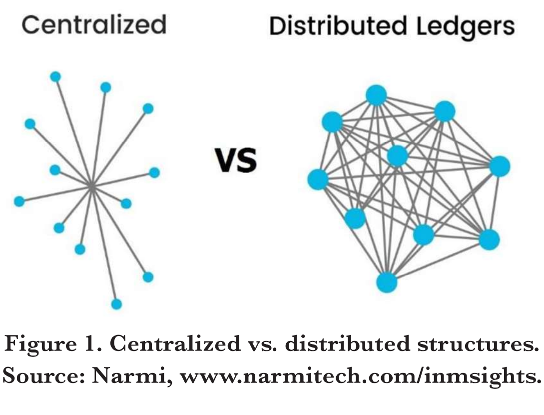

Figure 1. Centralized vs. distributed structures. Source: Narmi, www.narmitech.com/inmsights.

ger technology, problems associated with centralized structures can be resolved.

In a peer-to-peer energy trading system operating on a blockchain platform, any individual member of the network can enter into an energy exchange with any other network member without restrictions from a centralized authority or the need for an intervening third party. P2P energy exchanges are possible using smart contracts in which energy transactions are immediate, automated, and flexible based on supply and demand in the system. A *smart contract* is an executable code that operates on the blockchain to facilitate, execute and enforce an agreement between untrusted parties without the involvement of a trusted third party [4]. Its purpose is to automatically execute the terms of an agreement once its specified conditions are validated. Smart contracts are an appealing feature of the blockchain technology.

Blockchain technology has the potential to transform the entire contractual life cycle by minimizing the need for human intervention from the time of trade execution to the time payment. Blockchain technologies will improve market efficiency and potentially open and disrupt energy markets by creating unforeseen opportunities. Among these opportunities is providing incentives for DER development in developing countries.

CHALLENGES TO INTEGRATING DISTRIBITED ENERGY RESOURCES

Though microgrids provide a platform to implement more cost effective DERs, their development faces numerous technical challenges. Infrastructure associated with grid capacity and stability are barriers to the integration of renewable energy (RE) resources and distributed power generation. A microgrid's need for dual-mode switching functionality between grid-connected and island mode remains technically challenging. The conversion to island operating mode has two forms: 1) executing a *black start*, which allows a short period of outage before re-energizing the microgrid in island mode; and 2) performing a seamless transition within a short time period after disconnecting from the main grid [5]. The transition of reconnecting to the main grid also creates technical issues. Re-synchronizing the two grids is sometimes sensitive. Like any power system, microgrids need protection schemes against external and internal faults.

The lack of skilled utility workers in some regional markets limits the implementation and development of DERs. Another barrier is the lack of awareness and knowledge of personnel about the availability and performance of renewable energy.

Economic challenges that hinder the development of microgrids which use renewable energy sources include market and financial barriers. Identified market barriers include the following:

- Inconsistent pricing structures that disadvantage renewables, especially those in long term power purchase agreements.
- Subsidies for fossil fuels used to generate electricity make it difficult for RE resources to compete.
- The failure of pricing methods to include externalities such as health, social and environmental costs underprices electricity generated by fossil fuels.

Financial barriers include lack of adequate funding and financing for renewable energy. The commercialization of DERs heavily depend on reducing the production costs of RE, storage technologies and energy management systems.

Many developed and developing countries are adopting and promoting renewable energy resources and distributed generation to reduce their dependency on fossil fuels. Increasing the penetration of RE into the power generation system enhances their energy security. Many countries have established policies, directives and standards, and established targets to support the implementation of distributed generation, RE and microgrid development. The problem is not the absence of regulation but regulatory weaknesses and ambiguities. Some regulations are undefined or not clearly stated. An example is Article 16 (1) of the European Union's 2009/28/EC Renewable Energy Directive which requires member states to take *appropriate steps* to develop transmission and distribution grid infrastructure to allow the *secure operation of the electricity system*. The issue is that such directives can be subjectively interpreted.

Another barrier to the development of RE resources is the adequacy of existing transmission lines to transmit energy from the points of generation to the points of consumption. Existing regulatory barriers hinder efforts to deploy renewables and expand microgrid markets. These include:

- Lengthy administrative procedures for approval and permit.
- Policy instability with sudden changes and stop-and-go situations.
- Price competitiveness and cost friction, such as the direct and indirect costs related to the process such as commissions, interest rates, taxes, etc.

Identifying renewable energy zones is a regulatory barrier to the development of RE resources. Site selection is a regulatory issue during the design phase of large-scale RE power generation projects due to possible site conflicts with wildlife habitats, water reserves and other environmental concerns. Without clearly defined policies and regulatory instruments associated with distributed generation grid penetration, it is improbable that these systems can survive.

APPLICATIONS FOR BLOCKCHAIN

In industrialized countries, blockchain applications compete with advanced technological solutions supported by solid infrastructure embedded in the frameworks of trusted public institutions that enforce local regulations. In developing countries, these frameworks are not always available and often basic services (e.g., access to bank accounts) may be impossible. Alternatively, the market penetration of smartphones in many developing countries is as high as in industrialized countries. This has led many developing countries to adopt blockchain-based mobile money transfer applications. An example is M-Pesa, a mobile phone-based money transfer, financing and micro-financing service, launched in 2007 by Vodafone. According to Vodafone, after 10 years of operation M-Pesa is now available in 10 countries with more than 29.5 million active customers averaging 614 million monthly transactions [6]. The M-Pesa case proves that the developing countries offer fertile markets to develop new financial platforms.

The application of blockchain in the energy sector offers another potentially successful application. Next, some of the new ideas for blockchain applications in the energy sector are introduced.

Blockchain and Smart Meters

Using blockchain and cryptocurrencies for monetary transactions is an achievable application of blockchain technology in the energy sector. Blockchain eliminates the need for a third party in money transfer transactions and reduces transfer costs by eliminating administrative fees, bank fees and commissions. An example of such an application is the United Nations' World Food Program (WFP). The WFP is expanding its Ethereum-based blockchain payments system to avoid the transfer fees incurred when using the conventional banking system. The WFP performed a pilot test in the Jordanian refugee camp of Azraq to successfully facilitate cash transfers for more than 10,000 refugees on its blockchain payments platform. According to Bernhard Kowatsch, the chief of Munich WFP's innovation laboratory, the pilot project saved the agency $150,000 a month and eliminated 98% of the bank-related transfer fees [7]. Blockchain decreases fundraising and operational costs, improving transparency, accountability and control over how funds are used. Savings from using the blockchain's platform can be re-invested.

An early application of the blockchain in the energy sector is through the installation of smart prepaid electric meters that provide power to the end-user once money is transferred from the end-user's account to the utility account. This application improves end-user payment discipline and reduces the cost of reading meters, billing and collections. In Lebanon and many other countries, utility companies suffer from low billings and collections [8]. Prepaid electric meters offer a solution which decreases utility company losses, leads to lower energy rates, and avoids increases in electricity prices.

Another application of blockchain for energy sector money transfers is demonstrated by the South African company Bankymoon (bankymoon.co.za). It uses Bitcoin to perform remote payment transactions with compatible smart meters. The application works as follows: assume a donor wants to support a school in a developing country; the donor can send cryptocurrency directly to the school's smart meter, enabling electricity from the grid to be supplied to the school.

Smart Contracts and P2P Energy Trading

Completely decentralized cryptocurrencies like Bitcoin have been much more successful than any prior incarnations of electronic cash [9]. The ability to conduct smart contracts via a platform called Ethereum has increased blockchain applications. Ethereum is a public blockchain platform that can support advanced and customized smart contracts using a Turing-complete programming language [9,11]. The Ethereum platform supports withdrawal limits, loops, financial contracts and gambling markets. NXT is another public blockchain platform that allows non-customized smart contract templates. Smart contracts have a potentially major role in the integration of the blockchain in the energy sector.

One application of energy smart contracts is managing peer-to-peer energy transactions in private community micro-grids. U.S. based startup TransActive Grid, launched in early 2016, enables its users to trade energy using smart contracts via blockchain. The project consists of connecting five Brooklyn, New York households with photovoltaic (PV) systems with five nearby consumers interested in buying excess electricity produced by their neighbors [12]. Similar initiatives have been launched by Power Ledger in Perth, Australia and Grid Singularity in Austria. In addition to energy exchange, Grid Singularity offers data analysis, benchmarking, smart grid management, green certificates trading and energy trade validation. Collected technical and financial data can be used for real-time asset valuation of DER power plants. The collected data can be beneficial for refinancing or selling a power plant. When accessible, it allows investors to perform online due diligence. Other uses of the collected data include assessments of generation capacity, power availability, pricing, forecasting and energy trading [13]. For electric utilities, collected data has a future role in the development of grid balancing mechanisms.

Using blockchain platforms for P2P energy trading in community micro-grids provides a competitive advantage for innovative retailers, a better return for excess generation, plus a low cost, transparent, secure and instant payment system for electricity transactions. This model is ideal for households, building owners, and retailers who produce renewable electricity using DERs.

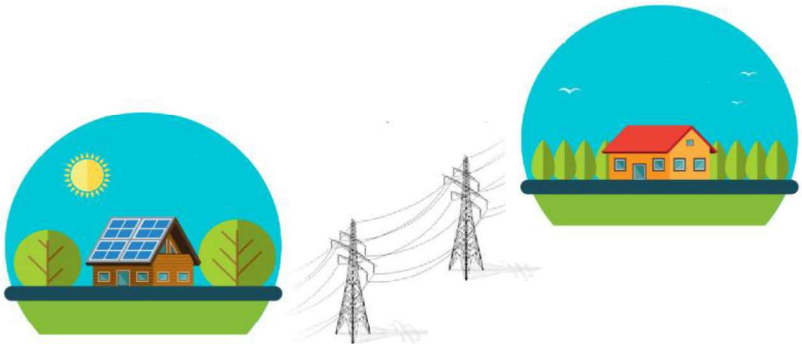

Figure 2. Peer-to-peer energy trading in community micro-grid. Source: Smart Energy Portal, https://www.smartenergyportal.ch/p2p-energy-trading-on-the-blockchain, image modified.

Energy Backed Currencies

The lack of financial incentives or funds is the main barrier facing the development of distributed energy resources. This challenge applies to both developed and developing countries. In 2016, approximately a third of Germany's electricity consumption was generated using renewables. Recently, the central government reduced financial incentives for new RE installations, particularly solar photovoltaic [13].

An energy-backed currency might be the type of incentive needed to improve the economic feasibility of renewable energy-based power generation. The concept of an energy-backed currency is similar to the gold reserves that are used to stabilize national currencies. An application of this concept is offered by the SolarCoin Foundation, a nonprofit organization. They focus on promoting solar energy generation by providing SolarCoin to solar energy producers [14]. Nick Gogerty and Joseph Zitoli, two founders of the SolarCoin Foundation, had an idea for an energy-backed currency called DeKo in 2011 [15]. In 2014, the DeKo was transformed by the SolarCoin Foundation into a digital asset reward program for RE installations based on a new cryptocurrency. SolarCoin is a digital currency, electronically representing a verified 1 MWh of solar-generated electricity. The main purpose of this initiative was to provide an incentive to produce solar energy by rewarding SolarCoin to producers of solar electricity. SolarCoin is active in 17 countries and is intended for worldwide circulation. It can be exchanged for other cryptocurrencies or conventional currencies. Holders can use their SolarCoin to pay for products and services from participating merchants and service providers.

The Jouliette is a currency backed by physical energy production. It was named after the joule, an SI energy measurement unit. In September 2017, Spectral and Alliander launched the Jouliette token at De Ceuvel, a city playground for innovation and creativity in Amsterdam and a showcase for sustainable urban development [16]. A private smart grid made the Jouliette model feasible for the De Ceuvel community. With the Jouliette token, the De Ceuvel community members make P2P energy transactions using blockchain. This ensures that the transactions are secure, without the need of bank or a trusted third party. Transaction histories can be shared with all community members enabling automatic verification. The De Ceuvel community is exploring the use of Jouliette tokens to trade for goods and services [17].

Energy-backed currencies using blockchain might provide incentives for communities in developing countries, especially if combined with smart contracts and P2P energy trading within community micro-grids.

Blockchain for Electric Vehicle Charging

In some countries the private sector is not allowed to supply electricity to the utility grid, or there are severe limitations which makes this infeasible. When incentives and development funds for DERs in developing countries are lacking, using blockchain for charging plug-in electric vehicles might be an alternative. Widespread use of electric vehicles (EV) becomes more feasible when drivers can universally access charging stations [18].

A concern is how to simplify billing at charging stations, especially ones located in public parking spaces. Blockchain can be used to build a secure billing model for EV battery charging, thus resolving this problem. EV drivers could park their vehicle at any blockchain compatible charging station while the vehicle autonomously logs on to a charging station and recharges automatically. Once the vehicle leaves the parking space, the charging station automatically invoices the driver for the electricity received using blockchain technology. Since EVs have energy storage systems, excess energy stored in their batteries can be fed back to the network with the owner earning money for storage services. The DAV Foundation's blockchain-based application for EVs is an example of this application which creates possibilities for vehicle owners, mobility services, riders and shippers. DAV Foundation's token enables exchange of energy between the grid and EVs. The platform records transactions and provides compensation using DAV tokens [19].

BlockCharge is another newly established blockchain application for EV battery charging. It uses the Ethereum blockchain to facilitate EV charging. This project was launched by the German utility Innogy, assisted by a company named Slock.it. The concept of BlockCharge is based on the *smart plug*, which can be used as a normal electrical outlet plug but is linked with an identification code [20]. Users install an application on their smartphones to authorize the EV charging process. It connects to Ethereum blockchain which negotiates the price, records the charging data, and manages the payment process (see Figure 3) [20]. BlockCharge uses a business model based on the one-time purchase of the Smart Plug and a transaction fee for the charging process [20]. BlockCharge is aiming for a worldwide authentication, charging and billing system with no intermediary. Once induction charging for electric vehicles becomes more widely adopted, applications like BlockCharge will manage the entire vehicle charging process.

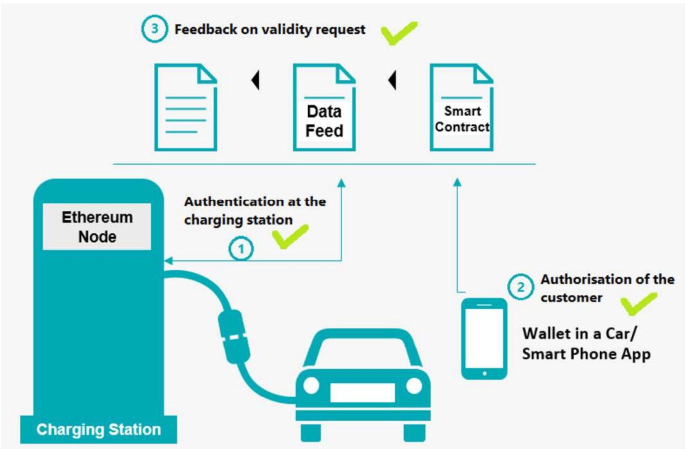

Figure 3. Blockchain based electric vehicle charging [21, image modified].

The application of blockchain technology for charging electric vehicles represents a change in how private businesses interface with their customers. This model is ideal for small businesses, shopping malls, office buildings, and car parks who offer customers renewable energy charging for their plug-in EVs.

KEY CHALLENGES AND BARRIERS

Blockchain energy-based applications provide solutions to the challenges and barriers associated with the development of DERs, especially in developing countries. Despite the number of blockchain startups that operate successfully worldwide, there are several technological constraints that challenge the implementation of the blockchain in the energy sector.

Unlike cryptocurrency transactions, energy transactions involve physically delivering the electricity. A blockchain-based energy model must reflect the physical configuration of the power grid. The large scale of the needed blockchain is a challenge due to the multiple interferences with the distribution or transmission networks. Implementing large-scale energy blockchains might cause network capacity problems. Blockchains such as Ethereum and Bitcoin are only capable of processing 3-5 transactions per second [22]. Therefore, transaction capacity must increase significantly to counter this challenge. It is technically easier to implement a blockchain-based energy model in small communities or in isolated or independent microgrids.

Another problem is encountered with the installation of blockchain compatible smart meters. In addition to cost, technical challenges arise from the physical connection between the electrical power system and the blockchain. These include information sharing, privacy and security.

Information sharing is an issue because of the transparent nature of the blockchain ledger. Due to this, it might be possible to deduce from the blocks the information related to energy transactions such as consumption patterns, quantity and price of purchased or sold energy. Such information might give indications to competitors and be a problem for utility providers and industrial consumers.

Privacy is a concern in a functional blockchain-operated electrical energy market. Because of the transparency of the ledger of the blockchain trading infrastructure it might be possible to deduce information about closed electrical energy transactions. This could compromise the privacy of consumers, electrical utilities and other energy suppliers within the electrical power system.

Due to the importance of energy in national security plans, the security of the energy supply and data should outweigh other considerations. The stability of a digital energy system is crucial. It must operate without internal complications and be protected against cybercrimes and espionage. Thus, cyber-security is a major challenge that should be resolved prior to the implementation of blockchain in the energy sector.

To be considered as a large-scale energy solution, blockchain has to prove that it is more effective and secure than other available alternatives.

CONCLUSION

The fourth industrial revolution is associated with a global trend towards a decentralized energy grid. Blockchain is the technology that can move the energy system from its centralized form to a smart decentralized network more appropriate for microgrid deployment. Blockchain can be viewed as an important overlay on the internet similar to the internet in the 1990s. Nevertheless, blockchain market infiltration will be met with resistance because it represents an extreme change to the present ways of doing business, especially since it eliminates the need for trusted intermediaries. The first stage of phasing out intermediaries was initiated with the internet and blockchain will be its second stage. Yet this resistance might be less vigorous in developing countries than in industrialized ones. Like the integration of smartphones, developing countries represent fertile markets for the growth and prosperity of blockchain technology. As a game changer, blockchain is an ideal technology for disrupting energy transaction processes.

The ability to conduct smart contracts via a platform is shown to enable and expedite peer-to-peer energy trades which will further decentralize the energy markets of the future. Electric vehicle charging offers an example. Considering the blockchain potential in developing countries from the distributed energy perspective, this article identified the challenges and barriers associated with the growth of DERs in developing countries. It suggested opportunities associated with the integration of blockchain-based solutions that help overcome these challenges. Moreover, this article provided a review of existing worldwide energy blockchain startups and detailed limitations regarding scalability, security, stability and privacy.

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CHAPITRE 4CHAPITRE 4
TRANSITION VERS UN RÉSEAU ÉLECTRIQUE AUTONOME TOTALEMENT DÉCENTRALISÉ BASÉ SUR LE CONCEPT DE STATION AUTONOME DÉCENTRALISÉE

4.1 INTRODUCTION

Les réseaux énergétiques centralisés constituent depuis des décennies l'épine dorsale de l'infrastructure électrique. Le modèle centralisé présente plusieurs avantages, notamment une prise en compte efficace des besoins de production et de transmission, des économies d'échelle et la capacité de répondre à la demande d'énergie des zones densément peuplées. L'un des principaux avantages d'un réseau centralisé est sa capacité à fournir une énergie fiable en fonctionnement normal. L'infrastructure à grande échelle et l'interconnexion d'un réseau centralisé réduisent les risques de défaillance et rendent le réseau plus rigide et plus résistant aux perturbations. Cependant, les réseaux centralisés sont également confrontés à des défis. Ils sont susceptibles de subir des défaillances massives en cas de problèmes, tels que des pannes d'équipement ou des phénomènes météorologiques extrêmes, et dans certains cas, ils subissent des pertes techniques importantes. Compte tenu de l'augmentation constante de la demande d'électricité et du besoin pressant d'une chaîne d'approvisionnement électrique décarbonée, il faut davantage de sources d'énergie distribuées et de systèmes de stockage d'énergie (SSE) pour rendre le réseau électrique distribué plus efficace, plus efficient, plus écologique et plus économique en gérant et en contrôlant le réseau et en distribuant l'énergie de manière plus efficace [125].

Cependant, le manque de modularité des réseaux centralisés peut nuire à leur flexibilité pour répondre aux changements rapides de la charge de la demande et s'adapter aux impacts des conditions météorologiques extrêmes et des perturbations. Cependant, sous la pression d'un secteur énergétique plus vert et plus durable, les réseaux électriques décentralisés gagnent du terrain. Les réseaux décentralisés offrent plusieurs avantages par rapport aux systèmes centralisés, notamment une meilleure résilience énergétique, une plus grande indépendance énergétique locale et l'intégration des ressources énergétiques renouvelables. La modularité est l'une des principales caractéristiques des réseaux décentralisés [126]. Au lieu de s'appuyer sur une infrastructure centralisée unique, les réseaux décentralisés sont constitués de micro-réseaux interconnectés ou de systèmes de production et de stockage à plus petite échelle. Cette modularité permet une gestion plus efficace des ressources énergétiques et une production et une distribution d'énergie décentralisées. En cas de perturbations, telles que des phénomènes météorologiques extrêmes ou des cyberattaques, les micro-réseaux peuvent se déconnecter et continuer à fonctionner de manière autonome, garantissant ainsi un approvisionnement continu en électricité aux installations critiques telles que les hôpitaux et les services d'urgence. Les réseaux décentralisés offrent également une plus grande flexibilité dans l'intégration des REDs qui comprennent des charges de contrôle, des services de données et des compteurs intelligents pour un contrôle et une surveillance efficace. Cette résilience et cette flexibilité font des réseaux décentralisés une option intéressante pour accroître la fiabilité et la durabilité de l'infrastructure énergétique.

Avec la pénétration croissante des DER, le nombre d'appareils appartenant aux consommateurs et contrôlés par eux a augmenté de manière significative. Par conséquent, un risque croissant de cyber-attaques est associé à ces appareils, car ils reposent sur la communication et le contrôle numériques. Un incident cybernétique important dans le système électrique pourrait avoir plusieurs effets négatifs sur le fonctionnement du réseau, notamment des impacts socio-économiques, des dommages aux équipements, des répercussions sur le marché, des pannes d'électricité et autres [127,128]. Les problèmes de sécurité apparaissent dans la superposition des trois couches du réseau électrique, illustrées dans la Figure 13, à savoir:

- L'infrastructure électrique physique (couche 1) englobant les fonctionnalités de production, de transmission et de distribution : cette couche repose sur la production distribuée, le stockage de l'énergie et les composants de réponse à la demande. La production distribuée est l'élément central d'un réseau décentralisé. Elle comprend une variété de technologies de production d'énergie, telles que les panneaux solaires et la production combinée de chaleur et d'électricité, qui génèrent de l'électricité à proximité de leur lieu d'utilisation. Le stockage de l'énergie comprend les batteries, les volants d'inertie, l'air comprimé et l'hydroélectricité pompée, qui peuvent stocker l'énergie et la réinjecter dans le réseau lorsque l'offre dépasse la demande. Les REDs peuvent contribuer à l'amélioration de la stabilité, de la résilience et de l'efficacité du réseau. Cette évolution est favorisée par l'émergence des prosommateurs, qui bénéficient de technologies avancées telles que les compteurs intelligents et les micro-réseaux intelligents. Les compteurs intelligents fournissent des données en temps réel sur la consommation et la production d'énergie, ce qui permet aux consommateurs d'optimiser leur utilisation de l'énergie et de réinjecter l'énergie excédentaire dans le réseau. Les micro-réseaux intelligents permettent la production, le stockage et la gestion de l'énergie au niveau local, réduisant ainsi la dépendance à l'égard des centrales électriques centralisées et améliorant la stabilité du réseau. En intégrant des sources d'énergie renouvelable (SER) et des systèmes de gestion avancés, la décentralisation facilite un écosystème énergétique plus durable et plus réactif, en répondant à la demande croissante d'énergie propre et en améliorant la robustesse globale du réseau électrique [129].

- Couche de communication du réseau (couche 2) : les réseaux électriques centralisés traditionnels reposent sur une communication unidirectionnelle entre l'opérateur du réseau et les consommateurs, alors que les réseaux décentralisés modernes assurent une communication bidirectionnelle. La communication bidirectionnelle permet l'utilisation de capteurs intelligents distribués, d'une production d'énergie distribuée, de mesures en temps réel, d'une infrastructure de comptage et de systèmes de surveillance. L'échange d'informations est essentiel pour assurer une production et une distribution d'énergie fiables. Cette couche est basée sur trois types de réseaux : le réseau domestique (*Home Area Network*, HAN), le réseau de voisinage (*Neighborhood Area Network*, NAN) et le réseau étendu (*Wide Area Network*, WAN) [130]. Les technologies sans fil (par exemple, l'IdO, la 5G, etc.) et câblées sont utilisées pour la communication dans la couche réseau. La couche 2 assure l'échange d'informations entre la couche 1 et la couche 3, la couche de gestion des données.

Néanmoins, le remplacement des systèmes de communication unidirectionnels et bidirectionnels des réseaux électriques actuels par des systèmes de communication multidirectionnels est essentiel pour répondre aux nouveaux besoins du réseau et de ses clients. La communication bidirectionnelle, qui prend principalement en charge le flux d'informations entre les points de contrôle centraux et les composants individuels du réseau, est insuffisante pour gérer les complexités des systèmes énergétiques modernes qui comprennent de nombreux DER, des micro-réseaux intelligents et des consommateurs actifs. Les systèmes de communication multidirectionnels permettent des interactions dynamiques en temps réel entre les différents éléments du réseau, ce qui permet une distribution plus efficace de l'énergie, une meilleure stabilité du réseau et une amélioration des capacités de réponse à la demande [131]. Cette mise à niveau facilite le commerce de l'énergie de P2P, où les consommateurs peuvent également agir en tant que producteurs, en échangeant directement de l'énergie entre eux. Elle prend également en charge des fonctionnalités avancées du réseau, telles que la détection automatisée des pannes et les mécanismes d'autoréparation [132], en permettant une prise de décision décentralisée et des temps de réponse plus rapides. En fin de compte, les systèmes de communication multidirectionnels sont essentiels pour créer un réseau souple, résilient et intelligent, capable de s'adapter à l'évolution de la demande d'énergie et d'intégrer des technologies innovantes de manière transparente.

- Couche de gestion des données (couche 3) : La couche de gestion des données est cruciale dans les réseaux électriques modernes, pour une opération fiable et efficace du réseau. Cette couche permet la collecte, le traitement et l'analyse de grandes quantités de données générées par divers composants du réseau, tels que les compteurs intelligents, les capteurs et les ressources énergétiques distribuées. Une gestion efficace des données améliore la visibilité du réseau, ce qui permet aux opérateurs de surveiller et de contrôler les performances du réseau en temps réel [133]. Elle favorise la maintenance prédictive en identifiant les problèmes potentiels avant qu'ils ne surviennent, ce qui permet d'éviter les pannes et de réduire les temps d'arrêt. En outre, la couche de gestion des données facilite l'intégration des sources d'énergie renouvelable en équilibrant l'offre et la demande de manière dynamique. Elle permet également aux consommateurs d'avoir une idée précise de leur consommation d'énergie, ce qui favorise les économies d'énergie et les réductions de coûts. En outre, en fournissant des données précises et opportunes, elle joue un rôle essentiel dans la détermination des tarifs du marché de l'énergie [134], en veillant à ce que les prix reflètent les conditions de l'offre et de la demande en temps réel. En fin de compte, une couche robuste de gestion des données est essentielle à la modernisation des réseaux électriques, garantissant qu'ils sont intelligents, efficaces et résilients face à l'évolution de la demande et des défis énergétiques.

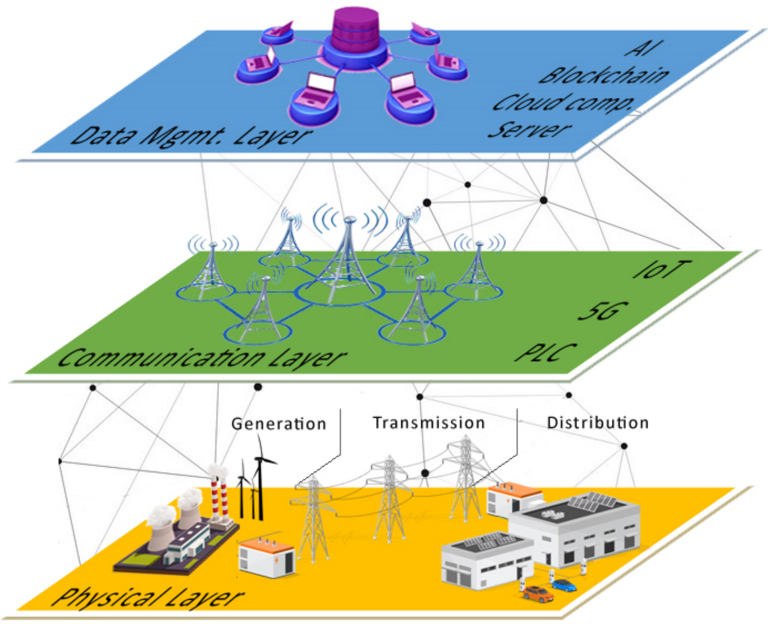

Figure 13. Les trois couches du réseau électrique distribué

Alors que la transformation numérique de la chaîne de valeur électrique continue de gagner en intérêt et que la pénétration des DER dans le mix énergétique continue d'augmenter, les données générées par la chaîne de valeur électrique continueront également de croître de manière exponentielle, entraînant ainsi de nouvelles tendances, de nouveaux concepts, de nouveaux défis en matière de sécurité et d'énormes difficultés en termes de stockage, d'analyse et de gestion des données. C'est pourquoi il est impératif de développer des réseaux électriques plus intelligents, plus résistants et plus efficaces, capables de fonctionner dans des conditions défavorables et de fournir les services requis en dépit de plusieurs défis. Bien que l'intégration des DER dans les réseaux électriques puisse être considérée comme la première étape vers une architecture décentralisée, le processus décisionnel et le contrôle des réseaux électriques restent centralisés. Il est donc essentiel de décentraliser les couches de communication, de contrôle et de données du réseau électrique pour compléter la décentralisation de l'infrastructure physique du réseau et atteindre en même temps une flexibilité, une résilience et une sécurité accrues. L'approche traditionnelle de la gestion centralisée des données ne répond pas aux exigences de sécurité et d'efficacité du stockage des données énergétiques en raison d'une protection insuffisante de la sécurité des données, d'un manque de cohérence, d'une traçabilité médiocre et d'une surveillance inadéquate des processus de partage des données. Les réseaux de communication décentralisés améliorent la fiabilité du réseau en réduisant le risque de points de défaillance uniques et en permettant un échange de données plus robuste entre les composants du réseau. Les systèmes de contrôle décentralisés favorisent la prise de décision au niveau local, ce qui permet de réagir plus rapidement et plus efficacement aux modifications des conditions du réseau et d'en améliorer la stabilité globale. En outre, une couche de gestion décentralisée des données permet de collecter et d'analyser des données provenant de nombreuses sources, ce qui facilite la surveillance et l'optimisation en temps réel des opérations du réseau. Cette décentralisation multicouche garantit que le réseau peut s'adapter à la complexité et à la variabilité croissantes des systèmes énergétiques modernes, ce qui permet d'améliorer la résilience, l'efficacité et la durabilité.

Pour décentraliser le réseau électrique à partir de la base, nous proposons dans cet article un nouveau concept inspiré de la chaîne de blocs : les organisations autonomes décentralisées (OAD). Contrairement aux organisations centralisées, les DAO n'ont pas d'autorité centrale et tous les membres participent à la prise de décision. Elles sont souvent alimentées par la technologie de chaîne de blocs et ont un niveau de sécurité relativement élevé. Le modèle proposé dans cet article est donc basé sur le concept de poste autonome décentralisé (PAD), où les postes électriques servent de nœuds vitaux pour la transmission et la distribution de l'électricité dans un réseau électrique. Ils constituent des éléments d'infrastructure importants qui permettent un fonctionnement fiable, efficace et sûr des réseaux électriques. Dans le cadre d'un futur réseau électrique, les PADs peuvent assurer un fonctionnement efficace et autonome grâce à des technologies avancées. La Figure 14 illustre notre proposition de concept de réseau électrique décentralisé basé sur les PADs par rapport aux réseaux électriques centralisés et décentralisés existants. Comme le montre la figure 2, les réseaux électriques centralisés, et même les réseaux modernes à forte pénétration de RED, reposent encore souvent sur un seul nœud de contrôle, qui constitue un point de défaillance unique (SPOF). Dans ces systèmes, toutes les décisions critiques et les commandes de contrôle sont acheminées par l'intermédiaire d'un nœud central. Cette architecture de contrôle centralisée présente des risques importants, car tout dysfonctionnement, cyber-attaque ou dommage physique au niveau du nœud de contrôle peut entraîner des perturbations généralisées du réseau ou des pannes totales. Malgré les progrès de la technologie des réseaux et l'intégration des REDs, la dépendance à l'égard d'un seul nœud de contrôle compromet la résilience et la fiabilité du réseau électrique. À mesure que les systèmes énergétiques deviennent plus complexes et distribués, la nécessité d'atténuer les vulnérabilités associées aux SPOF devient de plus en plus importante. Le passage à une structure de contrôle décentralisée, où plusieurs nœuds partagent la responsabilité de la gestion du réseau, peut renforcer la robustesse du système, assurer un fonctionnement continu et améliorer la capacité du réseau à répondre à des conditions dynamiques et à des menaces potentielles.

Par conséquent, pour répondre à ces défis et inspiré par les OADs de la chaîne de blocs, cet article présente un réseau électrique décentralisé sans autorité centrale où les PADs peuvent prendre des décisions et des ajustements de manière indépendante sur la base de données en temps réel, améliorant ainsi l'efficacité et la fiabilité du réseau électrique. De plus, la chaîne de blocs est une technologie de gestion de données décentralisée qui est transparente, traçable et inviolable ; dans l'industrie de l'énergie électrique, elle a été appliquée à de nombreux domaines tels que l'alerte précoce en cas de catastrophe du réseau électrique, le commerce sur le réseau électrique, la surveillance du réseau électrique en temps réel et le traçage des données énergétiques. Dans les futurs réseaux électriques, les PADs peuvent fournir des opérations efficaces et autonomes en incorporant des technologies avancées. En outre, l'application de la technologie de chaîne de blocs permet d'améliorer les schémas traditionnels de gestion des données en assurant une gestion précise des données, la protection des données sensibles et la traçabilité des données.

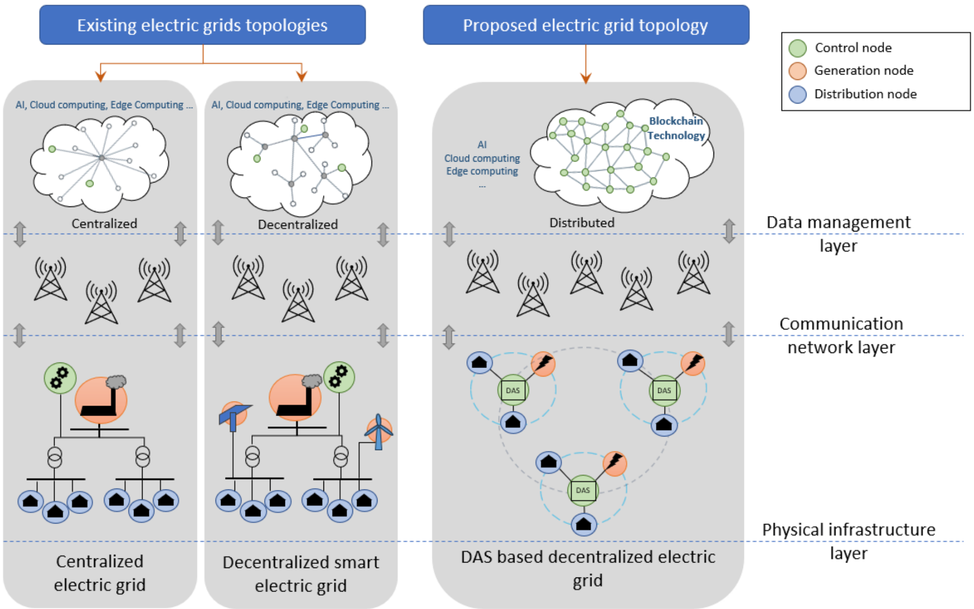

Figure 14. La différence entre les réseaux électriques existants et le concept du PAD.

Pour mieux élaborer ce concept, deux articles scientifiques ont été préparés. Le premier article présente le concept des postes autonomes décentralisés (PADs), proposant une approche révolutionnaire pour la gestion de l'énergie à travers des infrastructures locales, autonomes et intelligentes, en utilisant la technologie de chaîne de blocs. Le second article se concentre sur l'impact de la décentralisation sur la résilience des réseaux électriques. À travers une analyse détaillée et des simulations, il démontre comment une structure décentralisée peut renforcer la capacité du réseau à résister et à s'adapter aux perturbations, réduisant ainsi les risques de pannes et augmentant la fiabilité globale. Ensemble, ces deux articles offrent une vue d'ensemble intégrée des avancées technologiques et des avantages potentiels de la décentralisation pour la modernisation des réseaux électriques.

4.2 ARTICLE: FROM BOTTOM-UP TOWARDS A COMPLETELY DECENTRALIZED AUTONOMOUS ELECTRIC GRID BASED ON THE CONCEPT OF DECENTRALIZED AUTONOMOUS SUBSTATION

Cet article, intitulé « *From bottom-up towards a completely decentralized autonomous electric grid based on the concept of decentralized autonomous substation*», a été publié dans sa version finale en septembre 2024 par les éditeurs du journal MDPI – *Electronics*.

Référence: Aoun, A.; Kashmar, N.; Adda, M.; Ibrahim, H. From Bottom-Up Towards a Completely Decentralized Autonomous Electric Grid Based on the Concept of a Decentralized Autonomous Substation. Electronics 2024, 13, 3683. https://doi.org/10.3390/electronics13183683

En tant que premier auteur, j'ai contribué à la conceptualisation de la proposition, à l'essentiel de la recherche sur l'état de la question et au développement de la méthode, à la collecte et l'analyse des données et à la rédaction du manuscrit. Dr. Kashmar a participé à l'essentiel de la recherche sur l'état de la question et à la rédaction du manuscrit. Les professeurs Mehdi Adda et Hussein Ibrahim en tant que co-auteurs, ont participé à la supervision du travail, ainsi qu'à la révision de l'article et à la revue de la littérature.

Résumé : L'idée d'un réseau électrique décentralisé est passée du statut de concept à celui de réalité. L'intégration croissante des ressources énergétiques distribuées a transformé le réseau électrique centralisé traditionnel en un réseau décentralisé. Cependant, alors que la plupart des efforts pour gérer et optimiser cette décentralisation se concentrent sur la couche d'infrastructure électrique, la couche opérationnelle et de contrôle, ainsi que la couche de gestion des données, ont reçu moins d'attention. Les réseaux électriques actuels reposent sur des centres de contrôle centralisés (CCC) qui servent de cerveau au réseau électrique, où les opérateurs surveillent, contrôlent et gèrent l'ensemble de l'infrastructure du réseau. Par conséquent, toute perturbation causée par une cyberattaque ou un événement naturel, déconnectant le CCC, pourrait avoir de nombreux effets négatifs sur le fonctionnement du réseau, notamment des impacts socio-économiques, des dommages aux équipements, des

répercussions sur le marché et des pannes d'électricité. Cet article présente l'idée d'un réseau électrique entièrement décentralisé qui s'appuie sur des sous-stations intelligentes autonomes et sur l'intégration de la chaîne de blocs pour la gestion et le contrôle décentralisés des données. L'objectif est de démontrer une application réelle des réseaux électriques décentralisés basés sur la chaîne de blocs et leur impact potentiel sur les marchés de l'énergie, la durabilité et la résilience. Le modèle présenté souligne le potentiel de transformation des réseaux autonomes décentralisés en révolutionnant les systèmes énergétiques pour une meilleure opérabilité, gestion et flexibilité.

Contexte et Objectifs : La nécessité de décentraliser l'infrastructure, le contrôle et la gestion des données des réseaux électriques est cruciale pour renforcer leur résilience, leur sécurité et leur efficacité. En déplaçant le pouvoir décisionnel et les ressources vers des entités locales ou distribuées, on peut réduire la dépendance à l'égard de structures centralisées souvent vulnérables aux pannes et aux attaques cybernétiques. Une approche décentralisée permet également une prise de décision plus rapide et adaptative en réponse aux fluctuations de la demande et aux événements imprévus, améliorant ainsi la stabilité du réseau et réduisant les risques de blackouts. D’où notre proposition de créer un modèle de réseau électrique basé sur des stations autonomes décentralisées qui agissent comme nœuds dans un réseau décentralisé.

Méthodologie : Tout d'abord, une étude approfondie des risques et des menaces qui pèsent sur le réseau électrique moderne révèle des vulnérabilités critiques qui exigent une approche révolutionnaire pour renforcer sa résilience, sa sécurité et son efficacité, a été réalisée. Ensuite, le concept de station autonome décentralisée a été. Un mode de communication basé sur le protocole de *Byzantine Fault Tolerant* (BFT) a été proposé pour la communication des signaux de contrôle et d’acquisition de données. Et finalement, l’intégration de la technologie de chaine de blocs et des contrats intelligents au niveau de la gestion de données a été élaborée et un modèle a été proposé.

Résultats et Contributions : Cet article propose un nouveau concept et une nouvelle conception pour la structure des réseaux électriques décentralisés qui permet au réseau de fonctionner dans des conditions défavorables et de fournir les services requis en dépit de plusieurs défis. Aussi, il offre une nouvelle perspective aux chercheurs dans le domaine de la décentralisation et de la surveillance, du contrôle et de l'optimisation autonomes des futurs réseaux électriques, et ouvre différentes directions de recherche vers le remodelage et le développement d'un nouveau concept de réseau électrique décentralisé inspiré par les DAO et basé sur les DAS où ils servent de composants d'infrastructure importants qui permettent un fonctionnement fiable, efficace et sûr des réseaux électriques.

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Article

From Bottom-Up Towards a Completely Decentralized Autonomous Electric Grid Based on the Concept of a Decentralized Autonomous Substation

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Abstract: The idea of a decentralized electric grid has shifted from being a concept to a reality. The growing integration of distributed energy resources (DERs) has transformed the traditional centralized electric grid into a decentralized one. However, while most efforts to manage and optimize this decentralization focus on the electrical infrastructure layer, the operational and control layer, as well as the data management layer, have received less attention. Current electric grids rely on centralized control centers (CCCs) that serve as the electric grid's brain, where operators monitor, control, and manage the entire grid infrastructure. Hence, any disruption caused by a cyberattack or a natural event, disconnecting the CCC, could have numerous negative effects on grid operations, including socioeconomic impacts, equipment damage, market repercussions, and blackouts. This article introduces the idea of a fully decentralized electric grid that leverages autonomous smart substations and blockchain integration for decentralized data management and control. The aim is to propose a blockchain-enabled decentralized electric grid model and its potential impact on energy markets, sustainability, and resilience. The model presented underlines the transformative potential of decentralized autonomous grids in revolutionizing energy systems for better operability, management, and flexibility.

Keywords: autonomous energy grid; smart substation; decentralization; distributed energy resources; blockchain; grid resilience; cybersecurity

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1. Introduction

Centralized energy grids have long been the backbone of the electricity infrastructure for decades. The centralized model has several benefits, including efficient accounting for generation and transmission needs, economies of scale, and the ability to meet the energy demands of densely populated areas [1]. One of the key advantages of a centralized grid is its ability to provide reliable power during normal operations as well as in most exceptional situations, such as heat waves, natural disasters, etc.; however, its centralized nature makes it vulnerable to single points of failure, cyberattacks, and system-wide disruptions, limiting its resilience in the face of rapidly evolving grid demands and threats. The large-scale infrastructure and interconnectedness of a centralized grid reduces the chances of failures and render the grid more rigid and resistant to disruptions. However, centralized grids also face challenges. They are prone to significant failures when issues arise, such as equipment breakdowns or extreme weather events. In light of the ever-increasing demand for electricity and an urging need for a decarbonized electrical supply chain, more distributed energy sources (DERs) and energy storage systems (ESSs) are required to make the electric grid distributed for more efficient, effective, environmentally sustainable, and economical by managing and controlling the grid and distributing power more effectively [2].

However, the lack of modularity in centralized grids can hinder their flexibility in meeting rapid changes in demand load and adapting to the impacts of extreme weather conditions and disruptions [3]. However, under the pressure of a greener and more sustainable energy sector, decentralized electric grids are gaining momentum. Decentralized grids offer several advantages over centralized systems, including enhanced energy resilience, increased local energy independence, and integration of renewable energy resources. Modularity is one of the main characteristics of decentralized grids [4]. Instead of relying on a single centralized infrastructure, decentralized grids consist of interconnected microgrids or smaller-scale generation and storage systems. This modularity allows for more efficient management of energy resources and enables localized power generation and distribution. During disruptions, such as extreme weather events or cyberattacks, microgrids can disconnect and continue to operate independently, ensuring a continuous electricity supply to critical facilities like hospitals and emergency services. Decentralized grids also offer greater flexibility in integrating DERs, which include control loads, data services, and smart meters for effective control and monitoring. This resilience and flexibility make decentralized grids an attractive option for increasing the reliability and sustainability of the energy infrastructure.

With the increasing penetration of DERs, the number of consumer-owned and controlled devices has increased significantly, since each DER unit typically requires its own set of control systems to manage its operation, integration, and interaction with the grid. Subsequently, a growing risk of cyberattacks is associated with these devices because they rely on digital communication and control. A significant cyber incident in the electric system could have several negative effects on grid operations, including socioeconomic impacts, equipment damage, market repercussions, blackouts, and others [5,6]. Security concerns emerge in the superposition of three layers of the electric grid, illustrated in Figure 1, including:

- **Electrical physical infrastructure (Layer 1)**: This layer encompasses the generation, transmission, and distribution functionalities and relies on distributed generation, energy storage, and demand response components. Distributed generation is the core component of a decentralized grid. It includes a variety of energy-generating technologies, such as solar panels and combined heat and power, that generate electricity near their use. Energy storage includes batteries, flywheels, compressed air, and pumped hydroelectric storage, which can store energy and feed it back into the grid when supply exceeds demand. DERs can contribute to the enhancement of the grid's stability, resilience, and efficiency. This shift is driven by the emergence of prosumers empowered by advanced technologies such as smart meters and smart microgrids. Smart meters provide real-time data on energy consumption and production, allowing prosumers to optimize their energy usage and contribute excess power back to the grid. Smart microgrids enable localized energy generation, storage, and management, reducing dependency on centralized power plants and enhancing grid stability. By integrating renewable energy sources (RES) and advanced management systems, decentralization facilitates a more sustainable and responsive energy ecosystem, addressing the growing demand for clean energy and improving the overall robustness of the electric grid [7].
- **Network communication layer (Layer 2):** This layer is comprised of traditional centralized electric grids that rely on one-way communication between the grid operator and consumers, whereas modern decentralized grids provide two-way communication. Bi-directional communication enables the use of distributed smart sensors, distributed power generation, real-time measurements, metering infrastructure, and monitoring systems. Exchanging information is essential to providing reliable energy generation and distribution. This layer is based on three types of networks: home

area network (HAN), neighborhood area network (NAN), and wide area network (WAN) [8]. Both wireless and wired technologies are used for communication in the network layer. Layer 2 provides information exchange between Layer 1 and Layer 3, the data management layer. Nevertheless, replacing unidirectional and bi-directional communication systems in current electric grids with multi-directional communication systems is crucial to meet the emerging needs of both the grid and its customers. Bi-directional communication, which primarily supports information flow between central control points and individual grid components, is insufficient for managing the complexity of modern energy systems that include numerous DERs, smart microgrids, and active prosumers. Multi-directional communication systems enable dynamic, real-time interactions among various grid elements, allowing for more efficient energy distribution, enhanced grid stability, and improved demand-response capabilities [9]. This upgrade facilitates peer-to-peer (P2P) energy trading, where consumers can also act as producers, directly exchanging energy with one another. It also supports advanced grid functionalities, such as automated fault detection and self-healing mechanisms [10], by allowing decentralized decision-making and faster response times. Ultimately, multi-directional communication systems are essential for creating a flexible, resilient, and intelligent grid that can adapt to evolving energy demands and integrate innovative technologies seamlessly.

- **Data management layer (Layer 3):** The data management layer is crucial in modern electric grids, serving as the backbone for efficient and reliable grid operations. This layer enables the collection, processing, and analysis of vast amounts of data generated by various grid components, such as smart meters, sensors, and distributed energy resources. Effective data management enhances grid visibility, allowing operators to monitor and control grid performance in real-time [11]. It supports predictive maintenance by identifying potential issues before they escalate, thus preventing outages and reducing downtime. Additionally, the data management layer facilitates the integration of renewable energy sources by balancing supply and demand dynamically. It also empowers consumers with actionable insights into their energy usage, promoting energy conservation and cost savings. Moreover, by providing accurate and timely data, it plays a critical role in determining energy market rates [12], ensuring that prices reflect real-time supply and demand conditions. Ultimately, a robust data management layer is essential for the modernization of electric grids, ensuring they are smart, efficient, and resilient in the face of evolving energy demands and challenges.

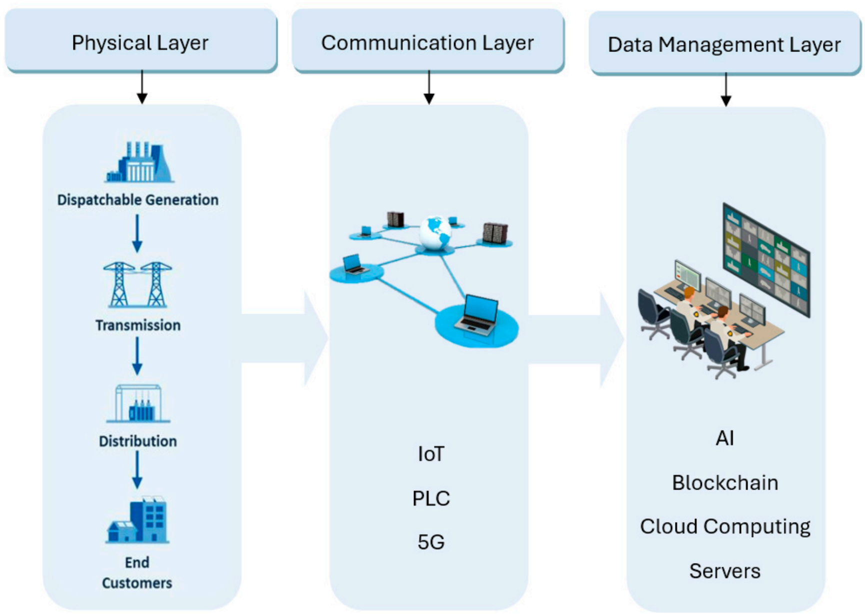

Figure 1. The three layers of the distributed electric grid.

As the digital transformation of the electric value chain keeps gaining interest and the penetration of DERs in the electric energy mix continues to increase, the data generated by the electric value chain will also continue growing exponentially, thus incurring new trends, concepts, security challenges, and enormous difficulties in terms of data storage, analysis, and management. Due to this fact, it is imperative to develop more intelligent, resilient, and efficient electric grids that can operate under adverse conditions and provide the services required despite several challenges. Although the integration of DERs in electric grids can be considered the first step towards a decentralized architecture, the decision-making process and control of electric grids remain centralized. Thus, a need for decentralizing the communication, control, and data layers of the electric grid is essential to complement the decentralization of the grid's physical infrastructure and attain higher flexibility, resilience, and security at the same time. The traditional centralized data management approach fails to meet the security and efficiency requirements of power data storage due to insufficient data security protection, inconsistency, poor traceability, and inadequate monitoring of data sharing processes [13]. Decentralized communication networks enhance grid reliability by reducing the risk of single points of failure and enabling more robust data exchange between grid components. Decentralized control systems empower local decision-making, allowing for faster and more efficient responses to changes in grid conditions and enhancing overall grid stability. Furthermore, a decentralized data management layer supports the collection and analysis of data from numerous sources, facilitating real-time monitoring and optimization of grid operations. This multi-layered decentralization ensures that the grid can adapt to the increasing complexity and variability of modern energy systems, leading to improved resilience, efficiency, and sustainability.

To decentralize the electric grid from the bottom up, in this article, we propose a novel concept inspired by the blockchain decentralized Autonomous organizations (DAO). Unlike centralized organizations, DAOs have no central authority where all members participate in decision-making; they are often powered by blockchain technology and have a relatively high level of security [13,14]. Thus, the model proposed in this article is based on the concept of the decentralized autonomous substation (DAS), where substations serve as vital nodes for both the transmission and distribution of electricity in an electric grid. They serve as significant infrastructure components that allow reliable, efficient, and safe operation of the electric grids.

As part of a future power grid, DAS can provide efficient and autonomous operation through advanced technologies. In Figure 2, we show an illustration of our proposed concept of a DAS-based decentralized electric grid compared to the existing centralized and decentralized electric grids. As shown in Figure 2, centralized electric grids, and even modern grids with a high penetration of DERs, often still rely on a single control node, which constitutes a single point of failure (SPOF) [15]. In these systems, all critical decisions and control commands are routed through one central hub. This centralized control architecture presents significant risks, as any malfunction, cyberattack, or physical damage to the control node can lead to widespread grid disruptions or total system outages. Despite the advancements in grid technology and the integration of DERs, the dependence on a singular control node undermines the resilience and reliability of the electric grid. As energy systems become more complex and distributed, the need to mitigate the vulnerabilities associated with SPOFs becomes increasingly important. Moving towards a decentralized control structure, where multiple nodes share the responsibility for grid management, can enhance system robustness, ensure continuous operation, and improve the grid's ability to respond to dynamic conditions and potential threats. Hence, to respond to these challenges and inspired by blockchain's DAOs, this article presents a decentralized electric grid with no central authority where DAS can make decisions and adjustments independently based on real-time data, enhancing efficiency and reliability in the power grid. Moreover, the blockchain is a decentralized data management technology that is transparent, traceable, and tamperproof; in the electric power industry, it has been applied to many areas such as early warning of power grid disasters, trading on the power grid, monitoring the power

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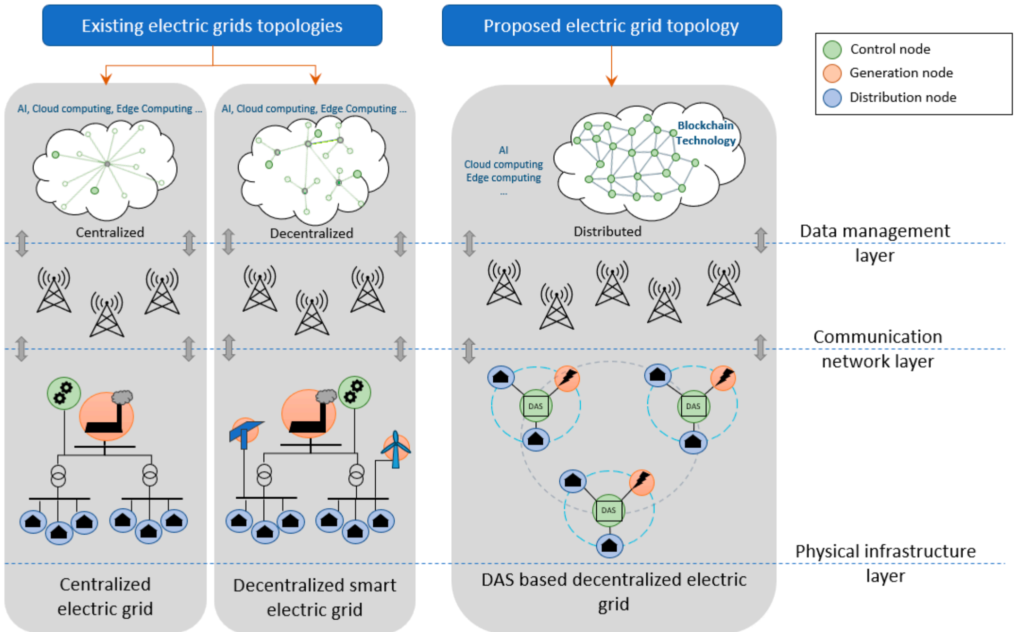

Figure 2. The difference between existing electric grids and our proposed concept.

Since all online activities are subject to some security risks, in this article, we present the different security challenges on the electric grid layers and explain the impact of each incident. To overcome these challenges, we propose using blockchain technology because it has several powerful properties, including decentralization, traceability, tamperproofness, openness and sharing, safety, and reliability [13]. However, the main contributions of this article can be summarized as follows:

- Proposes a new concept and design for the structure of decentralized electric grids that allows the grid to operate under adverse conditions and provide the services required despite several challenges.
- Offers a new perspective to the researchers in the domain regarding decentralization and autonomous monitoring, control, and optimization of future electric grids.
- Opens different research directions towards reshaping and developing a novel decentralized electric grid concept inspired by DAOs and based on DASs, where they serve as significant infrastructure components that allow reliable, efficient, and safe operation of the electric grids.

The remainder of this article is organized as follows: In Section 2, we summarize the electric grid security concerns and review some of the proposed research work to preserve the security of electric grids, as well as the security challenges and objectives in this domain. In Section 3, we describe how the DAO inspired us to develop a new concept for a decentralized autonomous electric grid, we explain how DAS substations could provide important infrastructure components for consistent and safe operation of electric grids, and we define the communication protocol between different DASs. Section 4 explains how blockchain could be applied as a data management platform to expand the decentralization to the control layer of the electric grid. Finally, Section 5 concludes this article.

2. Electric Grid Security Concerns

Today's decentralized electric grids are electrical power systems that combine information and communication technologies (ICTs) and electrical energy sources to provide reliable, stable, efficient, scalable, and clean power, also known as smart grids. This combination improves the operational performance of electric power systems, but at the same time exposes them to different cyber threats [17,18]. ICT technologies are used in electric grids to increase grid reliability and flexibility by integrating new power resources (such as renewable energy, wind, and solar power), able to increase flexibility and resilience, reduce the carbon footprint, and decrease energy losses [19]. As smart grid systems exchange valuable data, theft or alteration of these data are of major concern. The risk of data theft or alteration in smart grids poses significant threats to both the operation of the grid and the confidentiality of end-users. Smart grids rely heavily on the continuous flow of data for real-time monitoring, control, and optimization of grid operations. If these data are intercepted, tampered with, or stolen by malicious actors, it can lead to severe disruptions, such as incorrect demand-supply matching, grid instability, and even large-scale blackouts [20]. Furthermore, smart grid data often includes sensitive information about end-users' energy consumption patterns, personal habits, and device usage [21]. Unauthorized access to this data can lead to privacy breaches, identity theft, and unauthorized surveillance, compromising the confidentiality and security of individuals. Additionally, recent cyberattacks on electrical grids have highlighted the growing vulnerabilities and critical importance of cybersecurity in the energy sector. These incidents have demonstrated that cyber threats can penetrate even the most secure infrastructures, causing widespread disruptions, financial losses, and potential safety hazards. Notable examples include the 2015 and 2016 attacks on Ukraine's power grid [22], where sophisticated malware temporarily disabled power for hundreds of thousands of residents. Similarly, the 2020 SolarWinds attack [23] exposed vulnerabilities in the U.S. power grid by compromising several federal agencies and key infrastructure entities. These attacks illustrate how cybercriminals and state-sponsored actors can exploit weaknesses in grid security systems to disrupt operations, steal sensitive information, and undermine public trust. As the grid becomes more digitized and reliant on interconnected systems, the need for advanced cybersecurity measures, real-time threat detection, and resilient infrastructure design has never been more critical to protect against future cyber threats.

Therefore, optimizing electric grids becomes the most important part of the process for reducing the risks to national security, grid operations, and end-users' confidentiality. Besides, electric grid systems are affected by climate hazards and severe weather conditions that are capable of disabling any point of the electric value chain [24]. The electric grid's ability to generate and transmit electricity from fossil, nuclear, and renewable energy sources is affected by extreme temperatures, water scarcity, and increasing storm intensity. All this presents several challenges to electric grid operators. As a part of this section, we highlight recent works and research that address the security aspects and concerns in electric grids.

Several studies investigate the risks and threats of cyberattacks on the electric grid. Authors in [5,25] propose a comprehensive overview of cybersecurity in the smart electric grid, examine the principal cyberattacks threatening its infrastructure, network protocols, and applications, and propose countermeasures techniques to mitigate and counter them. A study of common cyber vulnerabilities in distributed electric power systems is presented by Li et al. [18], along with a discussion of how cyber incidents can affect microgrids physically. They also examine the risks associated with cyberattacks on microgrids and present methods for mitigating those risks that are affordable. Authors in [26] review the various security challenges and threats, as well as group them by possible sources of occurrence, and recommend a framework for achieving more secure smart grids. In [27], Rath et al. study the impact of various types of cyberattacks on the performance of communication links of microgrids. They present a framework that prevents false data injection, denial-of-service (DoS) attacks, and replay attacks that may compromise system stability. Dutta et al. [28] explain the importance of some technologies that improve the security around the microgrid and provide a more secure management of electric data while satisfying the consumers' needs; these technologies include security orchestration, automation, and response (SOAR), machine learning, artificial intelligence (AI), and blockchain technology.

However, all those measures have proven historically to be incapable of blocking all security threats and avoiding damage to the electric supply. Likewise, there is no universal approach or process to combine all security mechanisms to ensure security for the entire electric grid system [17]. Subsequently, the value of our proposed model is that it considers restructuring the current electric grid layers flexibly and dynamically based on DASs, where substations serve as vital nodes for both the transmission and distribution of electricity in an electric grid. By distributing control across multiple independent substations, the grid minimizes single points of failure, making it much harder for attackers to compromise the entire system. If one substation is targeted, it can be isolated without affecting the rest of the network. Additionally, this decentralized structure ensures that disruptions in one area due to natural disasters, such as storms or earthquakes, do not cascade through the entire grid, maintaining stability and functionality in unaffected regions. Furthermore, integrating blockchain technology provides an immutable and cryptographically secure ledger, safeguarding data integrity and enhancing overall security. This combination of decentralization and advanced security measures ensures a more robust, resilient, and reliable electric grid.

2.1. The Security Challenges

The smart electric grid architecture and infrastructure face multiple security threats and challenges, such as theft, cyberattacks, terrorism, and natural disasters. If any fundamental element of the electric grid fails, whether due to a cyberattack, natural disaster, or equipment malfunction, the consequences can be disastrous. These may include power system blackouts, IT infrastructure failures, false impressions of the system's condition, damaged consumer devices, chaos in the energy market, and threats to human safety [25]. For individual users, outages can halt essential services, affect home appliances, and compromise personal safety, especially in extreme weather conditions [29]. In businesses, power failures can lead to significant financial losses due to halted production, spoiled perishable goods, and disrupted supply chains [30]. Markets suffer as trading activities are interrupted, leading to volatility and potential financial instability [31]. Critical infrastructure, such as hospitals and transportation systems [32], faces severe risks, endangering lives and public safety [33]. Additionally, prolonged power failures can erode consumer confidence and trust in utility providers, potentially leading to long-term economic and social consequences. Overall, the cascading effects of power failures highlight the need for a resilient and reliable electric grid. Thus, securing the electric grid presents a complex set of challenges due to its interconnected and critical nature. Hereafter, we list some of the key security challenges and threats faced by electric grids. Table 1 summarizes the impact of these challenges and threats on the three layers of the electric grid, as defined in Figure 1.

- **Cybersecurity Threats:** Cybersecurity has become a major element of a secure and resilient electric grid. With the increasing digitalization and connectivity of grid components, cybersecurity threats such as hacking, malware, ransomware, and phishing attacks pose a significant risk. A successful cyberattack could disrupt operations, manipulate data, or even cause physical damage to grid infrastructure. Cyberattacks on electric grids can be grouped into the following two main categories [5,26,27]:
    - Passive attacks, where data are not compromised but only monitored by hackers for espionage purposes. Passive attacks may include eavesdropping attacks, where the attacker eavesdrops on the data packets shared between the sender and the receiver [34,35]; or traffic analysis attacks, where the attacker continuously monitors and analyzes the traffic between the sender and the receiver [35].

- ○ Active attacks are more critical since the attacker alters the data or stops a service. Active attacks include (1) masquerade attacks, where the sender is idle but the receiver continues to receive data from the attacker; (2) replay attacks, where an attacker eavesdrops on data packets, injects specific packets, and replays them to the receiver; (3) false data injection (FDI) attacks, where the original data (from the sender) is modified and transmitted by the attacker to the receiver; and (4) DoS attacks, where a large number of irrelevant requests to the server are generated by the attacker, and then the server serves these irrelevant requests until it has exhausted its resources.

Table 1. The security challenges on each layer of the electric grid network.

	Electric Grid Layers		
Security Challenges	**Physical Layer**	**Network Communication Layer**	**Data Management Layer**
Cybersecurity Threats	✔	✔	✔
Legacy systems	✔		
Interconnectedness	✔	✔	
Supply chain risks	✔		✔
Data integrity			✔
Regulatory and compliance challenges		✔	✔
Resilience to physical threats	✔		
Human factor	✔	✔	✔

On the other hand, several reasons make the smart electric grid vulnerable to cyberattacks. The lack of personnel training is one of the main cyber vulnerabilities in any system [18,27]. Proper training is crucial for operating any technology; otherwise, personnel might easily fall victim to phishing attempts. Another point of exposure is maintenance procedures. During maintenance, operators often disable the security system to perform testing, which can become a vector for cyberattacks. Attackers always aim to gain illegal access by compromising the most poorly secured components or elements of the network. Once breached, the network might be infected with trojans, which can then spread to other devices on the network, thus compromising the whole network. Another vulnerability of networks is internet protocols that use unencrypted data formats, making them easy targets for data extraction via man-in-the-middle (MITM) attacks. However, these are not the only vulnerabilities found in networks.

- **Legacy Systems:** Many components within the grid infrastructure were built before modern cybersecurity standards were established. Retrofitting or securing these legacy systems without disrupting operations can be challenging. Additionally, the devices and applications in legacy systems lack built-in security modules, making them vulnerable. It is also challenging to make the whole smart grid resistant to cyberattacks since it has so many connected electrical and electronic components as well as mighty communication channels. However, by analyzing and comparing the various attack points, it is possible to develop systems architectures and protocols that can make the smart grid less vulnerable to attacks [6,36].
- **Interconnectedness:** The heterogeneous nature of the decentralized electric grid, where different types of devices are interconnected and communicated through multiple connections and network protocols, poses a great challenge to the security of the grid as well as a potential threat to the entire smart grid infrastructure. Most industrial network protocols used in smart electric grids are designed for connectivity, not security. This means that these protocols cannot only ensure secure communication channels but may even serve as attack surfaces [18]. Moreover, the grid is interconnected with various systems, including IT (information technology) and OT

(operational technology) networks, smart meters, IoT devices, and renewable energy sources. Each of these entry points presents a potential vulnerability that could be exploited by cyber attackers.

- **Supply Chain Risks:** The global nature of supply chains for grid components introduces risks of compromised or counterfeit equipment. Malicious hardware or software inserted into these supply chains could compromise grid security.
- **Data Integrity:** Maintaining the integrity of data transmitted and stored within the grid is crucial. Manipulated or corrupt data can lead to incorrect decisions or operations, affecting grid stability and reliability. Data integrity attacks, such as false data injections, could cause inaccurate and invalid state estimation results, resulting in degradation and even disruptions of power systems [18,37]. However, the purpose of integrity attacks is to modify customer account information, billing information, control commands, voltage and sensor values, and the operation status of the devices. Examples of integrity attacks are false data injection, tampering, replay, wormhole, masquerading, MITM, time synchronization, spoofing, and load-drop attacks [37].
- **Regulatory and Compliance Challenges:** Adhering to evolving cybersecurity standards and regulatory requirements while maintaining operational efficiency and cost-effectiveness is a constant challenge for grid operators.
- **Resilience to Physical Threats:** Resilience refers to a system's ability to withstand, absorb, and quickly recover from low-probability, high-impact events, such as extreme weather or cyberattacks [38]. Apart from cyber threats, physical threats such as natural disasters, physical attacks, or electromagnetic pulses (EMPs) pose risks to the grid's security and resilience.
- **Human Factor:** Humans vary in their knowledge of technology and adapt to their environment at their own pace, making them easy targets for attackers. Social engineering attacks are the second most common type of attack after malware. Ransomware is a recent method that targets humans instead of machines directly. Another common attack is an insider attack, where a disgruntled employee uses their access to resources to harm the organization [25]. Additionally, insider threats, unintentional errors by employees, a lack of cybersecurity awareness, and inadequate training can also compromise grid security.

Addressing these challenges requires a multifaceted approach involving robust cybersecurity measures, continuous monitoring and detection systems, regular vulnerability assessments, employee training, information sharing among stakeholders, regulatory frameworks, and investments in resilient infrastructure and technologies. Grid operators, government entities, cybersecurity experts, and technology providers continually work to enhance the security posture of electric grids to ensure reliable, secure, and resilient energy supply to consumers and critical infrastructure.

2.2. Security Objectives and Goals

Security is an important element for the stability of the electric grid's operation. Different research works explain various smart grid security objectives and goals [5,17,18,36]. These objectives include:

- Availability refers to the continual supply of power following user requirements to ensure timely and reliable access and use of information for making operational decisions in critical circumstances. Any latency or loss of availability may disrupt and impact the operational performance of the electric grid. Availability attacks can corrupt, block, or delay information.
- Integrity refers to preventing improper modification of information as a result of improper modification that might disrupt the ability to make informed decisions and corrupt the exchange of smart grid data.
- Confidentiality refers to protecting information from unauthorized access and discovery; otherwise, any disclosure may reveal sensitive information and have devastating effects on electricity grid operations and customer behavior. Confidentiality attacks

can abuse information, keep track of the lifestyle of customers, learn what appliances they use, and whether they are at home or not.

- Accountability is to ensure the tractability of the system and that any action taken by a person, device, or public authority can be verified so that no one can deny it. For example, if smart meters are attacked, their information is no longer accurate because they have been altered. Consequently, the customer will receive two different electric bills, one from the smart meter and one from the electric utility.

Additionally, the goal of the decentralized electric grid is to give consumers more control, flexibility, customization, and convenience over their energy consumption. However, dynamicity and flexibility are also common objectives for today's electric grid networks for managing and controlling the grid operations and distributing power more effectively. The concept of dynamic measures refers to the ability to provide security and resilience to electric grids by introducing agility or flexibility to the system properties to ensure a high level of stability and security. The dynamicity/flexibility of electric grid operations rather than the static states should be considered so that the reactive measures to physical or cyber incidents can be fully demonstrated. It is therefore important to have clearly outlined security objectives to ensure an efficient and reliable operation of the grid. Furthermore, these security objectives must include all potential improvements and expansion plans for future grids.

On another level, article [39] analyzes cybersecurity risks in smart energy communities, highlighting vulnerabilities in common architectures and protocols while proposing mitigation strategies and emphasizing the need for secure-by-design systems in line with the EU's Renewable Energy Directive, relying on the implementation of proactive design approaches to mitigate electric grid security concerns. Such an approach is presented in article [40], where a novel flexibilization service for distribution systems using renewable energy communities and virtual islanding is introduced. Such a service enhances grid resilience and facilitates the integration of more renewable energy, with demonstrated technical and sustainability benefits. However, the decentralization of the electric grid, while offering flexibility, resilience, and increased integration of renewable energy sources, faces significant challenges due to the varying regulatory and operational constraints imposed by distribution system operators (DSOs) and transmission system operators (TSOs) across different countries. These entities are responsible for maintaining grid stability, ensuring reliability, and managing the flow of electricity, which introduces a layer of complexity when implementing decentralized architectures. Each country has its own set of regulations, technical standards, and market structures, making it difficult to create a one-size-fits-all decentralized solution. In many cases, decentralized approaches must navigate the hierarchical control systems and regulatory frameworks that prioritize centralized coordination, which can limit the degree of autonomy that can be granted to decentralized substations or microgrids. Therefore, while decentralization holds great potential for modernizing the grid, it must be carefully designed to align with the roles and responsibilities of DSOs and TSOs, ensuring a balance between local autonomy and overall grid security and reliability.

In the following sections, we explain how we employ the concept of DASs to serve as significant infrastructure components that allow reliable, efficient, and safe operation of the electric grids and how blockchain technology can improve traditional data management schemes by improving accurate data management, sensitive data protection, and data traceability.

3. The Concept of DAS—Decentralization of Layer 2

In the realm of the decentralized world of blockchain, the DAO emerged as a controversial breakthrough in the wall of venture capital funds. A DAO is a digital organization that is governed by clear rules encoded in computer programs, managed by its members, and independent of a central government [41]. DAOs are based on blockchain technology, which eliminates the need for a middleman or central authority and permits decentralized governance and decision-making in place of conventional hierarchical institutions. The operation mechanism of a DAO involves self-executing and self-enforcing smart contracts. Members propose actions or decisions, which are voted upon by the DAO community. Voting power is often proportional to members' contributions, basically in cryptocurrency. Once a decision reaches consensus, the smart contract automatically executes the action, whether it is transferring funds, changing rules, or other predefined operations, without the need for central authority. This decentralization aims to foster transparency and collective governance. DAOs can cover various purposes, from managing funds to making collective decisions.

DAOs aim to enable decentralized decision-making and governance by allowing participants to vote on proposals, allocate funds, and make collective decisions through a democratic or consensus-based process. They can be used for various purposes, such as managing funds, governing protocols, creating digital assets, or even running decentralized applications (dApps). DAOs are built on the principles of transparency, decentralization, and community governance, potentially offering increased efficiency, lower operational costs, and greater inclusivity by allowing anyone to participate and have a say in the organization's decisions. However, they also face challenges such as security vulnerabilities, regulatory uncertainties, and potential governance issues related to decision-making and conflicts of interest among participants.

First appearing in 2016, the DAO was a complex smart contract system built on the Ethereum blockchain that aimed to create a decentralized crowdfunding mechanism [42]. However, it famously suffered a significant security breach shortly after its launch, leading to a contentious hard fork of the Ethereum blockchain to reverse the theft. This incident triggered questions within the crypto community about governance, immutability, and the role of decentralized systems. However, today DAOs are perceived as innovative and potentially disruptive entities in various fields, particularly in decentralized finance (DeFi) [43]. Many pioneers see them as a promising way to organize and govern without traditional hierarchical structures, allowing for greater transparency, efficiency, and inclusivity. One of the success stories of DAO-based business models is DAOstack, a company that provides tools and frameworks for the creation and management of DAOs [44]. Their platform allows organizations to build decentralized governance structures and decision-making processes. Another example is MolochDAO, a decentralized grant-making organization focused on funding Ethereum ecosystem projects. Members pool funds and collectively decide on grant allocations through a decentralized voting process [44]. Similarly, Aragon facilitates the creation and management of DAOs, offering tools for governance, fundraising, and decision-making to empower communities to self-organize and collaborate [45]. Additionally, MakerDAO is a DAO that governs the Maker Protocol, a decentralized lending platform based on the Ethereum blockchain, which allows users to lock up collateral assets in smart contracts to generate Dai, a stable coin based on the US dollar [46]. Finally, limited liability autonomous organizations (LAOs) are venture capital DAOs that invest in early-stage blockchain projects and startups, with members pooling funds to make investment decisions and voting power based on contributions. As demonstrated by these use cases, DAOs can be used in a wide range of fields, from governance and funding to decentralized finance and venture capital.

The DAO inspired our work in the development of a new concept to decentralize the electric grid from the bottom up. Despite the first stage of decentralization driven by the integration of DERs in the architecture of modern grids, the decision-making procedure and control of electric grids still preserve a centralized topology. Thus, a need for decentralized autonomous control of the grid that increases its flexibility, resilience, and security at the same time. Hence, our proposal is the Decentralized autonomous substation (DAS). Substations play a critical role in electric grids by serving as vital nodes for the transmission and distribution of electricity. Their importance stems from several key functions and benefits, such as grid interconnection, load balancing, fault detection and control, power quality regulation, etc. Substations serve as significant infrastructure components that allow the efficient, reliable, and safe operation of electric grids. Their importance also grew as electricity systems evolved to meet the challenges of the rapidly changing energy landscape, including the integration of renewable energy, electrification of transportation, and adoption of digital technologies.

3.1. Proposed New Grid Topology

Today's electric grids are typically operated by utilities, grid operators, or system operators responsible for ensuring a reliable, safe, and efficient operation. This operation is performed via centralized control centers, also known as control rooms or dispatch centers. Using advanced monitoring and measurement systems, these control centers continuously monitor grid conditions, including electricity flows, voltages, frequencies, and equipment statuses. Real-time data from substations, transmission lines, generation facilities, and other grid assets provide operators with a comprehensive view of grid performance and situational awareness. Additionally, control centers are responsible for managing grid operations, including the dispatch of electricity generation, the coordination of power flows, and the restoration of service during outages or emergencies. Operators use control systems, energy management systems (EMSs), and supervisory control and data acquisition (SCADA) systems to adjust generation output, manage transmission congestion, and maintain grid stability within safe operating limits. Nevertheless, while CCCs offer numerous benefits for grid management, there are some disadvantages and challenges associated with their centralized nature. As grids become more interconnected, decentralized, and digitally enabled, advanced monitoring, control, and coordination capabilities are required to meet the challenges of the future energy transition.

As illustrated in Figure 3, a CCC represents an SPOF in the grid management system. If a control center experiences a technical failure, cyberattack, or natural disaster, this can disrupt grid operations and compromise grid reliability. Redundancy measures and backup systems are necessary to mitigate this risk, but they may not eliminate the potential for disruptions entirely. Moreover, centralized control centers rely on effective communication and data transmission networks to collect real-time data from various grid assets and control devices distributed across the grid. Any interruptions or failures in communication networks can hinder the ability of control centers to monitor grid conditions accurately and respond to operational needs promptly.

On the other hand, as electric grids evolve and expand to accommodate growing demand, renewable energy integration, and DERs, CCCs may face scaling challenges. Managing increasingly complex and interconnected grids requires scalable control systems, advanced analytics, and decision-support tools capable of handling large volumes of data and diverse grid configurations. Furthermore, CCCs may experience latency or delays in data processing and decision-making, particularly in large or geographically dispersed grid systems [47]. Delays in receiving and processing real-time data can impact the ability of operators to respond quickly to grid events, such as equipment failures, voltage fluctuations, or sudden changes in demand or generation. And not to forget as well their cybersecurity vulnerabilities. CCCs are vulnerable to cyberattacks, malicious intrusions, and cyber threats targeting critical infrastructure and control systems [48]. Hackers may attempt to disrupt grid operations, manipulate control systems, or steal sensitive information, posing risks to grid reliability, safety, and security. On the operation level, managing CCC involves coordinating multiple stakeholders, integrating diverse technologies, and navigating complex regulatory and compliance requirements. Operational complexity can increase with the introduction of new grid technologies, regulatory mandates, and industry standards, requiring ongoing training, collaboration, and resource allocation to ensure effective grid management and compliance. Also, establishing and maintaining CCCs requires significant investments in infrastructure, technology, personnel, and ongoing operational expenses. Utilities and grid operators must allocate resources effectively to support control center operations while balancing cost considerations, regulatory requirements, and performance expectations.

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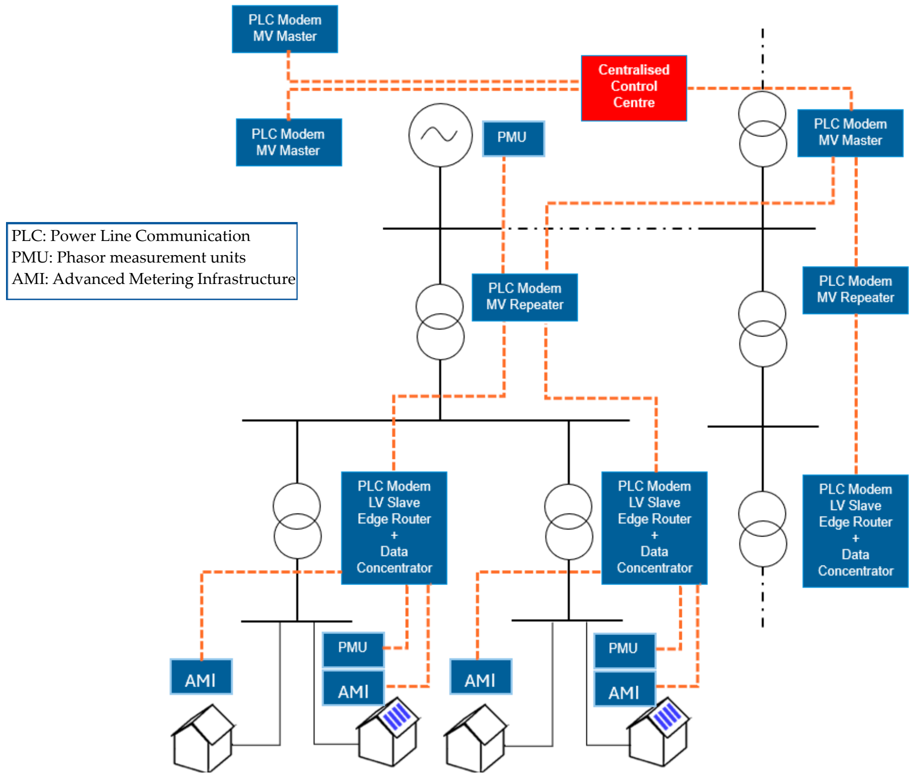

Figure 3. An illustration of conventional early electric grid with a centralized control center.

Hence, even though CCCs have long served the operation and management of electric grids, the transition towards a more decentralized framework of power distribution, as well as the emergence of new needs such as asset management optimization and smart grid control, necessitate a makeover in the current grid's topology. Hence, based on previous research on novel architectures for electrical distribution networks based on a decentralized control system where a substation automation and control system plays a key role, such as the works presented in [49], and inspired by the DAO, we propose the concept of a DAS. A DAS refers to an electrical substation that operates autonomously and is part of a decentralized distributed energy system. With such substations, smart technologies such as sensors and automation will be used to control and monitor the flow of electricity. Decentralization in this context implies that these substations are distributed across various locations of the electric grid rather than being solely reliant on a central control center, as illustrated in Figure 4. The autonomy aspect suggests that the substation can make decisions and adjustments independently based on real-time data, enhancing efficiency and reliability in the power grid. Both DAO and DAS involve decentralized structures and operate in a P2P fashion. Both systems aim to distribute decision-making and operational control across their network, reducing reliance on central authorities. Additionally, both systems may utilize smart contracts or other types of AI-based self-optimization algorithms to automate decision-making. This automation helps enforce rules without intermediaries. They commonly leverage blockchain technology for transparency, security, and immutability of records.

A DAS represents a technologically advanced and resilient approach to managing electricity distribution, incorporating decentralization, automation, and smart technologies for more efficient and reliable power grid operations. A DAS can be a component of future power grids that incorporate advanced technologies for efficient and autonomous operation. These substations utilize a variety of smart technologies, including sensors, communication devices, and advanced control systems. These elements work together to collect and analyze data in real-time, allowing for precise monitoring and control of electricity flow. The DAS, as its name indicates, is a combination of two main components: decentralization and automation. Unlike traditional centralized power systems, DASs are part of a decentralized energy network. This means that power generation is distributed across multiple smaller sources, such as solar panels, wind turbines, or local power plants. With this approach, grid resilience can be enhanced and single points of failure are reduced. Additionally, the substation's operations are automated to a significant extent. Automation helps in optimizing the flow of electricity, adjusting voltage levels, and identifying and responding to issues promptly. In turn, this can improve energy efficiency and reduce downtime. Moreover, the autonomy aspect refers to the ability of the substation to make decisions based on the data it collects. Through machine learning algorithms or other forms of AI, the substation can optimize its operations, predict potential failures, and take preventive actions without human intervention. DASs contribute to a more resilient and reliable power grid. By distributing power generation and enabling autonomous response to changing conditions these substations enhance the overall stability of the electrical system. Similarly, these substations are designed to seamlessly integrate with distributed energy sources, supporting the transition towards a cleaner and more sustainable electric grid.

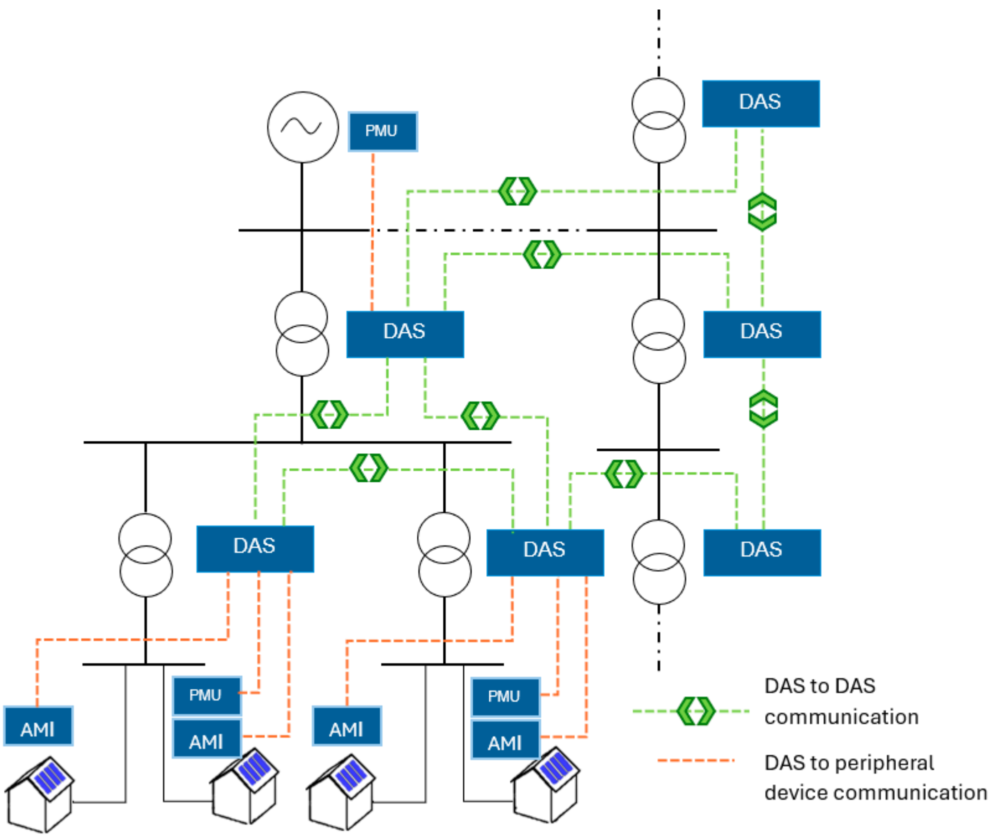

Figure 4. An illustration of our approach: a DAS-based distributed electric grid.

As previously mentioned, DAS operates through a combination of advanced technologies and intelligent systems to manage and optimize electricity distribution. The substation is equipped with various sensors that monitor different aspects of the electrical grid, such as voltage levels, current flow, temperature, and equipment health. These sensors continuously collect real-time data. The collected data are transmitted through communication networks, utilizing IoT, 5G, power line carrier (PLC), or similar technologies. This allows for seamless connectivity between the substation and other components of the power grid. Advanced analytics and machine learning algorithms process the collected data. These algorithms analyze patterns, predict potential issues, and make decisions based on the current state of the electrical grid. Analysis helps optimize energy distribution and identify anomalies or potential failures.

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The substation can make autonomous decisions based on the insights gained from data analysis. For example, it can adjust voltage levels, reroute electricity flow, or implement preventive measures to address potential issues without requiring manual intervention. Automation systems within the substation carry out the decisions made by intelligent algorithms. This includes adjusting equipment settings, switching between power sources, and implementing load-balancing strategies to ensure optimal performance. The substation's autonomous systems continuously adapt to changes in the grid conditions, responding to variations in demand, supply, and potential disturbances. This adaptability enhances the overall efficiency and resilience of the power distribution system; it also makes the DAS the adequate platform to integrate seamlessly with renewable energy sources. They can dynamically manage the fluctuations in power generation from sources like solar panels or wind turbines, ensuring a smooth and reliable supply of electricity. The substation also monitors its condition and the health of its components. It can schedule maintenance tasks based on actual usage and performance data, minimizing downtime and extending the lifespan of equipment.

By combining decentralized energy generation, real-time data analysis, and autonomous decision-making, DASs contribute to more efficient, reliable, and resilient electrical grids, especially in the context of evolving energy landscapes and the increasing integration of renewable energy sources. DAS topologies might change depending on particular design decisions and specifications. However, these substations will typically incorporate a combination of decentralized and distributed architecture, leveraging advanced communication technologies and smart devices. Unlike traditional centralized substations, a DAS is part of a broader trend in decentralizing power systems. This means that power generation and distribution are spread across various smaller units or sources. Each of these units, including the substation, operates semi-autonomously or autonomously. A DAS also includes a network of sensors that gather data in real-time about voltage, current, temperature, and equipment status. These sensors are distributed throughout the substation, enabling comprehensive monitoring. A robust communication infrastructure connects the sensors, control systems, and other devices within the substation. This communication network facilitates the exchange of data and instructions, enabling seamless coordination and control. To support real-time decision-making, DASs will incorporate edge computing capabilities. Edge devices within the substation can process and analyze data locally, reducing latency and enabling quick responses to changing conditions. Automation systems are considered a fundamental element of the topology since they are responsible for implementing decisions made based on data analysis. These systems control equipment, adjust settings, and manage the flow of electricity within the substation autonomously, using a distributed control system (DCS). A DCS will be used to coordinate and manage the various components of the substation. It distributes control functions across multiple controllers, enhancing flexibility and reliability. Further, to ensure a higher level of reliability and fault tolerance, DASs may incorporate redundancy in both communication and control systems. Redundancy helps mitigate the impact of component failures and enhances the overall resilience of the substation.

While the substation operates autonomously to a significant extent, it may also be integrated into a broader centralized energy management system. This integration allows for coordination with other substations and centralized power plants to achieve certain aspects of grid management. The specific topology of a DAS can vary based on factors such as the size of the substation, the complexity of the grid it serves, and the technologies implemented by the utility or operator. Overall, the goal is to create a resilient, flexible, and efficient power distribution system capable of adapting to changing conditions autonomously.

DASs and CCCs represent two different approaches to managing and controlling electrical power distribution systems. DASs operate with a degree of autonomy. They have embedded intelligence, utilized sensors, and employed local control systems to make real-time decisions based on data analysis. This autonomy enables quicker responses to change in the local environment. Moreover, power generation and distribution are decentralized in this model, with energy sources spread across various smaller units. Each substation operates semi-independently, making decisions locally to optimize efficiency and adapt to changing conditions. Likewise, the decentralized approach enhances the overall resilience of the power distribution system. If one substation faces an issue or goes offline, others can continue operating, minimizing the impact on the entire grid. On the other hand, in a CCC model, decision-making and coordination for the entire power grid occur at a central location. This central authority monitors and manages the overall system, making decisions for load balancing, fault detection, and grid optimization. Decentralized substations are designed to operate with minimal dependency on a CCC. They can make decisions locally, reducing the need for constant communication with a central authority. However, a centralized control center has a comprehensive view of the entire power grid. This allows for coordinated decision-making, especially in situations that require a system-wide perspective, such as load forecasting, grid maintenance planning, and large-scale disruptions. As well, centralized control enables efficient resource allocation and strategic decision-making. The central authority can optimize the use of available energy resources, balance loads across the grid, and respond to changes in demand more effectively. Ultimately, DASs prioritize local decision-making and resilience, while CCCs focus on global coordination and strategic planning for an entire power grid.

At the communication level, centralized control centers rely heavily on communication infrastructure to relay commands and receive real-time data from various substations. This dependency can introduce vulnerabilities due to the presence of an SPOF as well as disruptions in communication that may impact decision-making. In a DAS-based electric grid, each DAS is considered a node and a communication hub. Communication between the DASs will allow coordination and efficient operation and management of the decentralized power grid. Various communication technologies and protocols may be used to exchange information among these substations. Standardized communication protocols, such as IEC 61850 for substation automation [50], are often used in the power industry. These protocols define how information is exchanged between devices within a substation and, in some cases, between substations. They ensure interoperability and consistency in data exchange. Also, substations may be connected through a distributed communication network. This network may use wired or wireless technologies, including fiber optics, Ethernet, or radio frequency communication, depending on the specific requirements and constraints of the power grid. For larger geographical areas or regional grids, substations may be connected through wide-area networks. These networks enable communication over longer distances and facilitate coordination between substations that are not physically adjacent. Each substation can act as an intermediary hub, helping relay information between different remote substations and enabling a more interconnected and responsive grid, thus establishing a communication infrastructure that enables substations to share critical information, coordinate responses, and contribute to the overall stability and efficiency of the power grid.

In a conventional centralized electric grid with centralized control, the system is vulnerable to both faults and cyberattacks. In the event of a fault on the main transmission line feeding the substations, the load composed of four houses would experience a total outage, as no backup power sources or local generation are available. Additionally, in the case of a cyberattack on the central control system, the entire grid could suffer a blackout due to its reliance on centralized control. A smart grid with distributed resources and centralized control, on the other hand, offers more resilience in the event of a fault. When the transmission line feeding the substations fails, the houses equipped with excess photovoltaic (PV) power generation would continue to feed other houses, minimizing the impact of the outage. However, the system remains vulnerable to cyberattacks on the central control center. If such an attack occurs, the smart grid could still experience a blackout, as the centralized control remains the critical point of failure and will cripple the grid's ability to manage its components (motorized circuit breakers, disconnect switches, and control gears), disrupting energy management and jeopardizing grid stability, potentially of the outage. However, the system remains vulnerable to cyberattacks on the central control center. If such an attack occurs, the smart grid could still experience a blackout, as the centralized control remains the critical point of failure and will cripple the grid's ability to manage its components (motorized circuit breakers, disconnect switches, and control gears), disrupting energy management and jeopardizing grid stability, potentially leading to widespread outages and failure to maintain minimum power supply. In contrast, a system with DAS provides the highest level of resilience. In the event of a transmission line fault, similar to the smart grid, the houses with PV generation will continue to supply power to other DASes. However, the key advantage of the DAS model lies in its ability to withstand cyberattacks. Since there is no centralized control center, each substation operates autonomously. The DAS units will continue to communicate and exchange energy in order to maintain a minimum power supply (Figure 5). This decentralized architecture ensures that the grid continues to function even in the face of a cyberattack, providing superior operational continuity compared to both the conventional and smart grid models.

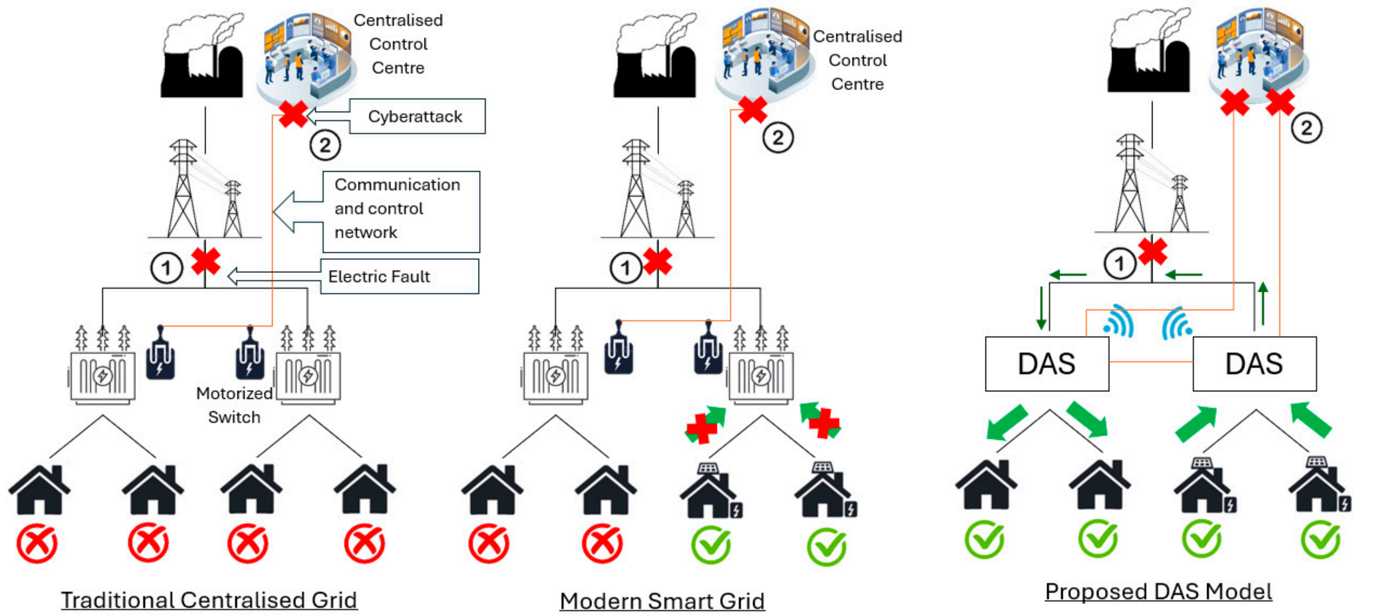

Figure 5. Comparison between the three grid models under grid fault and cyberattack on the centralized control center.

Hence the communication and control systems, as well as the decentralized data management system, are key features of the proposed DAS model. The communication system will allow DASs to exchange various types of data critical for the operation, monitoring, and management of the power grid. Such data include:

- Real-time information on the state of the power grid, including voltage levels, current flows, and frequency, is communicated to monitor the overall health and performance of the system.
- Data related to the status and health of equipment within substations, such as transformers, circuit breakers, and relays, is exchanged. This information helps in preventive maintenance and early detection of potential issues.
- Data on electricity consumption, load profiles, and demand forecasts are communicated. This information is crucial for balancing supply and demand, optimizing grid operations, and planning for future capacity needs.
- Information related to faults or disturbances on the grid, such as short circuits or equipment failures, is communicated. This facilitates quick detection and diagnostic analysis to minimize downtime and enhance grid reliability.
- Commands for controlling and adjusting the operation of various devices within the grid, including switching operations, voltage regulation, and reactive power control, are exchanged to ensure optimal grid performance.
- Data on the generation output and status of renewable energy sources, such as solar and wind farms, is communicated. This is crucial for integrating variable renewable energy into the grid and managing fluctuations in power generation.

- Information related to cybersecurity, including intrusion detection, authentication logs, and security events, is communicated to ensure the integrity and reliability of the grid's communication network.
- Data on weather conditions and environmental factors, such as temperature and humidity, may be communicated. This information is particularly relevant for managing the impact of weather on power lines and equipment.
- In deregulated energy markets, data on electricity market prices, transactions, and market conditions is communicated. This allows utilities and market participants to make informed decisions regarding energy trading and procurement.
- Information about the health and performance of the communication network itself, including latency, packet loss, and network reliability, is communicated to ensure the robustness of the communication infrastructure.
- Predictive analytics data are used to predict future grid conditions, equipment failures, and trends to optimize grid planning and operation.

The exchange of these diverse types of data will allow the electric grid to autonomously optimize its performance, enhance reliability, and respond effectively to changing conditions in the electric grid.

3.2. Proposed DAS Communication Protocol

Security of communication in electric grids is a critical concern as the integration of RESs, advanced metering infrastructure, and smart grid technologies continues to evolve. Electric grids, which once relied on isolated and relatively simple control systems, are now complex networks of interconnected devices, sensors, and communication channels. This complexity introduces a plethora of vulnerabilities, from cyberattacks targeting the communication protocols and infrastructure to physical attacks on substations and other critical components. Ensuring the reliability, availability, and integrity of the communication within these grids is paramount to preventing disruptions that could lead to widespread power outages, economic losses, and even threats to public safety. The solution we propose to enhance the security and resilience of communication in the DAS framework is the use of Byzantine fault-tolerant (BFT) communication technology. BFT is a consensus algorithm that can tolerate several faulty or malicious nodes within a network, ensuring that the correct and reliable operation of the system can continue even in the presence of faults. This is particularly advantageous for DASs. While the DAS itself is not inherently malicious, like any cyber equipment, there is a possibility that one or multiple DASs could be hacked or attacked, thus being compromised and its functionalities altered to serve malicious purposes.

The BFT communication protocol is a robust method used in distributed systems [51] to achieve consensus even when some nodes are faulty or malicious. The protocol is named after the Byzantine generals' problem, which illustrates the challenges of reaching an agreement in a distributed network where some participants may act deceitfully.

- Proposer: A designated node, often called the proposer or leader, initiates the consensus process by proposing a value. In the DAS context, the proposer could be one of the substation controllers detailed in Figure 6.
- Validators: Other nodes in the network act as validators, receiving and verifying the proposed value. Each DAS may have one or more controllers acting as validators. These controllers manage the substation's operations and participate in the consensus process to ensure coordinated and secure functionality across the network. Validators can be distributed across multiple nodes within the substation network. These nodes may include sensors, actuators, and other smart devices that contribute to data collection and validation. A hierarchical structure may exist where higher-level controllers or validators oversee the operations of lower-level nodes, ensuring a robust and scalable consensus mechanism.

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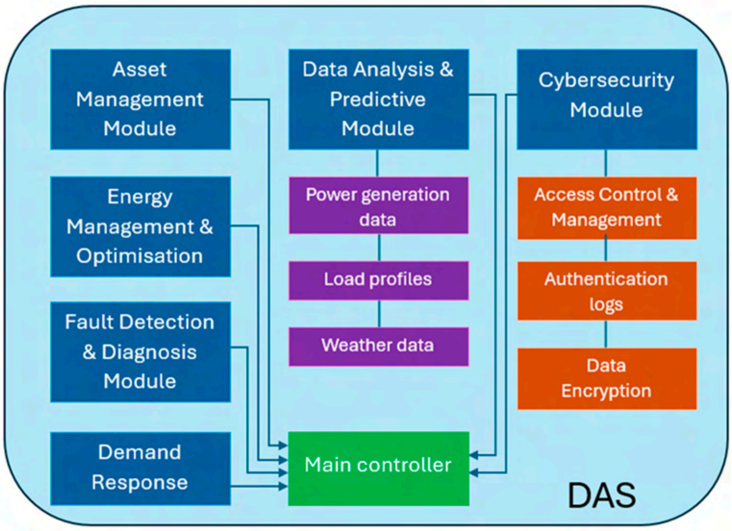

Figure 6. Components and elements of the DAS.
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Communication Rounds:

- First Round (Propose Phase): The proposer (which could be one of the substation controllers) sends its proposed value to all validators.
- Second Round (Prepare Phase): Upon receiving the proposal, each validator node verifies the proposal's validity. This involves checking the digital signatures and ensuring the proposal meets the protocol's criteria. If the proposal is valid, each validator node creates a prepared message. The prepared message includes the proposal value, the view number (indicating the current state of the consensus process), the sequence number (indicating the order of the proposal), and the digital signature of the validator, ensuring the authenticity and integrity of the message. Each validator then sends its prepared message to all other validator nodes in the network. The prepared message serves as an acknowledgment from the validators (nodes) that they have received and validated the initial proposal from the proposer (leader). It is part of the multi-stage process designed to build consensus in a distributed system where some nodes may be faulty or malicious.

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- Third Round (Commit Phase): Validators wait to receive a certain number of prepared messages from other validators. Specifically, they need to prepare messages from at least $2f + 1$ nodes, where f is the maximum number of faulty nodes the system can tolerate. Once a validator receives the required number of prepared messages, it can be confident that a sufficient number of honest nodes have seen and agreed on the proposal's validity. The validator then sends a commit message to all other validators, signaling that it is ready to finalize the proposal.
- Final Round (Decide Phase): Validators wait to receive a sufficient number of commit messages. Once a validator receives commit messages from a quorum, it finalizes and accepts the value, thus reaching a consensus.

Message Verification: Validators verify messages using cryptographic techniques to ensure authenticity and integrity. Each message is signed, allowing validators to detect and ignore messages from malicious nodes.

Quorum Requirements: BFT protocols generally require more than two-thirds of nodes to be honest to function correctly. This means the protocol can tolerate up to one-third of nodes being faulty or malicious. For a network of n nodes, the protocol needs at least $2f + 1$ validators to agree on a value to reach a consensus.

The protocol is designed to withstand Byzantine faults, where nodes can fail in arbitrary ways, including acting maliciously. It ensures that as long as the majority of nodes are honest, the system can reach a reliable consensus despite the presence of faulty nodes. Figure 7 illustrates the process of transmitting a control command from the controller to the third of nodes being faulty or malicious. For a network of n nodes, the protocol needs at least $2f + 1$ validators to agree on a value to reach a consensus.

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Figure 7 illustrates the process of transmitting a control command from the controller to the actuator using the BFT communication protocol. In this sequence, the controller generates and sends a control command to the actuator. The BFT protocol ensures that this command is securely and accurately delivered despite potential faults or malicious nodes within the system. The figure depicts each step, including the initial command generation, the dissemination of the command across multiple nodes for validation, and the final receipt and execution of the command by the actuator. This robust communication framework guarantees the integrity and reliability of the control command, ensuring the actuator performs the intended action correctly.

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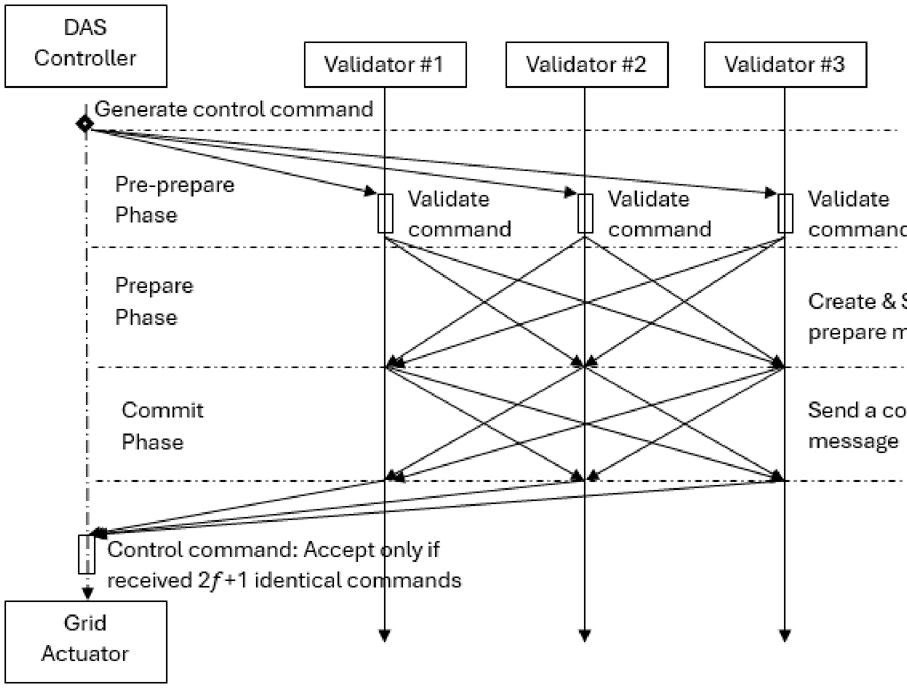

Figure 7. BFT control command operation model.

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DASs may benefit from BFT communication technology in several ways. First and foremost, BFT enhances the security of these substations by ensuring that communication between devices and control systems remains robust even if some nodes are compromised. This is achieved through the consensus mechanism, which requires agreement from a majority of nodes before any decision is finalized, thereby mitigating the risk posed by a small number of malicious actors. Secondly, BFT communication technology improves the reliability of DASs. In traditional communication systems, a SPOF can disrupt the entire network, but BFT's fault-tolerant nature allows the system to continue operating smoothly despite failures. This is crucial for maintaining continuous power supply and preventing outages, as substations are critical nodes within the electric grid. Moreover, BFT supports the scalability of DASs. As the number of devices and sensors within the grid increases, so does the complexity of managing communication and ensuring security. BFT algorithms are designed to scale efficiently, handling increased network traffic and maintaining performance without compromising security. This scalability is essential for the future expansion of smart grid technologies and the integration of more RESs, which demand flexible and reliable communication infrastructure.

Another significant benefit of BFT communication technology is its ability to support real-time decision-making and automation. DASs rely on real-time data to make autonomous decisions that optimize grid performance and respond to changing conditions. BFT ensures that these decisions are based on accurate and timely information, free from the influence of compromised nodes. This capability is essential for the dynamic and responsive nature of smart grids, where rapid adjustments are necessary to maintain stability and efficiency. Furthermore, the implementation of BFT communication technology can lead to cost savings in the management and operation of electric grids. By reducing the need for manual intervention and enhancing the reliability and security of communication, utilities can lower operational costs and allocate resources more effectively. The improved efficiency and reduced risk of outages also translate to economic benefits for consumers, who experience fewer disruptions and potentially lower electricity costs.

Nevertheless, one disadvantage of using BFT for DAS communication is its high computational complexity and resource requirements, which can lead to increased latency and reduced scalability, making it less efficient for real-time, large-scale energy grid operations compared to other protocols. Despite being difficult to hack due to its consensus mechanism, BFT is not entirely immune to cyberattacks, which poses a potential risk for grid security. Other mechanisms might also be considered, such as modifications of the original BFT mechanism (i.e., Practical BFT (PBFT), Istanbul BFT (IBFT), or Quorum BFT (BFT)), other consensus mechanisms, or a mix. Moreover, it is important to acknowledge that while BFT protocols provide fault tolerance for up to 1/3 of nodes, they do not resolve the underlying challenge of achieving consensus in scenarios with higher fault levels or where quorum thresholds are difficult to meet. While various BFT variations aim to improve computational efficiency, they still depend on the same quorum size, limiting their scalability in real-world applications. As such, this remains an open problem, particularly when considering large-scale decentralized systems with high degrees of heterogeneity and potential faults. One possible avenue for future exploration includes hybrid consensus mechanisms that combine elements of BFT with other approaches to reduce quorum dependencies.

On the other side, it is important to highlight that in order to address the potential risk of cyberattacks or malicious interventions targeting one or more DAS, it is critical to recognize that such incidents would not merely be handled by the system's internal protocols. In real-world scenarios, any significant disruption, particularly one caused by an attack, would likely trigger an immediate, higher-level response involving national grid operators and cybersecurity authorities. The DAS concept, while relying on decentralized decision-making and voting protocols during normal operations, must be equipped with advanced security measures such as real-time monitoring, encryption, and intrusion detection systems. These safeguards would not only help mitigate local failures but also ensure that any identified attack escalates to a national security alert when necessary, in line with modern cybersecurity practices. This approach ensures that the failure of one or more subsystems does not jeopardize overall grid stability and allows for swift coordination between grid operators and national emergency/security teams to protect critical infrastructure.

4. Blockchain as Data Management Platform—Decentralization of Layer 3

In an electric grid, the types of data exchanged, analyzed, and stored primarily include operational data such as voltage levels, current flows, power generation, and consumption metrics. This data ensures the balanced and efficient functioning of the grid, enabling operators to monitor and control the distribution of electricity. In contrast, a smart grid involves a more complex and extensive data ecosystem. It incorporates all the traditional operational data and adds a variety of additional information, such as real-time usage patterns from smart meters, predictive maintenance data from sensors on infrastructure, and data from DERs. Smart grids also handle data related to demand response programs, enabling dynamic pricing and load balancing based on real-time conditions. Furthermore, smart grids store and analyze historical data to improve grid performance, forecast energy demand, and integrate renewable energy sources more effectively. This comprehensive data collection and analysis capability enhances the grid's efficiency, reliability, and ability to support modern energy needs. Data exchanged in the framework of modern electric grids can be grouped as follows:

- Meter Data: Information collected from meters installed at various points in the grid, including residential, commercial, and industrial locations. This data includes energy consumption, voltage levels, peak demand periods, and sometimes more detailed information about power quality.

- Grid Operation Data: Data related to the operational status of the grid, such as real-time measurements of voltage, current, frequency, and power factor. This information helps grid operators monitor the health and performance of the grid infrastructure.
- Weather Data: Weather conditions have a significant impact on energy generation (especially renewables like solar and wind) and consumption patterns. Weather data, including temperature, wind speed, sunlight intensity, and forecasts, is crucial for predicting energy demand and optimizing generation resources.
- Asset and Maintenance Data: Information about the condition, maintenance schedules, and performance of grid assets like transformers, substations, and transmission lines. Predictive maintenance systems leverage this data to prevent failures and optimize asset lifespans.
- Market and Pricing Data: Data related to energy markets, including wholesale and retail energy prices, demand-response programs, and market mechanisms. This information influences energy trading, pricing strategies, and load balancing.
- Control and Command Data: Instructions and commands sent across the grid to control devices, manage load balancing, and ensure grid stability. These commands help regulate power flow, manage voltage levels, and respond to contingencies in real-time.
- Customer Information: Data about consumer behavior, preferences, and usage patterns, which can help utilities optimize services, design tariff structures, and offer tailored energy solutions.

The exchange and analysis of these diverse types of data play a crucial role in optimizing grid operations, ensuring reliability, improving efficiency, integrating RES, and meeting the changing demands of consumers and the broader energy market. Blockchain technology can significantly enhance the grid's data management by improving analysis, exchange, storage, and security. By providing a decentralized and immutable ledger, blockchain ensures that all data entries are securely recorded and cannot be altered, thus enhancing the integrity and reliability of grid data. For data exchange, blockchain facilitates transparent and trustless interactions between various grid stakeholders, such as utilities, prosumers, and DERs, enabling seamless and efficient data sharing. In terms of storage, blockchain offers a distributed database that reduces the risk of data loss and ensures high availability and redundancy, thereby enhancing data resilience. The advanced cryptographic techniques used in blockchain provide robust security measures, protecting sensitive grid data from unauthorized access and cyberattacks. Additionally, the use of smart contracts can automate and enforce data-driven decisions and transactions within the grid, further improving operational efficiency and trust. Blockchain's role in enhancing the analysis, exchange, storage, and security of data within modern electric grids is detailed hereafter:

- Analysis: Blockchain enables the integration and aggregation of diverse data sources within the electric grid, including real-time data from smart meters, IoT sensors monitoring grid infrastructure, and operational metrics from DERs like solar panels and battery storage systems. By consolidating these data streams onto a decentralized ledger, blockchain facilitates comprehensive data analytics and predictive modeling. Grid operators can leverage this unified data platform to optimize energy distribution, anticipate demand fluctuations, and implement proactive maintenance strategies. Advanced analytics powered by blockchain technology enable more accurate forecasting of energy supply and demand dynamics, supporting grid stability and efficiency. Additionally, smart contracts can automate data collection and processing tasks. For example, in a smart grid, smart contracts can be used to automatically collect data from smart meters at regular intervals, process it, and then store it on the blockchain. This automation reduces the risk of human error and ensures consistent data collection practices, which is vital for accurate analysis. Furthermore, blockchain can enable decentralized computing networks where multiple nodes (computers) contribute their processing power to perform complex computations. This is exemplified in blockchain projects like Ethereum and Filecoin, which use a decentralized approach to pool computing resources. By leveraging these distributed networks, large-scale data analysis can be performed more efficiently without relying on centralized servers. Moreover, distributed ledger technology (DLT) platforms like blockchain allow data to be stored across multiple locations, enhancing redundancy and resilience. In the context of data analysis, this distributed approach means that large datasets can be stored and accessed more efficiently. The distribution of data across nodes can also facilitate parallel processing, where multiple nodes work on different parts of a dataset simultaneously, thus speeding up data analysis.

- Data Exchange: One of blockchain's key strengths lies in its ability to facilitate secure and transparent data exchange among multiple stakeholders within the grid ecosystem. Traditional energy transactions often involve complex processes and intermediaries, leading to delays, inefficiencies, and increased costs. Blockchain's decentralized nature allows for P2P transactions facilitated by smart contracts—self-executing contracts with predefined rules encoded within the blockchain. These smart contracts automate and enforce agreements between energy producers, consumers, and grid operators, ensuring trustless transactions based on predefined conditions such as energy pricing, delivery terms, and validation of energy certificates (e.g., renewable energy credits). By eliminating intermediaries and streamlining transaction processes, blockchain enhances the efficiency and reliability of energy trading and other grid-related transactions.
- Storage: Blockchain technology employs a distributed ledger architecture where data are replicated and stored across multiple nodes (computers) in the network. This decentralized storage approach enhances data resilience and availability, minimizing the risk of data loss due to hardware failures or cyberattacks. Each transaction recorded on the blockchain is cryptographically secured and timestamped, ensuring its immutability and traceability. This feature is particularly valuable in auditing and compliance processes, where historical data integrity is crucial for regulatory purposes. Moreover, blockchain's distributed storage mitigates the risk of single points of failure and enhances the overall reliability of grid operations, even in the event of localized disruptions.
- Security: Security is a paramount concern in the management of grid data, given the sensitive nature of information such as consumer energy usage patterns, grid performance metrics, and operational commands. Blockchain addresses these security challenges through robust cryptographic algorithms and consensus mechanisms that validate and secure transactions within the network. Each transaction undergoes cryptographic verification before being added to the blockchain, ensuring that only authorized parties can access and modify data according to predefined permissions. The decentralized nature of blockchain reduces the risk of data breaches and unauthorized access, as the entire network must collectively agree on the validity of transactions. Additionally, blockchain's immutable ledger ensures that once data are recorded, they cannot be altered retroactively without consensus, providing a reliable audit trail for forensic analysis and compliance purposes.

In the context of a DAS electric grid topology, blockchain can be integrated with edge computing, where data processing occurs at the edge of the network, close to the data source. This integration reduces latency and bandwidth usage, as data does not need to travel to centralized data centers for processing. Blockchain ensures the security and integrity of data processed at the edge, allowing for real-time data analysis and decision-making. Additionally, DASs need to operate independently and coordinate with other substations without relying on a centralized control system, which can become an SPOF. Blockchain allows each substation to be a node in a decentralized network. This enables substations to communicate and coordinate their operations securely and efficiently without the need for central authority. Also, smart contract-enabled automated agreements executed on the blockchain can be used to manage interactions and transactions between substations.

These smart contracts can automate various operational tasks, such as load balancing, fault detection, and energy trading.

Figure 8 illustrates two blockchain-based models, one on the DAS side and the other on the prosumer's side. Each data management model integrates several smart contracts, each fulfilling a specific function. Also, it shows the acquisition of data from the real world via different oracles. Additionally, Figure 8 defines the communication between the DAS node and the prosumer node with types of exchanged data.

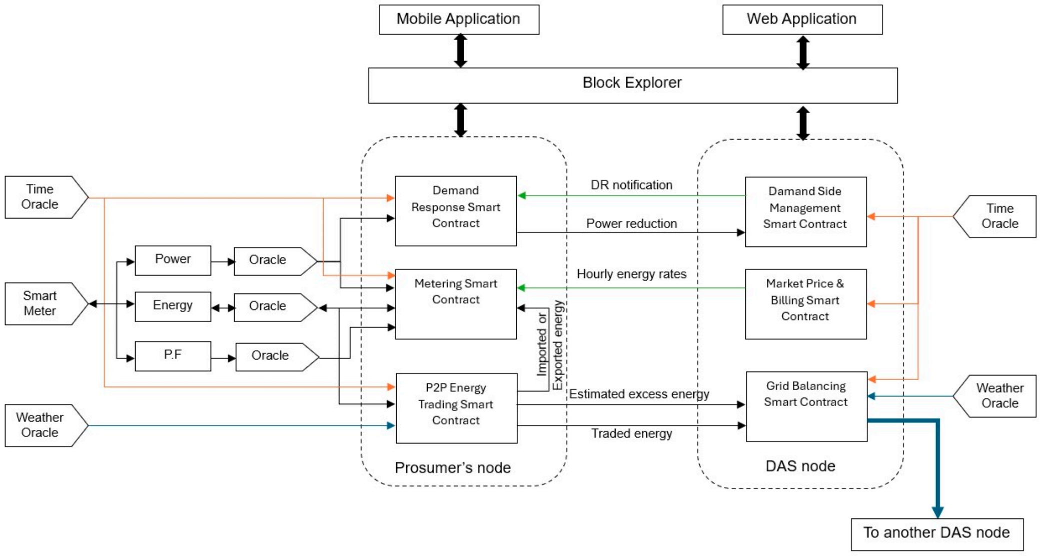

Figure 8. Blockchain-based model of a DAS.

5. Conclusions

A comprehensive investigation into the risks and threats confronting the modern electric grid reveals critical vulnerabilities that demand a revolutionary approach to bolster its resilience, security, and efficiency. The conventional centralized grid model, though historically effective, is increasingly susceptible to cyberattacks, natural disasters, and inherent operational inefficiencies. These threats not only jeopardize the reliability of the power supply but also compromise the confidentiality and integrity of grid data. To address these pressing issues, we propose a decentralized autonomous grid model based on blockchain-enabled decentralized autonomous substations (DASs). This innovative model decentralizes control, distributing it across multiple autonomous substations. This decentralization mitigates the risks associated with single points of failure, ensuring that no single attack or fault can compromise the entire grid. DASs, equipped with real-time data analysis capabilities, enhance grid responsiveness and adaptability. They can autonomously manage local energy production, storage, and distribution, optimizing efficiency and reliability. This model also empowers prosumers by enabling them to actively participate in the energy market, contributing to and benefiting from a more dynamic and resilient grid. Moreover, the decentralized model enhances the grid's ability to withstand and recover from natural disasters. Autonomous substations can isolate affected areas, preventing cascading failures and ensuring that the rest of the grid remains operational. This localized control capability significantly improves grid resilience and disaster recovery.

Additionally, this article underlines the importance of blockchain as a decentralized database that is capable of transforming how grid data are managed, analyzed, exchanged, stored, and secured. By leveraging blockchain's capabilities, electric grids can achieve greater operational efficiency, enhanced grid reliability, improved transparency in energy transactions, and strengthened cybersecurity measures. As the energy sector continues to evolve towards decentralized and sustainable energy systems, blockchain stands poised to play a pivotal role in shaping the future of grid management and energy transition initiatives globally. Furthermore, our proposed model suggests the usage of the BFT as a communication protocol between the different nodes (DASs) of the decentralized autonomous grid. Since the security of communication in electric grids is a fundamental aspect of ensuring the reliability and resilience of power systems, the adoption of BFT communication technology offers significant benefits for DASs, enhancing their security, reliability, scalability, and data integrity.

Nevertheless, to comprehensively evaluate the performance of the DAS concept, it is essential to develop a robust evaluation framework that incorporates both technical and operational metrics. This framework should focus on assessing the substation's ability to autonomously manage grid stability, optimize energy distribution, and efficiently handle dynamic grid conditions using real-time data and automated decision-making systems. Key performance indicators (KPIs) should be defined to measure critical aspects such as system reliability, fault tolerance, energy efficiency, and the DAS's response time to sudden changes in grid demand or supply, particularly during disruptions or fluctuations in energy generation from renewable sources. System reliability can be quantified by the substation's uptime and its ability to maintain uninterrupted service under various operational conditions, while fault tolerance can be gauged by its resilience to equipment failures and external disturbances. Additionally, energy efficiency should be evaluated by analyzing how well the DAS manages energy distribution to minimize losses and optimize usage, both within the substation and across connected DERs. The response time to dynamic grid conditions will be another vital metric, indicating the DAS's capability to rapidly adapt and make real-time decisions to stabilize the grid when dealing with fluctuating energy supply from renewable sources like solar and wind.

To facilitate this evaluation, simulation environments or pilot deployments can be utilized. In simulations, various scenarios such as peak demand periods, equipment malfunctions, and integration of intermittent renewable energy sources should be created to observe how the DAS operates under stress. Pilot deployments in real-world settings would further allow testing in live grid environments, enabling an assessment of how the DAS interacts with existing infrastructures such as renewable energy sources, peer-to-peer (P2P) energy trading platforms, and VPPs. These simulations and pilot studies will provide valuable insights into the operational viability of the DAS. Furthermore, comparative analysis with traditional centralized substations is crucial. By benchmarking the DAS's performance against conventional substations, the relative advantages and potential limitations of decentralization can be better understood. Metrics such as cost efficiency, scalability, ease of integration with renewable resources, and impact on grid flexibility should be compared to highlight the potential benefits of adopting the DAS model over traditional approaches. This comparative analysis will also inform areas where the DAS can be optimized further for improved scalability and integration into future smart grid architectures.

Ultimately, transitioning to a decentralized autonomous grid model represents a paradigm shift in how we think about and manage our electric infrastructure. It promises to enhance grid reliability, security, and efficiency, making it more resilient to emerging threats and better equipped to meet the evolving demands of the 21st century. This innovative approach not only addresses current vulnerabilities but also paves the way for a more robust, sustainable, and consumer-empowered energy system. However, this article introduces the concept of the DAS. Nevertheless, the transition from conceptualization to practical implementation requires further studies, extensive simulations, and rigorous testing. These steps are crucial to developing the concept into a robust proof of concept, ensuring that the proposed system can operate effectively under real-world conditions and meet the stringent demands of modern power grids.

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4.3 ARTICLE: CENTRALIZED VS. DECENTRALIZED ELECTRIC GRID RESILIENCE ANALYSIS USING LEONTIEF'S INPUT–OUTPUT MODEL

Cet article, intitulé « *Centralized vs. Decentralized Electric Grid Resilience Analysis Using Leontief's Input–Output Model* », a été publié dans sa version finale en mars 2024 par les éditeurs du journal *MDPI – Energies*.

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En tant que premier auteur, j'ai contribué à la conceptualisation du modèle, à l'essentiel de la recherche sur l'état de la question et au développement de la méthode, au développement du modèle de simulation, à la collecte et l'analyse des résultats et à la rédaction du manuscrit. Professeur Mehdi Adda a participé à la direction du projet, à la supervision du travail, validation des résultats ainsi qu'à la révision de l'article et à la revue de la littérature. Les professeurs Adrian Ilinca, Mazen Ghandour et Hussein Ibrahim en tant que co-auteurs, ont participé à la révision de l'article et à la revue de la littérature.

Résumé : La multiplication des événements, tels que les conditions météorologiques extrêmes, les incidents géopolitiques, les actes de guerre, les cyberattaques et l'intermittence des ressources énergétiques renouvelables, pose des défis considérables à la fonctionnalité des réseaux électriques mondiaux. Par conséquent, la recherche sur l'amélioration de la résilience des réseaux électriques est devenue de plus en plus cruciale. Simultanément, la décentralisation des réseaux électriques, motivée par une intégration accrue des REDs et l'impératif de décarbonisation, a entraîné des transformations significatives dans les topologies des réseaux. Ces changements peuvent avoir un impact profond sur la flexibilité, l'exploitabilité et la fiabilité. Cependant, il n'y a pas assez de recherches sur l'impact des REDs sur la résilience du réseau électrique ni de modèle simple pour simuler l'impact de

toute perturbation sur le réseau. Par conséquent, pour analyser la résilience du réseau électrique, cette étude utilise une extrapolation du modèle input-output (IO) de Leontief, conçu à l'origine pour étudier les effets d'entraînement dans les secteurs économiques. Les nœuds sont traités comme des industries, et la transmission d'énergie entre les nœuds est considérée comme la relation entre les industries. Notre recherche compare les changements d'opérabilité dans les réseaux centralisés, partiellement décentralisés et entièrement décentralisés dans des conditions de défaillance identiques. En utilisant l'inopérabilité du réseau comme ICP, cette étude teste les trois configurations de réseau dans deux scénarios de défaillance. Les résultats confirment l'efficacité de la décentralisation dans l'amélioration de la résilience et de la sécurité des réseaux électriques.

Contexte et Objectifs : Dans le contexte actuel de transition énergétique et de modernisation des infrastructures, il est crucial d'évaluer les performances des différents modèles de gestion des réseaux électriques. Cette étude de simulation comparative se situe à l'intersection de ces enjeux, visant à analyser de manière rigoureuse les différences entre les réseaux centralisés et décentralisés en termes de résilience et d'opérabilité. Les réseaux centralisés, historiquement dominants, présentent des vulnérabilités liées à leur dépendance à des points de contrôle uniques, tandis que les réseaux décentralisés offrent une répartition plus uniforme des ressources et des responsabilités, promettant une meilleure adaptation aux perturbations et aux demandes fluctuantes. Les objectifs de cette étude sont donc multiples : développer un modèle simple pour quantifier la résilience des deux modèles face à des scénarios de pannes et de cyberattaques, définir un indicateur clé de performance pour évaluer leur capacité à maintenir une opération continue et efficace, et identifier les avantages et les défis opérationnels inhérents à chaque configuration. En utilisant un modèle modifié d'IO de Leontief, l'étude cherche à fournir des données empiriques solides pour éclairer les décisions stratégiques dans la conception et l'implémentation des futurs réseaux électriques, en tenant compte des impératifs de sécurité, de fiabilité et d'opérabilité.

Méthodologie : La première étape de cette étude consistait à réaliser une revue exhaustive de la littérature existante sur les réseaux électriques centralisés et décentralisés.

Cela inclut l'analyse des modèles théoriques, des études de cas, et des recherches empiriques précédentes qui traitent des concepts de résilience et d'opérabilité des réseaux. La deuxième étape consistait à créer une modélisation des réseaux électriques centralisés et décentralisés en se basant sur le modèle IO de Leontief. Et finalement de simuler un réseau centralisé, avec et sans REDs, et comparer l'inopérabilité des deux modèles

Résultats et Contributions : Cette étude fournit des preuves concrètes de l'impact positif de la décentralisation physique sur la résilience du réseau électrique. Elle met également en lumière un sujet plus large qui mérite d'être approfondi dans le cadre de la recherche permanente d'un niveau élevé de fiabilité du réseau électrique. Les résultats soulignent l'importance de prendre en compte à la fois la décentralisation physique et numérique pour améliorer la résilience des infrastructures énergétiques modernes de manière globale. À un autre niveau, cet article propose une nouvelle simulation mathématique basée sur le modèle IO de Leontief pour évaluer et analyser la résilience du réseau électrique. Le modèle proposé ne nécessite pas de ressources informatiques considérables et requiert un temps de simulation minimal, ce qui le rend facile à coder dans un outil simple et à utiliser comme logiciel de simulation.

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Centralized vs. Decentralized Electric Grid Resilience Analysis Using Leontief's Input–Output Model

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Abstract: Escalating events such as extreme weather conditions, geopolitical incidents, acts of war, cyberattacks, and the intermittence of renewable energy resources pose substantial challenges to the functionality of global electric grids. Consequently, research on enhancing the resilience of electric grids has become increasingly crucial. Concurrently, the decentralization of electric grids, driven by a heightened integration of distributed energy resources (DERs) and the imperative for decarbonization, has brought about significant transformations in grid topologies. These changes can profoundly impact flexibility, operability, and reliability. However, there is a lack of research on the impact of DERs on the electric grid's resilience, as well as a simple model to simulate the impact of any disturbance on the grid. Hence, to analyze the electric grid's resilience, this study employs an extrapolation of Leontief's input–output (IO) model, originally designed to study ripple effects in economic sectors. Nodes are treated as industries, and power transmission between nodes is considered as the relationship between industries. Our research compares operability changes in centralized, partially decentralized, and fully decentralized grids under identical fault conditions. Using grid inoperability as a key performance indicator (KPI), this study tests the three grid configurations under two fault scenarios. The results confirm the efficacy of decentralization in enhancing the resilience and security of electric grids.

Keywords: electric grid; resilience; centralized; decentralized; distributed energy resources; input–output model

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1. Introduction

Modern electric power supply systems are governed by three key criteria: quantity, quality, and reliability. Quantity involves maintaining a balance between power generation and demand, while quality ensures that supplied electricity aligns with predefined characteristics such as voltage and frequency. Reliability, a crucial aspect, is defined as the consistent delivery of electricity without interruption or significant fluctuations, requiring stable flow, demand-meeting power generation, and minimal disruptions from various factors. Grid resilience is a fundamental element in ensuring the reliability of electric grids. It is characterized by the grid's ability to endure and recover from various disruptions or unforeseen events, such as natural disasters, cyberattacks, or equipment failures [1]. This resilience encompasses the grid's capacity to absorb shocks, adapt to dynamic conditions, and swiftly restore power following an outage. Strategies to enhance grid resilience often involve leveraging diverse energy sources, establishing a robust infrastructure, and implementing rapid response mechanisms. In contrast, reliability primarily aims to prevent disruptions and maintain an uninterrupted power supply.

infrastructure, and implementing rapid response mechanisms. In contrast, reliability primarily aims to prevent disruptions and maintain an uninterrupted power supply.

Grid resilience has become paramount in the contemporary energy landscape due to heightened reliance on electricity across all economic sectors. The interdependency of critical infrastructures, particularly electricity, communications, healthcare, and transportation [2], further underscores the significance of prioritizing grid resilience. Additionally, national security and independence concerns accentuate the urgency of ensuring grid resilience. Consequently, policymakers, utility companies, and governments worldwide have prioritized fortifying the resilience of electric grids [3].

Electric grids originated in the late 19th century as small-scale, primitive, and isolated town-based networks (Grid 1.0). However, driven by a growing reliance on electric power and a substantial surge in energy demand, electric grids evolved into national, large-scale centralized power grids centered around significant power plants (Grid 2.0). A new transformation occurred in less than a century, spurred by the imperative to decarbonize the energy sector. This shift, driven by the increasing integration of renewable energy (RE) systems and DERs, led to a decentralized topology (Grid 3.0).

Today, with the advent of advanced technologies such as artificial intelligence (AI), the blockchain, the Internet of Things (IoT), and the incorporation of concepts like peer-to-peer (P2P) energy trading, energy democracy, and virtual power plants (VPP), the grid is progressing towards complete decentralization, shaping the vision of the future grid (Grid 4.0) as a composite of thousands or even millions of microgrids. Simultaneously, these transformations in the electric grid's topology align with a surge in digitalization. Recognizing the necessity to address evolving needs and challenges, a core digital transformation occurred at the grid's operational and asset management levels. The integration of smart metering, advanced metering infrastructure (AMI), and the application of digital technologies for automation and optimization underlined the digital revolution in the electric grid [4]. Undoubtedly, the evolution of the electric grid into a decentralized, highly digitized network significantly enhanced its operational flexibility. Figure 1 depicts the progression of the grid's topology, digitalization, and flexibility.

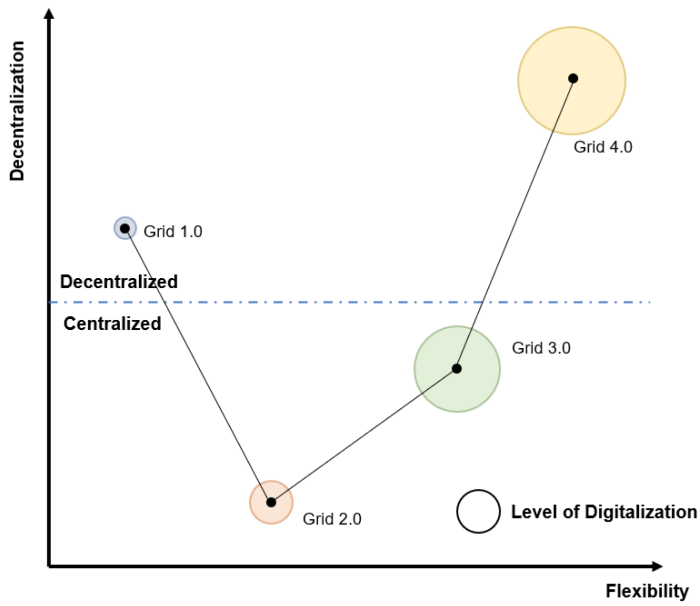


Figure 1. The electric grid's changes with time.

However, within the domain of grid resilience, ongoing discourse and analysis revolve around the advantages and disadvantages of centralized and decentralized approaches. Centralized approaches to grid resilience adopt a centralized control architecture, where decisions and actions are coordinated and executed by a central authority or operator. This approach provides superior controllability and predictability, facilitating efficient resource management and response to disruptions. Nonetheless, centralized networks operator. This approach provides superior controllability and predictability, facilitating efficient resource management and response to disruptions. Nonetheless, centralized networks have a notable drawback, known as a single point of failure (SPOF). This refers to a specific grid element, such as a control center, power station, or transmission line, whose failure can significantly disrupt or potentially collapse the entire grid's functionality. Essentially, it represents a vulnerability that, if compromised, could result in widespread power outages or disruptions [5].

Conversely, decentralized approaches to grid resilience embrace near-edge solutions, including small-scale power generation and energy storage systems [6]. This decentralized architecture provides a heightened level of scalability, allowing for greater flexibility. Additionally, decentralized systems have demonstrated increased resilience in the face of climate-related risks such as wildfires and extreme storm events. Distributed energy systems can effectively mitigate damage or disruption to primary utility components by leveraging end-user solutions like small generators, rooftop solar photovoltaic (PV) systems, and battery energy storage systems (BESS), enhancing overall resilience.

This article explores the impact of electric grid decentralization from a resilience perspective. However, assessing a grid's resilience necessitates the establishment of a KPI to gauge the effectiveness or inefficiency of a particular solution. In this study, we adopted inoperability as an indicator to assess the resilience health status of each node in the grid. Inoperability is defined as the ratio of the power decline at a specific node following a detected interruption to the baseline power level or essentially business as usual. Consequently, an inoperability value of zero signifies that the node was unaffected by the interruption, while a value of one indicates a complete loss of power at the node (Figure 2).

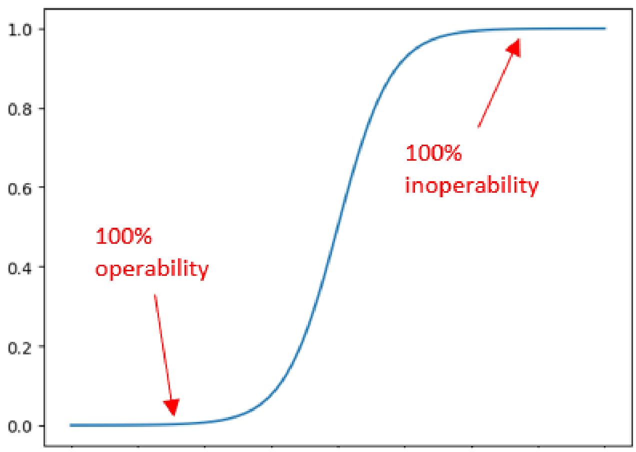


Figure 2. Electric grid inoperability curve.

However, the intricate interconnections among nodes in an electric grid can complicate the measurement of inoperability. Additionally, these interactions, referred to as power transmissivity between nodes, may trigger a chain reaction in the event of a power failure or fault affecting any node. Hence, the need arises for a mathematical model capable of simulating the interconnections between nodes and assessing the impact of any incident on other grid elements. Consequently, we opted to employ Leontief's IO analysis, a model initially introduced by Wassily Leontief in the 1930s to analyze the interdependencies between different sectors of an economy [7].

In this study, we construct a matrix of interdependency among various components of an electric grid, employing the power transmitted between nodes as a parameter. Subsequently, we apply Leontief's inoperability input–output model (IIM) to quantify the inoperability of each node. The calculated inoperability serves as a KPI for assessing the grid's resilience and gauging the repercussions of any incidents, failures, or interruptions in the grid. The proposed mathematical model for calculating the electric grid's resilience offers a relatively more straightforward, faster, and easier to implement method than conventional techniques such as dynamic system simulation or Monte Carlo simulation.

Additionally, the methodology employed to analyze the influence of decentralization on grid resilience involves three grid models. First, a traditional centralized grid model is utilized, with the IEEE-14 nodes grid as a representative example. Second, a fully decentralized model is derived from the IEEE-14 nodes model, incorporating a distributed power source connected to each grid node. Lastly, a partially decentralized model is created, with distributed power sources connected to only half of the nodes. Subsequently, all three grid models undergo the same interruption scenarios (simulating two scenarios). In each case, the inoperability of each node is calculated, and the results are thoroughly analyzed to assess and validate the positive impact of decentralization on the resilience of electric grids. The initial section of this article encompasses a literature review of pertinent works, followed by an introduction to Leontief's input–output model. Section 4 delves into implementing Leontief's IO model on the electric grid, providing intricate details on the mathematical modeling and equations. This section also outlines the grid models employed for simulation and specifies the interruption scenarios simulated. The subsequent section, Section 5, presents and analyzes the simulation results.

2. Related Works

Electric grid operators globally face a persistent challenge posed by natural, non-natural, predictable, and unpredictable factors. These elements can compromise the flexibility and reliability of the grid [8]. Incidents like extreme weather conditions, geodesic events, wildfires, acts of war, and cyberattacks constitute genuine threats to the electric grid's reliability. Consequently, there has been an increasing interest in recent research on electric grid resilience. However, a notable majority of these studies in the energy sector concentrate on centralized grids.

The initial phase in comprehending the issue of electric grid resilience involves defining it and establishing a framework. Article [9] delves into various terminologies related to grid resilience, presenting a comprehensive framework that defines the concept and explores diverse quantitative metrics and approaches for evaluating grid resilience. In [10], Liu et al. formulate a resilience assessment framework to design more resilient transmission lines, especially in the face of extreme weather events. Meanwhile, Jasiunas et al. [11] reviewed energy grid resilience and proposed a framework for mapping potential threats. To understand threats and vulnerabilities that compromise electric grid resilience, Sakshi et al. [12] define microgrid resilience, conducting an in-depth analysis of threats, vulnerabilities, and mitigation techniques. Furthermore, Nguyen et al. [13] surveyed the vulnerabilities of modern electric grids to cyber-attacks.

Addressing resilience strategies, ref. [14] introduces a multi-stage stochastic robust optimization model to enhance the management of distribution network resilience. The works presented in [15,16] comprehensively review recently adopted strategies to bolster grid resilience. In grid resilience, a central challenge lies in determining how to measure resilience and identifying the relevant metrics. In [17], Das et al. provide an in-depth exploration of the metrics for a resilient grid and the challenges and limitations involved in formulating and calculating these metrics. The study in [18] also delves into metrics that enable quantifying energy grid resilience, offering insights into proposed enhancement techniques.

Recent research also delves into electric grid resilience's regulatory and socio-economic dimensions, recognizing their pivotal roles. Regulations are instrumental in ensuring and enhancing grid resilience, providing a framework for utilities, operators, and stakeholders to manage, maintain, and upgrade grid infrastructure to withstand diverse challenges and disruptions. Article [19] examines federal regulations related to a resilient electric grid in the United States of America. From a complementary perspective, the active involvement of prosumers in energy production, consumption, and management diversifies grid resources, enhances flexibility, and contributes to overall improvements in electric grid resilience. The significance of the active role of prosumers in operating a modern electric grid is highlighted in the study presented in [20].

The currently applied metrics for grid resilience measurement are indices such as the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI), which measure the frequency and duration of outages experienced by customers over a specific period. Nevertheless, these metrics can only be calculated once incidents have occurred. Another method to simulate the grid's resilience is to use computer simulation techniques such as dynamic system simulation models. These models simulate the transient behavior of the grid, including the response to sudden changes such as equipment failures, disturbances, or switching events. This technique helps to assess the grid's stability, reliability, and response under various dynamic conditions. However, dynamic system simulation models can be highly complex, requiring detailed data on grid topology, equipment characteristics, control systems, and operating conditions. They may require significant computational resources, high-performance computing infrastructure, and long computation times, especially for large-scale grids with numerous components and complex interactions. Another used technique is Monte Carlo simulation. This technique involves running multiple simulations with randomly generated input parameters to assess the probabilistic behavior of the grid. It helps to evaluate the likelihood and impact of different events, such as extreme weather events, equipment failures, or cyberattacks, on grid resilience. Yet, Monte Carlo simulation involves running many iterations to simulate the probabilistic behavior of the grid under different scenarios. This also requires significant computational resources and time, especially for complex grid models or when simulating rare or extreme events. Also, this simulation relies on accurate and representative input data, including probability distributions for different parameters such as weather conditions, equipment failures, and demand patterns. Obtaining and validating these data can be challenging, and data uncertainties or inaccuracies can affect simulation results. Running Monte Carlo simulation also requires computational resources and expertise in statistical analysis, simulation techniques, and grid modeling. Small utilities or organizations with limited resources may struggle to implement Monte Carlo simulation effectively without access to specialized software, personnel, or external support. Therefore, the methodology proposed in this article for simulating the grid's resilience uses a simple mathematical model that does not require significant computational resources, unique expertise, or minimal simulation time.

On the other side of the spectrum, grid interruptions, such as power outages, can have profound and multifaceted impacts on the economy, affecting consumers and various sectors. This impact is elucidated in [21], where a dynamic inoperability input–output model (DIIM), combined with a customer interruption cost (CIC) model, is employed to assess the economic consequences of power interruptions. Likewise, the IIM has found applications in various economic analyses related to unexpected events and perturbations. In [22], Xu et al. introduced a dynamic IIM to simulate economic sector dynamics during emergencies, specifically when facing value-added perturbations or interruptions. Another instance is found in [23], where Jin et al. utilized the IIM to analyze the economic impact of COVID-19 in Shanghai. However, the utility of the inoperability input–output model extends beyond economic analysis. Numerous researchers have employed Leontief's input–output model to model and analyze the resilience of infrastructures and networks. For instance, in [24], Jia et al. applied the IIM to analyze the effects of disturbances, such as droughts, earthquakes, and terrorist attacks, on water systems in industrial parks.

Similarly, ref. [25] employed the IIM to analyze cascading effects induced by critical infrastructure dependencies. Nevertheless, much of the research on electric grid resilience primarily focuses on the traditional centralized electric grid as a fundamental model. While many articles underscore the significance of DERs in enhancing grid resilience, a detailed exploration of measuring this resilience with associated metrics is often lacking. Drawing from definitions, frameworks, and measurement metrics established for electric grid resilience and inspired by the application of the inoperability Input–output (IIO) model in similar contexts, this article proposes a comparative analysis between centralized and decentralized electric grids in terms of resilience. The objective is to quantify the importance of DERs in improving grid resilience and mitigating its vulnerability to unexpected perturbations and interruptions.

3. Leontief's Input–Output Model

Leontief's IO model, developed by Nobel laureate economist Wassily Leontief in the 1930s, is a quantitative economic technique that analyzes inter-industry relationships within an economy. This model examines dependencies between different sectors or industries, tracking the flow of goods and services among them. Represented in matrix format, it assesses how much output one industry requires from another to produce its own output. The model is crucial for understanding the ripple effects of changes in one sector on others within the economy, providing insights into potential impacts resulting from alterations in production, consumption, investments, or external shocks such as policy changes or disasters. Widely used in economics, Leontief's model is particularly valuable for studying regional economics, international trade, economic planning, and forecasting. Its application aids policymakers in making well-informed decisions by revealing complex interdependencies within an economy.

The main idea behind Leontief's IO model is to create a matrix of interdependency between different economic industries by using the items purchased as inputs and the sales as outputs.

In other words, this model represents the economy as a matrix of transactions between sectors, where each element of the matrix represents the amount of goods or services purchased from one sector by another. So, if we consider the model presented in Table 1, showing two industries X1 and X2, then:

- x_{11}: Proportion produced by X1 and consumed by X1
- x_{12}: Proportion produced by X2 and consumed by X1
- x_{21}: Proportion produced by X1 and consumed by X2
- x_{22}: Proportion produced by X2 and consumed by X2

Table 1. Leontief's IO matrix.

Industry	X1	X2
X1	x_{11}	x_{12}
X2	x_{21}	x_{22}

The following equation can present the above model:

$$X = A.X \tag{1}$$

where A is the input–output matrix.

However, the above model represents Leontief's closed model, wherein all production is assumed to be consumed by various entities within the economic group under study. Certain products may be exported to entities outside the studied industries. In such cases, the model is referred to as Leontief's open model, and the following equation represents it:

$$X = A.X + D \tag{2}$$

where D is the external demand vector.

In the context of Leontief's input–output model, the supply and demand sides represent distinct aspects of economic activity analyzed by the model. The supply side focuses on producing or supplying goods and services by various industries or sectors within an economy. It examines how different sectors generate output, including the goods and services they contribute as inputs to other sectors. This side of the model traces the flow of goods and services from industries to final consumption or intermediate use.

Conversely, the demand side in the input–output model scrutinizes the consumption or demand for goods and services from various sectors or industries. It centers on how different sectors utilize or demand these goods and services, encompassing households, businesses, government, and exports. The demand side tracks how final consumers and intermediate users stimulate the demand for goods and services produced by different industries.

Leontief's input–output model interconnects the supply and demand sides, enabling the analysis of interdependencies and linkages between sectors on both fronts. It illustrates how changes in one sector's output or demand can impact other economic sectors. Such understanding is crucial for economic planning, policymaking, and forecasting, offering insights into the interactions between production and consumption activities across the economy.

The versatility of Leontief's IO model finds application in various fields:

1. Economic Analysis: It aids in understanding an economy's structure by quantifying relationships between different sectors, helping to predict the effects of changes in one sector on others and the overall economy [26].
2. Policy Planning: Governments and policymakers use input–output analysis to assess the potential impact of policy changes, such as alterations in taxation, investments, or subsidies, on different sectors and the economy [27].
3. Regional Development: The model is valuable for assessing regional economies, identifying key sectors, and planning strategies for regional development by understanding economic linkages among various industries [28].
4. Supply Chain Management: The input–output model optimizes supply chains in the business sector, identifying dependencies and potential vulnerabilities [29].
5. Environmental Analysis: The model is adaptable to assessing environmental impacts by tracing resource use, energy consumption, and pollution across sectors, aiding in sustainability assessments and policy formulation [30].
6. Trade Analysis: It aids in understanding trade patterns, dependencies on imports/exports, and the effects of international trade on domestic industries [31].

One of the main characteristics of the electric grid is the complex interdependency between its nodes. Therefore, an interruption on any bus or transmission line can create a ripple effect in the grid and affect other parts. Hence, a mathematical model is needed to simulate the interdependent relationships between the different elements of an electric grid and calculate the ripple resulting from any interruption on any node. Leontief's IO model is a quantitative tool that allows for rigorous analysis of interdependent relationships and dynamics, such as the one between the nodes of an electric grid. The proposed model uses the power flow between buses as exchanged goods, which permits the development of interdependencies between all buses of a grid and quantifies the impacts of interruptions or outside impacts on any part of the grid.

Consequently, Leontief's IO model can be beneficial for analyzing grid resilience due to its ability to capture these interdependencies between nodes and identify critical ones within the grid. The IO model quantifies the relationships between different grid nodes, showing how changes on one bus or transmission line can affect others through input–output linkages. This is crucial for understanding the ripple effects of disruptions within the grid, such as power outages or infrastructure failures. Henceforth, the model proposed in this article represents a simple mathematical model that simulates the electric grid's resilience under different scenarios without the need for complex models, significant computational resources, or unique expertise outside the electric field.

4. Modelling and Numerical Study

Leontief's IIM is developed to quantify the impact of decentralization on the electric grid's resilience. This model calculates the inoperability of the grid following a disturbance, interruption, or perturbation, utilizing Leontief's open-loop, supply-side IO model. In the power grid, nodes are interconnected, with each node potentially housing a power genera-

Energies **2024**, *17*, x FOR PEER REVIEW 8 of 23

tor (considered a manufactured product), a connected load (representing the proportion produced by the node and consumed locally), and power transmitted from one node to another. This framework captures the interdependent relationship between nodes in an electric grid.

The open-loop model was employed to evaluate the reduction in power supplied to each load connected to the grid during a disturbance, treating the loads connected to each node as an external demand vector. The following relation defines the normalized power loss in this scenario:

$$Normalized\ power\ loss = \frac{Before\ disturbance\ power\ output - degraded\ power\ output}{Before\ disturbance\ power\ output}$$

Thus, we leverage this analogy to construct an IIM based on the power transmitted between nodes, the power generated at each node, and the loads connected to each node. The formulated electric grid inoperability input–output model is presented in Equation (3):

$$X = A.X + D\ or\ (I - A).X = D \tag{3}$$

where:

A: Interdependence Matrix

I: Identity matrix

D: Power supplied to the load connected to each bus (demand vector)

Since the interdependence matrix defines the portion produced by the *i*th node and consumed by the *j*th node, this can be translated in the case of the power grid as the power transmitted from the *i*th bus to the *j*th bus. Therefore, the interdependence matrix is given by Equation (4):

$$a_{ij} = \frac{S_{ij}}{S_j} \tag{4}$$

where:

S_{ij}: Power transmitted from node *i* to node *j*.

S_j: Power of node *j*.

And since the load consumed by the *i*th bus itself is considered as an external demand, then:

$$a_{ii} = 0 \tag{5}$$

In this case, the inoperability, defined as the percentage reduction from the ideal power output of each bus, is given by Equation (6):

$$Inoperability = \frac{\hat{D} - \tilde{D}}{\hat{D}} = (diag.X)^{-1}.\left(\hat{D} - \tilde{D}\right) \tag{6}$$

where:

$\hat{D}$: Power supplied to the load connected to each bus before disturbance.

$\tilde{D}$: Power supplied to the load connected to each bus after disturbance.

However, the calculation of power transmitted between nodes requires the use of the Newton–Raphson power flow analysis method. This method is employed to determine the steady-state operating conditions of the power grid, encompassing voltages, currents, and power flow through transmission lines and other network elements.

The summarized methodology of the Newton–Raphson power flow analysis is illustrated in the flow chart presented in Figure 3. The initial step involves calculating the admittance matrix based on the power grid lines' data, incorporating resistance, reactance, and ground admittance.

Energies **2024**, *17*, x FOR PEER REVIEW 9 of 23

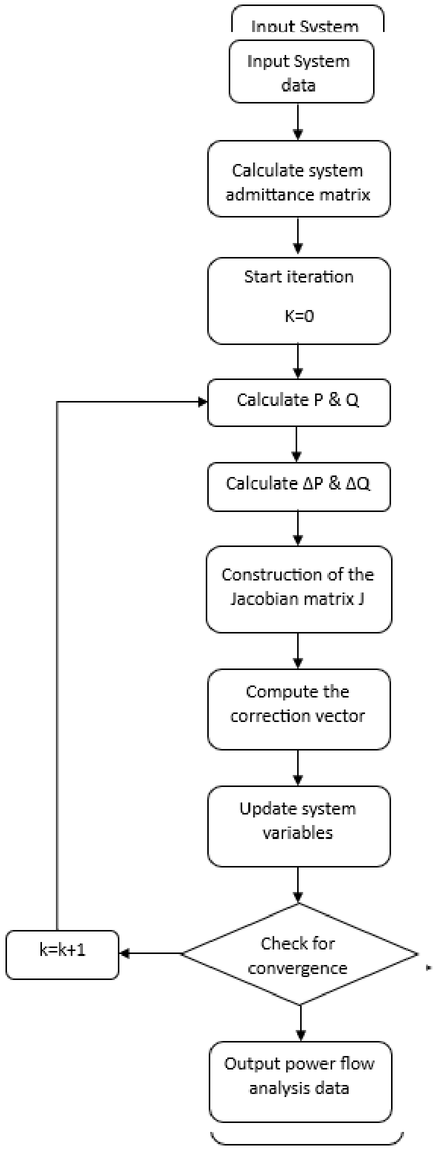


Figure 3. Newton–Raphson power flow analysis logic diagram.
Figure 3. Newton–Raphson power flow analysis logic diagram.

The bus admittance matrix can be constructed using the following equations:

$$z_i = r_i + ix_i \tag{7}$$

$$y_i = \frac{1}{z_i} \tag{8}$$

$$b_i = i.b_i \tag{9}$$

$$Y_{ii} = \sum_{\substack{j=0 \\ j \neq i}}^{N} y_j + b_j \tag{10}$$

$$Y_{ij} = -y_j \tag{11}$$

where:

r: Bus resistance in per unit
x: Bus reactance in per unit
b: Bus ground admittance in per unit
y: Admittance
z: Impedance

z: Impedance

Hence, the impedance matrix can be calculated using the following equation:

$$\boldsymbol{Y_{bus}^{-1}} = \boldsymbol{Z_{bus}} \quad (12)$$

The second step is to calculate the active and reactive power at each bus using the following equations:

$$\boldsymbol{P_i} = \boldsymbol{V_i}\sum_{j=1}^{N}|\boldsymbol{V_i}||\boldsymbol{V_j}|\left(\boldsymbol{G_{ij}}\cos\boldsymbol{\theta_{ij}} + \boldsymbol{B_{ij}}\sin\boldsymbol{\theta_{ij}}\right) \quad (13)$$

$$\boldsymbol{Q_i} = \boldsymbol{V_i}\sum_{j=1}^{N}|\boldsymbol{V_i}||\boldsymbol{V_j}|\left(\boldsymbol{G_{ij}}\sin\boldsymbol{\theta_{ij}} - \boldsymbol{B_{ij}}\cos\boldsymbol{\theta_{ij}}\right) \quad (14)$$

where $\boldsymbol{G_{ij}}$ and $\boldsymbol{B_{ij}}$ are, respectively, the real and imaginary parts of the admittance between the buses i and j.

The Newton–Raphson method compares the calculated power injections with the specified or desired ones at each bus. The ΔP and ΔQ values denote the mismatches between the specified and calculated power injections at each bus in the system. The Newton–Raphson algorithm utilizes these mismatches to iteratively update voltage magnitudes and phase angles until the mismatches converge to acceptable levels, signifying satisfaction of the power flow equations. The iterative process includes adjusting voltage magnitudes and phase angles using the calculated ΔP and ΔQ values to enhance the accuracy of the power flow solution until convergence is attained.

The Newton–Raphson method applied to power flow can be summarized as follows:

$$\begin{bmatrix} \Delta\boldsymbol{P_2} \\ \vdots \\ \Delta\boldsymbol{P_N} \\ \Delta\boldsymbol{Q_2} \\ \vdots \\ \Delta\boldsymbol{Q_{N'}} \end{bmatrix} = \boldsymbol{J} \times \begin{bmatrix} \Delta\boldsymbol{\delta_2} \\ \vdots \\ \Delta\boldsymbol{\delta_N} \\ \Delta|\boldsymbol{V_2}| \\ \vdots \\ \Delta|\boldsymbol{V_{N'}}| \end{bmatrix} \quad (15)$$

where J is the Jacobian square matrix: $\boldsymbol{J} = \begin{bmatrix} \boldsymbol{J_1} & \boldsymbol{J_2} \\ \boldsymbol{J_3} & \boldsymbol{J_4} \end{bmatrix}$

$$\boldsymbol{J_1} = \frac{\partial \boldsymbol{P_i}}{\partial \boldsymbol{\delta_j}}\ ;\ \boldsymbol{J_2} = \frac{\partial \boldsymbol{P_i}}{\partial |\boldsymbol{V_j}|}\ ;\ \boldsymbol{J_3} = \frac{\partial \boldsymbol{Q_i}}{\partial \boldsymbol{\delta_j}}\ ;\ \boldsymbol{J_4} = \frac{\partial \boldsymbol{Q_i}}{\partial |\boldsymbol{V_j}|} \quad (16)$$

$$\frac{\partial \boldsymbol{P_i}}{\partial \boldsymbol{\delta_i}} = \sum_{j\neq i}|\boldsymbol{V_i}|\,|\boldsymbol{V_j}|\,|\boldsymbol{Y_{ij}}|\,\sin\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right) \quad (17)$$

$$\frac{\partial \boldsymbol{P_i}}{\partial \boldsymbol{\delta_j}} = -|\boldsymbol{V_i}|\,|\boldsymbol{V_j}|\,|\boldsymbol{Y_{ij}}|\,\sin\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right)\ ;\ \boldsymbol{j} \neq \boldsymbol{i} \quad (18)$$

$$\frac{\partial \boldsymbol{P_i}}{\partial |\boldsymbol{V_i}|} = 2|\boldsymbol{V_i}|\,|\boldsymbol{Y_{ij}}|\,\cos\boldsymbol{\theta_{ii}} + \sum_{j\neq i}|\boldsymbol{V_j}|\,|\boldsymbol{Y_{ij}}|\,\cos\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right) \quad (19)$$

$$\frac{\partial \boldsymbol{P_i}}{\partial |\boldsymbol{V_j}|} = |\boldsymbol{V_i}|\,|\boldsymbol{Y_{ij}}|\,\cos\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right)\ ;\ \boldsymbol{j} \neq \boldsymbol{i} \quad (20)$$

$$\frac{\partial \boldsymbol{Q_i}}{\partial \boldsymbol{\delta_i}} = \sum_{j\neq i}|\boldsymbol{V_i}|\,|\boldsymbol{V_j}|\,|\boldsymbol{Y_{ij}}|\,\cos\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right) \quad (21)$$

$$\frac{\partial \boldsymbol{Q_i}}{\partial \boldsymbol{\delta_j}} = -|\boldsymbol{V_i}|\,|\boldsymbol{V_j}|\,|\boldsymbol{Y_{ij}}|\,\cos\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right)\ ;\ \boldsymbol{j} \neq \boldsymbol{i} \quad (22)$$

$$\frac{\partial \boldsymbol{Q_i}}{\partial |\boldsymbol{V_i}|} = -2|\boldsymbol{V_i}|\,|\boldsymbol{Y_{ij}}|\,\sin\boldsymbol{\theta_{ii}} - \sum_{j\neq i}|\boldsymbol{V_j}|\,|\boldsymbol{Y_{ij}}|\,\sin\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right) \quad (23)$$

$$\frac{\partial \boldsymbol{Q_i}}{\partial |\boldsymbol{V_j}|} = -|\boldsymbol{V_i}|\,|\boldsymbol{Y_{ij}}|\,\sin\left(\boldsymbol{\theta_{ij}} - \boldsymbol{\delta_i} + \boldsymbol{\delta_j}\right)\ ;\ \boldsymbol{j} \neq \boldsymbol{i} \quad (24)$$

where:

θ: Bus voltage phase angle (rad)
V: Bus voltage magnitude (V)
P: Active power (MW)
Q: Reactive power (MVAr)
Δ: Phase shift angle (rad)

In the final step of the Newton–Raphson power flow iteration, the correction vector is computed to update the system variables. This correction vector represents the adjustments made to the voltage magnitudes and phase angle estimates at each iteration of the algorithm. It plays a crucial role in iteratively refining the solutions until the power flow equations converge to a stable solution.

The correction vector, denoted as ΔX, encompasses changes in voltage magnitudes and phase angles at each bus within the power system. It is computed using the Jacobian matrix and the power mismatch vectors (ΔP and ΔQ) at each iteration. The general form of the correction vector in the Newton–Raphson method can be expressed as:

$$\boldsymbol{\Delta X}\text{=}\boldsymbol{J}^{-1}\begin{bmatrix}\boldsymbol{\Delta P}\\ \boldsymbol{\Delta Q}\end{bmatrix}$$

The Jacobian matrix, denoted as J, quantifies the sensitivity of power mismatches (ΔP and ΔQ) to voltage magnitudes and phase angle changes. It is computed using partial derivatives of power flow equations concerning voltage magnitudes and angles. Meanwhile, the correction vector ΔX, obtained by multiplying the inverse Jacobian matrix with the power mismatch vectors, facilitates necessary adjustments to update the voltage magnitudes and phase angle estimates at each bus. These updates enhance the accuracy of power flow solutions in subsequent iterations of the Newton–Raphson algorithm.

The iterative application of the correction vector to update the voltage magnitudes and phase angle estimates continues until the changes in these quantities reach sufficiently small values, indicating convergence to a solution where the power flow equations are satisfied within acceptable tolerances.

5. Simulation Model and Results Analysis

To assess the resilience of centralized versus decentralized electric grids, the IEEE-14 node power grid system was selected as the baseline model (Figure 4). The standard IEEE-14 node power system represents the centralized electric grid (Model A). Grid data details are provided in Appendix A.

Two modified IEEE-14 node power system models were employed for comparative analysis to represent decentralized electric grids. The first model, illustrated in Figure 5a, integrates a distributed energy resource of 10 MW connected to buses 3, 4, 5, 6, 9, 10, 11, 12, 13, and 14, categorizing it as the 100% decentralized model (Model B). The second model, depicted in Figure 5b, features a distributed energy resource of 10 MW connected to buses 3, 5, 9, 11, and 13, representing the 50% decentralized electric grid (Model C).

The perturbation simulation involved two scenarios. In the first scenario, a fault disconnected generator #2 from bus #2 and interrupted the transmission line between bus #2 and bus #5. Scenario #1 is depicted in Figure 6a. The second scenario extended the faults in scenario #1, introducing an additional interruption in the transmission line and substation connecting bus #4 to bus #9. Scenario #2's faults are illustrated in Figure 6b.

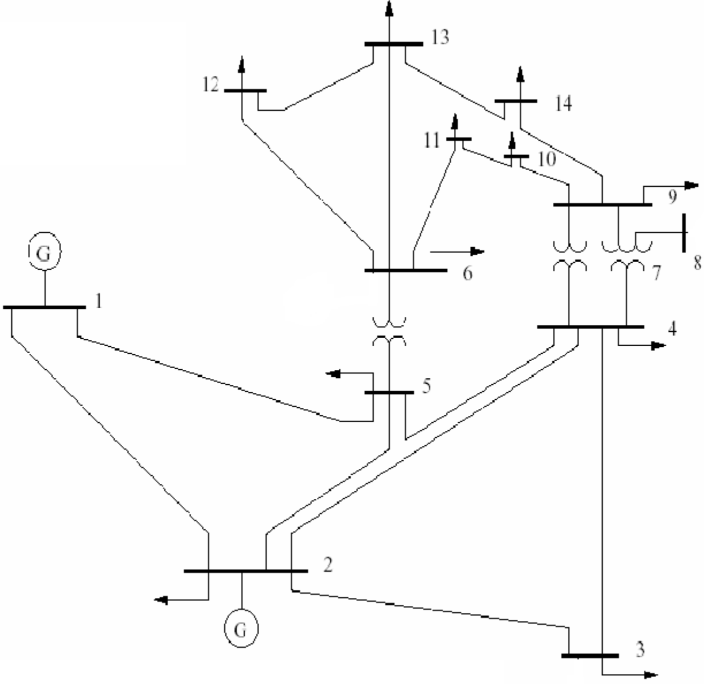


Figure 4. IEEE 14 node power grid system diagram (Model A).

Two modified IEEE-14 node power system models were employed for comparative analysis to represent decentralized electric grids. The first model, illustrated in Figure 5a, integrates a distributed energy resource of 10 MW connected to buses 3, 4, 5, 6, 9, 11, 12, 13, and 14, categorizing it as the 100% decentralized model (Model B). The second model, depicted in Figure 5b, features a distributed energy resource of 10 MW connected to buses 3, 5, 9, 11 and 13 representing the 50% decentralized electric grid (Model C).

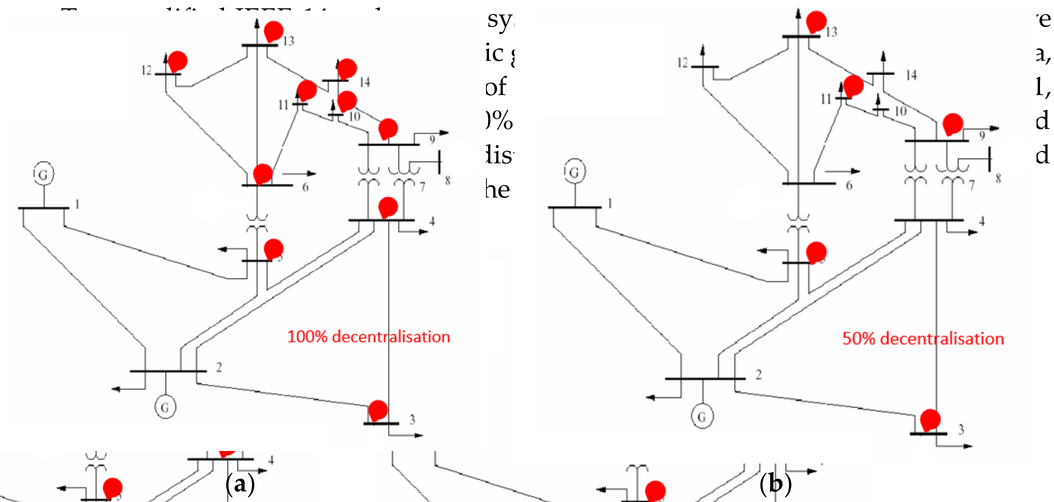


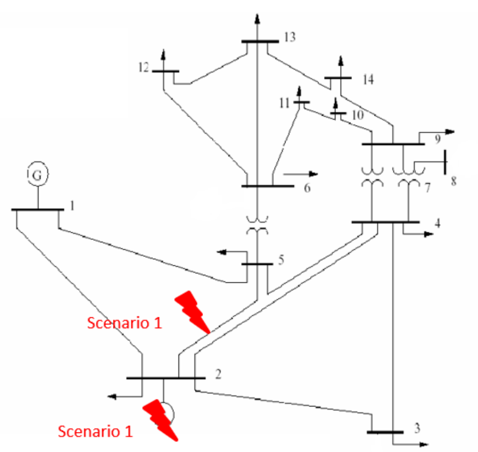
Figure 5. (**a**) IEEE 14 node power grid system diagram with 100% DERs (Model B). (**b**) IEEE 14 node power grid system diagram with 50% DERs (Model C).

The perturbation simulation involved two scenarios. In the first scenario, a fault connected generator #2 from bus #2 and interrupted the transmission line between bus #2 and bus #5. Scenario #1 is depicted in Figure 6a. The second scenario extended the faults in scenario #1, introducing an additional interruption in the transmission line and substation connecting bus #4 to bus #9. Scenario #2's faults are illustrated in Figure 6b.

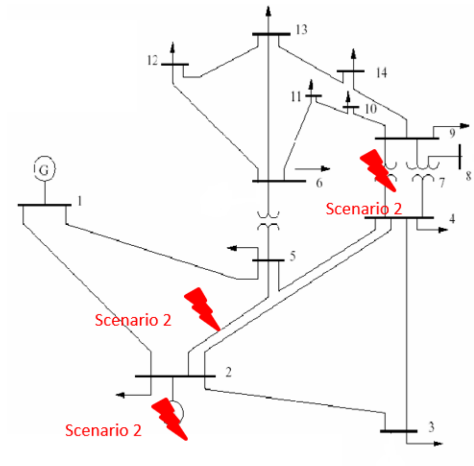
The experiment utilized an Intel i7-7500U, 2.70 GHz, dual-core CPU with 16 GB RAM, operating on Windows 120. The algorithms were implemented in MATLAB R2022a (codes provided in Appendices B and C). The outcomes were validated against results obtained by simulating the same models under the same scenarios using the Electrical Transient Analyzer Program version 12.6.0 (ETAP), a software platform used to design, simulate, analyze, control, optimize, and automate electrical power systems. Both models gave practically the same results.

The simulation flowchart for comparing the centralized and decentralized electric grid is presented in Figure 7. This simulation employed the interoperability value to assess the resilience of each electric grid model. At time t=0, the electric grid is considered undisturbed. The faults of scenario #1 are applied to each of the three grid models, and the interoperability of each bus is computed. Subsequently, the conditions of scenario #2 are uniformly applied to all three models, and the interoperability (codes provided in Appendices B and C). The outcomes were validated against resu obtained by simulating the same models under the same scenarios using the Electrical Tr sient Analyzer Program version 12.6.0 (ETAP), a software platform used to design, simul analyze, control, optimize, and automate electrical power systems. Both models gave pra cally the same results.

values are determined. By computing the inoperability value for each bus of each model using the IIM, we can compare the resilience of the centralized and decentralized grids under identical conditions.



(**a**)



(**b**)

Figure 6. (**a**) IEEE 14 node power grid system diagram faults under scenario #1. (**b**) IEEE 14 node power grid system diagram faults under scenario #2.

The simulation flowchart for comparing the centralized vs. decentralized electric g on employs the calculated inoperability value l model when facing similar interruptions. At ti disturbed. The faults of scenario #1 are applied e inoperability of each bus is computed. Sub re uniformly applied to all three models, and r computing the inoperability value for each bu pare the resilience of the centralized and decent

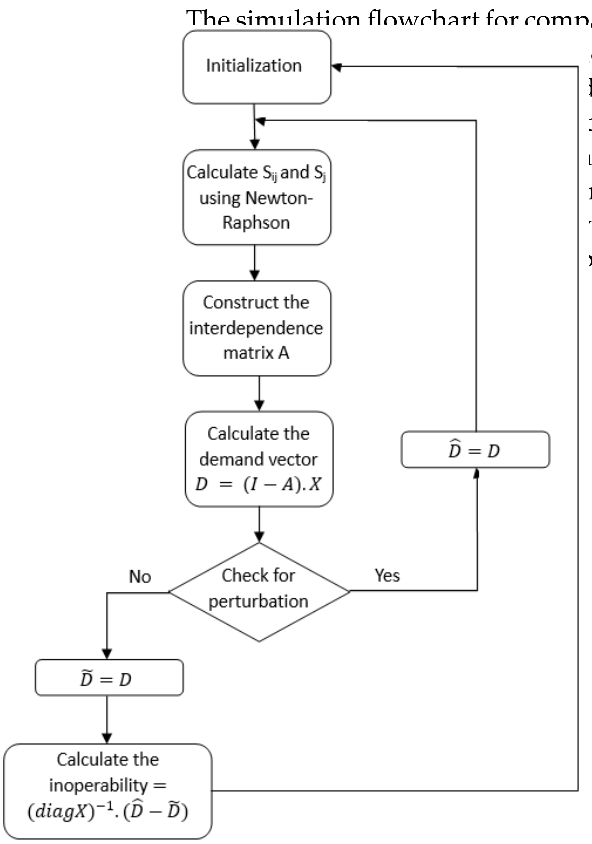
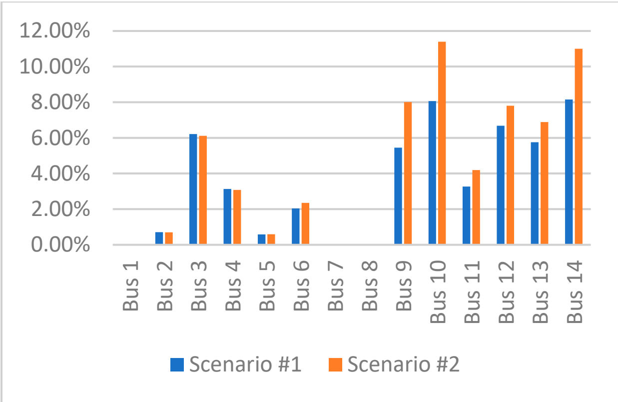


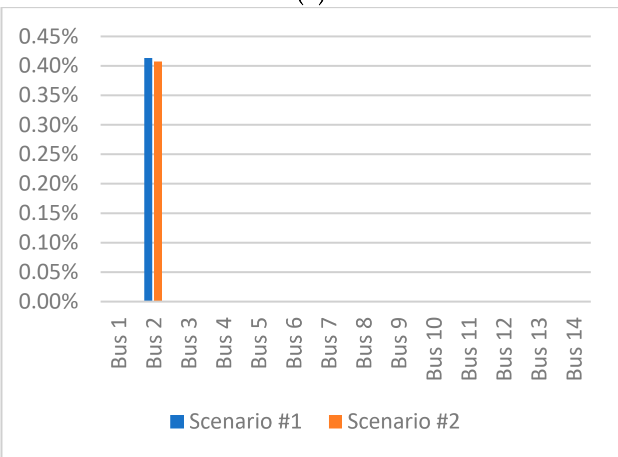
Figure 7. Simulation flow chart diagram.

The simulation results are depicted in Figure 8. As no load is connected to buses 1, 7, and 8, and considering the inoperability definition provided in Equation (6), zero inoperability is expected for these three buses, regardless of any interruption or disturbance to the grid.

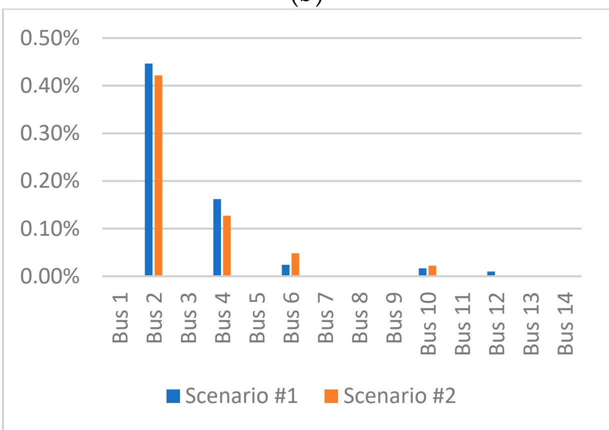
Energies **2024**, *17*, 1321 14 of 21



(**a**)



(**b**)



(**c**)

Figure 8. (**a**) Inoperability of model A. (**b**) Inoperability of model B. (**c**) Inoperability of model C.

The results depicted in Figure 8a clearly show that disturbances caused by scenarios #1 and #2 affected all buses except buses 1, 7, and 8, as explained earlier. The inoperability values resulting from the simulation of model A (centralized electric grid) demonstrate that in a centralized system, a perturbation or interruption on a single line or bus affects the entire grid, particularly the remote nodes such as buses 9, 10, 11, 12, 13, and 14. This contrasts with decentralized grids. The inoperability values of model B (fully decentralized model) indicate that only bus 2 was affected by the perturbations of scenario #1, mainly due to the disconnection of generator 2 supplying this bus. Additionally, the disconnection of buses 5–9 had minimal impact on the grid because the DERs connected to the buses had enough power to meet the demand. On the other hand, the simulation results of model C (partially decentralized model) show that several buses were affected by the interruptions, specifically the buses where no DERs are connected (buses 2, 4, 6, 10, and 12), highlighting the importance of connecting DERs to all nodes to increase the grid's flexibility, reduce technical losses, and enhance its resilience and reliability.

Notably, the intolerabilities calculated in models B and C are considerably lower than the results obtained with model A. The intolerabilities in model A ranged between 0.6% and 11.4%. However, with models B and C, these values did not exceed 0.45%. This emphasizes that decentralization affects the number of nodes impacted by a disturbance or interruption and reduces the magnitude of this interruption on the affected buses.

6. Conclusions

The future of grid resilience lies in balancing centralized and decentralized approaches. While centralized grids have been effective in the past, the demand for greater energy resilience, sustainability, and adaptability necessitates a shift towards decentralized grids. The findings of this study demonstrate that decentralized systems provide improved resilience through increased flexibility and modularity. Moreover, it proves that decentralization, through dispersing generation and storage assets across the grid, minimizes the impact of individual failures and makes the system more resilient to disruptions. In the event of a disruption or failure at one location, other distributed resources can continue to supply power, reducing the risk of widespread outages and enhancing overall system robustness. The results obtained in our simulation show that a completely decentralized electric grid is, to a certain extent, immune to interruptions caused by extreme weather events, natural disasters, and other emergencies that can disrupt conventional centralized infrastructure.

However, collaboration among policymakers, grid operators, utilities, and communities is essential in order to transition to decentralized grids successfully. Investments in research and development, infrastructure upgrades, and regulatory frameworks should be coordinated to support the growth of decentralized grids. Furthermore, while decentralized grids hold significant promise, notable challenges must be addressed. One major hurdle is the cost of implementing decentralized systems and upgrading existing infrastructure. The initial investments for distributed generation, energy storage, and grid interconnections can be considerable. However, with the ongoing decline in the costs of renewable energy technologies and storage systems, the economic feasibility of decentralized grids is improving. Another challenge lies in integrating decentralized systems into existing regulatory frameworks and grid management practices. Shifting from a centralized to a decentralized model necessitates the development of new policies and regulations that facilitate the deployment and operation of distributed energy resources. Grid operators and utilities must adapt their planning and operational models to accommodate the dynamic nature of decentralized grids, ensuring grid stability and reliability.

Despite these challenges, the opportunities presented by decentralized grids are substantial. They offer the potential for increased energy independence, reduced reliance on fossil fuels, and the integration of innovative technologies and business models. Decentralized grids empower communities and individuals to participate actively in the energy transition, fostering a sense of ownership and resilience at the local level.

Moreover, the modern electric grid comprises three physical, communication, and data management layers. While decentralization has enhanced the resilience of the physical layer, the other two layers remain vulnerable. Many electric grids, even those with significant integration of distributed energy resources, still depend on a centralized control center, acting as an SPOF. Consequently, there is a growing need to decentralize all three layers of the electric grid to achieve a higher level of resilience. Additionally, as the electric grid undergoes a rapid digital transformation, the securitization of data and digital processes lags behind. Addressing this discrepancy is crucial to ensure the comprehensive resilience of the electric grid in the face of evolving technological challenges.

This study provides concrete evidence of the positive impact of physical decentralization on electric grid resilience. It also highlights a broader topic that warrants further investigation in the ongoing pursuit of achieving an elevated level of electric grid reliability. The findings underscore the importance of considering both physical and digital decentralization to enhance the resilience of modern energy infrastructure comprehensively. On another level, this article offers a new mathematical simulation based on Leontief's IO model to assess and analyze the resilience of the electric grid. The proposed model does not require considerable computational resources and requires minimal simulation time, making it easy to code into a simple tool and use as simulation software.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A.

IEEE 14—Bus Details				
Starting Bus	Ending Bus	R (p.u.)	X (p.u.)	B (p.u.)
1	2	0.01938	0.05917	0.0528
1	5	0.05403	0.22304	0.0492
2	3	0.04699	0.19797	0.0438
2	4	0.05811	0.17632	0.034
2	5	0.05695	0.17388	0.0346
3	4	0.06701	0.17103	0.0128
4	5	0.01335	0.04211	0
4	7	0	0.20912	0
4	9	0	0.55618	0
5	6	0	0.25202	0
6	11	0.09498	0.1989	0
6	12	0.12291	0.25581	0
6	13	0.06615	0.13027	0
7	8	0	0.17615	0
7	9	0	0.11001	0
9	10	0.03181	0.0845	0
9	14	0.12711	0.27038	0
10	11	0.08205	0.19207	0
12	13	0.22092	0.19988	0
13	14	0.17093	0.34802	0

Appendix B. MATLAB Code to Calculate the Bus Admittance Matrix

```
% Construction of the bus admittance matrix

fb = linedata(:,1);                 % Starting bus
tb = linedata(:,2);                 % Arriving bus
r = linedata(:,3);                  % Resistance, R...
x = linedata(:,4);                  % Reactance, X...
b = linedata(:,5);                  % Ground Admittance, B/2...

z = r + 1i*x;                       % Z Matrix
y = 1./z;                           % Inverse of each element
b = 1i*b;

nb = max(max(fb),max(tb));          % No. of bus...
nl = length(fb);                    % No. of branches...
Y = zeros(nb,nb);                   % Initialize Y

% Construction of off-diagonal elements
for k = 1:nl
   Y(fb(k),tb(k)) = Y(fb(k),tb(k)) - y(k);
   Y(tb(k),fb(k)) = Y(fb(k),tb(k));
end

% Construction of diagonal elements
for m = 1:nb
   for n = 1:nl
      if fb(n) == m
         Y(m,m) = Y(m,m) + y(n)+ b(n);
      elseif tb(n) == m
         Y(m,m) = Y(m,m) + y(n) + b(n);
      end
   end
end
Y;                                  % Admittance matrix
Z = inv(Y);                         % Impedence Matrix

% End
```

Appendix C. MATLAB Code to Calculate the Power Flow Using the Newton–Raphson Method

```
nbus = max(busd(:,1));
BMva = 100;                         % Base MVA..
bus = busd(:,1);                    % Bus Number..
type = busd(:,2);                   % Type of buses
V = busd(:,3);                      % Voltage
del = busd(:,4);                    % Angle
Pg = busd(:,5)/BMva;                % P Sources
Qg = busd(:,6)/BMva;                % Q Sources
Pl = busd(:,7)/BMva;                % P loads
Ql = busd(:,8)/BMva;                % Q loads
Qmin = busd(:,9)/BMva;              % Minimum Reactive Power Limit..
Qmax = busd(:,10)/BMva;             % Maximum Reactive Power Limit..
P = Pg - Pl;                        % Pi = PGi PLi..
Q = Qg - Ql;                        % Qi = QGi - QLi..
Psp = P;                            % P Specified..
Qsp = Q;                            % Q Specified..
G = real(Y);                        % Conductance matrix..
B = imag(Y);                        % Susceptance matrix..
```

```
pv = find(type == 2 | type == 1);   % PV Buses..
pq = find(type == 3);                        % PQ Buses..
npv = length(pv);                            % No. of PV buses..
npq = length(pq);                            % No. of PQ buses..

Tol = 1;
Iter = 1;
while (Tol > 1 × 10^−5)              % Iteration starting..

  P = zeros(nbus,1);
  Q = zeros(nbus,1);
  % Calculate P and Q
  for i = 1:nbus
    for k = 1:nbus
      P(i) = P(i) + V(i)* V(k)*(G(i,k)*cos(del(i)-del(k)) + B(i,k)*sin(del(i)-del(k)));
      Q(i) = Q(i) + V(i)* V(k)*(G(i,k)*sin(del(i)-del(k)) - B(i,k)*cos(del(i)-del(k)));
    end
  end

  % Verification of Q-limit
  if Iter <= 7 && Iter > 2             % till the 7th Iteration
    for n = 2:nbus
      if type(n) == 2
        QG = Q(n) + Ql(n);
        if QG < Qmin(n)
          V(n) = V(n) + 0.01;
        elseif QG > Qmax(n)
          V(n) = V(n) - 0.01;
        end
      end
    end
  end

  % Calculation of Delta P and Delta Q
  dPa = Psp-P;
  dQa = Qsp-Q;
  k = 1;
  dQ = zeros(npq,1);
  for i = 1:nbus
    if type(i) == 3
      dQ(k,1) = dQa(i);
      k = k + 1;
    end
  end
  dP = dPa(2:nbus);
  M = [dP; dQ];                  % Vector delta P and delta Q

  % Construction of the Jacobian matrix
  % Matrix J1
  J1 = zeros(nbus-1,nbus-1);
  for i = 1:(nbus-1)
    m = i + 1;
    for k = 1:(nbus-1)
      n = k + 1;
      if n == m
```

```
            for n = 1:nbus
                J1(i,k) = J1(i,k) + V(m)* V(n)*(-G(m,n)*sin(del(m)-del(n)) + B(m,n)*cos(del(m)-del(n)));
            end
            J1(i,k) = J1(i,k) - V(m)^2*B(m,m);
        else
            J1(i,k) = V(m)* V(n)*(G(m,n)*sin(del(m)-del(n)) - B(m,n)*cos(del(m)-del(n)));
        end
    end
end

% Matrix J2
J2 = zeros(nbus-1,npq);
for i = 1:(nbus-1)
    m = i + 1;
    for k = 1:npq
        n = pq(k);
        if n == m
            for n = 1:nbus
                J2(i,k) = J2(i,k) + V(n)*(G(m,n)*cos(del(m)-del(n)) + B(m,n)*sin(del(m)-del(n)));
            end
            J2(i,k) = J2(i,k) + V(m)*G(m,m);
        else
            J2(i,k) = V(m)*(G(m,n)*cos(del(m)-del(n)) + B(m,n)*sin(del(m)-del(n)));
        end
    end
end

% Matrix J3
J3 = zeros(npq,nbus-1);
for i = 1:npq
    m = pq(i);
    for k = 1:(nbus-1)
        n = k + 1;
        if n == m
            for n = 1:nbus
                J3(i,k) = J3(i,k) + V(m)* V(n)*(G(m,n)*cos(del(m)-del(n)) + B(m,n)*sin(del(m)-del(n)));
            end
            J3(i,k) = J3(i,k) - V(m)^2*G(m,m);
        else
            J3(i,k) = V(m)* V(n)*(-G(m,n)*cos(del(m)-del(n)) - B(m,n)*sin(del(m)-del(n)));
        end
    end
end

% Matrix J4
J4 = zeros(npq,npq);
for i = 1:npq
    m = pq(i);
    for k = 1:npq
        n = pq(k);
        if n == m
            for n = 1:nbus
                J4(i,k) = J4(i,k) + V(n)*(G(m,n)*sin(del(m)-del(n)) - B(m,n)*cos(del(m)-del(n)));
            end
            J4(i,k) = J4(i,k) - V(m)*B(m,m);
        else
            J4(i,k) = V(m)*(G(m,n)*sin(del(m)-del(n)) - B(m,n)*cos(del(m)-del(n)));
        end
    end
end
```

```
    J = [J1 J2; J3 J4];                 % Jacobian matrix

    X = inv(J)*M;                        % Correction Vector
    dTh = X(1:nbus-1);                   % Change in Voltage Angle..
    dV = X(nbus:end);                    % Change in Voltage Magnitude..

    % Updating State Vectors..
    del(2:nbus) = dTh + del(2:nbus);         % Voltage Angle..
    k = 1;
    for i = 2:nbus
      if type(i) == 3
        V(i) = dV(k) + V(i);                 % Voltage Magnitude..
        k = k + 1;
      end
    end

    Iter = Iter + 1;
    Tol = max(abs(M));                       % Tolerance..
  end
  %end of the Newton Raphson Calculation
```

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CHAPITRE 5CHAPITRE 5
APPLICATION ET IMPACTS DE LA TECHNOLOGIE DE LA CHAÎNE DE BLOCS ET LA DÉCENTRALISATION DANS LA GÉNÉRATION DE PUISSANCE ÉLECTRIQUE.

5.1 INTRODUCTION

Dans le réseau électrique, l'équilibrage entre la production et la charge est essentiel pour maintenir la stabilité et éviter les coupures de courant. Deux méthodes principales sont couramment utilisées pour atteindre cet équilibre. La première méthode consiste à augmenter la production d'énergie. Cela peut être réalisé en mobilisant des centrales électriques supplémentaires, en augmentant la production des centrales existantes ou en intégrant des sources d'énergie renouvelable comme les panneaux solaires et les éoliennes. Cette approche permet de répondre à une demande accrue, mais peut être limitée par la capacité de production disponible et les contraintes environnementales. La deuxième méthode repose sur la réduction de la demande d'énergie, connue sous le nom de gestion de la demande. Cela peut inclure des mesures telles que l'incitation des consommateurs à réduire leur consommation pendant les périodes de pointe, l'utilisation de technologies intelligentes pour optimiser l'efficacité énergétique ou la mise en œuvre de programmes de réponse à la demande où les consommateurs sont rémunérés pour diminuer leur utilisation d'électricité. Cette approche sera discutée dans le chapitre 5.

Les REDs, telles que les panneaux solaires photovoltaïques, les éoliennes locales, et les systèmes de stockage d'énergie comme les batteries, jouent un rôle crucial dans l'équilibrage de la production et de la charge dans le réseau électrique. En augmentant la capacité de production décentralisée, les REDs permettent une réponse rapide et efficace aux fluctuations de la demande, ce qui renforce la résilience et la stabilité du réseau. Contrairement aux grandes centrales électriques centralisées, les REDs peuvent être installées proche des points de consommation, réduisant ainsi les pertes de transmission et améliorant l'efficacité globale du système. De plus, la flexibilité offerte par les REDs permet une meilleure intégration des énergies renouvelables, ce qui est essentiel pour la transition énergétique. En cas de perturbations, telles que des pannes ou des catastrophes naturelles, les REDs peuvent continuer à fournir de l'énergie localement, augmentant ainsi la résilience du réseau face aux interruptions. Enfin, les REDs contribuent à la réduction des coûts d'énergie en diminuant la dépendance aux sources de production centralisées et en favorisant l'utilisation d'énergies renouvelables, souvent moins coûteuses à long terme. Cette approche décentralisée permet également une meilleure gestion de la demande et une réduction des pics de consommation, ce qui se traduit par une optimisation des coûts et une meilleure stabilité tarifaire pour les consommateurs.

Les transactions P2P revêtent une importance cruciale dans le contexte des REDs et de l'équilibrage du réseau électrique. En permettant aux producteurs et aux consommateurs d'énergie de négocier directement l'achat et la vente d'électricité, les transactions P2P facilitent une gestion plus efficace et flexible de l'énergie. Ce modèle réduit la dépendance envers les intermédiaires traditionnels et les infrastructures centralisées, favorisant ainsi une distribution plus équitable et locale de l'énergie. Les transactions P2P permettent également une meilleure valorisation de l'énergie produite par les petites installations renouvelables, comme les panneaux solaires résidentiels ou les éoliennes locales, en offrant une plateforme pour vendre directement l'excédent d'énergie à des voisins ou à d'autres consommateurs locaux. Cela accroît la résilience du réseau en diversifiant les sources d'approvisionnement et en permettant une réponse plus rapide et adaptable aux variations de la demande. En outre, les transactions P2P peuvent contribuer à réduire les coûts énergétiques pour les consommateurs en éliminant certaines marges appliquées par les intermédiaires, tout en offrant des incitations financières aux producteurs locaux pour investir davantage dans les RED. En somme, les transactions P2P renforcent la stabilité, la flexibilité, et la durabilité du réseau électrique en favorisant une distribution plus décentralisée et participative de l'énergie.

D’autre part, les centrales VPPs jouent aussi un rôle significatif dans le contexte des REDs et de l'équilibrage du réseau électrique. Les VPPs agrègent et coordonnent diverses sources d'énergie distribuées, pour former une unité de production et de gestion de l'énergie capable de répondre de manière flexible et dynamique aux besoins du réseau. Cette approche permet d'optimiser la production et la consommation d'énergie en temps réel, améliorant ainsi la résilience et la stabilité du réseau.

À ce niveau-là, la technologie de la chaîne de blocs joue un rôle crucial dans la gestion des VPPs en fournissant une infrastructure sécurisée et transparente pour les transactions et la communication entre les différentes entités énergétiques. Grâce à la chaîne de blocs, les transactions entre producteurs et consommateurs peuvent être enregistrées de manière immuable et vérifiable, garantissant ainsi la confiance et l'intégrité des échanges. De plus, les contrats intelligents (*smart contracts*) peuvent automatiser les processus de gestion de l'énergie, comme l'équilibrage de la charge, la tarification dynamique, et la répartition de l'énergie, réduisant ainsi les coûts opérationnels et augmentant l'efficacité. La chaîne de blocs facilite également l'intégration des transactions P2P au sein des VPPs, permettant une distribution plus décentralisée et démocratisée de l'énergie. En somme, les VPPs, soutenues par la technologie de la chaîne de blocs, représentent une avancée majeure vers un réseau électrique plus flexible, résilient, et efficient, capable de répondre aux défis de la transition énergétique.

Ce chapitre introduit trois articles clés qui explorent divers aspects de l'intégration des REDs et des transactions énergétiques dans le réseau électrique. Le premier article réalise une étude économique comparative entre les transactions énergétiques peer-to-peer (P2P) et les mécanismes traditionnels tels que le tarif de rachat (FiT) et le *Net Metering*. Cette analyse met en lumière les avantages économiques potentiels des transactions P2P pour les producteurs et les consommateurs d'énergie, en soulignant les incitations financières et les économies possibles. Le deuxième article propose un modèle de régression dynamique pour évaluer la contribution de l'intégration des REDs à la réduction des pertes techniques dans le réseau électrique. En quantifiant les impacts positifs des REDs sur l'efficacité du réseau, cet article offre des perspectives précieuses pour les gestionnaires de réseau et les décideurs politiques. Enfin, le troisième article présente un algorithme d'optimisation des ressources dans les VPPs, visant à minimiser le coût moyen de l'énergie, les pertes techniques, et les émissions de gaz à effet de serre (GES). Cet algorithme innovant démontre comment une gestion optimale des VPPs peut non seulement réduire les coûts énergétiques, mais aussi améliorer la durabilité environnementale et l'efficacité opérationnelle du réseau électrique.

5.2 ARTICLE: COMPARISON BETWEEN BLOCKCHAIN P2P ENERGY TRADING AND CONVENTIONAL INCENTIVE MECHANISMS FOR DISTRIBUTED ENERGY RESOURCES - A RURAL MICROGRID USE CASE STUDY

Cet article, intitulé « Comparison between blockchain P2P energy trading and conventional incentive mechanisms for distributed energy resources - A rural microgrid use case study » a été a été publié dans sa version finale en août 2024 par les éditeurs du journal *MDPI – Applied Sciences.*

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En tant que premier auteur, j’ai contribué à la conceptualisation de la proposition, à l’essentiel de la recherche sur l’état de la question et au développement du modèle, à la collecte et l’analyse des données et à la rédaction du manuscrit. Professeur Mehdi Adda a participé à la direction du projet, à la supervision du travail, validation des résultats ainsi qu’à la révision de l’article et à la revue de la littérature. Les professeurs Adrian Ilinca, Mazen Ghandour et Hussein Ibrahim en tant que co-auteurs, ont participé à la révision de l’article et à la revue de la littérature.

Résumé : L'échange d'énergie de pair-à-pair (P2P) est un nouveau mécanisme de financement qui peut être adopté pour encourager le développement des REDs, en promouvant la vente d'énergie excédentaire à d'autres pairs sur le réseau à un taux négocié.

Les programmes d'incitation actuels, tels que le *Net Metering* et le *Feed-in-Tariff* (FiT), fonctionnent selon un cadre politique centralisé, où l'énergie n'est échangée qu'avec le réseau. Ainsi, c'est entre les mains de l'opérateur du réseau que réside le pouvoir de décider les tarifs d'achat de l'énergie excédentaire. Le commerce d'énergie P2P a le potentiel de présenter une solution pour les prosommateurs et les consommateurs afin de décider de la quantité d'énergie à échanger, du moment de la transaction, ainsi que des tarifs dans un modèle de marché ouvert, décentralisé et déréglementé. Néanmoins, pour que le commerce énergétique P2P soit réalisable, exécutable en temps réel, irréversible, immuable et rentable, il est essentiel de disposer d'une plateforme commerciale répondant à des exigences spécifiques qui ne peuvent être définies qu'en s'appuyant sur la technologie de la chaîne de blocs. Les nœuds participants conservent une copie de toutes les transactions, ce qui garantit la décentralisation, la transparence, l'immuabilité et la sécurité de la base de données. Le travail, présenté dans cet article, se concentre sur la comparaison du commerce d'énergie P2P avec le Net Metering (NEM) et le Feed-in-Tariff, d'un point de vue économique, en considérant un micro-réseau rural composé de deux prosommateurs et de quatre consommateurs. Les résultats de ce travail prouvent que l'échange d'énergie P2P basé sur la chaîne de blocs est un mécanisme de financement alternatif qui répond aux défis et aux limites de l'échange d'énergie bidirectionnel d'aujourd'hui.

Contexte et Objectifs : Les zones urbaines et rurales offrent des perspectives pour les systèmes solaires photovoltaïques, mais avec des considérations différentes. Dans les zones urbaines, l'énergie solaire sur les toits se concentre sur la production d'énergie distribuée, tandis que les zones rurales peuvent accueillir des installations de services publics à plus grande échelle. L'optimisation du potentiel photovoltaïque solaire implique la prise en compte de facteurs géographiques, de la demande énergétique, de l'infrastructure et des cadres réglementaires spécifiques à chaque environnement. Les zones urbaines présentent un potentiel important pour les installations solaires sur les toits des bâtiments. Cependant, l'ombre des autres bâtiments, l'espace limité sur les toits et les obstacles tels que les bouches d'aération ou les systèmes de chauffage, de ventilation et de climatisation peuvent réduire l'efficacité des panneaux solaires. Les zones urbaines ont généralement une demande énergétique plus élevée, ce qui fait de l'énergie solaire photovoltaïque sur les toits une option viable pour répondre à une partie de cette demande. Le photovoltaïque sur toiture permet également de réduire les pertes de transmission en produisant de l'électricité plus près de l'endroit où elle est consommée. Les zones rurales disposent souvent d'un plus grand nombre de terrains libres, ce qui les rend propices à l'installation de fermes solaires à grande échelle. Cela permet de réaliser des installations plus importantes sans les contraintes liées à l'espace urbain. Les zones rurales ont tendance à avoir moins d'obstacles tels que les bâtiments et les arbres, ce qui permet de maximiser l'exposition des panneaux solaires à la lumière du soleil. Cependant, la demande est limitée, ce qui pèse sur le retour sur investissement des projets REDs, en particulier dans le cadre du mécanisme de facturation NEM.

Méthodologie : À cette fin, nous avons décidé d'examiner le cas d'un micro-réseau rural qui comprend deux prosommateurs et quatre consommateurs. Ce micro-réseau est testé en utilisant trois mécanismes de facturation : NEM, FiT et P2P energy trading. Les mêmes conditions sont appliquées pour les trois scénarios et les indicateurs clés de performance tels que l'énergie non utilisée, le gain financier pour les consommateurs et la réduction de la facture annuelle pour les consommateurs, sont utilisés pour comparer les trois modèles. Dans le modèle simulé, nous avons considéré deux prosommateurs pour quatre consommateurs. En outre, le micro-réseau simulé considère comme sources d'énergie le réseau public pour tous les participants et les systèmes solaires photovoltaïques sur les toits pour les prosommateurs. En même temps, les consommateurs sont des charges résidentielles, commerciales et industrielles de petite taille.

Résultats et Contributions : La contribution de cet article réside dans son exploration approfondie et comparative des approches modernes et traditionnelles de gestion des REDs et des transactions énergétiques. En intégrant une analyse économique des transactions énergétiques peer-to-peer (P2P) par rapport aux mécanismes traditionnels tels que le FiT et le NEM, l'article apporte des éclairages nouveaux sur les bénéfices économiques potentiels et les incitations financières pour les producteurs et consommateurs d'énergie. Cette étude met en lumière un nouveau mécanisme de facturation qui peut bénéficier à toutes les parties prenantes. Grâce à la simulation et à l'analyse, nous avons démontré que l'échange d'énergie P2P peut être une meilleure option que les mécanismes de facturation conventionnels dans de nombreuses situations.

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Article

Comparison between Blockchain P2P Energy Trading and Conventional Incentive Mechanisms for Distributed Energy Resources—A Rural Microgrid Use Case Study

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Abstract: Peer-to-Peer (P2P) energy trading is a new financial mechanism that can be adopted to incentivize the development of distributed energy resources (DERs), by promoting the selling of excess energy to other peers on the network at a negotiated rate. Current incentive programs, such as net metering (NEM) and Feed-in-Tariff (FiT), operate according to a centralized policy framework, where energy is only traded with the utility, the state-owned grid authority, the service provider, or the power generation/distribution company, who also have the upper hand in deciding on the rates for buying the excess energy. This study presents a comparative analysis of three energy trading mechanisms, P2P energy trading, NEM, and FiT, within a rural microgrid consisting of two prosumers and four consumers. The microgrid serves as a practical testbed for evaluating the economic impacts of these mechanisms, through simulations considering various factors such as energy demand, production variability, and energy rates, and using key metrics such as economic savings, annual energy bill, and wasted excess energy. Results indicate that while net metering and FiT offer stable financial returns for prosumers, P2P trading demonstrates superior flexibility and potentially higher economic benefits for both prosumers and consumers by aligning energy trading with real-time market conditions. The findings offer valuable insights for policymakers and stakeholders seeking to optimize rural energy systems through innovative trading mechanisms.

Keywords: energy; energy trading; blockchain; peer-to-peer; distributed energy resources; financing mechanism; feed-in tariff; net metering

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1. Introduction

Nearly 140 years ago, the world witnessed the emergence of the first electrical grids. In the early stages, electrical grids were localized, decentralized, and unregulated. However, within the next five decades, driven by the increased demand for electricity induced by the second industrial revolution and a pressing need to regulate the energy markets, electrical grids metamorphosed into large, centralized power grids. The early primitive decentralized grids formed the first era of electrical grids, or what we define as Energy 1.0, followed by the centralized architecture that formed the second era, or Energy 2.0 (Figure 1). However, with both Energy 1.0 and Energy 2.0 grids, the consumer was completely dependent on the utility, and the energy flow was unidirectional (Figure 2), from the grid to the end-user. Concurrently, utility companies worldwide were under the continuous pressure of balancing their power generation capacities with the increasing demand, over and above a constantly fluctuating fuel supply market, environmental restraints, and growing end-user expectations [1]. Nevertheless, centralized electrical grids remained a substantial solution resource (DER) microgrids. The technological advancement and commercialization of RE-based solutions enabled the wide deployment of utility-scale strategies and small-scale DER projects. This change led to a new fundamental restructuring of the electrical grid's architecture that no longer relied on centralized power generation plants but was dependent on supply and demand resources mainly located towards the edge of the grid, at the consumers' side. Hence, the new electrical grid became a decentralized grid that encouraged a bidirectional flow of energy, from the grid to the end-user and vice versa, defined in this article as Energy 3.0 (Figure 1).

the electrical market until the end of the twentieth century, when the image started to change again.

For small-scale projects, billing arrangements such as net metering (NEM) and Feed-in Tariff (FiT) were adopted [6]. As for medium and large-scale projects, financial agreements such as Power Purchase Agreements (PPAs) were implemented to encourage investments in RE-based power generators [7].

Though microgrids provide a platform to implement more cost-effective DERs, their development faces numerous technical, economic, and infrastructure challenges associated with grid capacity and stability, hindering the wide integration of RE resources and distributed power generation. However, the variable and intermittent nature of RE resources has added a new level of complexity to the current formula [8]. Peak load management and power imbalance have developed into a fundamental dilemma that challenges the proper performance of electrical grids by impacting the quality and reliability of the power supply. Moreover, despite their wide acceptance by prosumers, billing arrangements like NEM and FiT face several limitations and challenges that can be unfavorable for both the utility and the end-user. Among those challenges is the problem of uncompensated excess energy injected into the grid in the case of NEM [9] and the issue of decreasing energy rates in the case of FiT [10]. Over and above, all existing compensation mechanisms share the same disadvantage of not reflecting the cost of electricity at the time of injection into the grid, as well as the lack of a competitive pricing mechanism, where a monopolist, the utility, has the upper hand in fixing the energy rates [11]. On the other hand, through the past decade, the energy market has witnessed a digital revolution driven by the need for a more intelligent, more efficient, more resilient, and more flexible grid, as well as by new client requirements. Under the influence of a global trend of digital transformation, the energy sector was not exempt from the impact of disrupting emerging technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), blockchain and Big Data, that affected the electrical grid's complete value chain, from generation to transportation and finally to distribution [12]. Furthermore, new energy apprehensions such as energy democracy and energy poverty [13,14], emerged in response to new socio-economic challenges. In addition, prosumers were requesting higher involvement and transparency in managing their energy consumption [15].

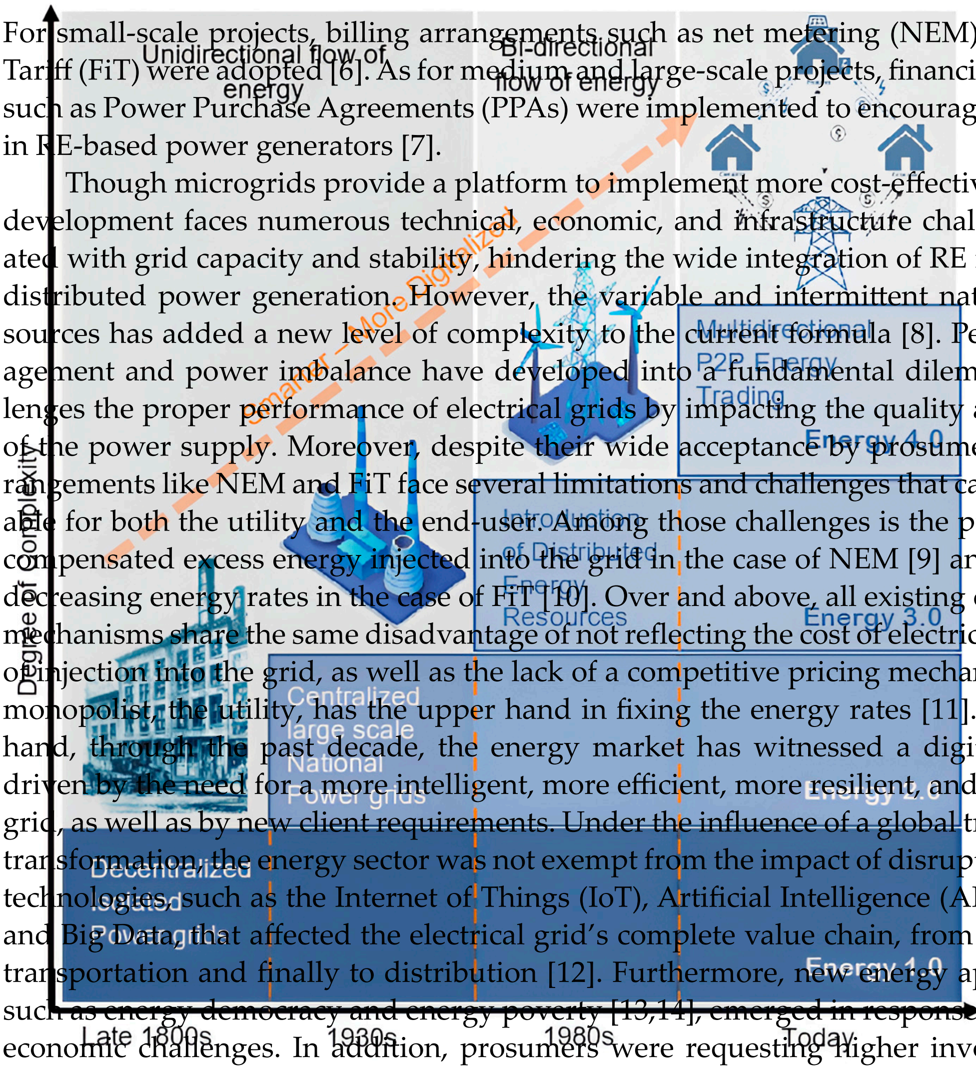

Figure 1. Evolution of the electric grid.

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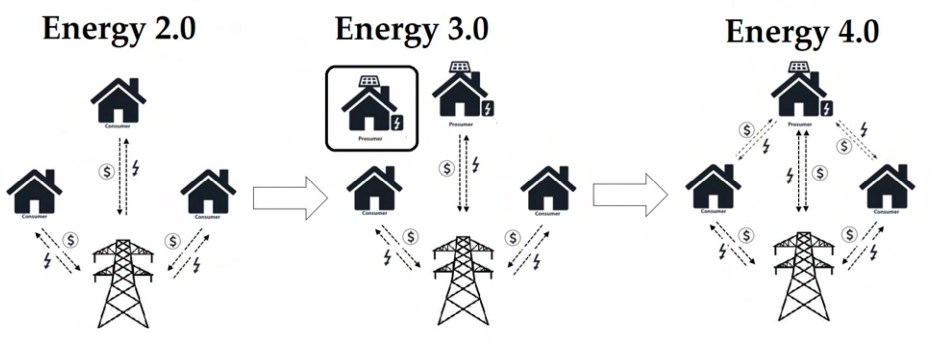

...er became a fun... ...ergy grid [3]. Th... energy and pa... ...ddition, the pro... ...grids [5], and fo... ...it had the optio... ...d not have bee... ...n DER solution...

Figure 2. Dependent, independent, and interdependent energy markets.

Figure 2. Dependent, independent, and interdependent energy markets.

Bounded by new global considerations such as climate change and new market trends such as energy security [2], renewable energy (RE)-based electrification (RE), the electrical grid developed into a decentralized architecture based on distributed energy resource (DER) microgrids. The technological advancement and commercialization of RE-based solutions enabled the wide deployment of utility-scale strategies and small-scale DER projects. This

Accordingly, in response to a higher digitalization and a more user-centric energy system, the energy market is once again propelled to change. This article is part of a larger project that proposes a new blockchain-based decentralized electric grid model. This new model, defined as Energy 4.0 (Figure 1), is based on P2P energy trading. P2P energy trading offers a new multidirectional decentralized model for selling and buying energy. Contrary to the previously existing model, the P2P energy trading model is considered an interdependent model (Figure 2), where the energy trading is not monopolized by the grid operator or the utility company but offers households, businesses, or even change led to a new fundamental restructuring of the electrical grid's architecture that no longer relied on centralized power generation plants but was dependent on supply and demand resources mainly located towards the edge of the grid, at the consumers' side. Hence, the new electrical grid became a decentralized grid that encouraged a bidirectional flow of energy, from the grid to the end-user and vice versa, defined in this article as Energy 3.0 (Figure 1).

Moreover, at the core of this new Energy 3.0 framework, the consumer became a fundamental stakeholder, a proactive, engaged member in managing the energy grid [3]. The active consumers became prosumers through their investments in clean energy and participation in power generation and demand-side management [4]. In addition, the progression of energy storage systems opened the door for off-grid microgrids [5], and for the first time, end-users were no longer dependent on the utility grid but had the option to be independent (Figure 2). Nonetheless, this energy transition would not have been possible without the proper incentives to encourage consumers to invest in DER solutions. For small-scale projects, billing arrangements such as net metering (NEM) and Feed-in-Tariff (FiT) were adopted [6]. As for medium and large-scale projects, financial agreements such as Power Purchase Agreements (PPAs) were implemented to encourage investments in RE-based power generators [7].

Though microgrids provide a platform to implement more cost-effective DERs, their development faces numerous technical, economic, and infrastructure challenges associated with grid capacity and stability, hindering the wide integration of RE resources and distributed power generation. However, the variable and intermittent nature of RE resources has added a new level of complexity to the current formula [8]. Peak load management and power imbalance have developed into a fundamental dilemma that challenges the proper performance of electrical grids by impacting the quality and reliability of the power supply. Moreover, despite their wide acceptance by prosumers, billing arrangements like NEM and FiT face several limitations and challenges that can be unfavorable for both the utility and the end-user. Among those challenges is the problem of uncompensated excess energy injected into the grid in the case of NEM [9] and the issue of decreasing energy rates in the case of FiT [10]. Over and above, all existing compensation mechanisms share the same disadvantage of not reflecting the cost of electricity at the time of injection into the grid, as well as the lack of a competitive pricing mechanism, where a monopolist, the utility, has the upper hand in fixing the energy rates [11]. On the other hand, through the past decade, the energy market has witnessed a digital revolution driven by the need for a more intelligent, more efficient, more resilient, and more flexible grid, as well as by new client requirements. Under the influence of a global trend of digital transformation, the energy sector was not exempt from the impact of disrupting emerging technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), blockchain, and Big Data, that affected the electrical grid's complete value chain, from generation to transportation and finally to distribution [12]. Furthermore, new energy apprehensions, such as energy democracy and energy poverty [13,14], emerged in response to new socio-economic challenges. In addition, prosumers were requesting higher involvement and transparency in managing their energy consumption [15].

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This article sheds light on the advantages of blockchain-based P2P energy trading models as an incentive mechanism for a higher implementation and integration of DERs. The main contribution of this work is that it offers a direct comparison between the P2P energy trading mechanism, NEM, and FiT in terms of rentability for prosumers using different key performance indicators (KPIs) such as the total amount of unremunerated excess energy and financial revenue from the traded energy. To validate the competitiveness of the P2P energy trading model as a new billing model for DERs, a rural microgrid composed of two prosumers and four consumers was considered. The microgrid was tested under different scenarios and billing models, and the results were analyzed to evaluate the most adequate model. Additionally, sensitivity and feasibility analyses were performed to complete the image. In Section 2 of this article, a review and evaluation of the existing billing models and related works is conducted. Afterward, the blockchain-based P2P energy trading model is introduced. In Section 4, our choice of a rural microgrid is justified, and our selected microgrid is presented in addition to the simulation algorithm and flow chart. In Section 5, the simulation results are presented and analyzed, and in Section 6, a financial study and sensitivity analysis are conducted.

2. Related Works

In a world grappling with the challenges of climate change, governments worldwide have taken significant steps to promote distributed energy sources and reduce dependence on fossil fuels. However, one of the main drivers is adopting the proper financing mechanism [17]. These mechanisms encourage consumers to become prosumers and contribute to power generation at the edge of the grid where energy is consumed. Moreover, they enable countries to achieve individual and collective renewable energy targets. The main idea behind these financing mechanisms, such as NEM, FiT, and PPA, is to incentivize consumers to generate their own electricity and contribute to the grid. However, despite this shared objective, each mechanism has significant differences in the operation and benefits offered. This section thoroughly explores these compensation mechanisms, highlighting their unique features, advantages, and considerations.

The NEM mechanism charges consumers for their net electricity consumption from the grid after deducting the electricity they have injected into the grid. This bidirectional flow of energy is measured with bidirectional meters, also known as net meters, which track the net flow of electricity. Prosumers are typically compensated for their injected electricity at the retail electricity tariff, as their electricity consumption is offset by the electricity they have injected into the grid.

In contrast, FiT schemes use two separate meters to track electricity generation and consumption from the grid and compensate for them differently. While energy consumed from the grid is priced at the retail electricity tariff, the excess energy injected by the prosumer into the grid is renumerated at a different predefined rate set by the regulator or the utility company, known as the "feed-in tariff." These FiTs are often set at a higher tariff than the retail market rate to incentivize consumers to install renewable energy power generators. However, they have led to some issues, such as in Germany and the United Kingdom (UK), where rooftop solar photovoltaic (PV) adoption increased due to higher FiTs but has since been reduced [18,19]. Under the FiT framework, consumers should consider the long-term stability and potential changes in FiT rates.

Although these systems are broadly adopted, they do not offer fair compensation to the prosumer since the timing of the energy injection into the grid is not considered. For instance, under a NEM scheme, 1 kWh injected into the grid during peak hours should not have the same weight as 1 kWh injected during off-peak hours [20] since excess renewable electricity is more valuable during peak load hours compared to off-peak hours. Additionally, an oversupply of renewable electricity during low demand can result in curtailment or negative electricity prices in wholesale markets [21]. Prosumers can optimize their earnings from distributed renewable generation by utilizing battery storage systems or adjusting their demand in response to time-varying compensation tariffs. Because prosumers are incentivized to feed electricity into the grid when necessary and draw from it when demand is low and renewable output is plentiful, this improves system flexibility. Additionally, incorporating locational signals in tariff designs can help reduce network congestion and potentially defer or minimize network investments [22]. These signals are used to incentivize efficient use of the electricity grid and resources, as well as to manage congestion and optimize system reliability. Moreover, electric tariffs may include additional charges such as customer fees, service fees, correction charges, and rebates, which are not accounted for in the compensation given to consumers under the NEM mechanism. Therefore, the best way to look at the NEM mechanism is that it offers a free virtual storage system for the prosumer, by injecting his excess energy into the grid when it is not needed and getting it back at any time for the same price. Recently, a new concept called virtual net metering (VNM) emerged as an alternative to NEM. VNM is a billing arrangement that allows multiple electricity consumers to share the benefits of a renewable energy system, such as solar panels, even if they are not physically connected to the same generation source. In a VNM setup, the electricity generated via a renewable energy system installed at one location can be credited against the electricity consumption of one or more separate accounts elsewhere [23]. VNM allows for greater flexibility and access to the benefits of renewable energy, particularly in scenarios where physical connections between the generation source and the consumers are not feasible or practical.

On the other hand, net billing schemes offer several benefits to the grid. The primary purpose behind most DER incentive mechanisms is to encourage end-users to maximize their self-consumption thus reducing their demand from the grid. Additionally, since energy is generated where it is needed, the grid's technical losses are reciprocally lowered, and in most cases, they contribute to a lower levelized cost of energy [24]. However, under schemes like NEM and FiT, energy retailers are at risk of induced "death spiral" phenomenon [25]. This happens when overcompensation for distributed renewable generation leads to oversupply, distorted price signals, and grid-integration challenges, resulting in revenue losses for retailers. The "electricity death spiral" is a term used to describe a potential scenario in which the traditional utility business model becomes economically unsustainable due to disruptive changes in the energy landscape, particularly the increasing adoption of DERs and renewable energy technologies. The concept of the electricity death spiral typically involves declining revenues, rising costs, and customer defection. As more customers install rooftop solar panels, battery storage systems, energy-efficient appliances, and other DERs, they may reduce their reliance on grid-supplied electricity. This can lead to decreased electricity sales for traditional utilities, resulting in declining revenue. Moreover, utilities usually incur fixed costs on end-user bills associated with maintaining the grid infrastructure, such as transmission lines, substations, and distribution networks. As electricity sales decline, these fixed costs per unit of electricity sold increase, putting upward pressure on electricity rates for remaining customers. Thus, to compensate for lost revenue and cover fixed costs, utilities may raise electricity rates for customers who remain connected to the grid. However, higher rates can further incentivize customers to invest in DERs or pursue energy efficiency measures, exacerbating the decline in electricity sales and perpetuating the cycle. Additionally, faced with higher electricity rates and the availability of cost-effective alternatives like rooftop solar and battery storage, more customers may choose to disconnect from the grid entirely or significantly reduce their reliance on utility-provided electricity. This further accelerates the decline in utility revenues and increases the financial strain on the remaining customers. The electricity death spiral poses significant challenges for utilities and regulators tasked with ensuring the electricity system's reliability, affordability, and sustainability. Regulators may need to reassess utility business models, rate structures, and regulatory frameworks to address the evolving energy landscape and mitigate the risks associated with declining grid revenues. However, it is important to note that the electricity death spiral is not an inevitable outcome but rather a potential scenario driven by market dynamics, technological advancements, policy decisions, and consumer behavior. To navigate these challenges, utilities may need to embrace innovation, invest in grid modernization and flexibility, and adapt their business models to accommodate distributed energy resources and emerging customer preferences for clean and resilient energy solutions. Regulatory reforms and supportive policies are also fundamental to the transition to a more sustainable and equitable energy system [26].

A third existing financing mechanism is PPA. A PPA is a contractual arrangement in the energy sector where a power generator, often a renewable energy project developer, sells electricity to a buyer, typically an off-taker such as a utility or corporation. One of the main advantages of PPAs is their capacity to give renewable energy projects a steady source of income, ensuring their long-term financial viability. [27]. The off-taker commits to purchasing the generated electricity at agreed-upon prices for an extended period, often 15 to 25 years, providing the project with predictable cash flows. In addition, PPAs have the potential to be a catalyst of private investments and help develop a sustainable energy infrastructure. However, challenges include the potential for off-taker credit risks and the dependence on policy and regulatory frameworks that may impact the stability of the agreed-upon terms. Additionally, technological changes or market conditions could pose risks to both parties. Despite these challenges, PPAs remain crucial for advancing renewable energy projects and fostering a transition to more sustainable energy sources. Overall, PPAs are well suited for large-scale renewable energy projects [28] because they can mitigate risks, provide long-term revenue certainty, leverage economies of scale, enhance creditworthiness, facilitate grid integration, and ensure regulatory compliance. These factors contribute to the attractiveness of PPAs for developers, purchasers, and investors involved in large-scale renewable energy ventures.

On the other hand, billing mechanisms are governed and influenced by the nature of the energy market. Two models exist: the regulated and deregulated markets [29]. The terms regulated and deregulated refer to the level of government intervention in setting prices and managing competition. In a regulated market, government authorities set prices, determine service standards, and may control the entry rights for generation, transmission, and distribution, thus creating a market monopoly. However, regulatory bodies typically set these prices to ensure affordability and fairness. This framework can be secure and beneficial for consumers as long as the government has everything it takes to offer an affordable energy supply to its end users. However, when the government or the utility are in no position to supply low-cost energy, end users are left with the single option of paying the high price due to the lack of alternatives caused by the government's monopoly. Hence, it is essential to note that regulated markets may limit innovation and efficiency. In contrast, the deregulated market allows competition by removing entry, exit, and pricing restrictions, enabling multiple entities to operate in the same market and promoting healthy competition. Prices in a deregulated market are determined by supply and demand and open market competition and are subject to negotiation between the supplier and the end user [30]. Therefore, a deregulated market has the potential for cost savings due to competition, innovation, and improved efficiency. However, while competition is expected to keep prices in check, monopolistic behavior can occur if one company gains too much control. The impact of regulated and deregulated markets on billing mechanisms such as NEM, FiT, and PPA varies depending on the regulatory environment and market structure. Regulated markets may offer more stability and control from the regulatory body, while deregulated markets may provide more flexibility and room for market-driven negotiations.

The choice of billing mechanism will be influenced by the goals of policymakers, the level of market competition, and the desired balance between stability and flexibility in the energy sector.

Nevertheless, today's energy market is driven by more significant needs and higher expectations [31]. Needs and expectations that can no longer be met with traditional financing models. Thus, there is a need for a new billing model capable of providing a higher customer contribution, not only to power generation but also to the management of the grid in general and precise control of prices. This is where the P2P energy trading model comes into play. Conversely, more than a decade ago, a new energy trading model surfaced. The emergence of P2P energy trading can be traced back to the early 2010s. The concept gained momentum as technological advancements, particularly blockchain and smart contracts, offered new possibilities for decentralized energy transactions. However, it was around the mid-to-late 2010s that P2P energy trading gained substantial recognition and saw practical implementations [32,33]. P2P energy trading has emerged as a promising paradigm in transitioning towards decentralized and sustainable energy systems. The evolution of this concept is ongoing, and its trajectory is influenced by technological advancements, regulatory developments, and the growing awareness of the need for more sustainable energy practices. The P2P energy trading mechanism enables the direct exchange of electrical energy between prosumers and consumers, at a price negotiated by the two parties, without selling this energy to the grid operator first. Therefore, P2P energy trading models eliminate the need for utility companies or grid operators to interfere as intermediaries. P2P energy trading offers several distinct advantages over traditional energy trading models. Primarily, P2P trading enhances the efficiency of energy distribution by enabling direct transactions between prosumers and consumers, effectively reducing intermediary costs and transmission losses. This direct exchange fosters a more dynamic and responsive energy market where prices can more accurately reflect real-time supply and demand conditions. The book in [34] systematically explores distributed economic operation in smart grids, addressing both model-based and model-free approaches to optimize coordination among generation units and loads, while also tackling the challenges of randomness in renewable energy and electric vehicle charging. Additionally, P2P trading promotes the utilization of locally generated renewable energy, thus supporting sustainability and reducing the reliance on centralized, non-renewable energy sources [35]. The increased adoption of renewable energy through P2P networks also contributes to lower greenhouse gas emissions and improves the overall environmental footprint. Moreover, P2P trading can enhance grid resilience by decentralizing energy resources, thereby mitigating the risk of widespread outages. It also empowers consumers by giving them more control over their energy choices and potentially reducing their energy bills through cost-effective transactions. Furthermore, the transparent and automated nature of blockchain-based P2P platforms can streamline administrative processes, reduce fraud, and improve trust among participants. Overall, P2P energy trading presents a promising approach for creating more efficient, sustainable, and consumer-centric energy systems [36,37].

P2P energy trading designs frequently use game theory approaches [38], auction-based procedures [39], optimization methods [40,41], and blockchain-based technology. Numerous studies have explored the technical aspects of P2P energy trading, including communication protocols [42], market mechanisms, and grid integration. Smart contracts based on blockchain technology are commonly used to automate transactions and ensure trust and transparency among participants. Other approaches utilize P2P networks or centralized platforms for energy trading. Economic models play a crucial role in P2P energy trading systems, determining pricing mechanisms, cost allocation, and incentives for participants [43]. Dynamic pricing based on supply and demand, time-of-use tariffs, and incentive-based schemes are commonly employed to optimize resource utilization and encourage renewable energy generation. However, thanks to blockchain technology and smart contracts, P2P energy trading systems were made possible and easy to implement [44]. This concept aims to create a more efficient and sustainable energy ecosystem by directly empowering individuals to participate in energy production, consumption, and transactions, fostering local energy communities. Nevertheless, despite its potential benefits, P2P energy trading faces several challenges, including regulatory hurdles, technical complexities, market design issues, and privacy concerns. Scalability, interoperability, and grid stability are significant challenges that need to be addressed for the widespread adoption of P2P trading models. The challenges and limitations of P2P energy trading are detailed in [45].

This article investigates the application of blockchain-based P2P energy trading as a financing mechanism for DERs. With the growing adoption of DERs such as solar PV systems and battery storage, there is a need for innovative financing solutions to overcome barriers to deployment and maximize their economic viability. Traditional financing models often face challenges related to uncompensated excess energy, monopolized energy tariffs, time of energy injection into the grid, and transaction costs. In this study, we explore how blockchain technology can facilitate decentralized energy trading among prosumers, enabling direct transactions and value exchange within a distributed energy network. We examine the potential benefits of blockchain-based P2P energy trading, including open market rate negotiation, fair energy compensation, higher asset revenue, and increased autonomy for energy consumers. Overall, this article contributes to providing insights into the potential of blockchain-based P2P energy trading as an alternative billing mechanism to NEM and FiT, especially for rural and isolated microgrids, as well as a financing mechanism for DER development, thus advancing the transition to a more sustainable and resilient energy future.

3. Blockchain-Based P2P Energy Trading Model

P2P energy can potentially revolutionize the energy landscape by promoting decentralization, flexibility, and consumer engagement. Free trade among peers offers more options for sellers and buyers, promoting mutually beneficial transactions. A blockchain-based P2P ecosystem would offer consumers access to a diversified portfolio of energy resources that can answer to their specific requirements in terms of time, price, and sustainability goals. The open aspect of the P2P energy trading model stimulates healthy competition among providers, ensuring high-quality service at the lowest possible prices. In contrast, a regulated market limits consumers' options, often leaving them with a single supplier. This lack of competition allows the supplier to dictate both the quality and price. An open market with diverse DERs, such as solar, wind, and electric vehicles, presents exciting opportunities and competitive market prices for the consumer as well as the prosumer. Hence, prosumers with surplus energy can manage the quantity and timing of their sales to maximize profit. The chance to sell energy among peers would encourage investors to expand into DER projects, benefiting developing countries suffering from electricity shortages. P2P energy trading would increase local energy exchange, reducing dependency on the utility grid and enhancing power reliability. Additionally, P2P energy trading can enhance grid resilience and flexibility by leveraging DERs, demand-side management, and local energy trading to mitigate grid disturbances and optimize grid operations. By decentralizing energy production and consumption, P2P trading can enhance grid reliability and reduce dependency on centralized generation and transmission infrastructure.

Similarly, P2P energy trading can help improve voltage regulation in the distribution grid by reducing voltage fluctuations and optimizing voltage profiles. When energy is generated and consumed locally within the same distribution network segment, it can help maintain voltage levels within acceptable limits, thereby reducing losses associated with voltage deviations. Moreover, P2P energy trading can facilitate load balancing within the distribution grid by enabling energy transactions between local producers and consumers. When surplus energy generated via DERs is consumed locally rather than being transmitted over long distances, it can help alleviate congestion on distribution feeders and reduce losses associated with overloaded circuits. Also, P2P energy trading can potentially reduce transmission losses by minimizing the need for long-distance energy transmission from centralized power plants to end-users. When energy is generated and consumed locally, it avoids the losses incurred during transmission over high-voltage transmission lines, which tend to have higher losses than distribution lines. At the distribution level, by promoting the use of distributed generation and localized energy consumption, P2P energy trading can improve the overall efficiency of the distribution system.

For a P2P energy trading model to properly operate, several prerequisites must be met:

- A power grid connecting the two ends of an energy transaction must be present, along with essential electrical components like cables, transformers, and meters;
- An advanced metering infrastructure is needed to manage transactions and ensure energy is transferred from the correct source to the correct user. A control system is also necessary to check and control energy quality parameters like frequency and voltage;
- A secure end-to-end device communication protocol is required for the flow of information between peers;
- An online platform is required to allow users to transparently and anonymously communicate and exchange information about available energy, load demand, and prices as well as other information.

The first two points are usually provided in most modern grids. However, the third and fourth points require a data management platform capable of offering transparency, auditability, anonymity, and immutability as well as security. These characteristics can be found in blockchain platforms. Blockchain technology is pivotal in P2P energy trading by providing a decentralized, autonomous, transparent, and secure platform for facilitating energy transactions between producers and consumers. Blockchain technology has the potential to further P2P energy trading mechanisms by offering the following features:

- Decentralization and distributed ledger technology: blockchain eliminates the need for centralized authorities, creating a distributed ledger across a network of computers. This ensures transactions are recorded transparently and immutably, enhancing trust among participants;
- Transparency: blockchain's distributed ledger technology maintains a transparent and immutable record of all energy transactions. Every transaction is cryptographically verified and recorded on the blockchain, providing transparency and auditability. This transparency helps build trust among participants and ensures the integrity of the energy trading process;
- Smart contracts: these are self-executing contracts with the terms of the agreement directly written into lines of code. They automate the energy trading process, executing transactions when predefined conditions are met, thus reducing the need for intermediaries, and streamlining processes;
- Real-time settlements: blockchain enables real-time settlement of energy transactions, allowing producers to receive payment immediately upon energy delivery to consumers. This instantaneous settlement process eliminates delays and reduces counterparty risk, enabling more efficient energy trading and cash flow management;
- Integration with IoT Devices: blockchain can be integrated with Internet of Things (IoT) devices to facilitate automated energy trading at a large scale. This allows real-time consumption data to be used in transactions, making the process more efficient and responsive to energy needs.

Furthermore, blockchain's ability to ensure security through robust encryption techniques and provide real-time prices to consumers makes it an ideal solution for P2P energy trading. This not only empowers prosumers by enabling them to trade surplus energy directly but also promotes the use of renewable energy sources by ensuring the traceability and authenticity of the energy traded.

The blockchain-based P2P energy trading model offers prosumers, with excess generated energy, the opportunity to sell it to other interested consumers at a negotiated price.

Ethereum and Hyperledger are common platforms used for such an application due to their smart contract capabilities that allow the automatic execution of transactions when predefined conditions are met. Prosumers list their excess energy for sale on the blockchain platform along with their desired price. Consumers browse available energy offers on the platform and select the ones that meet their price, quantity, and source requirements. Once a consumer selects an offer, the smart contract automatically executes the transaction, transferring the agreed-upon amount of energy from the producer to the consumer. Payment for the energy is transferred directly to the producer's digital wallet upon completion of the transaction.

Two layers are required to achieve a P2P energy exchange: a money exchange layer and an energy exchange layer. The concepts of money exchange and energy exchange layers refer to the distinct functionalities and processes involved in facilitating transactions between energy prosumers and consumers. The money exchange layer handles the financial aspect of P2P energy trading, including pricing, payment, and settlement. It involves the exchange of cryptocurrency or fiat currency in return for the energy consumed or produced. Smart contracts within the blockchain platform automatically execute payment transactions once energy transactions are completed. The money exchange layer ensures secure and transparent financial transactions between parties involved in energy trading. On the other hand, the energy exchange layer focuses on the actual energy exchange between producers and consumers. It involves listing available energy for sale by producers and selecting and purchasing energy by consumers. In this context, smart contracts govern the terms of energy transactions, including quantity, price, and timing. This layer ensures efficient and transparent energy transactions, allowing producers to monetize excess energy and consumers to access clean energy sources. Additionally, renewable energy certificates (RECs) or other verification mechanisms may be used to ensure the authenticity and sustainability of traded energy. Hence, the money exchange layer manages the financial transactions associated with P2P energy trading, while the energy exchange layer facilitates actual energy exchange between participants. These layers enable decentralized, transparent, and efficient energy trading while ensuring trust and security through blockchain technology (Figure 3).

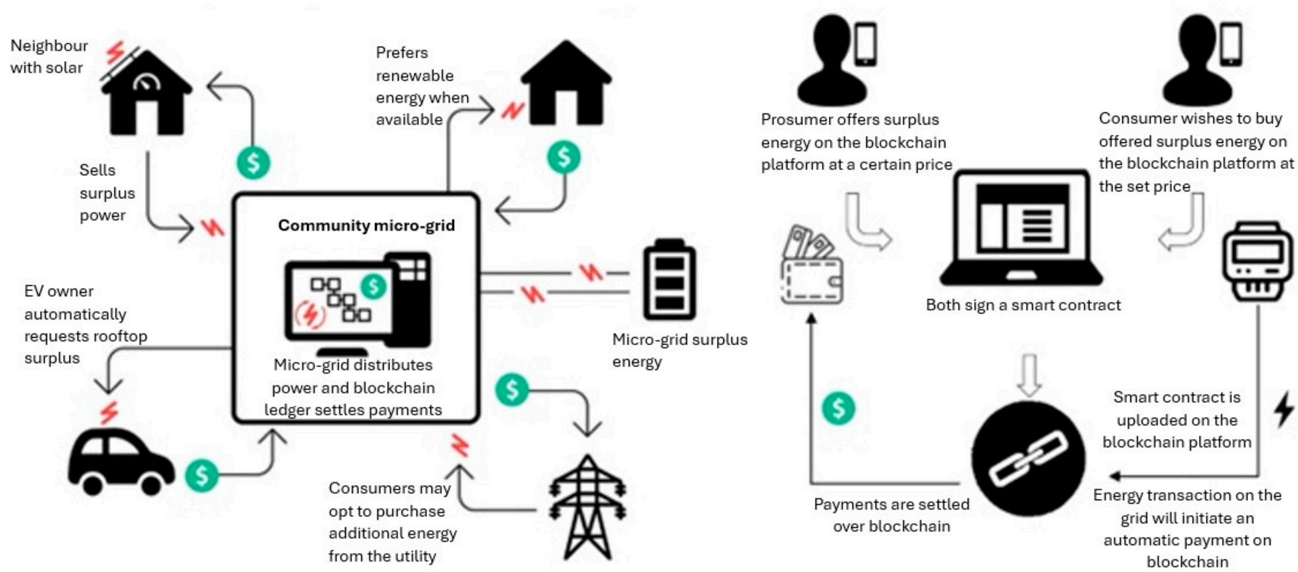

Figure 3. Blockchain-based P2P energy trading model.

Moreover, the blockchain's decentralized nature ensures transparency and security by recording all transactions across multiple nodes in the network. This eliminates the need for intermediaries and reduces the risk of fraud. Additionally, mechanisms for consumers and producers to leave feedback and ratings, based on their experiences, can be integrated to help build trust within the P2P energy trading community. This article, introducing a new blockchain-based P2P financing mechanism for DERs, offers substantial added value to renewable energy investment and deployment. By proposing to help build trust within the P2P energy trading community. This article, introducing a new blockchain-based P2P financing mechanism for DERs, offers substantial added value to renewable energy investment and deployment. By proposing an innovative billing approach explicitly tailored to DERs, this article addresses critical shortfalls in current billing mechanisms, thus providing an opportunity to overcome the traditional barriers associated with funding DER projects, such as wasted excess energy, tariffs monopoly, and fair compensation for the time of injection of energy back to the grid.

On the other hand, blockchain-based P2P energy trading can solve multidirectional billing. Today's energy billing systems are designed for unidirectional or at most bidirectional energy transactions. Thus, there is a need to develop an automatic decentralized energy trading system that can automatically collect energy consumption, offer a user-centric approach, and ensure a simple settlement for energy transactions in a multidirectional way. Furthermore, current billing systems are based on the Point-of-Delivery (PoD) concept, which means that the bill is issued per meter at a specific location where energy is delivered and not per end-user. Conversely, an aggregated bill per customer refers to a billing arrangement where multiple premises owned by the same customer are grouped together, and their energy consumption is aggregated for billing purposes. The aggregated bill per customer simplifies billing administration and can be fairer than a PoD billing in conditions where an increasing block rate billing structure is used, or demand side management (DSM) programs are applied. Moreover, the current data collection, processing, and financial settlement processes are highly inefficient and error-prone, resulting in significant time delays in value settlement and the need for costly reconciliation processes. Billing constitutes 5% to 15% of retailers' total operating costs. Blockchain technology can be the answer for an aggregated efficient, transparent, immune to tampering, and immutable billing system.

4. Modeling of the Microgrid

Urban and rural areas provide prospects for solar PV systems, but with different considerations [46]. Rooftop solar in urban areas focuses on distributed energy generation, while rural areas can cater to larger-scale utility installations. Optimizing solar PV potential involves considering geographical factors, energy demands, infrastructure, and regulatory frameworks specific to each setting. Urban areas have a substantial potential for rooftop solar installations on buildings [47]. However, shading from other buildings, limited roof space, and obstructions like vents or HVAC systems can reduce the effectiveness of solar panels. Urban areas generally have higher energy demands, making rooftop solar PV a viable option for meeting some of this demand. It also reduces transmission losses by generating electricity closer to where it is consumed. Rural areas often have more open land available, making them suitable for utility-scale solar farms. This allows for larger installations without the constraints of urban space limitations. Rural areas tend to have fewer obstructions like buildings and trees, which can maximize solar panels' exposure to sunlight. However, the demand is limited, burdening DER projects' return on investment, especially under the NEM billing mechanism. For this purpose, we decided to consider the case of a rural micro-gird that includes two prosumers and four consumers. This microgrid is tested using three billing mechanisms: NEM, FiT, and P2P energy trading. The same conditions are applied for the three scenarios and KPIs such as unused energy, financial gain for prosumers, and annual bill reduction for consumers are used to compare the three models.

In the simulated model, we considered two prosumers for every four consumers. This reflects an optimistic perspective where 1/3 of the population would have a renewable source of generation. Moreover, the simulated microgrid considers as sources of energy the utility grid for all participants and rooftop PV solar systems for prosumers. At the same time, the consumers are residential, small-commercial, and industrial loads (<100 kW). The use case microgrid, presented in Figure 4, is detailed hereafter:

– Prosumer A is a residential house occupied for the entire year and equipped with a 12.8 kWp solar PV system;

- Prosumer B is a residential summer house occupied only during the summer and equipped with a 12.8 kWp solar PV system;
- Consumer #1 is a residential house occupied for the entire year. Prosumer A and Consumer #1 have been modeled with the same load profile. They are a household of 4 family members where one family member works during the day. The house covers an area of around 180 m^2;
- Consumer #2 is an industrial load; it is a vehicle bodywork workshop that is operational during the entire year;
- Consumer #3 is a commercial load; it is a supermarket that is operational during the entire year;
- Consumer #4 is a residential house that is occupied during the entire year.

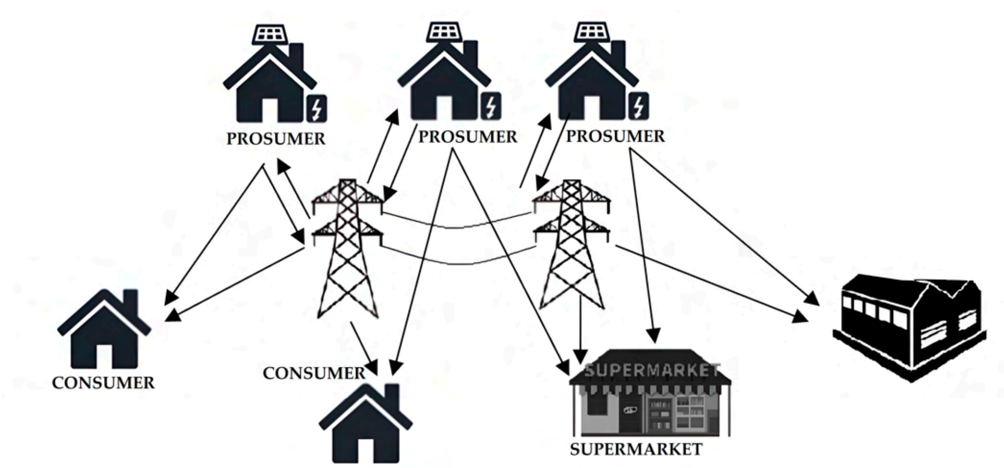

Figure 4. Simulated microgrid model.

Since an hourly load profile for an entire year was unavailable for all the loads, we decided to have an hourly load profile for over 4 weeks, each week corresponding to a different season. Then, the results of each week were extrapolated to 13 weeks to cover an entire season, and the overall result would be 52 weeks to represent an entire year.

The household used as a benchmark, Prosumer A, has a rooftop solar PV system. However, the current trend in the market is to replace traditional equipment with more efficient options. This includes switching from traditional lamps to light emitting diode (LED) lamps, using converter type air conditioning units, and upgrading to higher efficiency appliances. Given this trend, we have chosen to examine the scenario where Prosumer A is substituted with Prosumer A′. This substitution allows us to evaluate the effects of increased energy efficiency on our three billing models, resulting in lower energy demand. Prosumer A′ is an improved version of Prosumer A, with a 30% increase in efficiency. As a result, its residential load is 30% lower than Prosumer A's, which serves as our benchmark. Prosumer A′ could also represent a newly constructed house compared to an older one being represented by Prosumer A. The new house would have better insulation, reduce the need for heating and cooling, and be equipped with high efficiency appliances, decreasing overall energy consumption. The purpose of introducing Prosumer A′ in the model is to investigate the impact of a reduced load, with the same PV system capacity, on the use of P2P. This allows us to determine if it is a cost-effective option or not.

Prosumer B is a type of residential load where the owners only utilize the house for vacation during the summer season, specifically for 3 months from June 22nd to September 21st. The energy consumption for the remainder of the year is represented by a small and constant load, including gardening and operating the security system. Prosumer B is a unique type of load that may have different outcomes when subjected to incentive programs compared to a full-time load. It would be intriguing to investigate the effects of installing a PV system on this particular load, potentially resulting in surplus energy during the unoccupied period.

of installing a PV system on this particular load, potentially resulting in surplus energy during the unoccupied period.

Both Prosumer A/A′ and Prosumer B have a rooftop solar PV system with a capacity of 12.8 kWp. However, to evaluate the effect of the solar PV peak power on the three models, we have decided to analyze a situation where the 12.8 kWp system is replaced with a 10 kWp system. This particular scenario is referred to as scenario #2, while the original scenario will be referred to as scenario #1. We initially assumed that neither prosumer has a battery energy storage system (BESS). Therefore, we have simulated a scenario where a BESS was added for both prosumers. In this case, the BESS consists of 220 Ah, 12 V solar batteries, with 2 strings of 6 batteries connected in series, resulting in a total of 12 batteries. At a depth of discharge of 80%, the total capacity of the batteries is equivalent to 4.22 kWh. The purpose of including a BESS is to evaluate the impact of storing excess energy during hours of solar availability and selling it back to consumers during periods of low demand. This scenario is known as scenario #3.

The blockchain-based P2P energy trading model allows prosumers to sell their excess energy to two consumers. Prosumer A/A′ prioritizes using their own produced energy for their own use before selling any remaining excess to Consumers 3 and 4 at a negotiated rate. Similarly, Prosumer B uses the energy it produces for its own needs and then sells any extra to Consumers 1 and 2. It is assumed that consumers would be interested in buying excess energy from prosumers, whenever it is available, as it would typically be priced lower than the utility's tariff. However, any excess energy beyond the market demand would be wasted. Algorithm 1 summarizes the blockchain-based P2P energy trading model.

Algorithm 1: P2P Energy Trading

1: Initiate algorithm at time *t*
2: **if** PV power available, **then**
3: **if** Load of Prosumer < PV Generation, **then**
4: **if** the first consumer has a consumption, **then**
5: *Pi2k = min (Pk, PPV, i − Pi)*; *k* = 1
6: **else**, **if** the second consumer has a consumption,
7: **then** *Pi2k = min (Pk, PPV, i − Pi − Pi21)*; *k* = 2
8: **else**, no transfer of energy
9: **else,** PV generation totally consumed by load of Prosumer and complemented, if needed, by energy from the grid; no transfer of energy
10: **else,** no PV generation; no transfer of energy
11: *t* = *t* + 1
12: Goto 2//restart the algorithm

Under the NEM billing system, any excess solar PV generation is injected into the grid at the same rate as the applicable utility tariff. Any excess energy that surpasses the prosumer's total yearly consumption will not be compensated at the end of the year. Similarly, in the FiT billing model, the extra energy will be injected back into the grid at a lower rate based on current market trends. However, under this model, the yearly quantity of energy that exceeds the prosumer's total annual consumption is compensated at the applicable FiT rate. The power equations that govern the model are defined hereafter:

If solar PV AC power is greater than or equal to the prosumer load, the latter is met solely by solar PV power. The power provided via the utility grid $P_{U,i}$ is zero.

$$P_i = P_{PV,\,i} \tag{1}$$

The excess energy injected back into the grid or sold via the P2P energy trading model is calculated using Equation (2):

$$P_{sold} = P_{PV,\,i} - P_i \tag{2}$$

If solar PV AC power is less than the prosumer load, the latter is met by the solar PV power complemented by the utility grid power.

$$P_i = P_{PV,i} + P_{U,i} \quad (3)$$

where

P_i is the power demand of the consumer;
$P_{U,i}$ is the power provided by the utility company;
$P_{PV,i}$ is the power provided by the solar PV system;
P_{sold} is the excess power that can be used for trading.

In P2P energy trading models, managing the energy balance between supply and demand is crucial for ensuring stability and efficiency. When participants in a P2P network sell excess energy, this surplus is allocated to other users who need additional power. However, if the total amount of excess energy sold falls short of meeting the demand of buyers, the deficit must be supplemented from the traditional grid. This mechanism ensures that while P2P trading maximizes the use of locally generated renewable energy, it also maintains a reliable power supply by drawing from the grid when necessary. This integration helps to balance the fluctuating nature of renewable sources and ensures that energy needs are met even when P2P transactions alone cannot satisfy the demand. By effectively managing these scenarios, P2P systems can contribute to a more resilient and flexible energy infrastructure, supporting both sustainable energy use and grid stability.

In a real-world scenario of P2P energy trading, prices are determined through negotiations based on the balance of supply and demand, along with individual preferences and limitations. Despite the dynamic nature of markets, the presence of competition and price variations among markets or sources typically prevent drastic fluctuations, leading to price stability at a certain average level. An average negotiated rate was utilized to exchange energy in the blockchain-based P2P energy trading system to simplify the simulation model. Furthermore, in cases where electricity is not produced by the utility itself, such as in deregulated markets or P2P energy trading situations, the utility typically charges for electricity transmission through its networks. This charge, known as the wheeling charge, typically accounts for 15% of the applicable tariff. The tariffs and rates used in our simulation scenarios are defined in Table 1.

Table 1. Applied tariffs and rates.

Description	Tariff
Net metering	0.22 USD/kWh
Feed-in-Tariff	0.12 USD/kWh
P2P energy trading rate	0.18 USD/kWh
Wheeling charge	0.027 USD/kWh

Figure 5 depicts a flow chart demonstrating our simulation model's sequential processes and exchanges, providing a more organized and concise understanding of the workflow.

To simplify the calculations and maintain this paper's main objective, we have made certain assumptions in the model. The impact of holidays, where consumer loads may vary, has not been considered. This is because the proportion of holidays to the total number of days in a year is minimal and does not significantly affect the calculation results. As the PV system is connected to the main power source and operates in synchronization with it, it is assumed that the quality of the main source is standard in terms of voltage and frequency. The calculation does not consider energy transmission losses which occur when energy is transported over long distances from the source of generation to the point of consumption. These losses are usually significant at a transmission level. However, in our microgrid model on a regional distribution level, the distances are short, and when the

Sci. 2024, 14, x FOR PEER REVIEW 15 of

distribution cables are appropriately sized, the losses due to energy transportation become negligible. A time slot of one hour is used to determine the energy consumed or produced, assuming that the load remains constant during this period. Although this one-hour period is valid for the loads and production capacity used, a smaller time slot can be chosen for more accuracy if needed.

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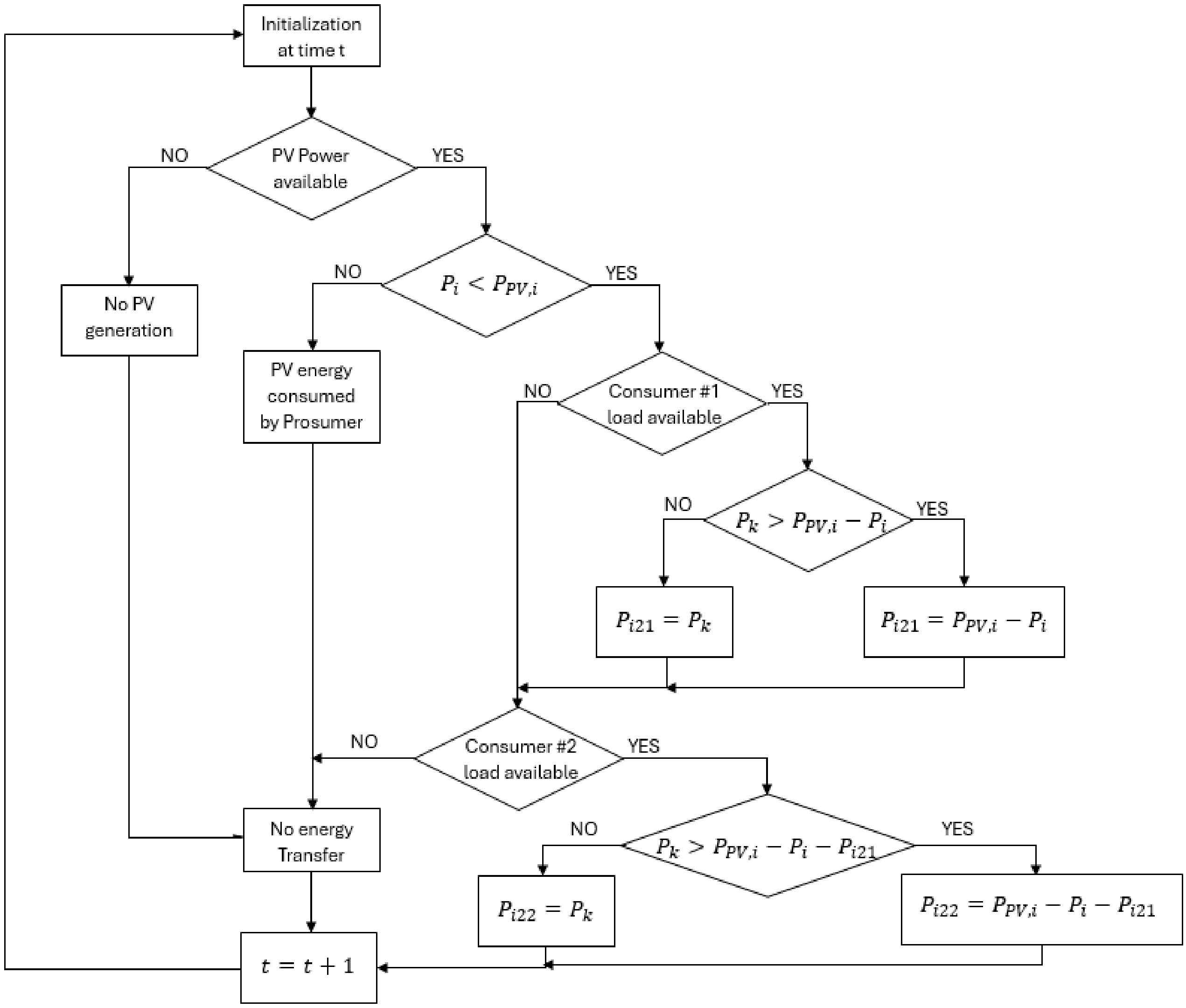

Figure 5. Simulation algorithm flow chart.

5. Simulation Results

The solar PV power generation was simulated using an hourly irradiance profile for Lebanon at a latitude of 33.8° N and a longitude of 35.5° E. The solar constant is around 1460 W/m^2, and the average annual solar radiation is 5.49 kWh/m^2/day. The monthly solar radiation profile is shown in Figure 6. The characteristics of the solar PV panels used are provided in Table 2.

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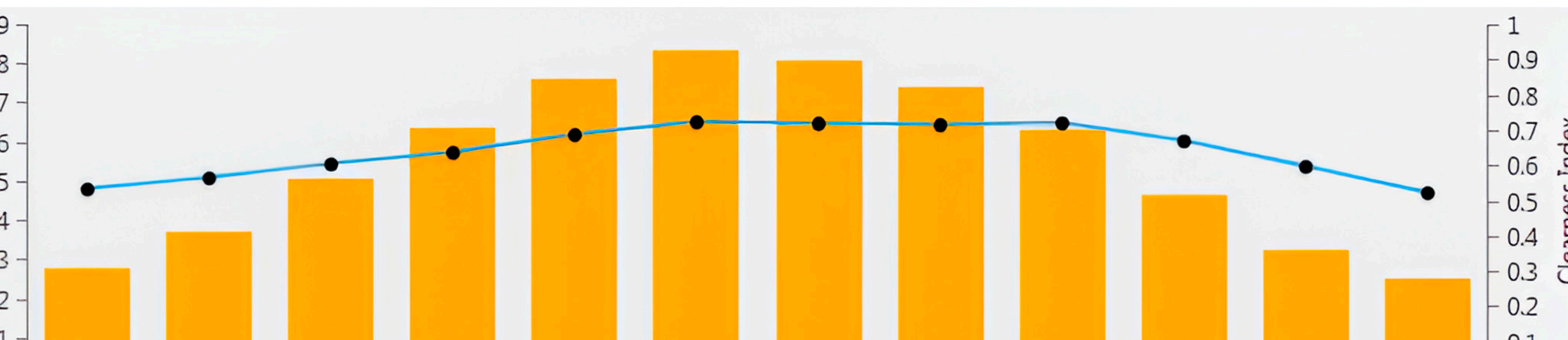

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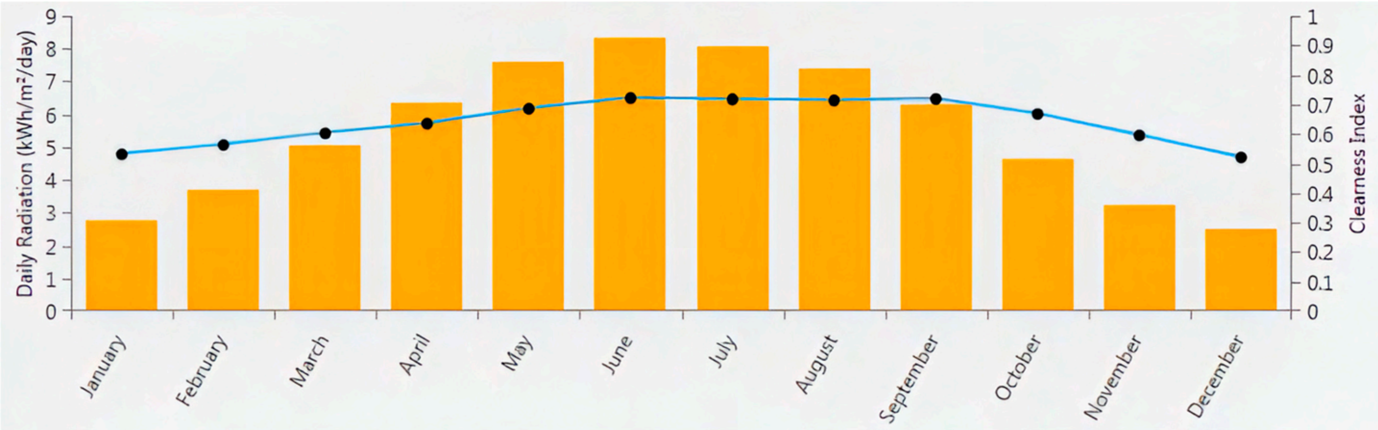

Figure 6. Monthly solar radiation profile.

Figure 6. Monthly solar radiation profile.

Table 2. Solar PV panel characteristics.

Panel Characteristics	
Maximum Power Pmax (W)	330 Wp
Maximum Power Voltage Vmpp (V)	37.8
Maximum Power Current Impp (A)	8.74
Open-Circuit Voltage Voc (V)	46.9
Short-Circuit Current Isc (A)	9.14
Module Efficiency (%)	17.01
Module Dimensions (mm)	1956 × 992 × 40
Module Weight (kg)	22.5
Cell Type	Polycrystalline 157 × 157 mm
Number of Cells	72 (6 × 12)

The primary limitation of the NEM billing scheme is the issue of unremunerated excess energy, which refers to the amount of energy that is injected back into the grid and exceeds the prosumer's annual energy demand. In NEM programs, any excess energy exported to the grid is credited at the same rate as retail electricity. These credits can accumulate over time if the customer consistently exports more energy than they consume. They can then be used to offset future electricity purchases, effectively rolling over the excess energy to the next billing period. However, at the end of the year, an annual settlement process takes place where all bills are reset, potentially resulting in a loss of any rolled over excess energy. This process may also involve reconciling any remaining excess energy credits, with the utility potentially compensating the customer at a predetermined rate for any unused credits. In our case, it is considered that at the end of the year, any rolled-over excess energy will be reset. Table 3 displays the amount of annual excess energy wasted by the three prosumer profiles under scenarios 1 and 2 using a NEM billing scheme. Under both scenarios, the annual energy bill will be null for all prosumers, because both solar PV systems (12.8 kWp and 10 kWp) can generate enough energy to fully compensate for the prosumer's annual energy consumption.

With Net Metering (Scenario 2)	Autumn Week	USD −16.58	USD −30.70	USD −63.05
	Winter Week	USD 12.37	USD −3.87	USD −41.52
	Spring Season	USD −267.08	USD −450.68	USD −871.25
	Summer Season	USD −434.14	USD −654.47	USD −360.51
	Autumn Season	USD −215.48	USD −399.09	USD −819.66
	Winter Season	USD 160.78	USD −50.37	USD −539.79
	Bill at the end of year (USD)	USD 0.00	USD 0.00	USD 0.00
	Unremunerated wasted excess energy at end of year (USD)	USD −916.71	USD −1554.60	USD −2591.21

Table 3. Lost energy with net metering under scenario 1 and 2.

		Prosumer A	Prosumer A′	Prosumer B
Energy Bill (USD) With Net Metering (Scenario 1)	Spring Week	USD −34.84	USD −48.66	USD −91.01
	Summer Week	USD −51.94	USD −82.89	USD −46.27
	Autumn Week	USD −29.78	USD −43.90	USD −76.25
	Winter Week	USD 3.47	USD −12.77	USD −50.42
	Spring Season	USD −449.02	USD −632.62	USD −1053.19
	Summer Season	USD −675.20	USD −895.52	USD −601.57
	Autumn Season	USD −387.10	USD −570.71	USD −991.28
	Winter Season	USD 45.13	USD −166.01	USD −655.43
	Bill at the end of year (USD)	USD 0.00	USD 0.00	USD 0.00
	Unremunerated wasted excess energy at end of year ($)	USD −1511.32 $	USD −2264.86	USD −3301.47
Energy Bill (USD) With Net Metering (Scenario 2)	Spring Week	USD −20.54	USD −34.67	USD −67.02
	Summer Week	USD −33.40	USD −50.34	USD −27.73
	Autumn Week	USD −16.58	USD −30.70	USD −63.05
	Winter Week	USD 12.37	USD −3.87	USD −41.52
	Spring Season	USD −267.08	USD −450.68	USD −871.25
	Summer Season	USD −434.14	USD −654.47	USD −360.51
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The gains under the NEM billing mechanism are the lowest for all prosumers due t the unremunerated lost excess energy, while FiT and P2P mechanisms present comparab gains. P2P has higher total savings because its average negotiated rate, even after the deduc tion of the wheeling charge, is higher than the FiT tariff. Additionally, simulation resul show that the gap between P2P energy trading and the other two billing mechanisms greater in the case of highly energy-efficient prosumers or occasionally occupied house holds. Additionally, the simulation results, shown in Figures 7 and 8, reveal a clear trend the more energy-efficient a prosumer is, the larger the disparity in total yearly gains betwee P2P energy trading and traditional mechanisms like NEM and FiT (by comparing the yearl gains of prosumer A and A′). Specifically, as prosumers reduce their energy consumptio and maximize the use of their own generated energy, the financial benefits of participatin in P2P energy trading become significantly more pronounced. This is because P2P tradin allows energy-efficient prosumers to sell their surplus energy at more competitive rates, d rectly to other consumers, rather than relying on the fixed rates offered via NEM or Fi Consequently, the yearly monetary gains for these prosumers are substantially higher in th P2P model, underscoring the economic advantage of this decentralized trading mechanism for those who have optimized their energy usage. Furthermore, the larger the size of th rooftop solar PV, the more significant this gap becomes, highlighting the financial ad vantages of P2P energy trading for prosumers with greater energy efficiency and larger re newable energy installations. In the case of scenario 1, the gap in yearly gains between P2 and NEM for Prosumer A′ is USD 1,065 and between P2P and FiT is USD 280. Additionally by looking at the gains of Prosumer B, it shows that this gap in yearly gains is maximum when the household is only occasionally occupied. In such scenarios, the energy generate via the rooftop solar PV system is often surplus to the household's needs, allowing mor energy to be sold through P2P energy trading. This results in significantly higher return compared to NEM or FiT, where excess energy may not be as effectively monetized. Th occasional occupancy, combined with the ability to capitalize on surplus energy, unde scores the financial benefits of P2P energy trading in these particular circumstances.

At another level, the issue with FiT billing schemes is the monopolized process of setting a tariff for grid-injected energy. Often, existing utilities are responsible for buying the energy and managing the grid. If there is only one utility company in an area (a monopoly), they have some control over setting the FiT rate. Critics argue that a monopoly utility might reduce the FiT rate to minimize costs, hindering renewable energy growth. This issue is avoided with P2P energy trading models since direct negotiations between the prosumer and the buyer set the rates. The annual gains of the three prosumers, under scenarios 1 and 2, are presented, respectively, in Figures 7 and 8.

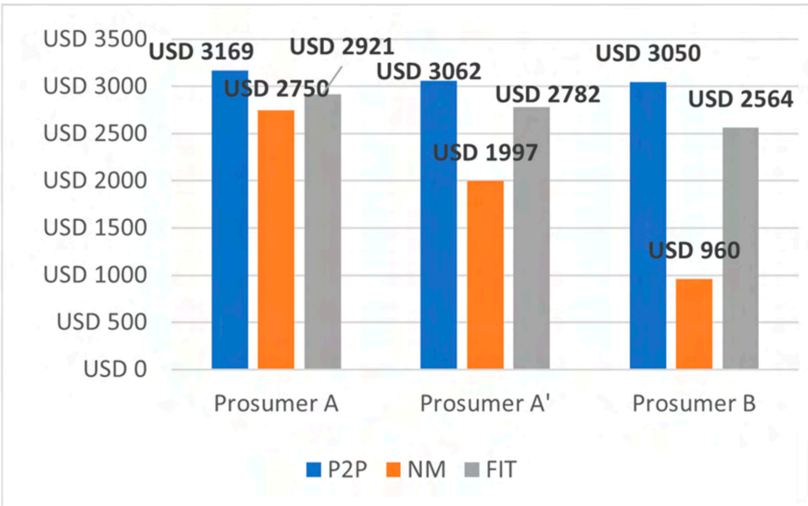

Figure 7. Total yearly gains—scenario 1.

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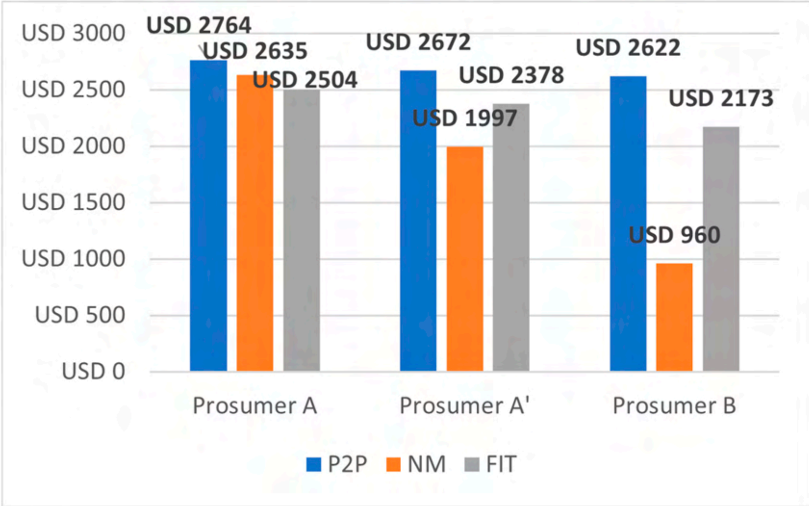

Figure 8. Total yearly gains—scenario 2.

The gains under the NEM billing mechanism are the lowest for all prosumers due to the unremunerated lost excess energy, while FiT and P2P mechanisms present comparable gains. P2P has higher total savings because its average negotiated rate, even after the deduction of the wheeling charge, is higher than the FiT tariff. Additionally, simulation results show that the gap between P2P energy trading and the other two billing mechanisms is greater in the case of highly energy-efficient prosumers or occasionally occupied households. Additionally, the simulation results, shown in Figures 7 and 8, reveal a clear trend: the more energy-efficient a prosumer is, the larger the disparity in total yearly gains between P2P energy trading and traditional mechanisms like NEM and FiT (by comparing the yearly gains of prosumer A and A′). Specifically, as prosumers reduce their energy consumption and maximize the use of their own generated energy, the financial benefits of participating in P2P energy trading become significantly more pronounced. This is because P2P trading allows energy-efficient prosumers to sell their surplus energy at more competitive rates, directly to other consumers, rather than relying on the fixed rates offered via NEM or FiT. Consequently, the yearly monetary gains for these prosumers are substantially higher in the P2P model, underscoring the economic advantage of this decentralized trading mechanism for those who have optimized their energy usage. Furthermore, the larger the size of the rooftop solar PV, the more significant this gap becomes, highlighting the financial advantages of P2P energy trading for prosumers with greater energy efficiency and larger renewable energy installations. In the case of scenario 1, the gap in yearly gains between P2P and NEM for Prosumer A′ is USD 1,065 and between P2P and FiT is USD 280. Additionally, by looking at the gains of Prosumer B, it shows that this gap in yearly gains is maximum when the household is only occasionally occupied. In such scenarios, the energy generated via the rooftop solar PV system is often surplus to the household's needs, allowing more energy to be sold through P2P energy trading. This results in significantly higher returns compared to NEM or FiT, where excess energy may not be as effectively monetized. The occasional occupancy, combined with the ability to capitalize on surplus energy, underscores the financial benefits of P2P energy trading in these particular circumstances.

The results of the simulations conducted under scenarios 1 and 2 are highly dependent on the synchronization between the prosumer's excess energy and the consumer's demand. If those two factors are not synchronized, the P2P energy trade would not be executed which can yield higher economic losses for the prosumer. Thus, it is important to add a BESS that allows storing excess energy in periods of low or no demand and trading it at a later time when there is consumer demand for that energy. For scenario 3, a 4.22 kWh BESS system was added to the 12.8 kWp rooftop mounted solar PV system. The simulations ent on the synchronization between the prosumer's excess energy and the consumer's de-mand. If those two factors are not synchronized, the P2P energy trade would not be executed which can yield higher economic losses for the prosumer. Thus, it is important to add a BESS that allows storing excess energy in periods of low or no demand and trading it at a later time when there is consumer demand for that energy. For scenario 3, a 4.2 kWh BESS system was added to the 12.8 kWp rooftop mounted solar PV system. The simulations

under scenario 3 aim to provide the economic feasibility of adding a BESS in the case of a P2P energy trading mechanism. The BESS was only used to store the excess energy whenever the power provided via the solar PV system was greater than the prosumer's demand and there were no requests to buy energy by other consumers. The additional gains resulting from adding a BESS are illustrated in Figure 9. A comparison of the gains generated in the case of a P2P energy trading mechanism, for the three scenarios, is shown in Figure 10.

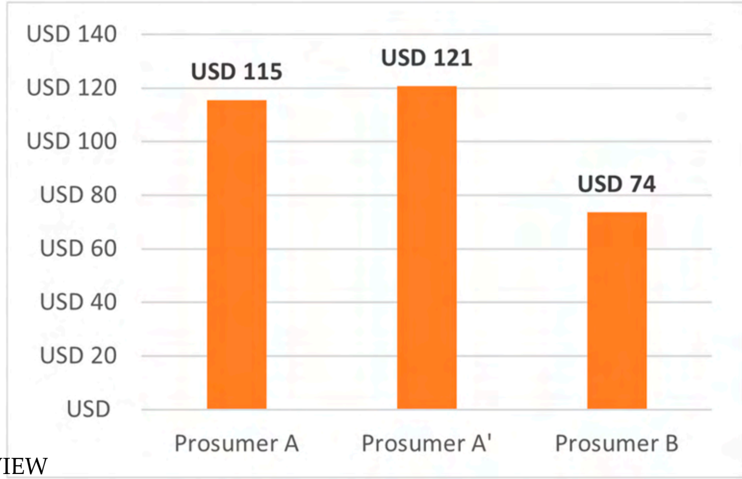

Figure 9. Additional gains generated by the addition of BESS.

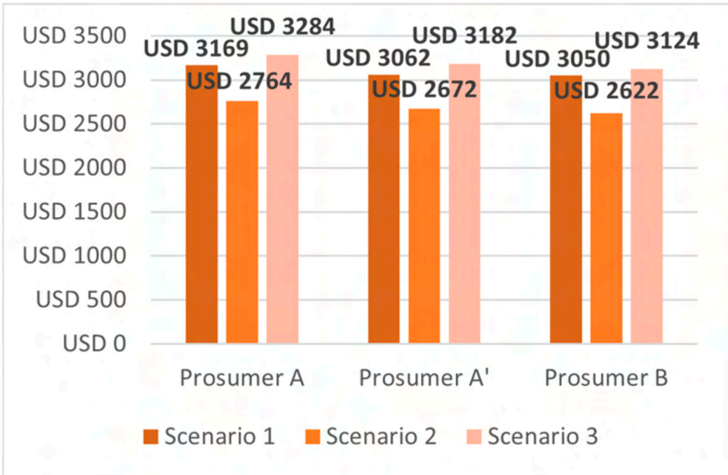

Figure 10. Total P2P gains comparison between all scenarios.

The highest gains are achieved when using a BESS since all the energy produced is being sold, while in scenarios 1 and 2, part of the energy that the solar PV could have generated was wasted due to the desynchronization of the solar PV potential and the consumers' demand. Nevertheless, even though the results of scenario 3 prove that a BESS can generate additional gains for the prosumers, its economic feasibility will be analyzed in the next section and its worthiness will be assessed.

However, two parties are involved in this microgrid: the prosumers and the consumers. Therefore, it is worth assessing the impact of the blockchain-based P2P energy trading model on the consumers' bills in terms of increase or savings. The NEM and FiT approaches do not offer consumers the option to purchase their energy from a third party other than the utility, so under any billing mechanism other than the P2P energy trading model, consumers' bills would remain the same. Therefore, the annual consumer bills resulting from the P2P energy trading model were compared to the baseline annual bills. It was observed that the P2P energy trading model is not only capable of generating income for prosumers, but also capable of generating savings for consumers. The consumers' savings generated under different scenarios are shown in Figures 11 and 12.

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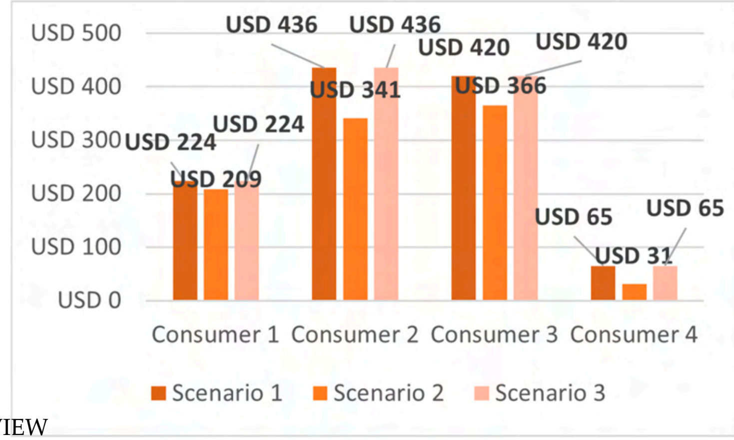

Figure 11. Consumers savings from buying energy from Prosumers A and B.

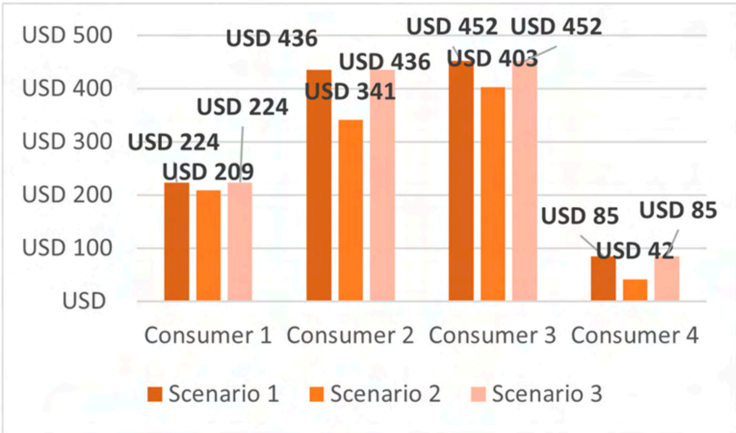

Figure 12. Consumers savings from buying energy from Prosumers A' and B.

6. Financial Feasibility Study and Sensitivity Analysis

Conducting a feasibility study is crucial for assessing the viability and potential success of any solution and comparing different financing mechanisms for the same project. Thus, under the three previously discussed scenarios, we conducted a Net Present Value (NPV) analysis to compare the savings generated from each of the three considered billing systems as a financing mechanism for the rooftop solar PV system. An NPV analysis is a financial technique used to evaluate the profitability of an investment or project by comparing the present value of its expected cash inflows with the present value of its expected cash outflows. It is based on the principle that a dollar received in the future is worth less than a dollar received today due to the time value of money. It is assumed that the initial cost of the solar PV system (with or without BESS) is covered by a bank loan over 10 years at an interest rate of 6%. The applied discount rate, which reflects the opportunity cost of capital or the minimum acceptable rate of return for the investment, is 10%. The discount rate is used to return future cash flows to their present value. It accounts for the riskiness of the investment, inflation, and the time value of money. All the assumptions considered to conduct the NPV analysis are shown in Table 4.

The NPV analysis results for the different billing mechanisms under scenarios 1 and 2 are shown in Figures 13 and 14. These results indicate that the P2P energy trading model favors the prosumer's investment in larger DER solutions since the NPV of the 12.8 kWp solar PV system is higher than the one for the 10 kWp system, which is not the case for the NEM billing system where a smaller size system would be more beneficial. Hence, a P2P

Table 4. Feasibility study parameters.

Main Parameters			
Initial cost of investment (USD) for 12.8 kWp solar PV	13,500	Loan Interest Rate/Year	6%
Initial cost of investment (USD) for 10.8 kWp solar PV	11,500	Interest Rate/Month	0.50%
Initial cost of investment (USD) for BESS	3000	Discounted Rate	10%
Grace period (years)	0	Payment Period as Monthly Inst. (years)	10

The NPV analysis results for the different billing mechanisms under scenarios 1 and 2 are shown in Figures 13 and 14. These results indicate that the P2P energy trading model favors the prosumer's investment in larger DER solutions since the NPV of the 12.8 kWp solar PV system is higher than the one for the 10 kWp system, which is not the case for the NEM billing system where a smaller size system would be more beneficial. Hence, a P2P energy trading mechanism can be considered as an incentive mechanism that encourages higher investments in DER solutions since it enables its users to exploit the full potential of their systems in an open market.

Appl. Sci. **2024**, *14*, x FOR PEER REVIEW 21

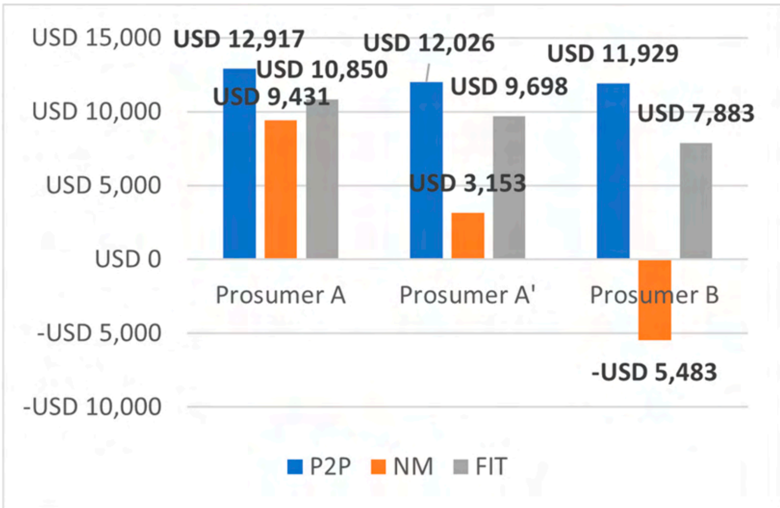

Figure 13. Scenario 1 NPV—all prosumers.

Additionally, the NPV analysis results under scenario 3 (Figure 15), as compared to the P2P NPV results shown in Figure 13, proves that there is no profit from adding a BESS since even though it generates additional savings for the prosumer, the generated savings are not enough to increase the financial viability of the system.

On the other hand, the results of our simulation model are affected by various factors, thus the necessity of conducting a sensitivity analysis. The first step in sensitivity analysis is to identify the key variables or assumptions that have the most significant impact on the analysis outcome. These variables are listed hereafter:

- Negotiated price for the P2P energy trading as compared to the NEM and FiT utility set rates;
- Applicable utility tariff structure;
- Peak power of the rooftop PV system;
- Prosumers' demand load profile;
- Consumers' demand profiles;
- Storage capacity of the BESS;

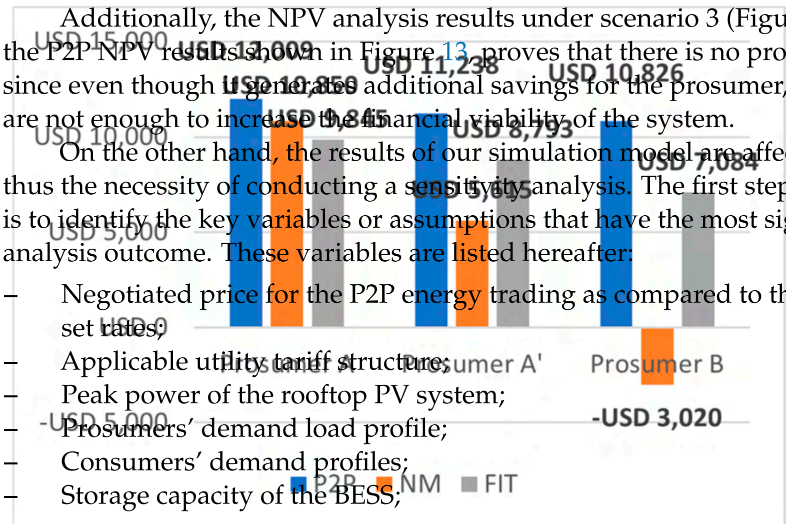

Figure 14. Scenario 2 NPV—all prosumers.

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Figure 13. Scenario 1 NPV—all prosumers.

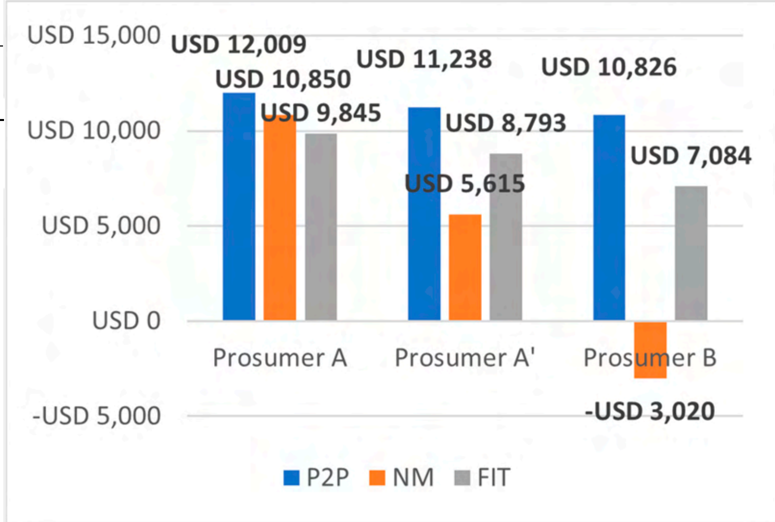

Figure 14. Scenario 2 NPV—all prosumers.

Additionally, the NPV analysis results under scenario 3 (Figure 15), as compared to the P2P NPV results shown in Figure 13, proves that there is no profit from adding a BESS, since even though it generates additional savings for the prosumer, the generated savings do not compensate for the additional costs. This would decrease the financial viability of the system.

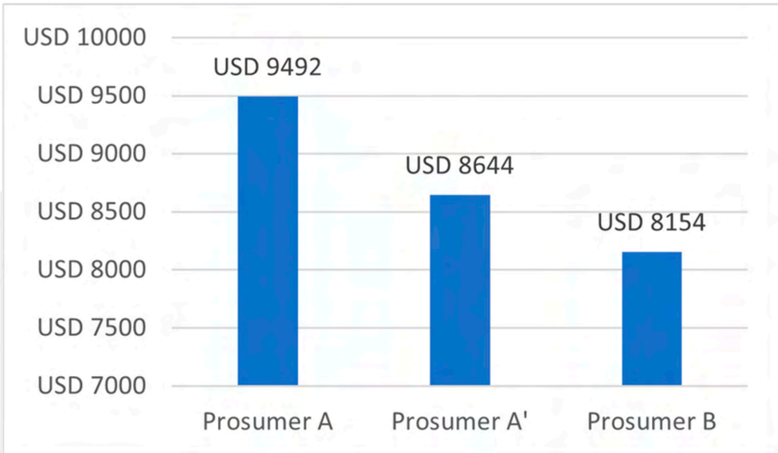

Figure 15. Scenario 3 NPV—all prosumers (P2P).

On the other hand, the results of our simulation model are affected by various factors, thus the necessity of conducting a sensitivity analysis. The first step in sensitivity analysis is to identify the key variables or assumptions that have the most significant impact on the analysis outcome. These variables are listed hereafter:

Considering the P2P energy trading negotiated price, if this rate is lower than the utility tariff, it would be considered a more appealing option for consumers. It increases the demand for traded energy, increasing the prosumer's revenue and the consumer's savings. However, any increase in the negotiated price, as long as it remains lower than the utility tariff, would favor the prosumer, leading to higher gains from his side but lower savings from the consumer's side.

Figures 16 and 17 show the variation in the prosumer's gains as a function of the solar PV peak power. For Prosumer A, a small-scale rooftop solar PV system under a NEM scheme can be more profitable than P2P or FiT. This is explained by the fact that a small-scale PV system will only be able to serve the prosumer's load and thus there will be little or no rolled-over energy and no considerable excess energy to trade. However, this would not be the case if the demand load of the prosumer is very low, such as that of Prosumer B. Additionally, this sensitivity analysis shows that P2P energy trading mechanisms may encourage prosumers to opt for larger DER systems to increase their profitability.

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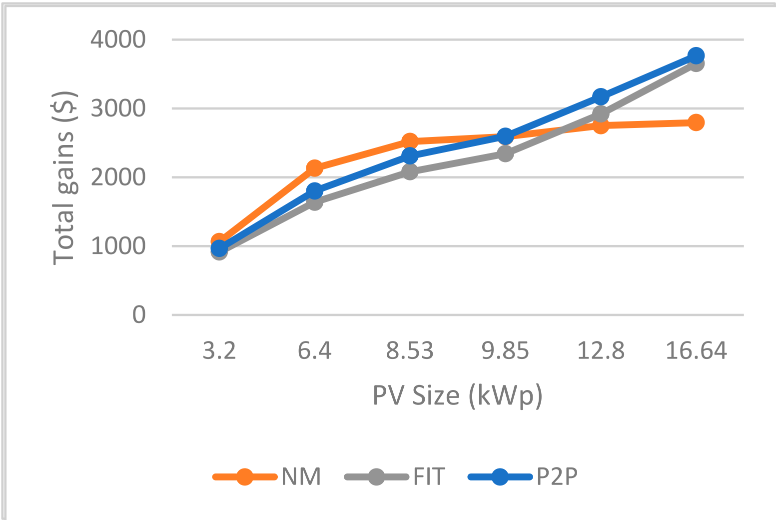

Figure 16. PV size impact on total savings—Prosumer A.

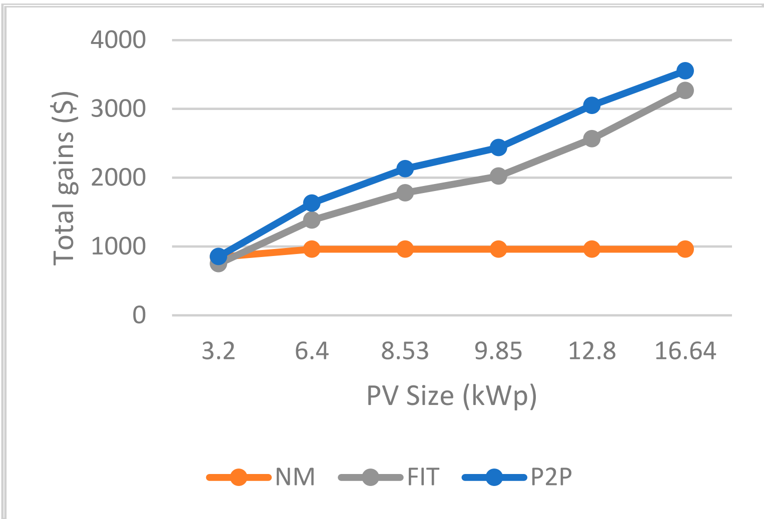

Figure 17. PV size impact on total savings—Prosumer B.

7. Conclusions

P2P energy trading is a new billing mechanism to incentivize prosumers to invest in DER projects, thereby contributing to the decentralization and decarbonization of the energy grid. This model allows private entities to generate and store energy and sell it back to other interested consumers in an open market ecosystem and without restrictions from the grid operator or the utility, thus turning the traditional electricity consumer into a proactive member of the electricity value chain and transforming the energy market into a consumer-driven model that can be beneficial to all stakeholders. Also, as shown in our simulations, the P2P energy trading model benefits consumers, allowing them to reduce their annual payments for electricity. In addition, P2P energy trading can also be beneficial for utilities. A utility's annual net profit would range from 10% to 30%. By applying a 15% wheeling fee to the P2P transactions and automating the billing process and management of these transactions through blockchain technology, the wheeling fee can be considered as a net profit for utility companies.

P2P energy trading promotes deregulation of the energy market, thus breaking the monopoly of utility companies faced with other billing systems such as NEM and FiT. However, P2P energy trading is challenging in handling the technical and financial aspects of the transactions without relying on a common third-party that has the trust of all peers to manage the energy exchanges in a secure and controlled manner. Hence, a P2P energy trading model would not be feasible without relying on blockchain technology. Blockchain is the perfect match for P2P energy trading because of its capability to automate energy and financial transactions and establish trust between unknown peers while maintaining the anonymity of the peers, immutability and traceability of transactions, and transparency in the process as well as security and immunity against tampering. Hence, blockchain offers a low-cost platform for managing and operating any P2P energy trading mechanism.

The current P2P energy trading simulation model can be further applied to assess its impact on other DERs such as electric vehicles and demand response programs. For electric vehicles, the P2P energy trading model can be used to incentivize vehicle-to-grid (V2G) energy exchange as well as vehicle-to-vehicle (V2V) energy trading. Similarly, combining P2P energy trading with demand response capabilities offers several benefits. Consumers can adjust their energy consumption based on real-time pricing signals or supply–demand imbalances within the local energy market. Consumers can save money by buying electricity from nearby prosumers at lower prices or reducing consumption during peak demand periods when prices are high. By actively managing energy consumption and generation within the local network, P2P energy trading with demand response can help enhance grid stability and reliability, particularly during peak demand periods or in regions with high levels of renewable energy generation.

In conclusion, this study sheds light on a new billing mechanism that can benefit all stakeholders. Through simulation and analysis, we have demonstrated that P2P energy trading can be a better option than conventional billing mechanisms in many situations. Moving forward, it is essential to investigate the P2P energy trading mechanism further under other scenarios to build upon the foundation laid by this study and address any remaining questions or uncertainties.

Author Contributions: Conceptualization, A.A.; methodology, A.A.; software, A.A.; validation, A.I., M.A. and M.G.; formal analysis, A.A.; investigation, A.A.; resources, H.I.; data curation, A.A.; writing—original draft preparation, A.A.; writing—review and editing, A.I. and M.A.; visualization, A.A.; supervision, M.A.; project administration, H.I.; funding acquisition, A.I. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

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5.3 ARTICLE: EFFICIENT MODELING OF DISTRIBUTED ENERGY RESOURCES' IMPACT ON ELECTRIC GRID TECHNICAL LOSSES: A DYNAMIC REGRESSION APPROACH

Cet article, intitulé « *Efficient Modeling of Distributed Energy Resources' Impact on Electric Grid Technical Losses : A Dynamic Regression Approach* », a été publié dans sa version finale en avril 2024 par les éditeurs du journal *MDPI – Energies*.

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En tant que premier auteur, j’ai contribué à la conceptualisation et développement du modèle, à l’essentiel de la recherche sur l’état de la question, à la collecte et l’analyse des données et à la rédaction du manuscrit. Mr. Saba Salloum a contribué à la construction du modèle numérique, l'exécution des simulations et la collecte des données. Professeur Mehdi Adda a participé à la direction du projet, à la supervision du travail, validation des résultats ainsi qu’à la révision de l’article et à la revue de la littérature. Les professeurs Adrian Ilinca, Mazen Ghandour et Hussein Ibrahim en tant que co-auteurs, ont participé à la révision de l’article et à la revue de la littérature.

Résumé : Les pertes techniques dans les réseaux électriques sont des inefficacités inhérentes à la transmission et à la distribution de l'électricité, qui se traduisent par des pertes d'énergie pouvant atteindre 40 % de l'énergie produite. Ces pertes posent des défis importants aux opérateurs de réseaux en termes de durabilité énergétique, de fiabilité et de viabilité économique. Les ressources énergétiques distribuées offrent des solutions prometteuses pour réduire les pertes techniques en décentralisant la production et la consommation d'énergie, en réduisant le besoin de transmission sur de longues distances et en optimisant l'utilisation des REDs. Par conséquent, l'estimation de l'impact des REDs sur les pertes techniques du réseau devient primordiale pour les opérateurs et les planificateurs du réseau. En réponse, cet article propose l'application de la modélisation de régression et d'algorithmes d'ajustement

de courbes non linéaires pour fournir une compréhension plus nuancée et mieux caractériser l'interaction complexe entre le déploiement des REDs et les pertes techniques. Grâce à une étude de cas complète basée sur plus de 1080 simulations informatiques, nous démontrons l'efficacité du modèle de régression dynamique à coefficient variable polynomial que nous proposons pour estimer les pertes techniques au sein des réseaux électriques. Le modèle proposé offre une méthodologie simple et efficace qui permet aux opérateurs de réseau de mieux comprendre la dynamique non linéaire de l'intégration des REDs et de prendre des décisions plus rapides et mieux informées concernant les stratégies de gestion du réseau, les investissements dans l'infrastructure et les interventions politiques. En outre, cette recherche contribue à faire progresser le domaine de l'optimisation des réseaux en proposant une équation simple qui améliore notre capacité et notre hâte à évaluer et à atténuer les pertes techniques dans le contexte d'un paysage énergétique en évolution, caractérisé par l'adoption croissante des REDs.

Contexte et Objectifs : Cette étude introduit une équation de régression polynomiale dynamique avec des coefficients variables pour évaluer l'impact de l'intégration des REDs en différents points du réseau électrique. L'équation tient compte de la puissance des REDs, de la charge connectée, et l'impédance totale au niveau du bus concerné, ce qui permet d'estimer avec précision la réduction des pertes techniques. Ce modèle de régression dynamique offre une approche rapide et directe de l'évaluation de ces réductions, en remplacement des méthodologies traditionnelles. Il offre des résultats plus rapides, demande moins de puissance de calcul et offre une précision comparable aux modèles de simulation, sans nécessiter d'expertise spécialisée. Le modèle proposé peut servir pour optimiser les points de connexion des REDs dans un réseau électrique, pour optimiser le choix des REDs dans le contexte des VPPs et pour calculer les réductions de pertes techniques résultant des REDs et compenser les prosommateurs pour cette contribution, ce qui peut rendre la faisabilité des projets de RED plus attirant.

Méthodologie : La méthodologie adoptée pour développer le modèle de régression dynamique visant à prédire les réductions des pertes techniques dues à l'intégration des REDs dans un réseau électrique commence par la simulation du modèle IEEE-33 bus pour extraire et nettoyer les données pertinentes. Ensuite, on identifie les variables indépendantes influençant les pertes techniques et on divise les données en ensembles d'apprentissages et de tests. Un algorithme de régression dynamique, à coefficients variables, est sélectionné et formé avec les données d'apprentissage, suivi d'une validation croisée pour évaluer sa robustesse. Le modèle est ensuite testé sur l'ensemble de tests, et des métriques comme le RMSE et le R^2 sont utilisées pour quantifier sa performance. Les résultats sont analysés pour comprendre l'impact des REDs sur les pertes techniques et identifier les facteurs clés influençant ces pertes. Enfin, si possible, le modèle est validé avec des données réelles et affiné pour améliorer sa précision et sa robustesse.

Résultats et Contributions : Dans l'ensemble, le modèle de régression présenté dans cet article représente une avancée significative dans le calcul des pertes techniques dans les systèmes de distribution d'électricité en fonction du niveau d'intégration des REDs. En fournissant, aux opérateurs des réseaux électriques, un outil fiable pour évaluer l'impact du niveau d'intégration des REDs sur les pertes techniques, le modèle contribue à l'optimisation des opérations du réseau, à une meilleure sélection des points d'intégration des REDs pour une résilience et une efficacité accrue du réseau, à une meilleure gestion de l'énergie et, en fin de compte, à la fourniture d'une électricité fiable et rentable aux consommateurs. La poursuite de la recherche et de la collaboration dans ce domaine permettra de mieux comprendre les pertes techniques et de soutenir le développement de solutions innovantes pour un avenir énergétique durable.

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Article

Efficient Modeling of Distributed Energy Resources' Impact on Electric Grid Technical Losses: A Dynamic Regression Approach

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Abstract: Technical losses in electrical grids are inherent inefficiencies induced by the transmission and distribution of electricity, resulting in energy losses that can reach up to 40% of the generated energy. These losses pose significant challenges to grid operators regarding energy sustainability, reliability, and economic viability. Distributed Energy Resources (DERs) offer promising solutions to lower technical losses by decentralizing energy generation and consumption, reducing the need for long-distance transmission and optimizing grid operation. Hence, estimating the impact of DERs on grid technical losses becomes paramount for grid operators and planners. In response, this article proposes the application of regression modeling and nonlinear curve fitting algorithms to provide a more nuanced understanding and better characterize the intricate interplay between DER deployment and technical losses. Through a comprehensive case study based on more than 1080 computer simulations, we demonstrate the effectiveness of our proposed dynamic polynomial varying coefficient regression model in estimating the impact of DERs on technical losses within electrical grids. The proposed model offers a simple and effective methodology that allows grid operators to gain insights into the nonlinear dynamics of DER integration and make quicker and more informed decisions regarding grid management strategies, infrastructure investments, and policy interventions. Also, this research contributes to advancing the field of grid optimization by offering a simple equation that enhances our ability and haste to assess and mitigate technical losses in the context of an evolving energy landscape characterized by increasing DER adoption.

Keywords: technical losses; distributed energy resources; regression model; nonlinear curve fitting; electric grid optimization

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1. Introduction

In today's constantly changing energy landscape, integrating distributed energy resources (DERs) is gaining popularity as a vital approach to improving the power grid. These DERs, including solar photovoltaic (PV) panels, wind turbines, battery energy storage systems (BESSs), electrical vehicles (EVs), small power generators, and demand side management (DSM), have the potential to transform the conventional concept of energy generation and consumption. In recent years, DERs have emerged as critical components in transforming traditional electric grids into modern, resilient, and sustainable systems. One of the primary roles of DERs lies in enhancing grid resilience. By providing backup power during outages or natural disasters, DERs contribute to the grid's reliability [1]. These resources can operate independently or in coordination with the main grid, mitigating disruptions and ensuring uninterrupted electricity supply to consumers. Grid stability is also bolstered by DERs, which provide ancillary services such as frequency regulation and voltage support [2]. Battery storage systems, in particular, can respond rapidly to fluctuations in supply and demand, thereby maintaining grid stability and reliability [3].

Furthermore, DERs facilitate demand response programs, allowing consumers to change their electricity usage in response to price signals or grid conditions [4]. This flexibility helps balance supply and demand, reducing the need for peaker plants and expensive infrastructure upgrades. With the rise of EVs, DERs play a pivotal role in integrating EV charging infrastructure into the grid. Smart charging stations and vehicle-to-grid (V2G) technology enable EV batteries to serve as distributed storage units, supporting grid stability and enhancing overall energy management [5]. In addition, DERs are integral to developing microgrids capable of operating equally in off-grid and on-grid modes. Microgrids enhance energy resilience by providing reliable power to critical infrastructure during emergencies or grid outages.

Last, DERs are crucial in managing peak electricity demand and alleviating grid infrastructure strain [6]. Solar panels, wind turbines, and battery storage systems can generate power during periods of high demand, reducing reliance on traditional power plants and minimizing electricity costs for consumers. Integrating renewable energy sources into the grid is another crucial function of DERs. With the increasing adoption of solar and wind energy, distributed generation technologies enable the efficient utilization of these intermittent resources. By generating electricity near where it is consumed, DERs reduce transmission losses and enhance the overall efficiency of the grid. However, integrating DERs into electrical grids presents opportunities and challenges; their full potential can only be realized if they are properly managed and optimized.

Regarding power management, DER integration has matured using advanced control techniques and accurate forecasting of renewable energy generation, load demand, and market prices. Additionally, on the energy level, DER's contribution is well remunerated via in-place financing mechanisms such as net metering (NM), Feed-in-tariff (FiT), and power purchase agreement (PPA). Yet, other contributions, such as reducing the electric grid's technical losses, remain less explored.

The operation of electric grids is inherently plagued by technical and nontechnical losses (Table 1), which result in energy dissipation and reduce overall system efficiency [7]. Technical losses in the electric grid refer to the energy lost during transmission and distribution. These losses occur due to resistance in power lines, transformer inefficiencies, and voltage drops. Technical losses lead to a waste of energy and result in increased costs for energy companies and potential disruptions in electricity supply to end-users. By understanding the causes and patterns of technical losses through data analysis, energy companies can take targeted actions to reduce them. Methodologies used today to assess the technical losses rely on simulation software [8,9], measurement and verification (M&V) studies [10], load flow analysis modeling tools [11,12], and Distribution System State Estimation (DSSE) [13–15]. However, despite their numerous advantages, these methodologies can be computationally intensive and time-consuming and require specialized knowledge and training to be used effectively. This is where regression models come into play, offering a powerful tool to analyze historical data and identify factors that contribute to technical losses. Regression models enable energy companies to make data-driven decisions and implement strategies to improve grid efficiency.

This study introduces a dynamic polynomial regression equation with varying coefficients to evaluate the impact of Distributed Energy Resources (DERs) integration across different points of the electric grid. The equation factors in DER power, the connected load, and total impedance at the relevant bus, accurately estimating the reduction in technical losses. This dynamic regression model offers a swift and straightforward approach to assessing such reductions as an alternative to traditional methodologies. It boasts quicker results, demands less computational power, and provides comparable precision to simulation models, all without requiring specialized expertise.

Table 1. Classification of electric grid losses.

Level 1	Level 2	Level 3	Components of Level 3
Losses	Technical Losses	Fixed Losses	Hysteresis losses Eddy current losses
		Variable Losses	Ohmic losses
	Nontechnical Losses	Network Equipment issues	Theft and fraud Measurement errors
		Network information issues	Missing or unregistered connection points Incorrect location or energization status of connection points Incorrect information on measurement equipment
		Energy data processing issues	Estimation of unmetered consumptions Estimation of consumptions between meter readings and calculations Estimation of technical losses Estimation of detected issues Other energy data processing issues

This model holds promise for integration into optimization algorithms and resource allocation strategies, facilitating efficient planning while minimizing technical losses. It can also offer valuable insights into the efficacy of different control strategies. Furthermore, it can aid in the development of targeted and cost-effective control mechanisms and help identify inefficiencies within the grid.

By analyzing data on technical losses, energy companies can pinpoint specific areas or factors contributing to these losses, enabling targeted actions to enhance grid resilience, reduce costs, and improve overall operational efficiency.

In the first part of this paper, and within the literature review context, we define the technical losses and the challenges and limitations of DER penetration level in electrical grids and identify the existing methodologies and techniques used to calculate the technical losses. In the Section 3, we introduce the methodology adopted to develop, train, and test our proposed regression model, and in Section 4, we introduce the built model. Finally, in Section 5, the testing results are presented, and an analysis of the accuracy and precision of the proposed model is provided.

2. Literature Review

The integration of DER into electric grids has emerged as a critical strategy for enhancing grid resilience, sustainability, and efficiency, with publications that address their impact on the grid dating back to the 1970s. The United States Public Utility Regulatory Policies Act (PURPA) [16] encouraged the development of renewable energy and cogeneration facilities by requiring electric utilities to purchase power from qualifying facilities, which included certain types of small-scale, decentralized power generation. This provision effectively incentivized the growth of customer-owned generation, as individuals or businesses could install renewable energy systems and sell excess electricity to utilities at favorable rates.

However, the degree of integration of DERs into the electric grid, defined as the penetration level, remains controversial. A higher DER integration diversifies the energy mix and reduces dependence on fossil fuels. It also helps alleviate stress on the grid during peak periods, reducing the need for costly infrastructure upgrades. However, an excessively high level of DER penetration can pose challenges related to grid stability, voltage regulation, frequency control, and power quality, requiring advanced grid management techniques and infrastructure upgrades [17,18]. Hence, the penetration level of DERs is a key metric used to assess the impact of DERs on the grid and to gauge the extent of their integration into the overall energy system.

Various factors, including technological advancements, regulatory policies, market dynamics, and consumer preferences, influence the penetration level of DERs. The term "DER penetration level" is typically defined as the maximum power capacity of DERs relative to the total installed capacity within a given system. It measures the physical presence of DERs in terms of their maximum potential power output rather than their actual energy production. However, slight variations in how the concept is defined and used may exist in different contexts.

In contrast to capacity penetration, the DER energy penetration's definition considers the actual energy output or contribution of DERs to the total energy consumed within a specified timeframe (e.g., hourly, daily, annually). It reflects the dynamic nature of DERs' energy generation or consumption patterns.

Additionally, there are two other definitions: DER market penetration and DER operational penetration. The DER market penetration perspective looks at DER technologies' market share or adoption rate within a particular market or customer segment. It considers factors such as the number of DER installations, customer participation in DER programs, and the percentage of customers with DER assets. The DER operational penetration definition focuses on the operational impact of DERs on the grid, including their influence on grid stability, reliability, and power quality. It considers factors such as DERs' ability to provide grid support services, participate in demand response programs, and mitigate grid constraints.

By nature, DERs are located closer to demand centers, hence contributing to reducing electric grid losses by generating electricity closer to where it is consumed. This can mitigate losses incurred during long-distance transmission from centralized power plants. Electric grid technical losses, encompassing both transmission and distribution losses, represent a significant challenge in operating and managing electrical grids worldwide. These losses, arising from conductor resistance, transformer inefficiencies, and voltage drops, contribute to energy wastage, reduced system efficiency, and increased operational costs. Effective modeling of technical losses is essential for optimizing grid performance, enhancing energy efficiency, and ensuring the reliability of the electricity supply [19,20]. This literature review explores various modeling techniques employed to quantify and mitigate electric grid technical losses, encompassing both traditional and advanced approaches.

Traditional methods for modeling electric grid technical losses include empirical formulas, analytical models, and statistical regression approaches. Empirical formulas, such as the I2R formula, estimate losses based on the product of current squared and resistance. Analytical models, such as load flow analysis and network impedance methods [21,22], provide a theoretical framework for calculating losses based on grid topology and operating conditions. Statistical regression approaches, including linear and multiple linear regression, correlate technical losses with load demand, network configuration, and environmental variables. Nevertheless, recent advancements in modeling techniques have expanded the scope and accuracy of electric grid loss estimation. These techniques include machine learning algorithms, such as artificial neural networks (ANNs) [23], support vector machines (SVMs) [24], and decision trees [25]. Machine learning models offer data-driven approaches for predicting technical losses based on historical data and system parameters. These models can capture nonlinear relationships and complex interactions among variables, improving prediction accuracy. Comparably, optimization-based approaches, including genetic algorithms [26], particle swarm optimization [27], and ant colony optimization [28], optimize grid configurations and operational parameters to minimize technical losses by iteratively adjusting system parameters to achieve optimal performance while considering constraints such as voltage limits and equipment ratings. Also, several hybrid models combining multiple techniques exist [29]. A hybrid model may use machine learning for the initial prediction of technical losses and optimization algorithms for fine-tuning system parameters to minimize losses further.

Different methods are also used to allocate the losses to each load connected to the grid. The prorated methodology is a simple empirical method for the electric grid's loss allocation (pro rata, PR). This methodology aims to equally distribute the grid losses among different components or sections of the distribution system based on their contribution to the overall energy flow, regardless of network configuration and the distance between the generator and the load [30]. The PR approach is straightforward to implement; however, it is unjust for loads located near generating sources. Hence, the distance-adjusted pro rata (DAPR) method may be a more accurate option.

The DAPR considers the distance of the load to a root node and the power demand to define the distance factors. Distance factors are calculated or assigned to each section of the distribution system based on the length of the distribution lines. Longer lines generally have higher losses due to increased resistance, so the distance factor represents the relative contribution of each section to the total line length [31]. The DAPR technique incorporates the distance factor but does not consider the nonlinearity of the power flow.

Another technique that is used is the incremental loss method. By using the linearization in the Newton–Raphson method for solving the power flow, this method calculates the incremental increase in losses caused by the addition of new components, such as transformers, conductors, or other equipment, to the existing system [32–34]. By quantifying these incremental losses, utilities and operators can assess the impact of new connections on system efficiency, reliability, and performance. However, high X/R ratio networks may involve complex interactions between resistive and reactive components, making the application of the incremental losses method more challenging. In contrast, network analysis approaches compute losses using the network's impedance or admittance matrix [35]. Methods under this category include the Z-bus method [36], the modified Y-bus method [37], the branch-current decomposition method [38], and the succinct method [39].

On the other hand, the power tracing method tracks losses through branch power flow and connected nodal injections. Some existing tracing methods use graph theory, as seen in [40,41], while others utilize various algorithms [42–44]. Normalization is necessary if the method yields an inaccurate estimate of total losses. A comprehensive overview of loss allocation methods can be found in [45]. Additionally, for radial distribution systems with multiple distributed generation points, article [46] discusses essential considerations such as the characteristics of net generation nodes (power sources) and net load nodes (power sinks), as well as the uncertainty of distributed generator output.

By strategically locating DERs at critical points along the distribution network, utilities can optimize energy delivery, improve system efficiency, and enhance overall grid performance. Optimizing the point of integration of DERs involves selecting the most suitable location within the electrical distribution system to connect DER assets. This optimization aims to maximize the benefits of DERs while minimizing potential negative impacts on system reliability, stability, and performance. Several methods and considerations can be employed to optimize the point of connection (PoC) of DERs. Ehsan and Yang [47] provide an overview of various analytical techniques for optimal integration of DERs in power distribution systems. It reviews a range of analytical methods, including linear programming, nonlinear optimization, heuristic algorithms, metaheuristic algorithms, and artificial-intelligence-based approaches such as genetic algorithms, particle swarm optimization, and ant colony optimization.

Aryani et al. [48] explored the application of genetic algorithms (GAs) to optimize the placement and sizing of DERs in electrical distribution systems, with the main objectives of reducing power losses and improving voltage profiles within the distribution network. Avchat and Mhetre [49] optimized the placement of distributed generation (DG) within distribution networks to achieve loss reduction and voltage improvement objectives using various optimization techniques such as heuristic algorithms, mathematical programming, and evolutionary algorithms to determine the best locations for installing DG units. In the article [50], the authors explore the use of Particle Swarm Optimization (PSO) to determine DG's optimal sizing and placement in distribution systems.

Thus, numerous case studies and applications demonstrate the effectiveness of modeling techniques for electric grid technical losses across different contexts and scales. These studies encompass urban, rural, and remote grid environments, as well as diverse energy sources and demand profiles. Researchers and practitioners have applied modeling techniques to optimize grid design, improve energy efficiency, integrate renewable energy sources, and improve grid resilience to interruptions and breakdowns. However, despite significant progress, several challenges remain in modeling electric grid technical losses. These challenges include data availability and quality, model complexity, computational requirements, and uncertainty in future scenarios (e.g., demand growth and renewable energy integration).

While simple regression models may not capture all nuances of grid losses' estimation, their simplicity, interpretability, and efficiency make them valuable tools for initial analysis and as benchmarks for more complex models. Simple regression models often require fewer computational resources, resulting in quicker training and deployment. This can benefit tasks that demand quick predictions in real-time or near-real-time situations. Moreover, simple regression models can be easily scaled to larger data sets and applied to different regions or periods without significant adjustments. This scalability is valuable for analyzing grid losses across diverse geographic areas.

Similarly, basic regression models serve as a benchmark for assessing the effectiveness of more advanced models. By comparing the results of complex models to those of a simple regression model, analysts can assess whether the additional complexity yields significant improvements in accuracy. While dealing with limited data or noisy input variables, complex models are at risk of overfitting. Simple regression models are less susceptible to overfitting, reducing the risk of producing inaccurate estimations. Our proposed model for estimating the technical loss reduction, considering the level of DER penetration at a specific grid node as an independent variable, requires little computational power. Hence, it allows high-frequency sampling, making it perfect for calculating energy losses in real time, considering the fast-changing and intermittent nature of DERs.

Additionally, the proposed model can serve other grid management and optimization algorithms, especially in managing virtual power plants (VPPs), and financially compensates prosumers' participation in distributed energy generation. Hence, instead of just compensating prosumers for the energy injected back into the grid, our proposed model can calculate the reduction in grid losses resulting from the prosumer's DER connection to the grid and financially remunerate him for the saved energy. Such a model might be beneficial in increasing the viability of DER deployment in ecosystems where financial incentives, like energy rates and technology prices, are insufficient to incentivize the end users.

3. Methodology

Regression models are statistical tools that analyze the relationship between a dependent variable and one or more independent variables. In the context of energy systems, regression models can be used to predict the performance of DERs based on various factors such as weather conditions, electricity demand, and grid infrastructure.

The main idea is to develop a predictive model capable of calculating the total energy losses in a grid using a DER's penetration level connected to a specific bus as a predictor.

The DER penetration level X is defined in the following equation:

$$X = \frac{P_{DER}}{Bus\ Load} \times 100 \tag{1}$$

A significant amount of data are required to build an accurate regression model capable of estimating the impact of DER integration at any grid bus on that grid's total losses. For this purpose, using ETAP 12.6.0 simulation software, the IEEE-33 bus grid model was used as a reference model to construct a baseline (grid details are provided in Appendix A). The baseline construction methodology was based on the following steps:

- Simulate the baseline model without any DER integration, and calculate the total losses of the reference grid model (IEEE-33 bus)
- Integrate a certain percentage of DER at a particular bus i, simulate the whole model, and calculate the total grid losses. The total loss output value is then logged.
- Increase the DER penetration by a step of 5%, and repeat the simulation and calculation process. Then, this step is repeated until 100% of DER integration at bus i is achieved.

– This process is repeated until all busses in our reference model are simulated with DER penetration levels ranging from 0% to 100% with a step of 5%.

Once the learning data are prepared, the regression model can be built. This involves training the model using historical data and optimizing its parameters to minimize the difference between the predicted and actual output. Various algorithms and techniques are available for building regression models, such as ordinary least squares, gradient descent, and machine learning algorithms like random forest and support vector regression. The choice of algorithm depends on the problem's complexity and data availability. In our case, the least squares method was adopted to develop our regression model. This method aims to minimize the sum of the squares of the differences between the observed and predicted values, also known as residuals. So, the first step is to select a mathematical model that describes the relationship between the independent variables (predictors) and the dependent variable (outcome). For example, in simple linear regression, the model could be represented as Y = β0 + β1X + ε, where Y is the dependent variable, X is the independent variable, β0 and β1 are the coefficients, and ε is the error term. Then, we implement the independent variable data set into the regression equation to generate our predicted data set. Then, we use the gathered data in the observed data set from the constructed baseline to test the precision of the regression model by calculating the difference between the observed and predicted values for each data point. These differences are called residuals. Afterward, we adjust the model coefficients to minimize the sum of the squared residuals; hence, the term "least squares". To assess how well the model fits the data, we examine various metrics such as the following:

– Mean Squared Error (MSE): MSE calculates the average squared difference between predicted and actual values. It penalizes significant errors more heavily than more minor errors.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - \widetilde{y}_i\right)^2 \quad (2)$$

where $\hat{y}_i$ is the observed value, $\widetilde{y}_i$ is the predicted value, and n is the number of observations.

– Root Mean Squared Error (RMSE): RMSE is the square root of the MSE and represents the average magnitude of the errors in the same units as the dependent variable.

– Mean Absolute Error (MAE): MAE calculates the average absolute difference between the predicted and actual values, providing a measure of the average magnitude of the errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - \widetilde{y}_i\right| \quad (3)$$

– The coefficient of determination measures the proportion of the variance in the dependent variable explained by the model's independent variables. It ranges from 0 to 1, where a higher value indicates a better fit of the model to the data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - \widetilde{y}_i\right)^2}{\sum_{i=1}^{n}\left(\hat{y}_i - \overline{y}_i\right)^2} \quad (4)$$

where $\overline{y}_i$ is the mean of the observed values.

– Mean Percentage Error (MPE): MPE measures the average percentage difference between the predicted and actual values, providing insights into the average directional accuracy of the predictions.

– Mean Absolute Percentage Error (MAPE): MAPE calculates the average percentage difference between the predicted and actual values, providing a measure of the overall accuracy of the predictions relative to the observed values.

After the regression model is built, it is important to evaluate its performance to ensure its accuracy and reliability. This can be carried out by comparing the predicted values with the actual values and calculating various metrics such as mean squared error, root mean difference between the predicted and actual values, providing a measure of the overall accuracy of the predictions relative to the observed values.

After the regression model is built, it is important to evaluate its performance to ensure its accuracy and reliability. This can be carried out by comparing the predicted values with the actual values and calculating various metrics such as mean squared error, root mean squared error, and coefficient of determination (R-squared). The performance evaluation provides insights into the effectiveness of the regression model and helps identify any areas for improvement. For this purpose, we decided to use a 14-bus grid model and the IEEE-10 bus model to test the accuracy of the proposed predictive model. Hence, 3 grid models and 1080 simulation results were used to train and test our regression model, as detailed in Figure 1.

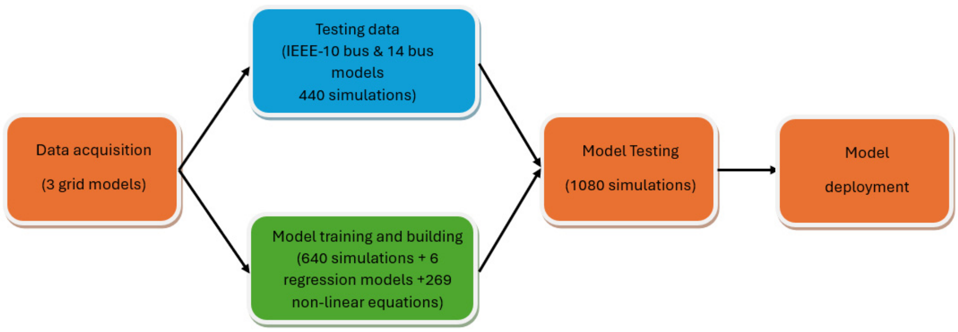

Figure 1. Regression model training and testing process.

4. Model Building

The model was built using an Intel i7-7500U, 2.70 GHz, dual-core CPU with 16 GB RAM, operating on Windows 10. The training and testing data were obtained by simulating three grid models (14-bus grid model, IEEE-10 bus, and IEEE-33 bus models) using the Electrical Transient Analyzer Program version 12.6.0 (ETAP), a software platform used to design, simulate, analyze, control, optimize, and automate electrical power systems. Both models gave practically the same results. The linear regression least square algorithm and nonlinear curve fitting algorithm were programmed using MATLAB R2022a.

After testing various regression equations, we found that a second-degree polynomial equation best fits the data sets from different buses with an acceptable coefficient of determination (R2).

$$y = ax_i^2 + bx_i + c \quad (5)$$

where y is the estimated total technical loss in the electric grid, both variable and fixed as detailed in Table 1, and x_i is the DER penetration level at bus i, as defined in Equation (1).

However, it was remarkable that the leading coefficient (a) and the linear coefficient (b) varied from bus to bus. In contrast, the constant coefficient (c) showed minor variations and could be considered constant, as illustrated in Figure 2.

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Hence, we needed to identify the independent variables that affect the variabilities of coefficients a and b. It is well known that the load demand (L) directly influences active power losses in the grid. Higher loads increase line currents, leading to higher resistive losses in transmission and distribution lines. Similarly, the impedance of transmission lines contributes to resistive losses as current flows through the conductors. Higher impedance lines experience more significant losses due to increased resistance. Thus, we tried to find a relation between the coefficients a and b from one side and the total impedance Z and load L on the other.

The bus impedance z (in Ohm) is calculated using the resistance r and the reactance x as follows:

$$z = \sqrt{x^2 + r^2} \quad (6)$$

The total impedance Z of a certain bus constitutes the sum of all the impedances from the utility grid connection to that specific bus. It is defined as the sum of the impedances of all the transmission lines and other components such as transformers, if applicable, that directly connect the power source of the grid to the subject load.

$$Z = \sum z \quad (7)$$

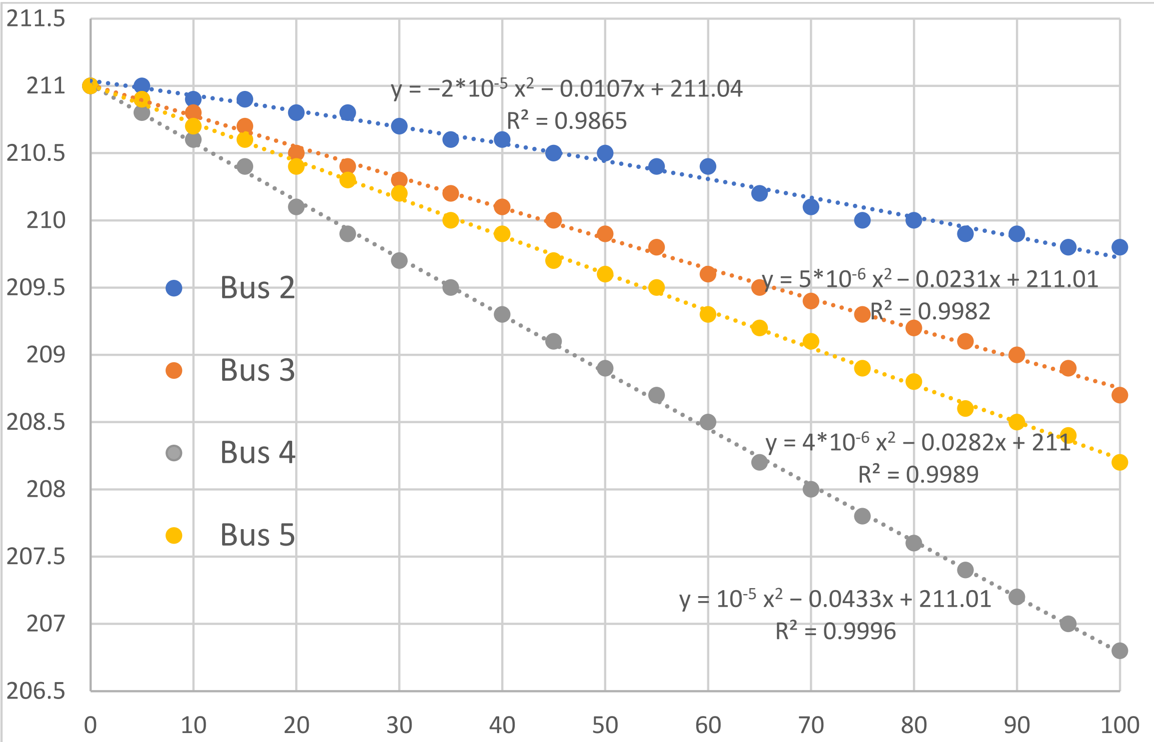

Figure 2. Regression equations of buses 2 to 5.

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To clarify the total impedance formula, let us consider the total impedance for bus 20 of the IEEE-33 bus grid. In this case, the connection between the power source and bus 20 includes bus 0_1, bus 1_18, bus 18_19, and bus 19_20. Hence, $Z_{20} = z_1 + z_{18} + z_{19} + z_{20}$.

Therefore, we moved from a simple polynomial regression model into a dynamic model with varying coefficients. A varying coefficient regression model is considered a type of dynamic regression model. Dynamic regression models are considered when the relationship between the dependent variable and the independent variables changes over time or across different subsets of the data. Varying coefficient regression models fit this definition because they allow the coefficients associated with the independent variables to vary across observations or over time.

In a varying coefficient regression model, the coefficients are not fixed but are allowed to change, which captures the dynamic nature of the relationship between the variables. This flexibility enables the model to capture complex patterns and variations in the data that traditional regression models with fixed coefficients may not adequately capture. Hence, our objective was to find functions $f_a(L, Z)$ and $f_b(L, Z)$ that define the variabilities of the leading coefficient (a) and the linear coefficient (b). So, our predictive regression model is presented by Equation (8):

$$y = f_a(L_i, Z_i).x_i^2 + f_b(L_i, Z_i).x_i + c \quad (8)$$

The values of a_i, b_i, c_i, L_i and Z_i of our training model (IEEE-33 bus) are shown in Table 2.

At first, we tried to find a regression model that predicted the relation between the initial regression model's coefficients a and b and the Load (L) and total impedance (Z). However, none of the regression models provided an acceptable coefficient of determination. Then, we decided to apply nonlinear curve fitting techniques since, as shown in Figure 3, the relation between the coefficients (a and b) and the load and impedance is nonlinear. A nonlinear curve fitting algorithm is a mathematical technique used to estimate the parameters of a nonlinear model that describes the relationship between variables in the data. Unlike linear regression, which assumes a linear relationship between the

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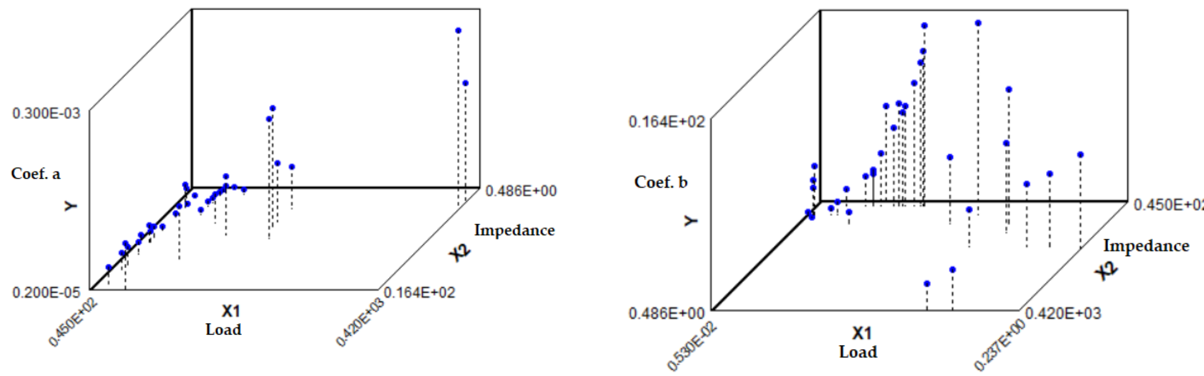
independent and dependent variables, nonlinear curve fitting algorithms allow for more complex relationships by fitting a nonlinear function to the data. These algorithms typically involve iteratively adjusting the parameters of the nonlinear model to minimize the difference between the observed and predicted values, often using optimization techniques such as gradient descent, Levenberg–Marquardt algorithm, genetic algorithms, or simulated annealing.

Table 2. Values of a, b, c, L, and Z of the buses in the IEEE-33 bus model.

Bus	a	b	c	Z (Ohm)	L (kW)	Bus	a	b	c	Z (Ohm)	L (kW)
2	0.000004	0.0107	211	0.4858	100	18	0.00008	0.1342	211	16.4247	90
3	0.000005	0.0231	211	1.0391	90	19	0.000009	0.0053	211	0.7125	90
4	0.00001	0.0433	211	1.4498	120	20	0.00001	0.0092	211	2.7373	90
5	0.000004	0.0282	211	1.8775	60	21	0.00001	0.0098	211	3.3670	90
6	0.000002	0.0424	211	2.9595	60	22	0.00001	0.0107	211	4.5422	90
7	0.00007	0.1513	211	3.6060	200	23	0.000008	0.0279	211	1.5856	90
8	0.0001	0.1948	211	5.7165	200	24	0.0002	0.1668	211	2.7298	420
9	0.000008	0.0639	211	6.9848	60	25	0.0003	0.1864	211	3.8675	420
10	0.00002	0.0707	211	8.2644	60	26	0.00003	0.0477	211	3.1873	60
11	0.000008	0.0548	211	8.4715	45	27	0.00004	0.0483	211	3.5063	60
12	0.00002	0.0727	211	8.8658	60	28	0.000008	0.0539	211	4.9181	60
13	0.00002	0.0793	211	10.7337	60	29	0.00005	0.1189	211	5.9847	120
14	0.00009	0.1631	211	11.6290	120	30	0.0002	0.2118	211	6.5542	200
15	0.00003	0.0835	211	12.4202	60	31	0.0001	0.1678	211	7.9054	150
16	0.00003	0.0855	211	13.3443	60	32	0.0002	0.2369	211	8.3822	210
17	0.00003	0.0863	211	15.4945	60	33	0.00003	0.0678	211	9.0126	60



(a) **(b)**

Figure 3. Plot of the leading coefficient (a) and the linear coefficient (b) as a function of L and Z.

Figure 3. Plot of the leading coefficient (a) and the linear coefficient (b) as a function of L and Z.

In our case, we used the Levenberg–Marquardt algorithm. It is an optimization technique commonly used for fitting nonlinear least squares curves. The algorithm iteratively adjusts the model's parameters to minimize the sum of squared differences between the observed and predicted values. The Levenberg–Marquardt algorithm steps are detailed hereafter:

1. Initialization: Start with initial guesses for the model's parameters.

2. Compute the Jacobian Matrix: Calculate the Jacobian matrix, which contains the partial derivatives of the model equations with respect to each parameter. This matrix provides information about the sensitivity of the model to changes in the parameters.

$$J_{ij} = \frac{\partial r_i}{\partial p_j} \quad (9)$$

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where p is the parameter vector, and r is the residual vector.

3. Compute the Approximate Hessian Matrix: The Hessian matrix represents the second derivatives of the sum of squared residuals with respect to the parameters. In Levenberg–Marquardt, an approximate Hessian matrix is computed using the Jacobian matrix.

$$H = J^T.J \tag{10}$$

4. Update the Parameters: Adjust the model parameters using an iterative update rule that considers both the gradient of the objective function (sum of squared residuals) and the curvature of the objective function surface.

5. Control Step Size: The Levenberg–Marquardt algorithm uses a damping parameter, typically denoted as λ (lambda), which controls the step size during each iteration. If the step improves the fit, λ is decreased to allow larger steps. If the step worsens the fit, λ is increased to take smaller steps.

$$\lambda_{k+1} = \lambda_k \times \frac{trace\left(J^T, J\right)}{m \times diag(J^T.J)} \tag{11}$$

where

λ_k is the damping parameter at the k-th iteration;

m is the number of observations (or residuals).

6. Convergence Criterion: Repeat steps 2–5 until a convergence criterion is met, such as reaching a specified tolerance level for the change in the parameters or the objective function.

The Levenberg–Marquardt algorithm was coded in Matlab as a function that tested 269 nonlinear equations (list of equations provided in Appendix B) to find the best nonlinear equation that defines the relation between the initial regression model's coefficients (a) and (b) and the Load (L) and total impedance (Z). The function calculates the best curve-fitting parameters for each nonlinear equation and the Chi-square (χ^2) value. The Chi-square (χ^2) is a statistical measure used to evaluate the goodness of fit between observed data and expected values based on a specific model. It is commonly employed in testing the goodness-of-fit tests. The formula for the Chi-square (χ^2) is given by Equation (12):

$$X^2 = \sum_i \frac{(O_i - E_i)^2}{E_i} \tag{12}$$

where

O_i = Observed frequency for category i

E_i = Expected frequency for category i

The complete process including the development of the linear regression models using the least square method, as well as using the Levenberg–Marquardt nonlinear curve fitting technique to define the relationship of the leading coefficient (a) and the linear coefficient (b) with respect to the Load (L) and total impedance (Z) is illustrated in Figure 4.

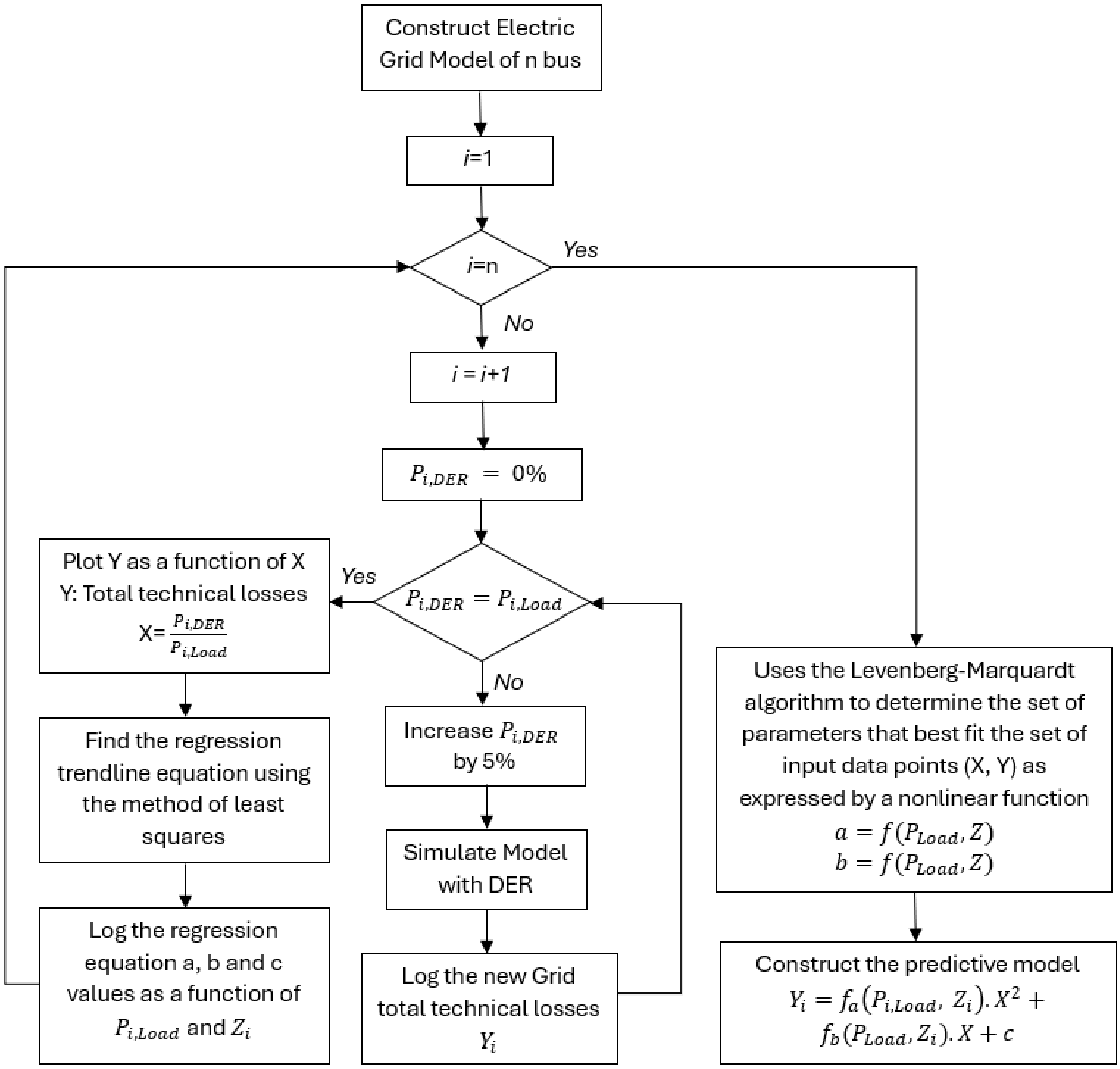

Figure 4. The full process logic diagram.

The precision of the developed dynamic varying coefficient was tested by comparing the predicted dependent variable outputs (generated by the regression model) to the observed dependent variable values (generated by the simulations using ETAP 22.6.0). The metrics in Section 3 were used to assess the model's accuracy. Results are presented in Table 3.

Additionally, we compared the performance of our dynamic varying coefficient regression model with a baseline model, which was, in this case, the polynomial regression model developed for each bus separately. The calculated coefficient of determinations for each bus is presented in Figure 5, while the criteria for correlation intensity in regression models according to R2 values is shown in Table 4.

Table 3. Regression model testing results using IEEE-33 bus grid.

IEEE-33 Bus Model	MSE	RMSE	MAE	MAPE	R²
Value	3.28	1.81	1.12	0.55	0.89
Recommendation				<10	~1

Using the IEEE-33 bus grid model as a learning model, we found the regression equation that allows us to calculate the total grid losses as a function of the DER level of integration at a specific grid node. The equation $y = f_a(L_i, Z_i).x_i^2 + f_b(L_i, Z_i).x_i + c$ is defined as follows:

$$f_a(L_i, Z_i) = \frac{L_i}{(0.64289 \times 10^7 - 0.450559 \times 10^6 \times Z_i)} \quad (13)$$

$$f_b(L_i, Z_i) = 1.472 \times 10^{-4} \times Z_i \times L_i \quad (14)$$

$$c = Initial\ losses\ of\ the\ grid \quad (15)$$

If X_i is defined as a percentage:

$$X = \frac{P_{DER}}{Bus\ Load} \quad (16)$$

Then, the regression model coefficients will be as follows:

$$f_a(L_i, Z_i) = \frac{L_i}{(642.896 - 45.0559 \times Z_i)} \quad (17)$$

$$f_b(L_i, Z_i) = 0.001472 \times Z_i \times L_i \quad (18)$$

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Table 4. Characterization of correlation intensity in regression models according to R^2 values.

R^2 Value	Correlation Intensity
0.00	(N) null
(0.00–0.09)	(L) low
(0.09–0.36)	(M) moderate
(0.36–0.81)	(H) high
(0.81–0.98)	(VH) very high
1.00	(P) perfect

Additionally, we compared the performance of our dynamic varying coefficient regression model with a baseline model, which was, in this case, the polynomial regression model developed for each bus separately. The calculated coefficient of determinations for each bus is presented in Figure 5, while the criteria for correlation intensity in regression models according to R2 values is shown in Table 4.

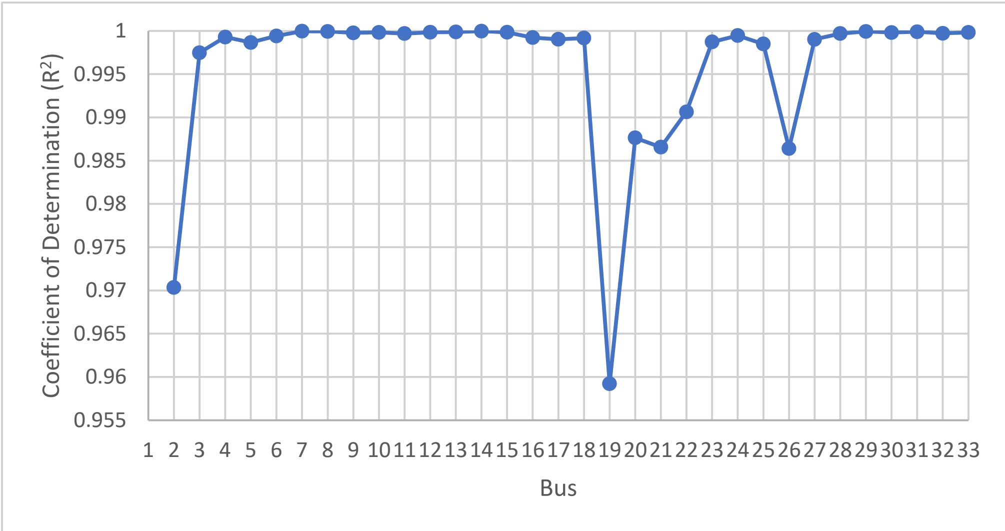

Figure 5. The CoD of the predictive regression model tested on the IEEE-33 bus.

Table 4. Characterization of correlation intensity in regression models according to R2 values.

R^2 Value	Correlation Intensity
0.00	(N) null
(0.00–0.09)	(L) low
(0.09–0.36)	(M) moderate
(0.36–0.81)	(H) high
(0.81–0.98)	(VH) very high
1.00	(P) perfect

To obtain a more in-depth evaluation of the performance of the proposed dynamic varying coefficient regression model, we decided to calculate the error distribution. The error distribution can help identify any systematic biases in the predictive model. The predictive model error distribution refers to the distribution of errors between the predicted values generated by the model and the actual observed values in the data set. Understanding the error distribution provides insights into the performance and reliability of the predictive model. Additionally, by analyzing the distribution of errors between predicted and actual values, you can understand the spread and variability of prediction errors, thus providing insights into how well the model captures the underlying patterns in the data. A good predictive model error distribution typically exhibits the following characteristics:

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- Symmetry: The error distribution is approximately symmetric around zero, indicating that the model is equally likely to overpredict and underpredict the target variable. A symmetric error distribution suggests that the model is unbiased and does not systematically overestimate or underestimate the outcomes.
- Normality: The error distribution closely follows a normal (Gaussian) distribution. Normality implies that most prediction errors are minor, with fewer extreme errors. A normal error distribution simplifies interpretation and analysis and is often assumed by many statistical techniques.
- Constant Variance (Homoscedasticity): The variance of the errors remains relatively constant across different levels of the predictor variables. Homoscedasticity indicates that the model's predictive performance is consistent across the entire range of the

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- Symmetry: The error distribution is approximately symmetric around zero, indicating that the model is equally likely to overpredict and underpredict the target variable. A symmetric error distribution suggests that the model is unbiased and does not systematically overestimate or underestimate the outcomes.
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- Constant Variance (Homoscedasticity): The variance of the errors remains relatively constant across different levels of the predictor variables. Homoscedasticity indicates that the model's predictive performance is consistent across the entire range of the data, and the spread of errors does not systematically change with the magnitude of the predicted values.
- Zero Mean: The mean of the error distribution is close to zero, indicating that, on average, the model predictions are accurate. A non-zero mean suggests systematic bias in the model predictions, which should be investigated and corrected.
- No Outliers: The error distribution does not contain extreme outliers or anomalies. Outliers may indicate data points with unusual characteristics or errors in the data collection process. Identifying and addressing outliers is important for improving the overall reliability and performance of the model.
- Low Dispersion: The dispersion of the error distribution is relatively low, indicating that most prediction errors are concentrated around the mean. Low dispersion suggests that the model provides consistent and precise predictions with little error variability.

The error distribution of our predictive model is shown in Figure 6. The curvature of the error distribution meets the criteria of a normal error distribution curve, as detailed here.

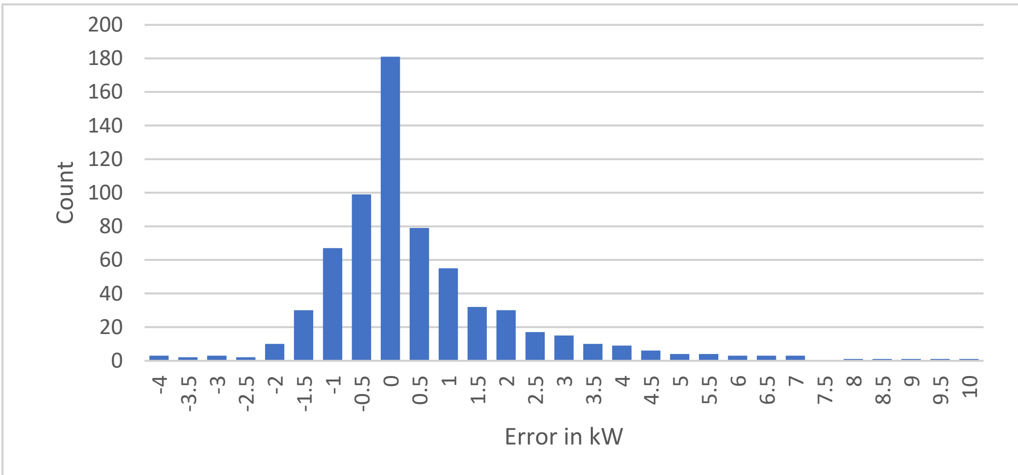

Figure 6. The predictive model error distribution.

5. Testing and Results Analysis

Following the learning phase, it is important to test the predicting model to evaluate its performance and accuracy using a separate data set not used during the training process. This process helps assess how well the model generalizes to new, unseen data and provides insights into its predictive capabilities. Hence, to obtain a separate data set that was not used during the regression model training, we used two grid models: IEEE-10 bus model and a 14-bus grid model (grid models data are provided in Appendices C and D). The testing data were generated and processed the same way as the training data, using the same simulation software, ETAP 12.6.0. Then, we used the trained regression model to predict the dependent variable using the same independent variables as the testing data set. And finally, we applied the same comparison criteria to assess the accuracy and precision of our models. Both grid model results are, respectively, shown in Tables 5 and 6.

Energies **2024**, *17*, x FOR PEER REVIEW 15 of 28

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Table 5. Regression model testing results using IEEE-10 bus grid.

IEEE-10 Bus Model	MSE	RMSE	MAE	MAPE	R^2
Value	618.24	24.86	13.33	2.32	0.95
Recommendation				<10	~1

Table 6. Regression model testing results using 14-bus grid model.

14-Bus Grid Model	MSE	RMSE	MAE	MAPE	R^2
Value	970.55	31.15	21.89	2.24	0.95
Recommendation				<10	~1

The evaluation metrics indicate that the predictive model performs well, with low error values and a high coefficient of determination (R^2). Compared to a baseline model using simple polynomial regression, the developed predictive model demonstrates comparable performance, with slightly higher error metrics and lower R^2 value (Appendix C—Table A5).

While the developed predictive model demonstrates strong performance in predicting the impact of a DER integration on the total technical losses of an electric grid, several limitations should be acknowledged to provide a comprehensive understanding of its capabilities and constraints. Firstly, the model's predictive accuracy may be influenced by the quality and representativeness of the training data. Hence, a larger data set for training might help improve the predictivity of the model.

Additionally, the analysis of the predicted values across the three tested models showed that the model tends to divert from the baseline model, thus resulting in higher error when the load connected to the bus is high and the total impedance is high. This divergence was less noticed once just one of these factors (high load or high total impedance) was applicable. Lastly, the developed dynamic varying coefficient regression model was not tested for radial topology. Additionally, the model was tested on a symmetrical balanced load, considering a pure sine wave for voltage and current. Hence, further analysis is required to test the validity of the proposed dynamic regression model for non-symmetrical unbalanced loads. Therefore, while the predictive model offers valuable insights into the impact of DER integration on the grid's technical losses, it should be used judiciously to make informed decisions in real-world scenarios. Ongoing refinement and validation of the model are essential to address these limitations and enhance its robustness and applicability in diverse contexts.

6. Conclusions

As the energy landscape continues to evolve, optimizing DERs and minimizing technical losses in the electric grid will play an increasingly crucial role. Regression models offer a powerful tool for achieving these goals by analyzing vast amounts of data and predicting the performance of DERs. By leveraging the power of predictive modeling, grid operators, energy providers, and end consumers can unlock the true potential of DERs. This will lead to a more sustainable and efficient energy system and pave the way for a greener and more resilient future.

This article introduces a novel regression model for calculating technical losses in electric power distribution systems. Developing accurate methods for estimating technical losses is crucial for utilities to optimize their operations, enhance grid efficiency, and reduce financial losses. The regression model proposed in this study offers a data-driven approach to estimate technical losses based on key system parameters and operational characteristics such as DER integration level, line impedance, and active load connected to a certain bus. One of the strengths of the proposed dynamic varying coefficient regression model is its flexibility and simplicity, making it suitable for easy implementation in optimization algorithms, control loops, or calculation models. The main advantage of such a model is that it does not require considerable computational power or time and can be used without unique technical expertise. Moreover, we have demonstrated the model's ability to accurately predict technical losses across various scenarios and operating conditions through comprehensive data analysis and regression modeling techniques.

While the regression model shows promising results, it is essential to acknowledge its limitations and areas for further improvement. Future research could focus on enhancing the model's predictive capabilities by training the model with a more extensive data set and incorporating additional factors such as voltage levels, equipment conditions, and grid modernization initiatives. Furthermore, validation studies in real-world utility settings are valuable for assessing the model's performance and practical utility.

Overall, the regression model presented in this article represents a significant advancement in technical loss calculation in electric power distribution systems as a function of the DER integration level. By providing utilities with a reliable tool for assessing the impact of DER integration level on technical losses, the model contributes to the optimization of grid operations, better selection of DER integration points for higher grid resilience and efficiency, improved energy management, and, ultimately, the delivery of reliable and cost-effective electricity to consumers. Continued research and collaboration in this area will further advance our understanding of technical losses and support the development of innovative solutions for a sustainable energy future.

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Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. IEEE-33 Bus Grid Model Data

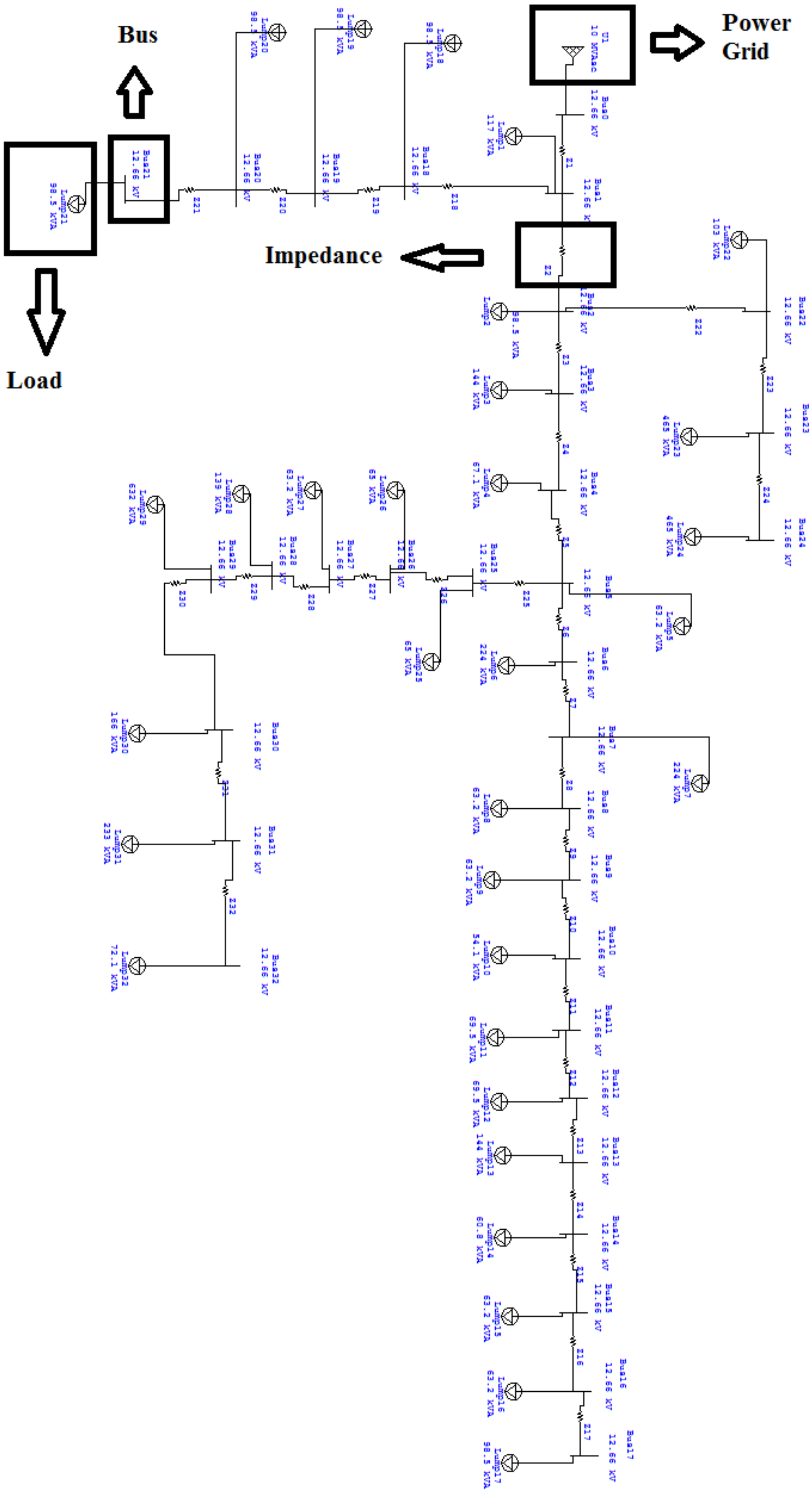

Table A1. Buses resistance and reactance data.

Impedance Reference	Connection	x (Ohm)	r (Ohm)	Impedance z (Ohm)
Z1	Bus 0_1	0.0922	0.477	0.485829023
Z2	Bus 1_2	0.493	0.2511	0.553263238
Z3	Bus 2_3	0.366	0.1864	0.410732224
Z4	Bus 3_4	0.3811	0.1941	0.427682148
Z5	Bus 4_5	0.819	0.707	1.081947318
Z6	Bus 5_6	0.1872	0.6188	0.646496156
Z7	Bus 6_7	1.7114	1.2351	2.110535944
Z8	Bus 7_8	1.03	0.74	1.268266534
Z9	Bus 8_9	1.044	0.74	1.279662455
Z10	Bus 9_10	0.1966	0.065	0.207066559
Z11	Bus 10_11	0.3744	0.1238	0.394337165
Z12	Bus 11_12	1.468	1.155	1.867899623
Z13	Bus 12_13	0.5416	0.7129	0.895297141
Z14	Bus 13_14	0.591	0.526	0.791174443
Z15	Bus 14_15	0.7463	0.545	0.924115085
Z16	Bus 15_16	1.289	1.721	2.150200456
Z17	Bus 16_17	0.732	0.574	0.930215029
Z18	Bus 1_18	0.164	0.1565	0.226689766
Z19	Bus 18_19	1.5042	1.3554	2.02477821
Z20	Bus 19_20	0.4095	0.4784	0.629727568
Z21	Bus 20_21	0.7089	0.9373	1.175189559
Z22	Bus 2_22	0.4512	0.3083	0.546470795
Z23	Bus 22_23	0.898	0.7091	1.144214495
Z24	Bus 23_24	0.896	0.7011	1.137698207
Z25	Bus 5_25	0.203	0.1034	0.227816944
Z26	Bus 25_26	0.2842	0.1449	0.319007288
Z27	Bus 26_27	1.059	0.9337	1.411834512
Z28	Bus 27_28	0.8042	0.7006	1.066573017
Z29	Bus 28_29	0.5075	0.2585	0.56954236
Z30	Bus 29_30	0.9744	0.936	1.351129661
Z31	Bus 30_31	0.3105	0.3619	0.47684574
Z32	Bus 31_32	0.341	0.5302	0.63039118

Table A2. Buses load and total impedance values.

Bus Number	Load (KW)	Load (KVA)	Total Impedance Z (Ohm)
1	100	117	0.4858
2	90	98.5	1.0391
3	120	144	1.4498
4	60	67.1	1.8775
5	60	63.2	2.9595

Table A2. *Cont.*

Bus Number	Load (KW)	Load (KVA)	Total Impedance Z (Ohm)
6	200	224	3.6060
7	200	224	5.7165
8	60	63.2	6.9848
9	60	63.2	8.2644
10	45	54.1	8.4715
11	60	69.5	8.8658
12	60	69.5	10.7337
13	120	144	11.6290
14	60	60.8	12.4202
15	60	63.2	13.3443
16	60	63.2	15.4945
17	90	98.5	16.4247
18	90	98.5	0.7125
19	90	98.5	2.7373
20	90	98.5	3.3670
21	90	98.5	4.5422
22	90	103	1.5856
23	420	465	2.7298
24	420	465	3.8675
25	60	65	3.1873
26	60	65	3.5063
27	60	63.2	4.9181
28	120	139	5.9847
29	200	632	6.5542
30	150	166	7.9054
31	210	233	8.3822
32	60	72.1	9.0126

Appendix B. Non Linear Fitting Equations

Ref.	Equation	Ref.	Equation
1	Y = A*(X1^B)*X2^C	136	Y = (A+X2)/(B+C*X1^2)+D*X1
2	Y = X1/(A+B*X2)	137	Y = A*X1^(B*X2^C)+D*X1
3	Y = X2/(A+B*X1)	138	Y = A*X2^(B*X1^C)+D*X1
4	Y = A*X1^(B*X2)	139	Y = A*X1+B*X2+C*X1^4
5	Y = A*X2^(B*X1)	140	Y = A*X1+B*X1^3+C*X2+D*X2^3
6	Y = A*X1^(B/X2)	141	Y = A*(X1^B)*LOG(X2+C)+D*X2
7	Y = A*X2^(B/X1)	142	Y = A*(X2^B)*LOG(X1+C)+D*X2
8	Y = A*X1+B*X2^2	143	Y = A/X1+B*EXP(C/X2)+D*X2
9	Y = A*X2+B*X1^2	144	Y = A/X2+B*EXP(C/X1)+D*X2

Table A2. *Cont.*

Ref.	Equation	Ref.	Equation
10	Y = X1/(A+B*X2^2)	145	Y = A/X1+B*EXP(C*X2)+D*X2
11	Y = X2/(A+B*X1^2)	146	Y = A/X2+B*EXP(C*X1)+D*X2
12	Y = A*(B^X1)*X2^C	147	Y = A*X1^(B+C*X2)+D*X2
13	Y = A*(B^X2)*X1^C	148	Y = A*X2^(B+C*X1)+D*X2
14	Y = A*(X1*X2)^B	149	Y = A*X1^(B+C/X2)+D*X2
15	Y = A*(X1/X2)^B	150	Y = A*X2^(B+C/X1)+D*X2
16	Y = A*(X1/X2)^B+C	151	Y = A*X1^(B+C*LOG(X2))+D*X2
17	Y = A*(B^(1/X1))*X2^C	152	Y = A*X2^(B+C*LOG(X1))+D*X2
18	Y = A*(B^(1/X2))*X1^C	153	Y = A*X2^(B+C/LOG(X1))+D*X2
19	Y = A+B/X1+C/X2^2	154	Y = A*X1^(B+C/LOG(X2))+D*X2
20	Y = A+B/X2+C/X1^2	155	Y = A*EXP(B*X1+C*X2^2)+D*X2
21	Y = A+B*X1+C/X2	156	Y = A*EXP(B*X2+C*X1^2)+D*X2
22	Y = A+B*X2+C/X1	157	Y = A*EXP(B/X1+C*X2)+D*X2
23	Y = A*((X1/B)^C)*EXP(X2/B)	158	Y = A*EXP(B/X2+C*X1)+D*X2
24	Y = A*((X2/B)^C)*EXP(X1/B)	159	Y = (A+X1)/(B+C*X2)+D*X2
25	Y = A+B*X1+C*X2^2	160	Y = (A+X2)/(B+C*X1)+D*X2
26	Y = A+B*X2+C*X1^2	161	Y = (A+X1)/(B+C*X2^2)+D*X2
27	Y = A*(X1^B)*X2^C+D	162	Y = (A+X2)/(B+C*X1^2)+D*X2
28	Y = X1/(A+B*X2)+C	163	Y = A*X1^(B*X2^C)+D*X2
29	Y = X2/(A+B*X1)+C	164	Y = A*X2^(B*X1^C)+D*X2
30	Y = A*X1^(B*X2)+C	165	Y = A*X1+B*X2+C*X2^4
31	Y = A*X2^(B*X1)+C	166	Y = A*X1+B/X1^3+C*X2+D/X2^3
32	Y = A*X1^(B/X2)+C	167	Y = A*(X1^B)*LOG(X2+C)+D/X2
33	Y = A*X2^(B/X1)+C	168	Y = A*(X2^B)*LOG(X1+C)+D/X2
34	Y = A*(B^(1/X1))*X2^C+D	169	Y = A/X1+B*EXP(C/X2)+D/X2
35	Y = A*(B^(1/X2))*X1^C+D	170	Y = A/X2+B*EXP(C/X1)+D/X2^2
36	Y = X1/(A+B*X2^2)+C	171	Y = A/X1+B*EXP(C*X2)+D/X2
37	Y = X2/(A+B*X1^2)+C	172	Y = A/X2+B*EXP(C*X1)+D/X2^2
38	Y = A*(B^X1)*X2^C+D	173	Y = A*X1^(B+C*X2)+D/X2
39	Y = A*(B^X2)*X1^C+D	174	Y = A*X2^(B+C*X1)+D/X2
40	Y = A*((X1/B)^C)*EXP(X2/B)+D	175	Y = A*X1^(B+C/X2)+D/X2
41	Y = A*((X2/B)^C)*EXP(X1/B)+D	176	Y = A*X2^(B+C/X1)+D/X2
42	Y = 1/(A+B*X1+C/X2)	177	Y = A*X1^(B+C*LOG(X2))+D/X2
43	Y = 1/(A+B*X2+C/X1)	178	Y = A*X2^(B+C*LOG(X1))+D/X2
44	Y = A+B*X1+C/X2^2	179	Y = A*X2^(B+C/LOG(X1))+D/X2
45	Y = A+B*X2+C/X1^2	180	Y = A*X1^(B+C/LOG(X2))+D/X2
46	Y = A*X1^(B+C*X2)	181	Y = A*EXP(B*X1+C*X2^2)+D/X2
47	Y = A*X2^(B+C*X1)	182	Y = A*EXP(B*X2+C*X1^2)+D/X2
48	Y = A*X1^(B+C/X2)	183	Y = A*EXP(B/X1+C*X2)+D/X2
49	Y = A*X2^(B+C/X1)	184	Y = A*EXP(B/X2+C*X1)+D/X2
50	Y = A*X1^(B+C*LnX2)	185	Y = (A+X1)/(B+C*X2)+D/X2

Table A2. *Cont.*

Ref.	Equation	Ref.	Equation
51	Y = A*X2^(B+C*LnX1)	186	Y = (A+X2)/(B+C*X1)+D/X2
52	Y = A*X2^(B+C/LnX1)	187	Y = (A+X1)/(B+C*X2^2)+D/X2
53	Y = A*X1^(B+C/LnX2)	188	Y = (A+X2)/(B+C*X1^2)+D/X2
54	Y = A*EXP(B*X1+C*X2^2)	189	Y = A*X1^(B*X2^C)+D/X2
55	Y = A*EXP(B*X2+C*X1^2)	190	Y = A*X2^(B*X1^C)+D/X2
56	Y = A*EXP(B/X1+C*X2)	191	Y = A*X1+B*X2+C/X2^4
57	Y = A*EXP(B/X2+C*X1)	192	Y = A*X1+B/X1^2+C*X2+D/X2^2
58	Y = (A+X1)/(B+C*X2)	193	Y = A*(X1^B)*LOG(X2+C)+D/X1
59	Y = (A+X2)/(B+C*X1)	194	Y = A*(X2^B)*LOG(X1+C)+D/X1
60	Y = (A+X1)/(B+C*X2^2)	195	Y = A/X1+B*EXP(C/X2)+D/X1^2
61	Y = (A+X2)/(B+C*X1^2)	196	Y = A/X2+B*EXP(C/X1)+D/X1
62	Y = A*EXP(B*X1)+C*EXP(D*X2)	197	Y = A/X1+B*EXP(C*X2)+D/X1^2
63	Y = A*(EXP(B*X1)-EXP(C*X2))	198	Y = A/X2+B*EXP(C*X1)+D/X1
64	Y = A*X1^B+C*X2^D	199	Y = A*X1^(B+C*X2)+D/X1
65	Y = A*X1^B+C*EXP(D*X2)	200	Y = A*X2^(B+C*X1)+D/X1
66	Y = A*X2^B+C*EXP(D*X1)	201	Y = A*X1^(B+C/X2)+D/X1
67	Y = A*(X1^B)*(C-X2)^D	202	Y = A*X2^(B+C/X1)+D/X1
68	Y = A*(X2^B)*(C-X1)^D	203	Y = A*X1^(B+C*LOG(X2))+D/X1
69	Y = (A+B*X1^C)/(D+X2^C)	204	Y = A*X2^(B+C*LOG(X1))+D/X1
70	Y = (A+B*X2^C)/(D+X1^C)	205	Y = A*X2^(B+C/LOG(X1))+D/X1
71	Y = (A+B*X1)/(1+C*X2+D*X2^2)	206	Y = A*X1^(B+C/LOG(X2))+D/X1
72	Y = (A+B*X2)/(1+C*X1+D*X1^2)	207	Y = A*EXP(B*X1+C*X2^2)+D/X1
73	Y = A*X1^(B*X2^C)	208	Y = A*EXP(B*X2+C*X1^2)+D/X1
74	Y = A*X2^(B*X1^C)	209	Y = A*EXP(B/X1+C*X2)+D/X1
75	Y = X1/(A+B*X2+C*SQ	210	Y = A*EXP(B/X2+C*X1)+D/X1
76	Y = X2/(A+B*X1+C*SQ	211	Y = (A+X1)/(B+C*X2)+D/X1
77	Y = A*X1^B+C*EXP(D/X2)	212	Y = (A+X2)/(B+C*X1)+D/X1
78	Y = A*X2^B+C*EXP(D/X1)	213	Y = (A+X1)/(B+C*X2^2)+D/X1
79	Y = A*X2^2+B*X2+C*X1+D	214	Y = (A+X2)/(B+C*X1^2)+D/X1
80	Y = A*X1^2+B*X1+C*X2+D	215	Y = A*X1^(B*X2^C)+D/X1
81	Y = A*X1^3+B*X1^2+C*X1+D*X2	216	Y = A*X2^(B*X1^C)+D/X1
82	Y = A*X2^3+B*X2^2+C*X2+D*X1	217	Y = A*X1+B*X2+C/X1^4
83	Y = EXP(A+B/X1+C*LOG(X2))	218	Y = A*X1+B/X1^3+C*X2+D*Ln(X2)^3
84	Y = EXP(A+B/X2+C*LOG(X1))	219	Y = A*(X1^B)*LOG(X2+C)+D*Ln(X2)
85	Y = EXP(A+B/X1+C*LOG(X2))+D	220	Y = A*(X2^B)*LOG(X1+C)+D*Ln(X2)
86	Y = EXP(A+B/X2+C*LOG(X1))+D	221	Y = A/X1+B*EXP(C/X2)+D*Ln(X2)
87	Y = A*(X1^B)*LOG(X2+C)	222	Y = A/X2+B*EXP(C/X1)+D*Ln(X2)^2
88	Y = A*(X2^B)*LOG(X1+C)	223	Y = A/X1+B*EXP(C*X2)+D*Ln(X2)
89	Y = A*(X1^B)*LOG(X2+C)+D	224	Y = A/X2+B*EXP(C*X1)+D*Ln(X2)^2
90	Y = A*(X2^B)*LOG(X1+C)+D	225	Y = A*X1^(B+C*X2)+D*Ln(X2)
91	Y = A/X1+B*EXP(C/X2)+D	226	Y = A*X2^(B+C*X1)+D*Ln(X2)

Table A2. *Cont.*

Ref.	Equation	Ref.	Equation
92	Y = A/X2+B*EXP(C/X1)+D	227	Y = A*X1^(B+C/X2)+D*Ln(X2)
93	Y = A/X1+B*EXP(C*X2)+D	228	Y = A*X2^(B+C/X1)+D*Ln(X2)
94	Y = A/X2+B*EXP(C*X1)+D	229	Y = A*X1^(B+C*LOG(X2))+D*Ln(X2)
95	Y = A*X1^(B+C*X2)+D	230	Y = A*X2^(B+C*LOG(X1))+D*Ln(X2)
96	Y = A*X2^(B+C*X1)+D	231	Y = A*X2^(B+C/LOG(X1))+D*Ln(X2)
97	Y = A*X1^(B+C/X2)+D	232	Y = A*X1^(B+C/LOG(X2))+D*Ln(X2)
98	Y = A*X2^(B+C/X1)+D	233	Y = A*EXP(B*X1+C*X2^2)+D*Ln(X2)
99	Y = A*X1^(B+C*LOG(X2))+D	234	Y = A*EXP(B*X2+C*X1^2)+D*Ln(X2)
100	Y = A*X2^(B+C*LOG(X1))+D	235	Y = A*EXP(B/X1+C*X2)+D*Ln(X2)
101	Y = A*X2^(B+C/LOG(X1))+D	236	Y = A*EXP(B/X2+C*X1)+D*Ln(X2)
102	Y = A*X1^(B+C/LOG(X2))+D	237	Y = (A+X1)/(B+C*X2)+D*Ln(X2)
103	Y = A*EXP(B*X1+C*X2^2)+D	238	Y = (A+X2)/(B+C*X1)+D*Ln(X2)
104	Y = A*EXP(B*X2+C*X1^2)+D	239	Y = (A+X1)/(B+C*X2^2)+D*Ln(X2)
105	Y = A*EXP(B/X1+C*X2)+D	240	Y = (A+X2)/(B+C*X1^2)+D*Ln(X2)
106	Y = A*EXP(B/X2+C*X1)+D	241	Y = A*X1^(B*X2^C)+D*Ln(X2)
107	Y = (A+X1)/(B+C*X2)+D	242	Y = A*X2^(B*X1^C)+D*Ln(X2)
108	Y = (A+X2)/(B+C*X1)+D	243	Y = A*X1+B*X2+C*Ln(X2)^4
109	Y = (A+X1)/(B+C*X2^2)+D	244	Y = A*X1+B/X1^2+C*X2+D*Ln(X2)^2
110	Y = (A+X2)/(B+C*X1^2)+D	245	Y = A*(X1^B)*LOG(X2+C)+D*Ln(X1)
111	Y = A*X1^(B*X2^C)+D	246	Y = A*(X2^B)*LOG(X1+C)+D*Ln(X1)
112	Y = A*X2^(B*X1^C)+D	247	Y = A/X1+B*EXP(C/X2)+D*Ln(X1)^2
113	Y = A*X1+B*X2+C	248	Y = A/X2+B*EXP(C/X1)+D*Ln(X1)
114	Y = A*X1+B*X1^2+C*X2+D*X2^2	249	Y = A/X1+B*EXP(C*X2)+D*Ln(X1)^2
115	Y = A*(X1^B)*LOG(X2+C)+D*X1	250	Y = A/X2+B*EXP(C*X1)+D*Ln(X1)
116	Y = A*(X2^B)*LOG(X1+C)+D*X1	251	Y = A*X1^(B+C*X2)+D*Ln(X1)
117	Y = A/X1+B*EXP(C/X2)+D*X1	252	Y = A*X2^(B+C*X1)+D*Ln(X1)
118	Y = A/X2+B*EXP(C/X1)+D*X1	253	Y = A*X1^(B+C/X2)+D*Ln(X1)
119	Y = A/X1+B*EXP(C*X2)+D*X1	254	Y = A*X2^(B+C/X1)+D*Ln(X1)
120	Y = A/X2+B*EXP(C*X1)+D*X1	255	Y = A*X1^(B+C*LOG(X2))+D*Ln(X1)
121	Y = A*X1^(B+C*X2)+D*X1	256	Y = A*X2^(B+C*LOG(X1))+D*Ln(X1)
122	Y = A*X2^(B+C*X1)+D*X1	257	Y = A*X2^(B+C/LOG(X1))+D*Ln(X1)
123	Y = A*X1^(B+C/X2)+D*X1	258	Y = A*X1^(B+C/LOG(X2))+D*Ln(X1)
124	Y = A*X2^(B+C/X1)+D*X1	259	Y = A*EXP(B*X1+C*X2^2)+D*Ln(X1)
125	Y = A*X1^(B+C*LOG(X2))+D*X1	260	Y = A*EXP(B*X2+C*X1^2)+D*Ln(X1)
126	Y = A*X2^(B+C*LOG(X1))+D*X1	261	Y = A*EXP(B/X1+C*X2)+D*Ln(X1)
127	Y = A*X2^(B+C/LOG(X1))+D*X1	262	Y = A*EXP(B/X2+C*X1)+D*Ln(X1)
128	Y = A*X1^(B+C/LOG(X2))+D*X1	263	Y = (A+X1)/(B+C*X2)+D*Ln(X1)
129	Y = A*EXP(B*X1+C*X2^2)+D*X1	264	Y = (A+X2)/(B+C*X1)+D*Ln(X1)
130	Y = A*EXP(B*X2+C*X1^2)+D*X1	265	Y = (A+X1)/(B+C*X2^2)+D*Ln(X1)
131	Y = A*EXP(B/X1+C*X2)+D*X1	266	Y = (A+X2)/(B+C*X1^2)+D*Ln(X1)
132	Y = A*EXP(B/X2+C*X1)+D*X1	267	Y = A*X1^(B*X2^C)+D*Ln(X1)

Table A2. *Cont.*

Ref.	Equation	Ref.	Equation
124	Y = A*X2^(B+C/X1)+D*X1	259	Y = A*EXP(B*X1+C*X2^2)+D*Ln(X1)
125	Y = A*X1^(B+C*LOG(X2))+D*X1	260	Y = A*EXP(B*X2+C*X1^2)+D*Ln(X1)
126	Y = A*X2^(B+C*LOG(X1))+D*X1	261	Y = A*EXP(B/X1+C*X2)+D*Ln(X1)
127	Y = A*X2^(B+C/LOG(X1))+D*X1	262	Y = A*EXP(B/X2+C*X1)+D*Ln(X1)
128	Y = A*X1^(B+C/LOG(X2))+D*X1	263	Y = (A+X1)/(B+C*X2)+D*Ln(X1)
129	Y = A*EXP(B*X1+C*X2^2)+D*X1	264	Y = (A+X2)/(B+C*X1)+D*Ln(X1)
130	Y = A*EXP(B*X2+C*X1^2)+D*X1	265	Y = (A+X1)/(B+C*X2^2)+D*Ln(X1)
131	Y = A*EXP(B/X1+C*X2)+D*X1	266	Y = (A+X2)/(B+C*X1^2)+D*Ln(X1)
132	Y = A*EXP(B/X2+C*X1)+D*X1	267	Y = A*X1^(B*X2^C)+D*Ln(X1)
133	Y = (A+X1)/(B+C*X2)+D*X1	268	Y = A*X2^(B*X1^C)+D*Ln(X1)
134	Y = (A+X2)/(B+C*X1)+D*X1	269	Y = A*X1+B*X2+C*Ln(X1)^4
135	Y = (A+X1)/(B+C*X2^2)+D*X1		

Appendix C. The 14-Bus Grid Model Data

Appendix C. The 14-Bus Grid Model Data

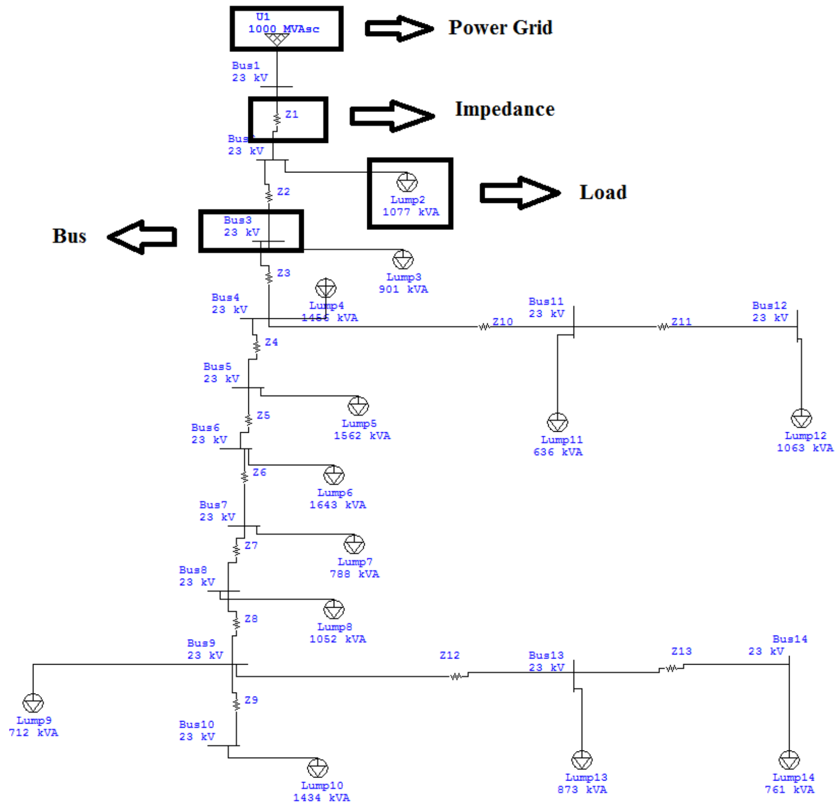

Table A3. Buses resistance and reactance data.

Bus	Impedance Reference	R (Ohm)	X (Ohm)	Z (Ohm)
Bus 1_2	Z1	0.1233	0.4127	0.430725179
Bus 2_3	Z2	0.018	0.0609	0.063504409
Bus 3_4	Z3	0.8463	1.1	1.38788461
Bus 4_5	Z4	0.6984	0.6084	0.926235996
Bus 5_6	Z5	1.531	1.622	2.230436056
Bus 6_7	Z6	0.9	0.78	1.190965994
Bus 7_8	Z7	2.2	1.05	2.437724349
Bus 8_9	Z8	4.52	2.1	4.984014446
Bus 9_10	Z9	5.5	3	6.264982043
Bus 4_11	Z10	0.54	0.92	1.066770828
Bus 11_12	Z11	1.29	1.06	1.66964068
Bus 9_13	Z12	0.93	0.8	1.226743657
Bus 13_14	Z13	2.1	1	2.32594067

Table A4. Buses load and total impedance values.

Bus Reference	Load (KVA)	Load (KW)	Total Impedance Z (Ohm)
2	1077	1000	0.430725179
3	901	850	0.494229588
4	1456	1400	1.882114198
5	1562	1200	2.808350194
6	1643	1530	5.03878625
7	788	780	6.229752245
8	1052	1050	8.667476593
9	712	700	13.65149104
10	1434	1420	19.91647308
11	636	550	2.948885027
12	1063	1020	4.618525706
13	873	800	14.8782347
14	761	635	17.20417537

Table A5. Regression equation coefficients and coefficient of determination (CoD).

	R^2	a	b	c
Bus 2	0.999773182	2.35×10^{-5}	−0.06599	1116.619
Bus 3	0.999812644	1.91×10^{-5}	−0.06524	1116.616
Bus 4	0.999998579	0.000353	−0.6958	1116.585
Bus 5	0.999999199	0.000479	−0.93365	1116.58
Bus 6	0.999999694	0.001858	−2.07243	1116.599
Bus 7	0.999953147	0.000752	−1.27143	1116.459
Bus 8	0.999999724	0.002145	−2.37369	1116.556
Bus 9	0.999991109	0.001346	−2.27562	1117.953
Bus 10	0.999993147	0.012075	−5.53086	1115.824
Bus 11	0.998644071	7.86×10^{-5}	−0.29256	1116.588
Bus 12	0.998644071	0.001013	−0.67768	1117.429
Bus 13	0.999999455	0.002947	−2.77489	1116.533
Bus 14	0.999999423	0.002144	−2.25015	1116.548

Appendix D. IEEE-10 Bus Grid Model Data

Appendix D. IEEE-10 Bus Grid Model Data

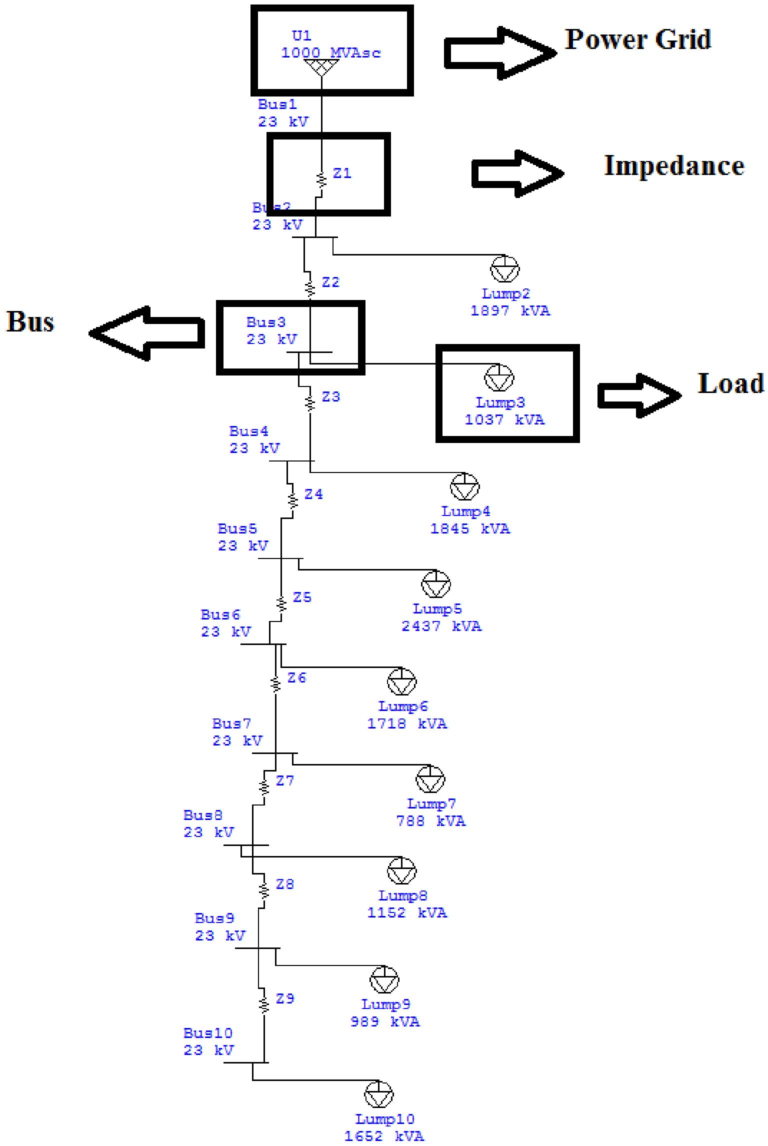

Table A6. Buses resistance and reactance data.

Table A6. Buses resistance and reactance data.

Bus	Impedance Reference	X (Ohm)	R (Ohm)	Z (Ohm)
Bus 1_2	Z1	0.1233	0.4127	0.430725
Bus 2_3	Z2	0.014	0.6057	0.605862
Bus 3_4	Z3	0.7463	1.205	1.417388
Bus 4_5	Z4	0.6984	0.6084	0.926236
Bus 5_6	Z5	1.9831	1.7276	2.630074
Bus 6_7	Z6	0.9053	0.7886	1.200607
Bus 7_8	Z7	2.0552	1.164	2.361936
Bus 8_9	Z8	4.7943	2.716	5.51017
Bus 9_10	Z9	5.3434	3.0264	6.14093

Table A7. Buses load and total impedance values.

Bus Reference	Load (KW)	Load (KVA)	Total Impedanc
2	1840	1897	0.4307
3	980	1037	0.6059
4	1790	1845	1.4174

Table A7. Buses load and total impedance values.

Bus Reference	Load (KW)	Load (KVA)	Total Impedance Z (Ohm)
2	1840	1897	0.4307
3	980	1037	0.6059
4	1790	1845	1.4174
5	1598	2437	0.9262
6	1610	1718	2.6301
7	750	788	1.2006
8	1150	1152	2.3619
9	980	989	5.5102
10	1640	1652	6.1409

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5.4 ARTICLE: OPTIMIZING VIRTUAL POWER PLANT MANAGEMENT: A NOVEL MILP ALGORITHM TO REDUCE LEVELIZED COST OF ENERGY, TECHNICAL LOSSES, AND GREENHOUSE GAS EMISSIONS

Cet article, intitulé « *Optimizing Virtual Power Plant Management: A Novel MILP Algorithm to Reduce Levelized Cost of Energy, Technical Losses, and Greenhouse Gas Emissions*», a été publié dans sa version finale en avril 2024 par les éditeurs du journal *MDPI – Energies.*

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En tant que premier auteur, j’ai contribué à la conceptualisation de la proposition, à l’essentiel de la recherche sur l’état de la question et au développement du modèle de simulation, à la collecte et l’analyse des données et à la rédaction du manuscrit. Professeur Mehdi Adda a participé à la direction du projet, à la supervision du travail, validation des résultats ainsi qu’à la révision de l’article et à la revue de la littérature. Les professeurs Adrian Ilinca, Mazen Ghandour et Hussein Ibrahim en tant que co-auteurs, ont participé à la révision de l’article et à la revue de la littérature.

Résumé : La perspective énergétique moderne est en train de subir une transformation significative vers des sources d'énergie plus propres et décentralisées. Ce changement est motivé par des besoins en matière d'environnement et de développement durable, ce qui entraîne le remplacement des réseaux électriques centralisés traditionnels, qui dépendent fortement des combustibles fossiles, par une gamme diversifiée de ressources énergétiques décentralisées et distribuées. Les VPPs sont apparues comme une solution flexible dans cette transition. Le rôle principal d'une centrale virtuelle est d'optimiser la production, le stockage et la distribution de l'énergie en coordonnant la production de diverses sources connectées. En s'appuyant sur des systèmes de communication et de contrôle avancés, une centrale de production d'énergie peut équilibrer l'offre et la demande en temps réel, offrir des services

auxiliaires et soutenir la stabilité du réseau. Cependant, l'alignement des pratiques économiques et opérationnelles des centrales de production d'électricité sur des objectifs et des politiques environnementaux plus larges est un aspect difficile, mais crucial. Cet article présente un nouvel algorithme de gestion et d'optimisation des centrales de production d'électricité conçue pour une prise de décision rapide et intelligente, visant le coût le plus bas de l'énergie (LCOE), des pertes techniques minimales du réseau et des émissions de GES. L'efficacité de l'algorithme est confirmée en utilisant le réseau de bus IEEE-33 avec 10 générateurs d'énergie distribués différents. Les résultats de la simulation montrent la réactivité de l'algorithme aux variables complexes que l'on trouve dans les scénarios pratiques.

Contexte et Objectifs : Dans le contexte des PADs, l'intégration d'un algorithme d'optimisation des REDs pour des VPPs est cruciale pour maximiser l'efficacité et la résilience du réseau électrique. Ces sous-stations autonomes doivent gérer de manière optimale la production et la distribution d'énergie provenant de multiples sources REDs, telles que les panneaux solaires, les éoliennes et les batteries de stockage. L'algorithme d'optimisation permet de coordonner ces diverses sources pour équilibrer la production et la demande en temps réel, tout en minimisant les coûts énergétiques, les pertes techniques et les émissions de GES. De plus, en exploitant la flexibilité et la décentralisation offertes par les VPPs, l'algorithme peut améliorer la stabilité et la sécurité du réseau, en offrant une réponse rapide aux fluctuations de la demande et aux perturbations potentielles. L'intégration de cet algorithme dans les PADs représente une avancée significative vers la création de réseaux électriques intelligents, autonomes, plus durables et résilients.

Méthodologie : L'algorithme d'optimisation présenté utilise la technique d'optimisation Mixed-Integer Linear Programming (MILP), une méthodologie utilisée pour résoudre des problèmes impliquant des variables de décision continues et discrètes. L'algorithme proposé a été testé à l'aide du modèle de réseau de bus IEEE-33, intégrant plusieurs REDs à différents nœuds. Notamment, les simulations ont pris en compte plusieurs scénarios en tenant compte de plusieurs facteurs tels que le LCOE des différentes sources d'énergie, le coût des émissions de GES, la réserve tournante et la charge de la demande. Compte tenu de la nature intermittente de la plupart des sources d'énergie renouvelable, de l'évolution rapide de la demande d'électricité et de la fluctuation des tarifs d'électricité sur les marchés dynamiques modernes, il est essentiel que notre algorithme puisse s'adapter rapidement à ces changements. Il doit fournir le plus rapidement possible la combinaison de REDs optimale la plus récente pour la VPP. Par conséquent, une analyse de sensibilité est réalisée pour évaluer le temps de réponse de l'algorithme aux changements rapides de la charge ou des prix du marché.

Résultats et Contributions : Cet article présente un algorithme d'optimisation basé sur la méthode MILP, conçu pour améliorer le fonctionnement des VPPs en minimisant le LCOE, les pertes techniques et les émissions de gaz à effet de serre. Grâce à des simulations complètes utilisant le modèle IEEE 33-bus, l'algorithme a démontré son efficacité dans l'optimisation de l'allocation des ressources et des stratégies opérationnelles dans le cadre des centrales électriques virtuelles. Les résultats soulignent la capacité de l'algorithme à atteindre un faible LCOE, tout en tenant compte des pertes techniques du réseau et des émissions de gaz à effet de serre des différentes sources d'énergie. La convergence rapide de l'algorithme MILP souligne en outre son applicabilité pratique pour les scénarios de gestion de l'énergie en temps réel et à grande échelle. Cette étude confirme le potentiel des techniques d'optimisation avancées dans la transformation de la gestion des ressources énergétiques distribuées, ouvrant la voie à des systèmes électriques plus durables et économiquement viables.

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Article

Optimizing Virtual Power Plant Management: A Novel MILP Algorithm to Minimize Levelized Cost of Energy, Technical Losses, and Greenhouse Gas Emissions

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Abstract: The modern energy landscape is undergoing a significant transformation towards cleaner, decentralized energy sources. This change is driven by environmental and sustainability needs, causing traditional centralized electric grids, which rely heavily on fossil fuels, to be replaced by a diverse range of decentralized distributed energy resources. Virtual power plants (VPPs) have surfaced as a flexible solution in this transition. A VPP's primary role is to optimize energy production, storage, and distribution by coordinating output from various connected sources. Relying on advanced communication and control systems, a VPP can balance supply and demand in real time, offer ancillary services, and support grid stability. However, aligning VPPs' economic and operational practices with broader environmental goals and policies is a challenging yet crucial aspect. This article introduces a new VPP management and optimization algorithm designed for quick and intelligent decision-making, aiming for the lowest levelized cost of energy (LCOE), minimum grid technical losses, and greenhouse gas (GHG) emissions. The algorithm's effectiveness is confirmed using the IEEE 33-bus grid with 10 different distributed power generators. Simulation results show the algorithm's responsiveness to complex variables found in practical scenarios, finding the optimal combination of available energy resources. This minimizes the LCOE, technical losses, and GHG emissions in less than 0.08 s, achieving a total LCOE reduction of 16% from the baseline. This work contributes to the development of intelligent energy management systems, aiding the transition towards a more resilient and sustainable energy infrastructure.

Keywords: virtual power plant (VPP); MILP; optimization; LCOE minimization; distributed energy resources; energy management

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1. Introduction

Virtual power plants (VPPs) represent a groundbreaking approach in the management and optimization of distributed energy resources (DERs) [1], enabling a more flexible, resilient, and sustainable energy system [2]. VPPs aggregate various DERs, such as solar panels, wind turbines, battery storage systems, and demand response assets, to operate as a single power plant. This integration allows for the coordinated management of these resources, optimizing their collective output and providing a range of grid services. The concept of VPPs leverages advanced software and communication technologies to monitor, control, and dispatch DERs in real time [3], thereby enhancing the efficiency and reliability of the energy grid. The growing adoption of VPPs is driven by several factors, such as the increasing use of renewable energy sources, advancements in energy storage technology, and the need for greater grid flexibility to accommodate variable demand loads [4]. Traditional power plants, which depend on large, centralized generation units, often struggle to respond quickly to changes in demand or supply. In contrast, VPPs can rapidly adjust their output by aggregating and dispatching energy from multiple, smaller sources. This capability is especially valuable in mitigating the intermittency of renewable energy, like solar and wind, subject to weather-induced fluctuations. One of the main benefits of VPPs is their ability to provide ancillary services to the grid [5]. These services include frequency regulation, voltage support [6], and spinning reserve, which are crucial for maintaining grid stability and reliability. VPPs can respond to grid imbalances faster than traditional power plants by coordinating the output of diverse DERs. For example, during high-demand periods or when there is a sudden drop in generation, VPPs can quickly dispatch stored energy from batteries or reduce demand through demand response mechanisms [7]. This rapid response helps prevent blackouts and ensures a stable electricity supply. Moreover, VPPs improve the economic efficiency of the energy system [8,9]. By optimizing the dispatch of DERs based on real-time market signals and grid conditions, VPPs can reduce the overall cost of electricity. They enable small-scale generators and consumers to participate in energy markets, allowing them to sell excess energy or provide grid services, creating new revenue streams. This democratization of the energy market can result in more competitive pricing and increased adoption of renewable energy technologies. VPPs also contribute to reducing greenhouse gas emissions [10]. By maximizing the use of renewable energy sources and improving energy storage and consumption efficiency, VPPs can significantly lower the energy sector's carbon footprint. Additionally, VPPs facilitate the integration of electric vehicles (EVs) into the grid [11], using them as mobile storage units that provide additional grid flexibility and support. This symbiotic relationship between EVs and VPPs can accelerate the transition to a low-carbon energy system. Additionally, VPPs' role in enhancing grid resilience is especially relevant in the context of climate change, which is increasing the frequency and severity of extreme weather events. VPPs can improve the grid's ability to withstand and recover from disruptions by providing decentralized and distributed power sources [12]. During natural disasters, when centralized power plants and transmission lines may be compromised, VPPs can continue to supply electricity from local sources, supporting critical infrastructure and community resilience [13].

The development and deployment of VPPs are supported by advancements in digital technologies like the Internet of Things (IoT), artificial intelligence (AI), and blockchain. IoT devices enable real-time monitoring and control of DERs, ensuring optimal performance and coordination. AI algorithms can analyze vast amounts of grid and DER data to predict demand patterns, optimize energy dispatch, and identify potential issues before they escalate. Blockchain technology enhances the security and transparency of transactions within the VPP ecosystem, facilitating trust and cooperation among participants [14]. Nevertheless, despite VPPs' numerous benefits, several challenges must be addressed to fully realize their potential. One key challenge is the integration of diverse DERs with varying characteristics and capabilities. Ensuring seamless communication and interoperability among these resources requires standardized protocols and robust communication infrastructure. Also, regulatory and market frameworks must evolve to accommodate VPPs' unique features. This includes creating fair compensation mechanisms for the services provided by VPPs and removing barriers to market entry for small-scale participants [15]. Another significant challenge is the cybersecurity of VPPs. The energy system's increasing digitalization and interconnectedness make it more vulnerable to cyberattacks [16]. Protecting VPPs from potential threats requires stringent cybersecurity measures and continuous monitoring for suspicious activities. Ensuring data privacy and securing communication channels are also crucial for a resilient VPP infrastructure. VPPs' role in enhancing grid resilience is especially relevant in the context of climate change, which is increasing the frequency and severity of extreme weather events. VPPs can improve the grid's ability to withstand and recover from disruptions by providing decentralized and distributed power sources. During natural disasters, when centralized power plants and transmission lines may be compromised, VPPs can continue to supply electricity from local sources, supporting critical infrastructure and community resilience.

Still, efficiently dispatching DERs to match supply with demand while minimizing operational costs and losses remains one of the most crucial points in the VPP's framework. This requires advanced algorithms capable of real-time optimization based on market prices and grid conditions. VPPs must prioritize the integration and optimal use of renewable energy sources (RESs) like solar and wind. This involves balancing intermittency and ensuring that renewables are utilized to their fullest potential, which requires advanced forecasting and energy management systems. Optimizing the selection of energy sources in the context of VPPs is imperative to achieving multiple objectives: minimizing costs, enhancing the grid's efficiency, and addressing environmental concerns. By strategically integrating diverse and RESs, VPPs can reduce reliance on expensive and polluting fossil fuels. This optimization allows for a more flexible and responsive energy system, capable of dynamically adjusting to demand fluctuations and resource availability, thereby maximizing operational efficiency. Moreover, the prioritization of cleaner energy sources within VPPs significantly mitigates GHG emissions, contributing to climate change mitigation efforts and promoting sustainable development. Thus, careful selection and management of energy sources in VPPs not only ensure economic benefits and energy security but also align with broader environmental and social responsibilities.

This article introduces a novel optimization algorithm designed to enhance the selection of energy sources within VPPs, effectively balancing supply and demand while minimizing the LCOE. The proposed algorithm not only aims to reduce energy losses but also focuses on decreasing GHG emissions, addressing critical environmental concerns. By leveraging advanced computational techniques and real-time data analytics, this optimization framework ensures efficient and sustainable energy distribution. The implementation of this algorithm promises to bolster the economic viability of VPPs and contribute significantly to the global transition towards cleaner and more resilient energy systems. The algorithm's most significant feature is its adaptability when the power demand is lower than the available power generation capacity. It can intelligently disconnect specific energy sources or shift energy storage systems to charging mode, while ensuring the balance between the supply and demand, reducing energy costs, decreasing energy losses, and minimizing GHG emissions, thus enhancing the overall grid's efficiency and sustainability. The presented optimization algorithm uses the MILP optimization technique, a methodology used to solve problems that involve both continuous and discrete decision variables. It combines linear programming (LP) and mixed integer (MI) programming to handle a wide range of optimization problems.

The proposed algorithm was tested using the IEEE 33-bus grid model, integrating multiple DERs at various nodes. Notably, the simulations considered several scenarios taking several factors into consideration such as the LCOE of the different power sources, the cost of GHG emissions, the spinning reserve, and the demand load. Given the intermittent nature of most DERs, rapidly changing electrical load demands, and the fluctuating electric rates in modern dynamic markets, it is essential that our algorithm can adapt quickly to these changes. It should provide the most up-to-date optimal DER combination for the VPP as swiftly as possible. Therefore, a sensitivity analysis is performed to evaluate the algorithm's response time to rapid changes in load or market prices. Simulation results have demonstrated that the proposed algorithm is capable of providing the optimal combination of DERs every time the input values change within an average time of 0.07 s.

This article is structured to provide a comprehensive examination of the proposed optimization algorithm for VPP management. Following this introduction, the Related Works Section outlines existing research on VPP optimization and highlights the gaps that this study addresses. The MILP Optimization Algorithm Section then details the development and implementation of the optimization algorithm, including its mathematical foundations and computational techniques. Finally, in the Results Analysis Section, the performance of the algorithm is evaluated through various simulations, with a focus on balancing supply and demand, minimizing costs, and reducing greenhouse gas emissions.

2. Related Works

VPPs have emerged as a significant innovation in modern energy management, offering an advanced approach to aggregating and optimizing DERs. The latest advancements in VPP management and optimization aim to tackle various challenges and barriers associated with their deployment, such as lowering the LCOE, minimizing technical losses, reducing GHG emissions, providing the highest grid stability, and achieving the grid's resilience and security.

However, VPPs are data-driven systems. Data play a pivotal role in the effective operation and optimization of VPPs. The integration and analysis of vast amounts of data from various sources, such as smart meters, weather forecasts, market prices, and DERs, are essential for making informed decisions. Accurate and real-time data enable precise forecasting of energy production and consumption, which is critical for balancing supply and demand. The work conducted in article [17] provides a unique perspective on the importance in the context of VPPs, as well as recent real-world projects from around the world, highlighting the most recent VPP practices. Additionally, data analytics help in identifying patterns and trends, optimizing energy dispatch, and improving the overall efficiency and reliability of the power system. Data also facilitate advanced predictive maintenance of equipment, reducing downtime and operational costs. Furthermore, in the context of regulatory compliance and sustainability, comprehensive data collection and analysis are vital for monitoring and reporting greenhouse gas emissions and other environmental impacts. Therefore, robust data management and analytics are fundamental to the success and sustainability of VPPs, enabling them to operate more efficiently, cost-effectively, and environmentally responsibly. Hence, the core of VPP management lies in the optimization algorithms that coordinate the dispatch of DERs. Recent advancements have seen the development of sophisticated algorithms utilizing artificial intelligence (AI) and machine learning (ML). These algorithms can analyze vast amounts of data in real time, enhancing the efficiency and responsiveness of VPPs. AI and ML algorithms can forecast energy demand and supply more accurately by analyzing historical data, weather patterns, and market signals. This predictive capability enables VPPs to balance supply and demand more effectively. Additionally, advanced optimization techniques, like MILP and dynamic programming, are used to solve complex scheduling problems in VPPs. These techniques consider multiple objectives to provide optimal solutions. Article [18] explores the effects of renewable production sources and storage devices on an electrical grid using an MILP optimization model to enhance the economic profitability of a VPP. Similarly, the work conducted in [19] uses an MILP-based algorithm that optimizes the daily profit of a VPP. On the other side, other researchers have adopted non-linear methodologies to deal with the intermittent and dynamic nature of VPPs. The authors in article [20] have adopted the information gap decision theory (IGDT) methodology to deal with the high level of uncertainties associated with VPPs. The IGDT is a powerful framework for making decisions under severe uncertainty, where the probability distributions of uncertainties are not well defined or are completely unknown. In the context of VPPs, IGDT can be particularly beneficial given the inherent uncertainties in renewable energy generation, market prices, and load demands. IGDT and MILP can be synergistically integrated to optimize the management of VPPs by addressing both uncertainty and operational efficiency. IGDT provides a robust framework for decision-making under uncertainty, allowing for the consideration of various scenarios and the management of risks associated with unpredictable factors such as fluctuating energy demands or supply disruptions. On the other hand, MILP offers a structured approach to optimize complex systems by formulating the problem as a set of linear equations and inequalities, which can efficiently handle operational constraints and objectives. By layering IGDT on top of MILP, VPP management can be optimized to account for the uncertainty in input parameters, such as renewable energy availability or market prices, while still adhering to operational constraints and maximizing performance metrics. This combined approach enables the development of robust strategies that balance risk and efficiency, ensuring that VPPs can effectively respond to dynamic conditions and optimize their performance across various scenarios. However, the subject article does not address the issue of uncertainty in input parameters but focuses solely on providing an optimization algorithm aimed at enhancing operational efficiency. By concentrating on this aspect, the article presents a method for optimizing the performance of VPPs based on fixed, predetermined inputs rather than exploring how variations and uncertainties in these inputs might affect the optimization process.

As the field evolved, heuristic and metaheuristic algorithms, including genetic algorithms (GAs) and particle swarm optimization (PSO), were introduced to tackle the computational complexity and scalability issues inherent in large-scale VPP optimization problems. In article [21], the authors use a GA to solve the operation issues resulting from the interaction of the VPP and the distribution network. Also, article [22] uses a genetic algorithm to manage the charge and discharge of EVs to enhance the economic and technical performance of a VPP. The authors of article [23] propose an accelerated particle swarm optimization (PSO) for optimal dispatch of renewable energy sources in a VPP context.

Stochastic and robust optimization methods have also gained prominence, addressing the fluctuations in renewable energy generation and market conditions by incorporating probabilistic and worst-case scenario analyses. The work presented in article [24] offers a multistage stochastic programming approach to model the trading of a VPP, and in article [25] the authors use a bi-level stochastic scheduling optimization model that combines day-ahead and real-time scheduling to mitigate the impact of uncertainty on VPP operations and reduce system power shortfall costs. On the other hand, the authors in article [26] apply a robust optimization method to maximize the profit of the VPP in the energy market and similarly in article [27] also a robust optimization method is applied to achieve an efficient VPP bidding technique in pool-based electricity markets. Additionally, hybrid approaches that combine multiple optimization techniques have been explored to leverage their respective strengths, resulting in more robust and efficient VPP management strategies, as applied in article [28].

Furthermore, the application of big data analytics and digital twins (DTs) has facilitated enhanced decision-making through detailed simulations and real-time data processing. The efficient management and analysis of vast amounts of data generated by VPPs are crucial for optimizing their performance. Leveraging big data analytics enables the processing and analysis of large datasets to extract valuable insights. Cloud computing provides scalable storage and processing capabilities, allowing VPPs to handle large volumes of data efficiently. The work presented in [29] proposes the use of DTs to address VPPs' restrictions and barriers, as well as to improve their performance in a prosumer centric framework, focusing on dynamic state estimation, real-time control, and optimization.

In contrast to conventional AI techniques, recent research explores the potential of quantum computing for optimizing the operational management of VPPs, offering new avenues for addressing complex optimization problems with enhanced computational power and efficiency. The work conducted in [30] introduces a novel stochastic framework using the quantum teaching–learning-based optimization (QTLBO) algorithm for optimizing energy flow in microgrids, demonstrating its superior performance over traditional metaheuristic algorithms by addressing seasonal variations and uncertainties in distributed energy resources with improved accuracy and convergence. Similarly, article [31] presents a hybrid policy-based reinforcement learning (HPRL) approach for adaptive energy management in island energy systems with transmission constraints, using an island energy hub (IEH) model to optimize energy utilization and ensure supply, and demonstrates the effectiveness of this approach through numerical simulations.

Improving the accuracy of demand and supply forecasts enhances the efficiency and reliability of VPPs. AI algorithms, including neural networks and deep learning, can analyze historical data and external factors to provide highly accurate forecasts. Advanced weather prediction models improve the accuracy of renewable energy forecasts, particularly for solar and wind power. Therefore, artificial neural networks (ANNs) have become an integral part of optimization models for VPPs due to their ability to handle complex, non-linear relationships and process large volumes of data efficiently. ANNs are particularly effective in forecasting, optimization, and real-time management within VPP frameworks. In article [32], the authors present an ANN model for optimal scheduling and improving the cost effectiveness of a VPP. Moreover, real-time monitoring and control of DERs is also vital for the efficient operation of VPPs. Recent advancements in the Internet of Things (IoT) and communication technologies have significantly enhanced the real-time capabilities of VPPs. IoT devices and sensor networks provide real-time data on the performance and status of DERs. These data are essential for making informed decisions about resource allocation and dispatch. Edge computing allows data processing to occur closer to the source of data generation, enabling faster decision-making and enhancing the responsiveness of VPPs. The importance of IoT-based real-time management for VPPs is highlighted in article [33].

The future of VPPs is shaped by ongoing innovations and emerging trends that promise to enhance their capabilities and address existing challenges. Energy storage systems play a critical role in the functionality of VPPs [34] by storing excess energy during periods of low demand and releasing it during peak demand. Recent advancements in battery technology and energy management systems have significantly improved the efficiency and cost-effectiveness of ESS. Innovations in battery technology, like solid-state batteries and advanced lithium-ion batteries, offer higher energy density, longer lifespan, and improved safety compared to traditional batteries. Advanced energy management systems (EMSs) optimize the charge and discharge cycles of batteries, ensuring that energy storage is used efficiently. In article [35], the authors propose a GA-based smart energy resources allocation algorithm to account for depreciation of batteries resulting from discharges in the context of a VPP. Likewise, EVs are increasingly being integrated into VPPs, providing additional flexibility and storage capacity. V2G technology allows EVs to act as mobile energy storage units, providing power to the grid during peak demand and charging during low demand as highlighted in article [36]. Smart charging systems optimize the charging and discharging of EVs based on grid conditions and market signals [37]. Blockchain technology offers a decentralized and transparent platform for energy trading, enhancing the efficiency and security of VPP operations. Blockchain enables P2P energy trading, allowing consumers to buy and sell energy directly with each other. Smart contracts automate and enforce agreements between participants, ensuring transparency and reducing administrative overhead [38].

The latest advancements in VPP management and optimization are transforming the energy landscape, offering innovative solutions to mitigate the challenges and barriers associated with their deployment. By leveraging advanced algorithms, real-time monitoring, enhanced energy storage, supportive policies, and emerging technologies, VPPs are poised to lower the levelized cost of energy, minimize technical losses, and reduce greenhouse gas emissions. These advancements not only enhance the economic viability of VPPs but also contribute to a more sustainable and resilient energy future. As the energy sector continues to evolve, VPPs will play an increasingly critical role in integrating renewable energy, improving grid stability, and empowering consumers to participate actively in the energy market. Ongoing innovation and collaboration among stakeholders will ensure that VPPs remain at the forefront of the transition to a cleaner and more efficient energy system. Building on this perspective, the MILP-based VPP optimization algorithm, presented in this article, makes a significant contribution by effectively minimizing the LCOE while simultaneously accounting for carbon costs and grid technical losses. By integrating carbon pricing into the optimization model, the algorithm ensures that the economic implications of greenhouse gas emissions are considered, promoting environmentally sustainable energy production. Hence, the proposed MILP algorithm developed for minimizing the LCOE of a VPP incorporates several critical technical indicators to achieve its objective. Firstly, the algorithm meticulously accounts for the technical losses associated with the integration of DERs, ensuring that these losses are minimized to enhance overall system efficiency. This is achieved by optimizing the scheduling and dispatch of DERs to reduce energy waste and improve the reliability of energy delivery. Therefore, the cost of the total technical losses of the grid are included in the calculation of the overall LCOE. By incorporating technical losses into the grid's operational costs, the algorithm provides a more accurate reflection of the true advantages of energy distribution, leading to more efficient resource allocation and energy dispatch. Additionally, the algorithm evaluates the cost implications of GHG emissions produced by various energy sources, integrating these costs into the optimization process to ensure that the environmental impact is considered alongside economic factors. By including both the reduction in technical losses and the cost of GHG emissions, the MILP algorithm provides a comprehensive approach to minimizing LCOE, balancing operational efficiency with environmental and economic sustainability. This multi-faceted approach ensures that the VPP operates at an optimal level while addressing both technical and ecological concerns. The algorithm's ability to balance these complex factors underscores its potential to transform VPP management, paving the way for more sustainable and cost-effective energy systems.

3. MILP Optimization Algorithm

In order to provide an optimized cost-effective and efficient energy management for VPPs, the MILP optimization technique has been used. MILP is a mathematical optimization technique used to solve problems involving both continuous and discrete decision variables. The MILP algorithm is based on two main mathematical functions. The first function is the mixed integer (MI) element, and the second one is the linear programming function. The MI element refers to the inclusion of integer or binary decision variables, which allows for the modelling of discrete decisions within the optimization problem. The LP function is a mathematical method used to optimize a linear objective function subject to linear constraints. The key characteristics of LP are that the objective function and constraints are linear equations or inequalities, and the decision variables are continuous, meaning they can take any real value within a specified range. MILP algorithms are designed to find the best possible solution that satisfies all constraints, ensuring optimality in decision-making. MILP is widely used in fields such as energy management and scheduling, supply chain and logistics optimization, financial planning and portfolio optimization, and manufacturing and production planning. The objective function in MILP is a linear function that needs to be maximized or minimized. It typically takes the following form:

$$Min_x(or\ Max_x)c^T x \tag{1}$$

where c is a vector of coefficients, and x is a vector of decision variables that can either be continuous or discrete. Vector c contains coefficients that represent the contribution of each decision variable to the objective function, such as cost, profit, or resource usage. Vector x consists of the decision variables, which are the elements that the optimization process will determine. These variables can be continuous, integer, or binary. Additionally, the constraints of the MILP model are expressed in the following form:

$$Ax \leq b \tag{2}$$

where A is a matrix of constraint coefficients, x is the vector of decision variables, and b is a vector of constants representing the right-hand side of the constraints. The constraints ensure that the solution adheres to various restrictions such as resource limits, capacity constraints, or operational bounds. Through this formulation, the MILP model aims to find the optimal values for the decision variables that satisfy all constraints while optimizing the objective function.

In the context of optimizing VPPs, MILP is used to optimize the selection of energy sources and their operation schedules to achieve objectives like minimizing the LCOE, balancing supply and demand, reducing losses, and decreasing GHG emissions. The vector of coefficients includes the incurred costs of energy, GHG emissions, and technical losses, while the constraints involve load balancing, maximum emissions value in kg of CO_2 per kWh, and maximum accepted total LCOE. Hence, in our case the MILP is used to minimize the total cost of power supply of the VPP by minimizing the total LCOE of the connected DERs, minimizing the cost of emissions resulting from penalties paid for CO_2e emissions, and minimizing the cost of technical losses. Hence, the MILP formula is given by Equation (3):

$$Min\ Costfunction = \varphi_{LCOE} + \varphi_{GHG} + \varphi_{Losses} \quad (3)$$

where φ_{LCOE} is the combined LCOE of all the power sources connected to the grid including both the utility power generators and the DERs, φ_{GHG} is the combined cost of GHG emissions from the different power sources, and φ_{Losses} is the combined cost incurred by the grid's technical losses.

The first step of the MILP algorithm is to formulate the problem as a mathematical optimization model. This involves defining the decision variables, the objective function to be minimized, and the constraints that the solution must satisfy. Thus, the first item of the MILP equation is the combined LCOE of the different considered generators. The LCOE is a measure of the average net present cost of electricity generation for a generator over its lifetime. It is a metric used to assess the average cost of producing electricity from a specific power source and it accounts for all the costs associated with the project, including initial capital costs, ongoing operation and maintenance costs, fuel costs, and financing costs. The LCOE is typically expressed in monetary terms per unit of electricity generated ($/kWh). When combining different energy sources to form a composite or blended LCOE, it is essential to consider the proportional contributions of each energy source to the total energy mix. Thus, the combine LCOE (φ_{LCOE}) is provided by Equation (4):

$$\varphi_{LCOE} = \frac{\sum_{i=1}^{N} x_i \times LCOE_i \times P_i}{\sum_{i=1}^{N} x_i \times P_i} \quad (4)$$

where $LCOE_i$ is the levelized cost of energy of the power source i, P_i is the power in kW provided by the power source i in kW, x_i is a binary decision variable (equal to 1 if the power source is selected to be connected to the grid and 0 if not), and N is the set of available power sources to select among and optimize the VPP.

The second item of the MILP equation is the combined cost of GHG emissions. The cost of GHG emissions rights, also known as carbon pricing, can vary significantly depending on the specific market, regulatory framework, and geographical region. Carbon pricing, usually expressed in dollars per tonne of CO_2 ($/t CO_2), is a financial measure used to assign a cost to the emission of one metric tonne of carbon dioxide CO_2 into the atmosphere. This pricing mechanism is a key tool in climate policy aimed at reducing greenhouse gas emissions by making it more expensive to emit CO_2. In the context of a VPP that aggregates multiple energy sources, calculating the combined carbon pricing involves determining the weighted average carbon cost based on the contributions and carbon emissions of each energy source, as presented in Equation (5):

$$\varphi_{GHG} = \partial \times \frac{\sum_{i=1}^{N} x_i \times GHG_i \times P_i}{\sum_{i=1}^{N} x_i \times P_i} \quad (5)$$

where GHG_i is the CO_2e emissions of the power source i in kg of CO_2e/kWh, and ∂ is the carbon price of the power source i in $/kg of CO_2e.

Finally, the last element of the MILP equation is to determine the cost of the technical losses in the grid. Technical losses refer to the energy losses that occur in the process of transmitting and distributing electricity from power plants to end-users. These losses are inherent to the physical and electrical properties of the transmission and distribution infrastructure and are different from non-technical losses, which result from theft, billing errors, or other non-physical causes. Technical losses in the electrical grid, such as transmission and distribution losses, are not typically included in the calculation of the LCOE. In order to account for the technical losses cost, first it is fundamental to determine the total technical losses in the grid, then calculate the cost associated with technical losses, which involves multiplying the amount of lost energy by the cost of generating that energy, and finally distribute the cost of technical losses among consumers based on their consumption. However, the trickiest part of the procedure is to calculate the grid's technical losses. Usually, calculating the technical losses involves sophisticated and time-consuming techniques such as power flow analysis. Nevertheless, for the proper performance of our optimization algorithm, it is very important to rapidly calculate these losses. For this reason, we used the dynamic varying coefficient regression model, presented in article [39], to analytically estimate the grid's technical losses. The aforementioned model is given by Equation (6):

$$y = f_a(L_i, Z_i) \cdot x_i^2 + f_b(L_i, Z_i) \cdot x_i + c \tag{6}$$

where

$$f_a(L_i, Z_i) = \frac{L_i}{(642.896 - 45.0559 \times Z_i)} \tag{7}$$

$$f_b(L_i, Z_i) = 0.001472 \times Z_i \times L_i \tag{8}$$

$$c = Initial\ losses\ of\ the\ grid \tag{9}$$

Therefore, by using Equation (6) to calculate the contribution of each DER to the reduction in the grid's technical losses, the cost of the technical losses (φ_{Losses}) can be calculated using Equation (10):

$$\varphi_{Losses} = \varphi_{LCOE} \times \frac{\left[c - \sum_{i=1}^{N} (c - y_i) \times x_i\right]}{Load} \tag{10}$$

where the contribution of DER to the reduction in grid technical losses is given by $(c - y_i)$, the total reduction in grid technical losses from all connected DERs is given by $c - \sum(c - y_i)$, and the distribution of the cost of technical losses over the load is given by $\frac{\left[c - \sum_{i=1}^{N} (c - y_i) \times x_i\right]}{Load}$.

The second step of the MILP algorithm, after formulating the problem as a mathematical optimization model, involves defining the constraints. The first constraint equation balances energy production with load demand, factoring in grid losses and the spinning reserve when necessary for improved grid stability. Therefore, every combination of available connected resources, including both utility grid power generation and DERs, must satisfy Equation (11):

$$\sum (x_i \times P_i) \geq Load + Losses + Spinning\ Reserve \tag{11}$$

In order to ensure that environmental objectives are met alongside economic and operational goals, a second constraint equation (Equation (12)) is added to the algorithm to make sure that the selected combination of power sources (grid and DERs) do not exceed the threshold set for GHG_{Max}.

$$\frac{\sum x_i \times GHG_i \times P_i}{\sum x_i \times P_i} \leq GHG_{Max} \tag{12}$$

Similarly, in order to ensure that the selected mix of DERs remains cost-effective, a third constraint equation (Equation (13)) is added to the algorithm. $LCOE_{Max}$ is a value set by the grid operator and guarantees that the optimized mix of DERs meets the economic limitations. For simulation purposes, the $LCOE_{Max}$ value is set to 0.21 $/kWh.

$$\frac{\sum x_i \times LCOE_i \times P_i}{\sum x_i \times P_i} \leq LCOE_{Max} \tag{13}$$

In a VPP, the power mix includes both grid power and DERs. Hence, with the aim to simulate a real-world scenario, when optimizing the DER selection within the VPP, we extended the MILP model to incorporate both sources while adhering to constraints on CO_2 emissions and LCOE. Thus, the MILP algorithm explores combinations that include the grid alone, a mix of the grid and DERs, and only DERs if they can satisfy the total load demand without additional power from the grid. However, when a mix of the grid and DERs is considered, the power provided by the grid must satisfy Equation (14):

$$P_{grid} = Load - \sum x_i \times P_i \tag{14}$$

In the context of optimizing VPPs using MILP, balancing multiple objectives inherently involves navigating trade-offs between conflicting goals. One of the primary trade-offs is between minimizing the LCOE and reducing greenhouse gas (GHG) emissions. Achieving a lower LCOE often involves utilizing energy sources that may have higher emissions but are cost-effective, while prioritizing lower emissions might necessitate investing in more expensive, cleaner technologies. Additionally, optimizing operational efficiency by reducing technical losses may require adjusting energy dispatch and storage strategies, which could impact both the economic performance and the reliability of the VPP. The MILP model addresses these trade-offs by employing objective functions and constraints that reflect the relative importance of each goal, allowing for a balanced solution. This process involves iterative adjustments to the model parameters and constraints, which are conducted by the grid operator and provided as inputs to the MILP algorithm to find an optimal compromise that meets the predefined performance criteria. By methodically setting the constraints, like $LCOE_{Max}$, GHG_{Max}, and the spinning reserve, the MILP framework facilitates informed decision-making that aligns with the strategic objectives of the VPP, ensuring that the trade-offs between cost, efficiency, and environmental impact are effectively managed.

The overall process of the applied MILP algorithm is summarized in the flow diagram shown in Figure 1. In theory, optimization using the MILP technique can result in one of three outcomes: an optimal solution found, an infeasible model, or an unbounded objective. If an optimal solution is found, it means the algorithm has identified the best possible values for the decision variables that satisfy all constraints and maximize or minimize the objective function. If the model is infeasible, it indicates that no solution exists that meets all the given constraints, implying a contradiction or overly restrictive conditions. Finally, if the objective is unbounded, the algorithm determines that the objective function can be increased indefinitely (for maximization problems) or decreased indefinitely (for minimization problems) without violating any constraints, suggesting that the model lacks necessary bounds or constraints to limit the solution space. The convergence of an MILP algorithm to an optimal value is highly dependent on the set of constraints defined in the model. Constraints shape the feasible region, dictating which solutions are permissible within the problem's context. Tight or well-defined constraints can guide the algorithm efficiently toward the optimal solution, reducing the search space and improving convergence speed. Conversely, poorly defined constraints can lead to a larger feasible region, making it more challenging for the algorithm to navigate and identify the optimal solution. Infeasible or conflicting constraints can prevent convergence entirely, while unbounded constraints can lead to an unbounded objective.

This is because one combination, for sure, can meet these conditions—connecting all the load to the grid without relying on any DER.

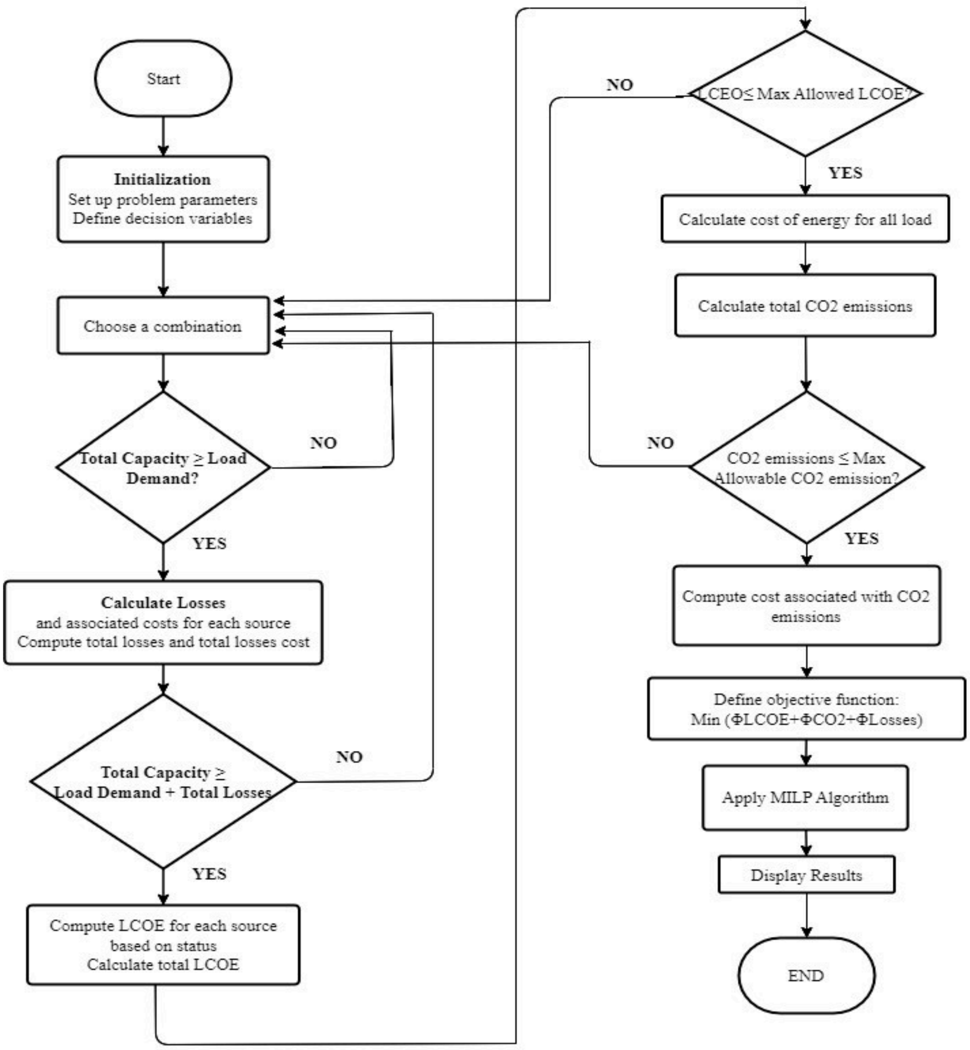

Figure 1. VPP MILP-based optimization algorithm flow chart.

Figure 1. VPP MILP-based optimization algorithm flow chart.

In our case, as long as P_{Grid} is infinite, $LCOE_{Max} \geq LCOE_{Grid}$, and the environmental constraint exceeds the grid's emissions limit, the model will always converge to a value. This is because one combination, for sure, can meet these conditions—connecting all the load to the grid without relying on any DER.

4. Simulation Results

The VPP MILP-based optimization algorithm was built and tested using an Intel i7-7500U, 2.70 GHz, dual-core CPU with 16 GB RAM, operating on Windows 10. The model was tested using the IEEE 33-bus grid model with 10 different DERs. The algorithm was programmed and tested using both Microsoft 365 Excel and Matlab/Simulink R2022a version.

The IEEE 33-bus system is a standard test case in power system engineering used for studying the distribution network. This test case is commonly utilized for various purposes, such as the analysis of power flow, voltage stability, and optimization algorithms for distribution networks. The IEEE 33-bus grid model data are provided in Appendix A. The VPP is formed by 10 DERs, one wind turbine, four diesel generators, and five solar photovoltaic (PV) systems. The 10 DER generators' connection points to the IEEE 33-bus grid, as well as the nominal power of each generator, are detailed in Table 1.

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Table 1. DERs connected to the IEEE 33-bus model.

Bus Number	Load Connected to the Bus (kW)	Power Generation Capacity (kW)	DER Int. (%)	Type	DER Contribution to Tech. Losses Reduction (kW)	LCOE ($/kWh)	GHG (kg of CO_2e/kWh
0	0	∞	0	Grid	0	0.18	0.7
3	120	84	0.7	Wind	3	0.09	0
7	200	140	0.7	PV	13.1	0.06	0
13	120	102	0.85	Gen	13.2	0.22	0.3
18	90	27	0.3	PV	0.3	0.06	0
21	90	63	0.7	PV	4.1	0.06	0
23	420	399	0.95	Gen	15.3	0.22	0.3
26	60	42	0.7	PV	2.1	0.06	0
29	200	80	0.4	PV	7.6	0.06	0
30	150	105	0.7	Gen	12	0.22	0.3
31	210	147	0.7	Gen	17.7	0.22	0.3

In the simulation study, key variables and constraints are defined to assess the performance and optimization of the VPP within the IEEE 33-bus system. These variables include the power output from each DER and the power imported from the grid, as well as the total demand load and the required spinning reserve. They also consider the LCOE per unit of power generation and the environmental impact of each source, measured through the CO_2 emissions variables for each DER and grid power. By adjusting these variables and constraints, the simulation seeks to test the performance of the MILP algorithm. This algorithm aims to optimize the DER selection and operation strategy to reduce costs, satisfy demand, and comply with environmental regulations. The baseline model is considered as the scenario where all available DERs are fully used, and the grid provides the remaining necessary power. In this baseline scenario, all decision variables are set to 1. For this purpose, we have defined the following scenarios:

- Scenario #1: This scenario assumes a total demand load of 3926 kW and no spinning reserve is assumed to be provided by the VPP. The $LCOE_{Grid}$ is set at 0.18 \$/kWh, $LCOE_{PV}$ at 0.06 \$/kWh, $LCOE_{Wind}$ at 0.09 \$/kWh, and $LCOE_{Gen}$ at 0.22 \$/kWh. Additionally, it presumes that both the wind turbine and solar PV produce no GHG emissions. However, the utility grid's emissions are set at 0.7 kg of CO_2e/kWh, and the diesel generators' emissions are at 0.3 kg of CO_2e/kWh. The carbon price is estimated to be \$0.01/kg CO_2e. In terms of constraints, GHG_{Max} is set to 0.65 kg of CO_2e/kWh. $LCOE_{Max}$ is set to 0.21 \$/kWh;
- Scenario #2: This scenario maintains the same conditions as scenario #1, with the sole difference being a demand load that is half of scenario #1's load;
- Scenario #3: This scenario maintains the same conditions as scenario #1, with the sole difference being an $LCOE_{Grid}$ equal to 0.24 \$/kWh and $LCOE_{Max}$ is set to 0.25 \$/kWh;
- Scenario #4: This scenario maintains the same conditions as scenario #1, with the addition of 25% spinning reserve to be provided by the VPP;
- Scenario #5: This scenario maintains the same conditions as scenario #1, with the sole difference being a demand load that is one quarter of scenario #1's load;
- Scenario #6: This scenario maintains the same conditions as scenario #5, with the sole difference being an $LCOE_{Grid}$ equal to 0.24 \$/kWh.

The calculated LCOE (the value of the objective function) of all feasible integer solutions which satisfy all the constraints for scenarios #1 and #2 is depicted in Figures 2 and 3. From the simulations, it was observed that 831 (out of 2^{11} possible combinations) feasible integer solutions adhered to the constraints of the MILP algorithm for scenario #1 and 1024 for scenario #2. Figures 2 and 3 also illustrate the output of the MILP function (orange curve), showing the model's convergence toward the optimal minimum LCOE.

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curve), showing the model's convergence toward the optimal minimum L
culated LCOE of valid combination outputs and the MILP function output
the same graph to validate the model's convergence towards the optimal v
ulation times for both scenarios were 0.075 and 0.078 s, respectively. Both s
dicated that the same combination of DERs resulted in the lowest total LCO
DERs are displayed in Tables 2 and 3. The total LCOE in scenario #1 was 0.
2.5% lower than the baseline model LCOE. However, when the demand loa
this LCOE dropped to 0.167197 $/kWh, nevertheless achieving 6.7% redu
baseline model LCOE. In the first scenario, the power supplied by the utility
kW, while in the second scenario, P_{grid} equaled 1527 kW. Moreover, die
were excluded from the selected DERs in both scenarios. This is due to the
the generators being higher than the grid's LCOE. The lower GHG emission
tribution to decreasing the grid's technical losses from the diesel generator
cient to bridge this gap.

Both calculated LCOE of valid combination outputs and the MILP function output are shown on the same graph to validate the model's convergence towards the optimal value. The simulation times for both scenarios were 0.075 and 0.078 s, respectively. Both simulations indicated that the same combination of DERs resulted in the lowest total LCOE. The selected DERs are displayed in Tables 2 and 3. The total LCOE in scenario #1 was 0.181243 $/kWh, 2.5% lower than the baseline model LCOE. However, when the demand load was halved, this LCOE dropped to 0.167197 $/kWh, nevertheless achieving 6.7% reduction from the baseline model LCOE. In the first scenario, the power supplied by the utility grid was 3490 kW, while in the second scenario, P_{grid} equaled 1527 kW. Moreover, diesel generators were excluded from the selected DERs in both scenarios. This is due to the total LCOE of the generators being higher than the grid's LCOE. The lower GHG emissions and the contribution to decreasing the grid's technical losses from the diesel generators were insufficient to bridge this gap.

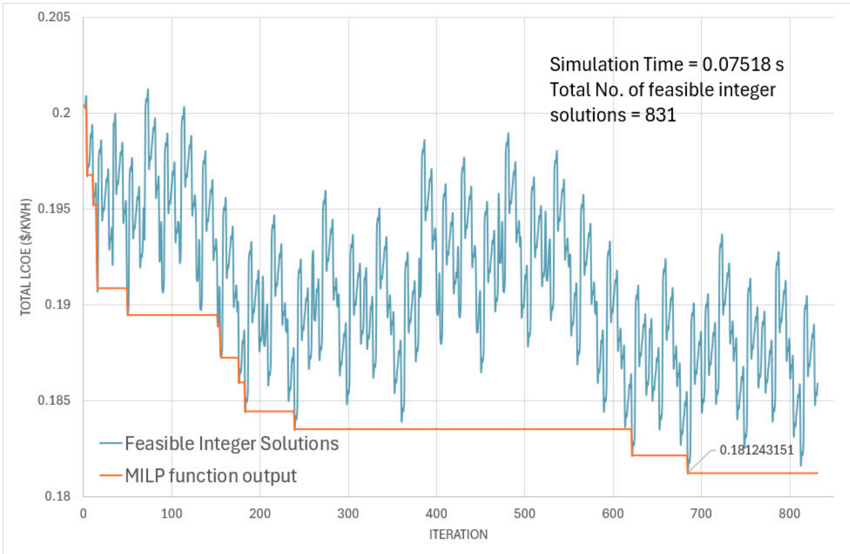


Figure 2. Scenario #1 with a total load of 3926 kW and no spinning reserve.

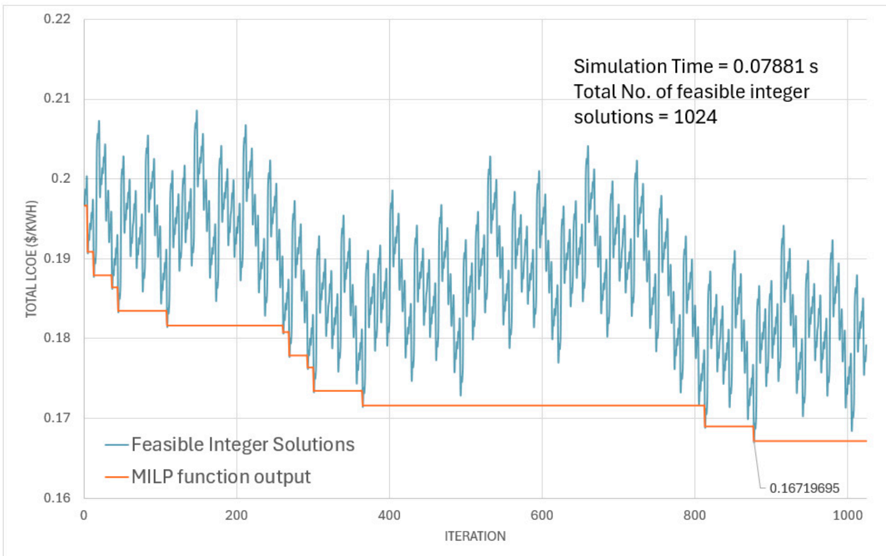


Figure 3. Scenario #2 with a total load of 1963 kW and no spinning reserve.

Table 2. Scenario #1 with a total load of 3926 kW and no spinning reserve.

	Scenario #1		
LCOE_Grid	0.18 $/kWh	LCOE_PV	0.0
LCOE_W	0.09 $/kWh	LCOE_Gen	0.2

Table 2. Scenario #1 with a total load of 3926 kW and no spinning reserve.

Scenario #1			
LCOE_Grid	0.18 $/kWh	LCOE_PV	0.06 $/kWh
LCOE_W	0.09 $/kWh	LCOE_Gen	0.22 $/kWh
GHG_Grid	0.7 kg CO_2e/kWh	GHG_PV	0 kg CO_2e/kWh
GHG_Gen	0.3 kg CO_2e/kWh	GHG_Wind	0 kg CO_2e/kWh
Grid Power	3490 kW	P_CO_2e	0.01 $/kg CO_2e
Total Load	3926 kW	Spinning Res.	0%
Total LCOE		0.181243 $/kWh	
Total GHG emissions		0.628 kg CO2e/kWh	
Baseline LCOE		0.185907 $/kWh	
Bus_3 (Wind)	84 kW	Bus_23 (Wind)	0 kW
Bus_7 (PV)	140 kW	Bus_26 (PV)	42 kW
Bus_13 (Gen)	0 kW	Bus_29 (Gen)	80 kW
Bus_18 (PV)	27 kW	Bus_30 (PV)	0 kW
Bus_21 (PV)	63 kW	Bus_31 (Gen)	0 kW

Table 3. Scenario #2 with a total load of 1963 kW and no spinning reserve.

Scenario #2			
LCOE_Grid	0.18 $/kWh	LCOE_PV	0.06 $/kWh
LCOE_W	0.09 $/kWh	LCOE_Gen	0.22 $/kWh
GHG_Grid	0.7 kg CO_2e/kWh	GHG_PV	0 kg CO_2e/kWh
GHG_Gen	0.3 kg CO_2e/kWh	GHG_Wind	0 kg CO_2e/kWh
Grid Power	1527 kW	P_CO_2e	0.01 $/kg CO_2e
Total Load	1963 kW	Spinning Res.	0%
Total LCOE		0.167197 $/kWh	
Total GHG emissions		0.556 kg CO_2e/kWh	
Baseline LCOE		0.179193 $/kWh	
Bus_3 (Wind)	84 kW	Bus_23 (Wind)	0 kW
Bus_7 (PV)	140 kW	Bus_26 (PV)	42 kW
Bus_13 (Gen)	0 kW	Bus_29 (Gen)	80 kW
Bus_18 (PV)	27 kW	Bus_30 (PV)	0 kW
Bus_21 (PV)	63 kW	Bus_31 (Gen)	0 kW

Scenario #3 demonstrates that when the LCOE provided by the grid increases to 0.24 $/kWh, compared to a diesel generator LCOE at 0.22 $/kWh, the optimization algorithm prioritizes extracting maximum power from diesel generators and other DERs. It also minimizes the power provided by the grid (P_{grid} = 2737 kW). In this scenario, the total LCOE equals 0.229042 $/kWh (Table 4), which is the same as the baseline model. The LCOEs of the different feasible integer solutions are shown in Figure 4.

Table 4. Scenario #3 with a load of 3926 kW and no spinning reserve, with $LCOE_{Grid}$ = 0.24 $/kWh and $LCOE_{Max}$ = 0.25 $/kWh.

Scenario #3			
LCOE_Grid	0.24 $/kWh	LCOE_PV	0.06 $/kWh
LCOE_W	0.09 $/kWh	LCOE_Gen	0.22 $/kWh
GHG_Grid	0.7 kg CO_2e/kWh	GHG_PV	0 kg CO_2e/kWh
GHG_Gen	0.3 kg CO_2e/kWh	GHG_Wind	0 kg CO_2e/kWh
Grid Power	2737 kW	P_CO_2e	0.01 $/kg CO_2e
Total Load	3926 kW	Spinning Res.	0%
Total LCOE		0.229042 $/kWh	
Total GHG emissions		0.545 kg COe/kWh	
Baseline LCOE		0.229042 $/kWh	

Bus_7 (PV)	140 kW	Bus_26 (PV)	
Bus_13 (Gen)	0 kW	Bus_29 (Gen)	
Bus_18 (PV)	27 kW	Bus_30 (PV)	
Bus_21 (PV)	63 kW	Bus_31 (Gen)	

Table 4. *Cont.*

Scenario #3			
Bus_3 (Wind)	84 kW	Bus_23 (Wind)	299 kW
Bus_7 (PV)	140 kW	Bus_26 (PV)	42 kW
Bus_13 (Gen)	102 kW	Bus_29 (Gen)	80 kW
Bus_18 (PV)	27 kW	Bus_30 (PV)	105 kW
Bus_21 (PV)	63 kW	Bus_31 (Gen)	147 kW

Scenario #3 demonstrates that when the LCOE provided by the grid in $/kWh, compared to a diesel generator LCOE at 0.22 $/kWh, the optimiza prioritizes extracting maximum power from diesel generators and other minimizes the power provided by the grid (P_{grid} = 2737 kW). In this scen LCOE equals 0.229042 $/kWh (Table 4), which is the same as the baselin LCOEs of the different feasible integer solutions are shown in Figure 4.

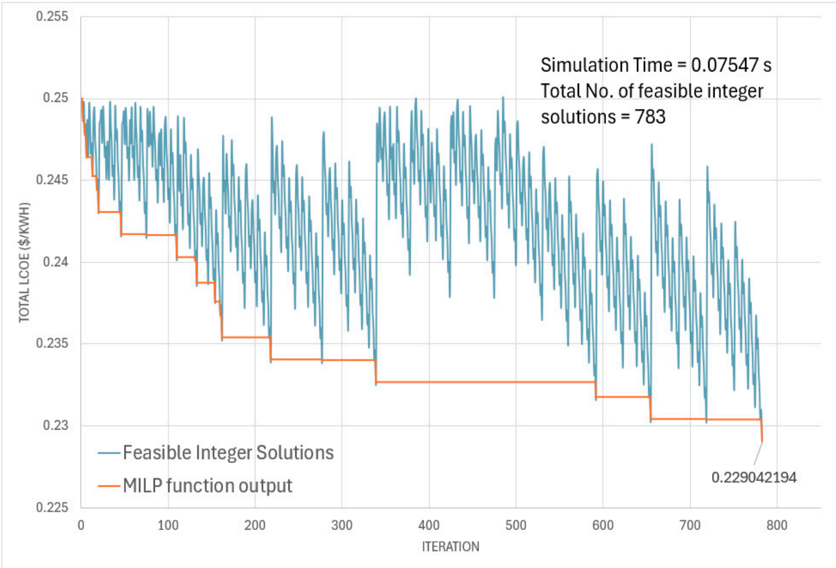


Figure 4. Scenario #3 with a total load of 3926 kW and no spinning reserve, with $LCOE_{grid}$ = 0.24 $/kWh.

Scenario #4 examines the effect of adding a spinning reserve to the energy mix provided by the DERs. The results show that adding a spinning reserve incurs a minimal increase in the total LCOE, leading to an LCOE of 0.182487 $/kWh (Table 5), 2% lower than the baseline model. This is compared to 0.181243 $/kWh under the same conditions, but without a spinning reserve (scenario #1). The simulation for the 695 feasible integer solutions is 0.07506 s, as shown in Figure 5.

Table 5. Scenario #4 with a total load of 3926 kW and 25% spinning reserve.

Scenario #4			
LCOE_Grid	0.18 $/kWh	LCOE_PV	0.06 $/kWh
LCOE_W	0.09 $/kWh	LCOE_Gen	0.22 $/kWh
GHG_Grid	0.7 kg CO_2e/kWh	GHG_PV	0 kg CO_2e/kWh
GHG_Gen	0.3 kg CO_2e/kWh	GHG_Wind	0 kg CO_2e/kWh
Grid Power	4471 kW	P_CO_2e	0.01 $/kg CO_2e
Total Load	3926 kW	Spinning Res.	25%
Total LCOE		0.182487 $/kWh	
Total GHG emissions		0.637 kg COe/kWh	
Baseline LCOE		0.186151 $/kWh	
Bus_3 (Wind)	84 kW	Bus_23 (Wind)	0 kW
Bus_7 (PV)	140 kW	Bus_26 (PV)	42 kW
Bus_13 (Gen)	0 kW	Bus_29 (Gen)	80 kW
Bus_18 (PV)	27 kW	Bus_30 (PV)	0 kW
Bus_21 (PV)	63 kW	Bus_31 (Gen)	0 kW

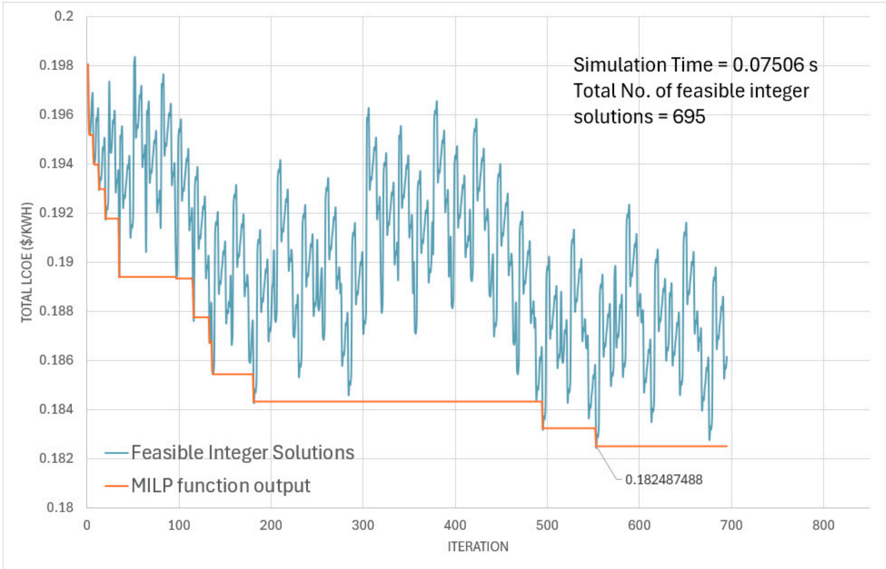


Figure 5. Scenario #4 with a total load of 3926 kW and 25% spinning reserve.

Scenario #5 explores the case of a demand load reduced to 25% of the baseline load. As shown in Table 6, the total LCOE decreases to 0.13913 $/kWh. This drop results from the DERs with low LCOE, like solar PV systems and wind turbines, serving a higher share of the load (around 40%). Consequently, the utility grid's share decreases to 546 kW. The MILP algorithm achieved an LCOE 16% lower than the baseline model.

Table 6. Scenario #5 with a total load of 982 kW and no spinning reserve.

Scenario #5			
LCOE_Grid	0.18 $/kWh	LCOE_PV	0.06 $/kWh
LCOE_W	0.09 $/kWh	LCOE_Gen	0.22 $/kWh
GHG_Grid	0.7 kg CO_2e/kWh	GHG_PV	0 kg CO_2e/kWh
GHG_Gen	0.3 kg CO_2e/kWh	GHG_Wind	0 kg CO_2e/kWh
Grid Power	546 kW	P_CO_2e	0.01 $/kg CO_2e
Total Load	982 kW	Spinning Res.	0%
Total LCOE		0.13913 $/kWh	
Total GHG emissions		0.39 kg COe/kWh	
Baseline LCOE		0.16577 $/kWh	
Bus_3 (Wind)	84 kW	Bus_23 (Wind)	-
Bus_7 (PV)	140 kW	Bus_26 (PV)	42 kW
Bus_13 (Gen)	0 kW	Bus_29 (Gen)	80 kW
Bus_18 (PV)	27 kW	Bus_30 (PV)	0 kW
Bus_21 (PV)	63 kW	Bus_31 (Gen)	0 kW

Like scenario #5, scenario #6 also explores the case of reduced demand load. However, this scenario assumes that the LCOE of the grid is higher than that of diesel generators. As a result, Table 7 shows that under these conditions, the power supplied by the grid is replaced by diesel generators connected to buses 23 and 31, leading to a total LCOE of 0.158897 $/kWh, 6.7% lower than the baseline.

In order to assess the impact of the set constraints on the algorithm, we tested the model defined in scenario #1 under various constraint values for GHG_{Max} and $LCOE_{Max}$ (scenarios 7–12). The results are presented in Table 8. When GHG_{Max} is lowered to 0.55 kg of CO_2e/kWh, only one solution respects the constraints which is the baseline model where all DERs are online, and the grid provides the remaining power needed to serve the total load. When GHG_{Max} and $LCOE_{Max}$ are both lowered, it is noticed that the number of feasible integer solutions decreases a lot compared to the same number calculated in scenario #1. Hence, it proves that a good set of tight constraints can guide the algorithm efficiently toward the optimal solution, reducing the search space and improving convergence speed. Lastly, when GHG_{Max} or $LCOE_{Max}$ are extremely tightened, it leads to an infeasible solution.

Table 7. Scenario #6 with a load of 982 kW and no spinning reserve, with $LCOE_{Grid}$ = 0.24 \$/kWh and $LCOE_{Max}$ = 0.25 \$/kWh.

Scenario #6			
LCOE_Grid	0.24 \$/kWh	LCOE_PV	0.06 \$/kWh
LCOE_W	0.09 \$/kWh	LCOE_Gen	0.22 \$/kWh
GHG_Grid	0.7 kg CO_2e/kWh	GHG_PV	0 kg CO_2e/kWh
GHG_Gen	0.3 kg CO_2e/kWh	GHG_Wind	0 kg CO_2e/kWh
Grid Power	0 kW	P_CO_2e	0.01 \$/kg CO_2e
Total Load	982 kW	Spinning Res.	0%
Total LCOE		0.158897 \$/kWh	
Total GHG emissions		0.16 kg COe/kWh	
Baseline LCOE		0.17045 \$/kWh	
Bus_3 (Wind)	84 kW	Bus_23 (Wind)	399 kW
Bus_7 (PV)	140 kW	Bus_26 (PV)	42 kW
Bus_13 (Gen)	0 kW	Bus_29 (Gen)	80 kW
Bus_18 (PV)	27 kW	Bus_30 (PV)	0 kW
Bus_21 (PV)	63 kW	Bus_31 (Gen)	147 kW

Table 8. Various scenarios based on the conditions of scenario #1 but with different constraints.

Scenario	GHG_{Max} (kg of CO_2e/kWh)	$LCOE_{Max}$ (\$/kWh)	No. of Feasible Integer Solutions	Total LCOE (\$/kWh)	Baseline Model LCOE (\$/kWh)
7	0.55	0.21	1	0.185907	0.185907
8	0.6	0.21	239	0.182306	0.185907
9	0.6	0.19	115	0.182306	0.185907
10	0.57	0.19	26	0.185053	0.185907
11	0.5	0.19	0	-	-
12	0.65	0.18	0	-	-

In the second part of the simulation, we conducted a sensitivity analysis of the proposed MILP optimization algorithm for the VPP, focusing on examining how variations in the LCOE of the solar PV systems and the carbon price impact the total LCOE results. By systematically varying the LCOE of the solar PV system, we can evaluate the influence of changes in solar energy costs on the selection and operation of DERS within the VPP. Simultaneously, altering the carbon price allows us to assess the effect of different carbon pricing scenarios on the economic and environmental performance of the VPP. The sensitivity analysis provides insights into the robustness of the optimization algorithm, revealing how shifts in key economic parameters can affect the total cost, CO_2 emissions, and the optimal mix of energy sources. This analysis is crucial to understand the potential financial and environmental implications under varying market conditions and to make informed decisions for sustainable and cost-effective energy management. Figure 6 shows the variation in the total LCOE as a function of the variation in the solar PV's LCOE. An increase in the solar PV's LCOE certainly incurs an augmentation in the total LCOE. However, it is also to be noted that the proposed MILP algorithm has a rapid response time that allows it to quickly respond to fluctuations in market prices, and this is revealed in the response time (Rs_Time) shown in Figure 6. The decreasing LCOE for solar PV systems has a significant impact on the LCOE of the overall energy mix. As solar PV becomes more cost-competitive, it increasingly displaces more expensive and less environmentally friendly energy sources, like the grid power plants and the diesel generators, thus lowering the average cost of electricity generation. Similarly, Figure 7 shows the impact of the carbon price on the total LCOE. As the carbon price increases from 0.01 to 0.055 \$/kg of CO_2e, the total LCOE goes from 0.181243 \$/kWh to 0.209166 \$/kWh. Higher prices for carbon emissions have a substantial impact on the overall LCOE. As carbon pricing mechanisms, such as carbon taxes or cap-and-trade systems, increase the cost of emitting carbon dioxide, fossil fuel-based power generation becomes more expensive. This cost pressure incentivizes a shift towards cleaner, renewable energy sources like wind, solar, and hydropower, which do not incur carbon costs. Consequently, the overall LCOE of the grid may initially rise due to the increased costs associated with fossil fuels. However, over time, as the energy mix transitions to a higher proportion of renewables, the grid's LCOE can stabilize or even decrease due to the declining costs of renewable technologies and improved efficiencies.

can stabilize or even decrease due to the declining costs of renewable technologies and improved efficiencies.

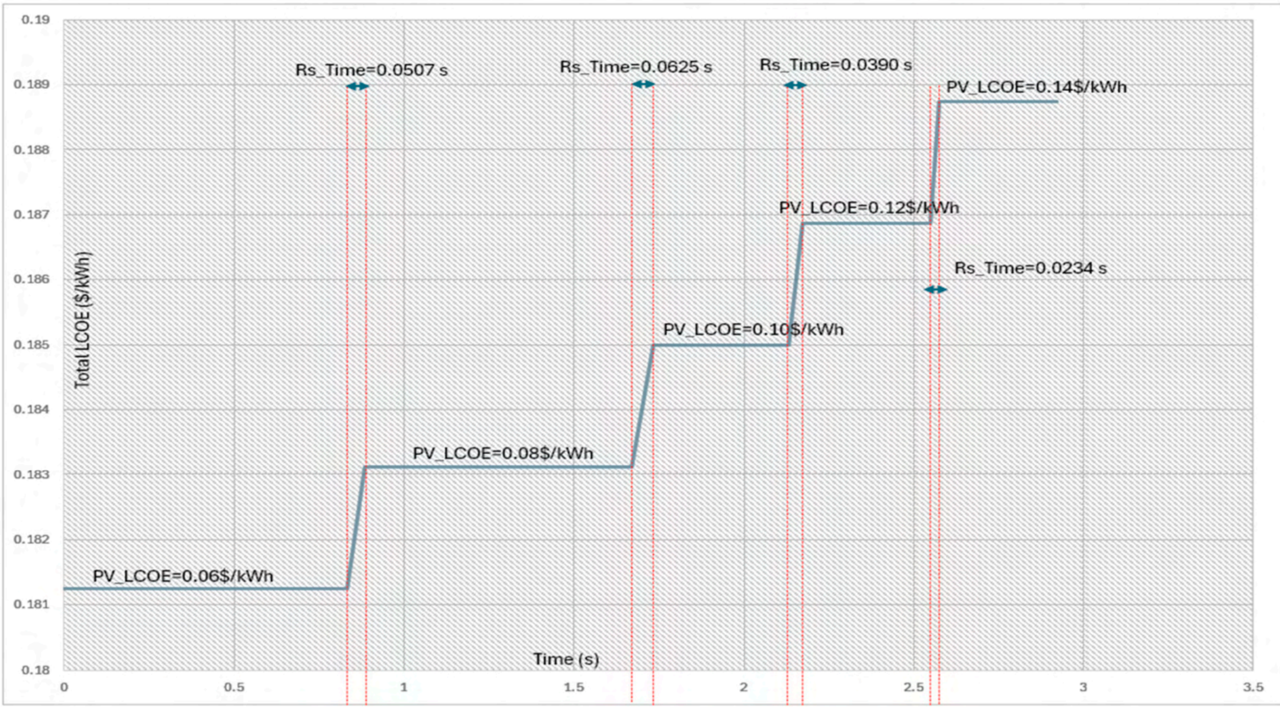
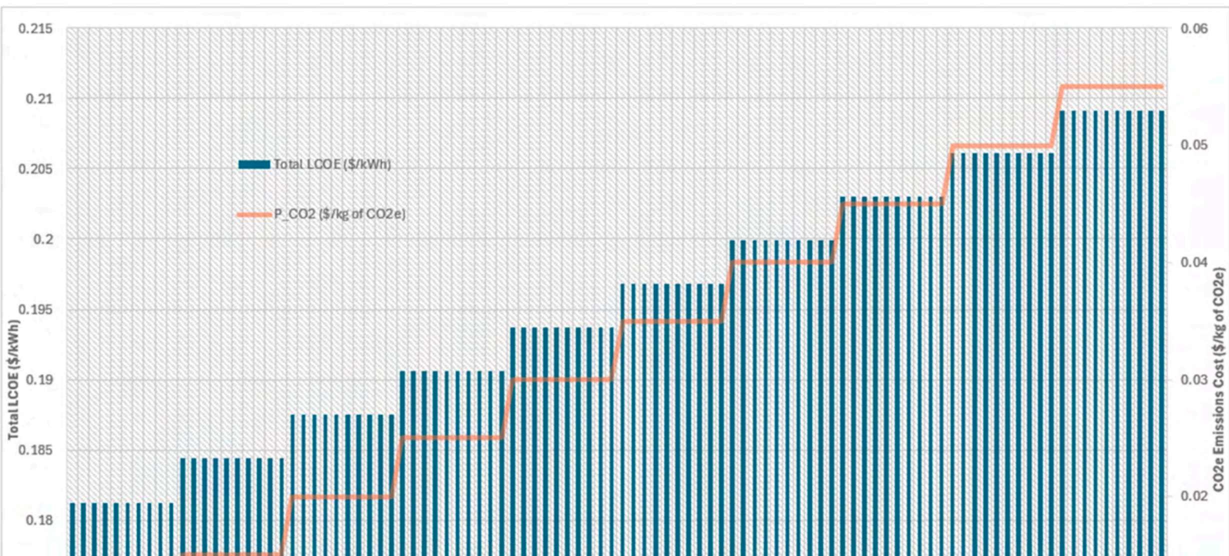


Figure 6. Sensitivity analysis taking into consideration the variation in the $LCOE_{PV}$.

Figure 6. Sensitivity analysis taking into consideration the variation in the $LCOE_{PV}$.



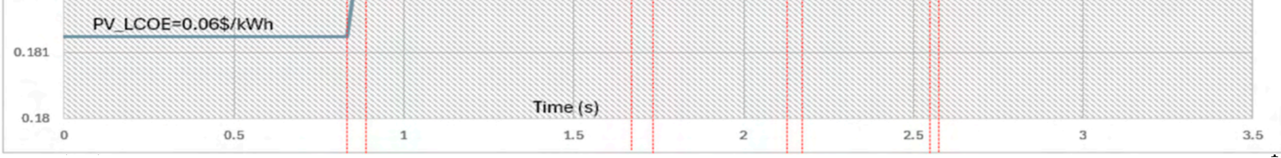


Figure 6. Sensitivity analysis taking into consideration the variation in the $LCOE_{PV}$.

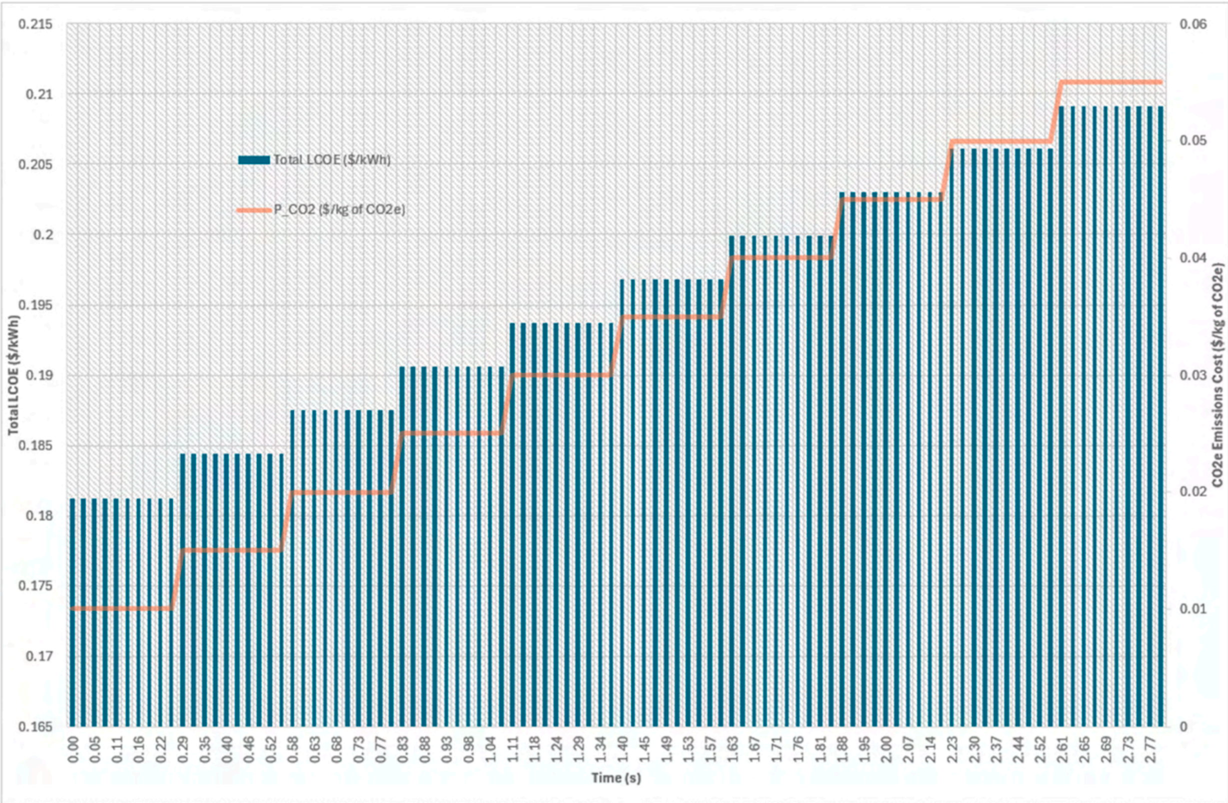


Figure 7. Sensitivity analysis taking into consideration the variation in the carbon price (∂ in $/kg of CO_2e).

5. Conclusions

Looking ahead, the continued evolution of VPPs will be shaped by technological innovations, regulatory developments, and market dynamics. The integration of advanced energy storage technologies, like solid-state batteries and hydrogen fuel cells, can enhance the storage capacity and flexibility of VPPs. Emerging technologies, like vehicle-to-grid (V2G) systems, where EVs can both draw from and supply power to the grid, hold promise for expanding VPPs' capabilities. Additionally, the development of P2P energy trading platforms can further democratize the energy market, allowing consumers to directly trade energy with each other through VPPs. However, the optimization of the resources remains a cornerstone of any VPP. By strategically selecting and operating DERs, VPPs can efficiently balance supply and demand, minimize operational costs, and reduce greenhouse gas emissions. This optimization ensures that energy generation and consumption are managed in the most cost-effective and environmentally friendly manner. Advanced algorithms, such as MILP, play a crucial role in this process by enabling the precise allocation of resources, considering various constraints and objectives. The ability to dynamically optimize resources allows VPPs to adapt to changing market conditions, integrate renewable energy sources, and enhance the reliability and resilience of the power grid. Therefore, the continuous improvement and application of optimization techniques are fundamental to the success and sustainability of VPPs.

This article has presented an MILP-based optimization algorithm designed to enhance the operation of VPPs by minimizing the LCOE, technical losses, and GHG emissions. Through comprehensive simulations utilizing the IEEE 33-bus model, the algorithm demonstrated its effectiveness in optimizing resource allocation and operational strategies within the VPP framework. The results underscore the algorithm's capability to achieve a low LCOE, while accounting for the grid's technical losses and the GHG emissions of the different power sources. The rapid convergence of the MILP algorithm further highlights its practical applicability for real-time and large-scale energy management scenarios.

This study confirms the potential of advanced optimization techniques in transforming the management of distributed energy resources, paving the way for more sustainable and economically viable power systems. Nevertheless, the future research direction in VPP optimization is poised to integrate real-time operational data with advanced analytical frameworks, such as chance-constrained programming (CCP) and Nash bargaining models [40], to enhance the accuracy and effectiveness of decision-making processes. By leveraging actual operational data, researchers can conduct more in-depth analyses and fine-tune VPP strategies to better accommodate dynamic conditions and improve performance. The combination of CCP with Nash bargaining models offers a promising approach to addressing the inherent uncertainties in renewable energy generation and market fluctuations. Additionally, the development of multilevel decision models can provide a comprehensive network of interactions and optimizations across various levels of VPP operations, such as using a stochastic bi-level optimal allocation model for intelligent energy storage sharing services to reduce investment and operating costs, addressing uncertainties in electricity prices [41]. Moreover, challenges such as managing the inherent uncertainties in renewable energy sources, fluctuating demand, and integration complexities will need to be addressed. These challenges require innovative approaches to data integration, model accuracy, and computational efficiency to ensure that VPPs can operate optimally in increasingly complex and variable environments.

Additionally, in a real-world scenario, several systems can induce delays in data acquisition and control of VPP resources, impacting overall operational efficiency. One primary source of delay is the communication infrastructure, including network latencies and bandwidth limitations, which can affect the timely transmission of data from DERs to the central control system. Additionally, the integration of various types of generators and storage systems, each with different communication protocols and data formats, can cause compatibility issues and slow down the data aggregation process. The data processing systems, which include data analytics and real-time monitoring tools, may also contribute to delays if they lack sufficient computational power or efficiency in processing large volumes of data. Furthermore, software and algorithmic delays can occur due to the complexity of optimization and control algorithms used for managing the VPP's operations. Lastly, external factors such as cybersecurity measures and regulatory compliance checks can introduce additional delays, as ensuring data security and meeting regulatory requirements often involves rigorous verification processes. Collectively, these factors can lead to slower response times in controlling generators, potentially affecting the VPP's ability to balance supply and demand effectively. However, the proposed MILP algorithm has proven to be able to provide an optimal solution very quickly, significantly reducing software and algorithmic delays.

In conclusion, virtual power plants represent a transformative approach to energy management, offering multiple benefits for grid stability, economic efficiency, and environmental sustainability. By harnessing the collective power of distributed energy resources, VPPs can provide flexible, reliable, and clean energy solutions. The successful implementation of VPPs will depend on overcoming technical, regulatory, and cybersecurity challenges, as well as fostering collaboration and innovation across the energy sector. As the energy landscape continues to evolve, VPPs will play a pivotal role in shaping a resilient, sustainable, and decentralized energy future.

Author Contributions: Conceptualization, A.A.; methodology, A.A.; software, A.A.; validation, A.I., M.A. and M.G.; formal analysis, A.A.; investigation, A.A.; resources, H.I.; data curation, A.A.; writing—original draft preparation, A.A.; writing—review and editing, A.I. and M.A.; visualization, A.A.; supervision, M.A.; project administration, H.I.; funding acquisition, A.I. All authors have read and agreed to the published version of the manuscript.

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Energies 2022, 15, x FOR PEER REVIEW 21 of 23

Appendix A. IEEE 33-Bus VPP Grid Model

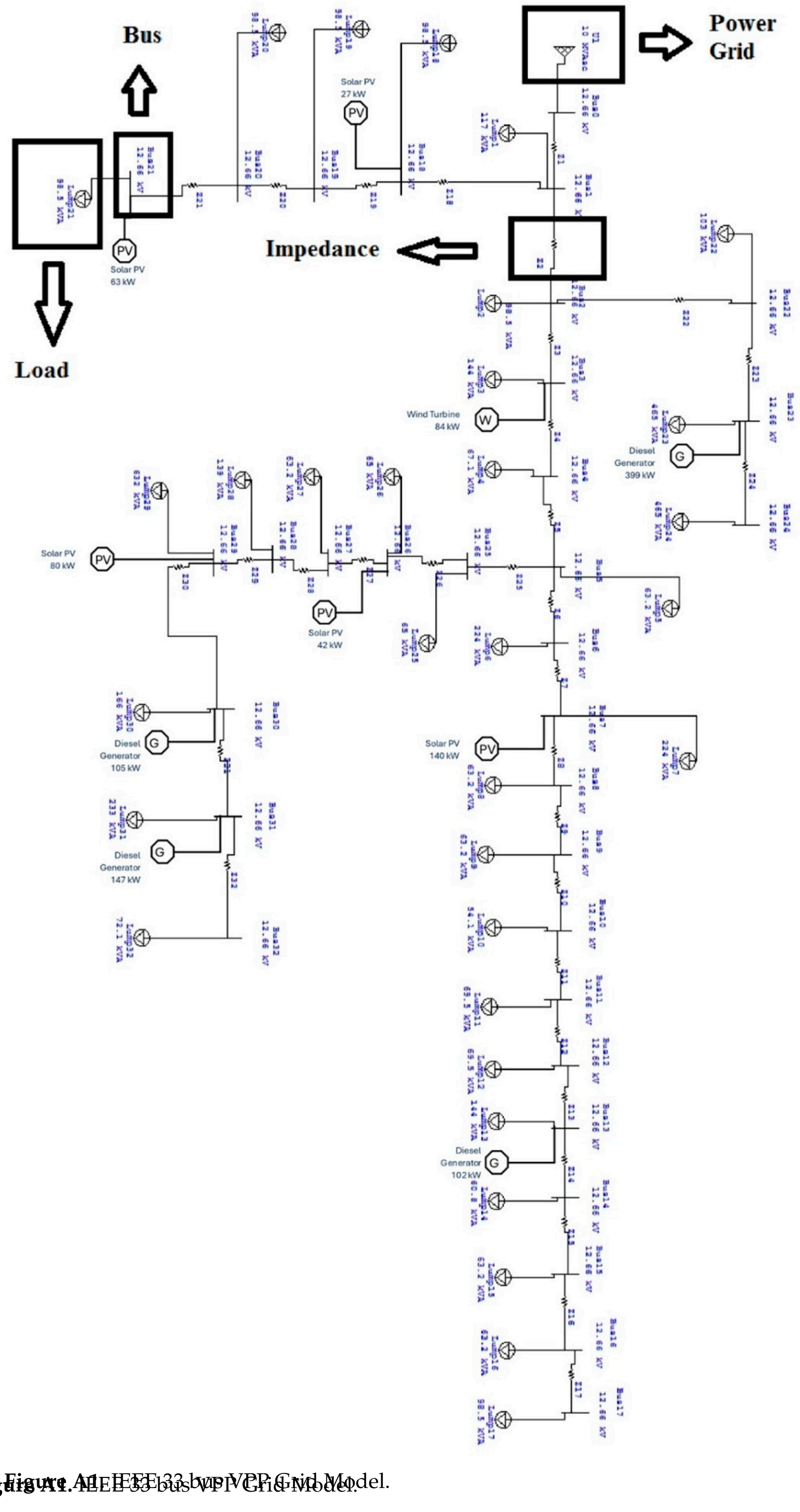

Figure A1. IEEE 33-bus VPP Grid Model.

Figure A1. IEEE 33-bus VPP Grid Model.

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CHAPITRE 6CHAPITRE 6
APPLICATION ET IMPACTS DE LA TECHNOLOGIE DE LA CHAÎNE DE BLOCS ET LA DÉCENTRALISATION DANS LA GESTION DE LA DEMANDE.

6.1 INTRODUCTION

La deuxième façon pour atteindre un équilibre énergétique dans les réseaux électriques est de contrôler la charge. La gestion de la demande joue un rôle crucial dans l'équilibre des réseaux électriques en offrant des avantages économiques, techniques, environnementaux et sociologiques. Économiquement, elle permet de réduire les coûts liés à la production d'électricité en limitant le recours aux centrales de pointe, souvent plus coûteuses et moins efficaces. Techniquement, elle améliore la stabilité du réseau en ajustant la consommation pour correspondre à la production disponible, réduisant ainsi les risques de surcharge et de pannes. Sur le plan environnemental, une gestion efficace de la demande contribue à la réduction des émissions de GES en favorisant l'utilisation d'énergies renouvelables et en minimisant la dépendance aux sources d'énergie fossile. Sociologiquement, elle favorise une plus grande sensibilisation et participation des consommateurs à la gestion de leur consommation énergétique, ce qui peut mener à des comportements plus responsables et durables. En intégrant des technologies avancées comme les compteurs intelligents et les systèmes de contrôle automatisés, la gestion de la demande devient un pilier essentiel pour atteindre un réseau électrique plus équilibré, résilient et durable.

La gestion permet de réduire la charge durant les heures de pointe à court terme et de limiter l'augmentation de la demande énergétique à long terme. À court terme, elle permet de décaler ou de moduler la consommation d'énergie des utilisateurs afin d'éviter les pics de demande qui mettent sous pression les infrastructures électriques et nécessitent le recours à des centrales de pointe coûteuses et souvent polluantes. Par des mécanismes tels que la tarification dynamique, les incitations financières ou les programmes de réponse à la demande, les consommateurs sont encouragés à consommer de l'électricité durant les périodes de faible demande, ce qui a pour effet de lisser la courbe de charge quotidienne. À long terme, une gestion efficace de la charge contribue à contenir l'augmentation globale de la demande énergétique en favorisant des comportements de consommation plus durables et en intégrant des technologies d'efficacité énergétique. Cela permet de retarder ou d'éviter la nécessité d'investir dans de nouvelles capacités de production et d'infrastructure, réduisant ainsi les coûts pour les opérateurs et les consommateurs tout en minimisant l'empreinte environnementale du réseau électrique. En somme, la gestion de charge est un levier essentiel pour la transition vers un système énergétique plus équilibré, durable et résilient.

Dans le contexte des PADs et la décentralisation intelligente des réseaux électriques, la gestion de la demande joue un rôle primordial. Elle permet d'optimiser l'utilisation des ressources énergétiques locales, en adaptant la consommation d'énergie en temps réel aux fluctuations de la production. Cela garantit une stabilité accrue du réseau en évitant les surcharges et en réduisant la nécessité de recourir à des sources d'énergie de secours coûteuses et polluantes. Dans le cadre de la décentralisation intelligente des réseaux électriques, la gestion de la demande facilite une interaction dynamique entre les consommateurs et les producteurs d'énergie, permettant une réponse rapide aux variations de la demande et aux incidents éventuels. Cette approche améliore la résilience du réseau en distribuant la charge de manière plus équilibrée et en intégrant des solutions énergétiques renouvelables et durables. En encourageant une consommation d'énergie plus flexible et responsable, la gestion de la demande contribue à la réalisation d'un réseau électrique plus efficace, économique et écologique.

Ce chapitre introduit trois articles qui explorent le potentiel de la technologie de la chaine de blocs dans le domaine de la gestion de la demande. Le premier article en question présente une revue de littérature exhaustive sur les techniques de gestion de la demande, mettant en lumière à la fois leurs avantages potentiels, leurs défis et leurs limitations. Cette revue explore les diverses stratégies utilisées pour modérer la consommation d'énergie, telles que les programmes de tarification dynamique, les programmes de réponse à la demande pendant les périodes de pointe, et les technologies d'efficacité énergétique. Elle examine également les bénéfices économiques, environnementaux et sociaux associés à ces méthodes, tout en identifiant les défis techniques, réglementaires et comportementaux qui peuvent limiter leur efficacité et leur adoption à grande échelle. Le second article introduit un nouveau concept de gestion de la demande basé sur le concept de plafonnement et échange d'énergie. Ce modèle inclut un système de plafonnement de la consommation mensuelle d'énergie des consommateurs et un système de récompense des consommateurs qui ne dépassent pas ce plafond par des crédits d'énergie négociables qui peuvent être échangés à l'aide d'un système d'échange d'énergie P2P basé sur la chaîne de blocs. Le troisième article explore le potentiel d'intégration de la chaîne de blocs et des contrats intelligents dans le processus de CPE en collectant automatiquement les données des mesures de conservation de l'énergie (MCE) mises en œuvre, en calculant leurs économies d'énergie et en gérant les paiements et les pénalités. Une fois que les processus de mesure et de vérification (M&V) sont terminés et que les conditions du contrat sont satisfaites, les contrats intelligents appliquent automatiquement le déblocage des paiements du portefeuille électronique du client à l'entreprise de services énergétiques (ESCO). Cette configuration résout les problèmes rencontrés dans le processus CPE, tels que la confiance, l'exécution des paiements, les frais de transaction et les risques financiers, et pourrait servir comme levier pour les petites organisations et les nouvelles ESCO.

6.2 CHAPITRE DE LIVRE : DEMAND-SIDE MANAGEMENT

Ce chapitre, intitulé « *Demand Side Management* », a été accepté pour publication dans sa version finale en 2021 par les éditeurs de la maison d'édition ELSEVIER – ACADAMIC PRESS dans leur livre intitulé : « *Hybrid Renewable Energy Systems and Microgrids* ».

Référence : Aoun, Alain, et al. "Demand-side management." Hybrid Renewable Energy Systems and Microgrids. Academic Press, 2021. 463-490.

En tant que premier auteur, j'ai contribué à l'essentiel de la recherche sur l'état de la question, à la collecte et l'analyse des données et à la rédaction du manuscrit. Les professeurs Mazen Ghandour, Adrian Ilinca et Hussein Ibrahim en tant que co-auteurs, ont participé à la supervision du travail, ainsi qu'à la révision de l'article et à la revue de la littérature.

Résumé : L'équilibre énergétique entre l'offre et la demande d'un réseau électrique est l'une des questions les plus importantes dans le fonctionnement du réseau. La prévision de la production et de la demande d'électricité est la base essentielle de l'organisation de la production et de la gestion de l'électricité. Historiquement, les réseaux électriques conventionnels ont été conçus avec de grandes centrales de production centralisées où la production suivait la demande d'électricité, ce qui permettait d'atteindre un certain niveau d'équilibre. Cependant, l'intégration de générateurs d'énergie renouvelable, dans le cadre des réseaux intelligents, a compliqué le processus en raison de leur nature incertaine et intermittente. Le déséquilibre de puissance et la charge de pointe sont devenus deux problèmes critiques dans le fonctionnement d'un réseau électrique qui peuvent affecter de manière significative la fiabilité et la qualité de l'énergie. La charge de pointe résulte généralement des caractéristiques de la demande de puissance des utilisateurs finaux. Bien que la durée de la charge de pointe puisse être relativement courte, les capacités redondantes des centrales électriques doivent toujours être en attente pour garantir que la demande d'électricité puisse être satisfaite à tout moment. Afin de maintenir l'équilibre entre l'offre et la demande d'électricité de manière rentable, les services publics ont développé deux mécanismes. Le premier mécanisme est basé sur l'intégration de systèmes de stockage d'énergie et le second se concentre sur la minimisation de la charge de pointe en encourageant les utilisateurs finaux à modifier leurs comportements en matière de consommation d'énergie grâce à des mesures incitatives. Le premier mécanisme est principalement limité par ses coûts initiaux et d'exploitation élevés. Le second mécanisme est très dépendant des capacités et du volontariat des utilisateurs finaux. Par conséquent, les programmes de gestion de la demande doivent être soigneusement conçus afin d'encourager les capacités des utilisateurs finaux au niveau de la demande d'électricité.

Contexte et Objectifs : Ce chapitre vise à fournir une revue exhaustive des pratiques existantes en matière de gestion de la demande, en examinant les diverses stratégies et technologies employées pour moduler la consommation d'énergie. Les objectifs de ce chapitre sont de présenter les avantages et les inconvénients des différentes approches, d'identifier les défis techniques et économiques rencontrés, et d'évaluer l'impact potentiel de ces pratiques sur la stabilité du réseau électrique et la satisfaction des consommateurs. En outre, ce chapitre explore les tendances émergentes et les innovations dans ce domaine, offrant ainsi une perspective complète sur l'état actuel et les perspectives futures de la gestion de la demande énergétique.

Méthodologie : Pour mener à bien cette revue des pratiques de gestion de la demande énergétique, une méthodologie rigoureuse et systématique a été adoptée. Tout d'abord, une recherche documentaire exhaustive a été effectuée à travers des bases de données académiques et industrielles afin de recueillir les études et rapports les plus pertinents. Cette recherche a inclus des articles scientifiques, des livres blancs, des rapports d'agences gouvernementales, et des publications d'organisations internationales. Ensuite, une analyse comparative des différentes pratiques a été réalisée, en mettant en évidence les points forts et les limitations de chaque approche. Par ailleurs, des études de cas spécifiques ont été examinées pour illustrer l'application concrète de ces pratiques dans divers contextes. Enfin, les résultats de cette analyse ont été synthétisés pour identifier les tendances émergentes et les recommandations pour les futures recherches et applications dans le domaine de la gestion de la demande énergétique.

Résultats et Contributions : Cette revue exhaustive a permis de dresser un panorama complet des pratiques actuelles, mettant en lumière les approches les plus efficaces et innovantes pour optimiser la consommation énergétique. Les analyses comparatives ont révélé les avantages et les limitations de chaque méthode, fournissant des insights précieux pour les décideurs et les gestionnaires de réseau. En identifiant les tendances émergentes, cette étude a contribué à orienter nos recherches pour mieux identifier de nouvelles techniques de gestion de la demande basées sur la technologie de la chaîne de blocs.

Demand-side management

13

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13.1 Chapter overview

The embargo of 1973 is without doubt a serious turning point in the history of global energy markets. Following the decision of 12 OPEC (Organization of Petroleum Exporting Countries) members to stop exporting oil to the United States (US), the prices of crude oil skyrocketed, creating an economic and political crisis. This event triggered a wake-up call on energy security and as a result several policies and measures targeting energy demand and energy efficiency (EE) took off. Concerns provoked by the sensitivity of economies to energy prices, oil dependency and more recently climate change, are the main drivers behind the development of demand-related policies and programs. The main target behind these policies and programs, referred to in most cases as demand-side management (DSM) programs, is to influence the quantity, quality, and patterns of traditional energy use. DSM has been traditionally seen as all measures that can be applied to the load side of any energy system in both on-peak and off-peak periods. A typical DSM program may incorporate energy conservation, EE, distributed and on-site power generation, energy storage, load shifting, and market share adjustments.

From the utility point of view the DSM approach may help power companies worldwide to face acute and repetitive power crisis brought on by a combination of supply-side problems, including fuel shortage, maintenance needs and unplanned outages, and a continuous increase in energy demand specially electricity caused by global economy growth, demographic explosion, digitization, increased mobility, and greater demand for heating and cooling. Instead of acting on the supply side by integrating alternative means of power generation, such as renewable energy generators and standby power generation units, or investing in costly energy storage systems, the DSM method offers a substantial alternative that focuses on the management of the load with the aim of minimizing the overall energy demand [1] (Fig. 13.1). Although power generation might not be a major concern to most utility companies, it is rather the grid capacity that worries most stakeholders. Electric grids might soon reach their limits and DSM is one possibility of stretching the boundaries a little further. The decrease in the energy demand can free up

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generation, transmission, and distribution capacity and by promoting distributed energy resources (DERs), DSM helps to moderate new investments in power generation units and long-distance transmission lines, mitigate electrical system emergencies, and increase system reliability. From a consumer point of view, DSM programs encourage consumers to optimize their demand profile against an incentive, using means such as increasing their EE, reducing their energy consumption, or even shifting their energy loads to off-peak periods. Thus, eventually, a DSM program will offer consumers the possibility to reduce their electricity bills, also not to forget the environmental benefits resulting from the reduction in greenhouse gas (GHG) emissions.

Using the load as an additional degree of freedom in the management of electricity grids is not a new concept; nevertheless, the advancement of technology and communication infrastructure make it a relatively easy-to-apply solution and a main piece of the smart grid (SG) puzzle, driven by the fact that, despite the increase of electrical equipment efficiency, the demand load, in most countries, is steadily rising by a certain percentage every year. With the rise of SGs, prosumers are being able to share real-time data, based on tariffs, power consumption, and energy demand with the utility company. This two-way communication system is beneficial for both sides, utility company and prosumers, at the same time.

The remainder of this chapter is organized as follows. In the first section a brief overview of the different DSM techniques is presented along with the main drivers behind DSM programs and the involved stakeholders. Moreover, a review of the cost-effectiveness tests used to evaluate DSM programs will be presented. In

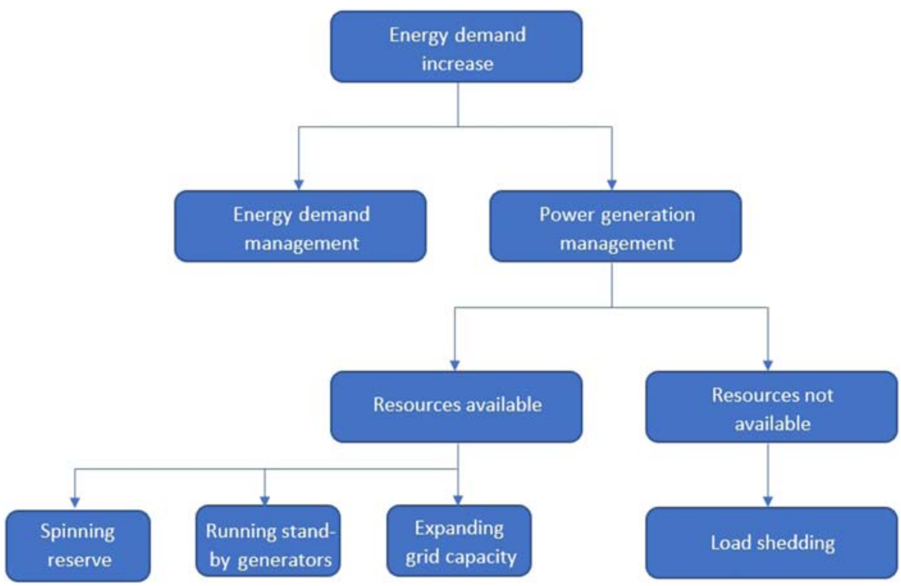

Figure 13.1 Different schemes to meet demand load increase.

Section 13.2, price- and incentive-based demand response (DR) programs will be presented with the potential benefits and limitations of each technique. Since the global energy trend is moving toward a digitalized, decarbonized, and decentralized energy grid, advanced technologies implementation, such as blockchain and smart loads, will be investigated in the DSM framework.

13.2 Demand-side management

DSM first emerged as a response to rising costs of energy sources during the energy crisis of the 1970s, and it incorporates programs that help consumers manage their energy use, such as appliance rebates, energy-efficient lighting programs, as well as programs that reward customers for shifting their load during times of peak energy use [2]. "Demand-side management" is the term used to describe these programs developed by utilities to influence the electricity usage patterns of their customers, and in return, the achieved energy savings allow utilities to avoid or delay new investments in supply-side generation, transmission lines, or even distribution networks.

Nevertheless, the implementation of DSM programs in the market was not a smooth process. Historically, energy utilities used their substantial political control to often oppose and challenge DSM policies, considering that such programs reduce electricity sales, which can pose a challenge to the financial dominance of utility companies. Moreover, DSM empowers regulators over utilities, which creates a serious threat to utilities' political dominance in the sector [3]. But soon after, utility companies got convinced that the savings achieved from DSM programs will allow them to avoid or delay further investments in new supply-side resources. Utility DSM programs experienced a rapid expansion during the late 1980s, as state regulators offered incentives for utilities to adopt lower cost resource integrated based mechanisms. DSM programs reached their largest market share in 1993, accounting for $2.7 billion of utility spending or about 1% of US utility revenues [4]. By the late 1990s, DSM governance started to change. In states such as New England and California, utilities and DSM believers engaged in joint policy-making to develop new DSM mechanisms that would mutually favor utilities and other involved stakeholders [3].

In the electricity industry, DSM is defined as the planning, implementation, and monitoring of a set of programs and actions carried out by electric utilities to influence energy demand to modify electric load curves in a way that is advantageous to both parties [5]. Such activities may include any action aimed at modifying the consumer's load curve by affecting his electricity consumption behavior [6]. However, the implementation of a DSM program in any grid does not come without several technical challenges emerging from the fact that DSM mechanisms require continuous monitoring of both power generators and consumers demand [7].

Fig. 13.2 defines the different factors of a DSM program architecture. A typical DSM program entails different criteria to be considered for the planning, implementation execution, and assessment of energy utilities targeting the consumers in attempts

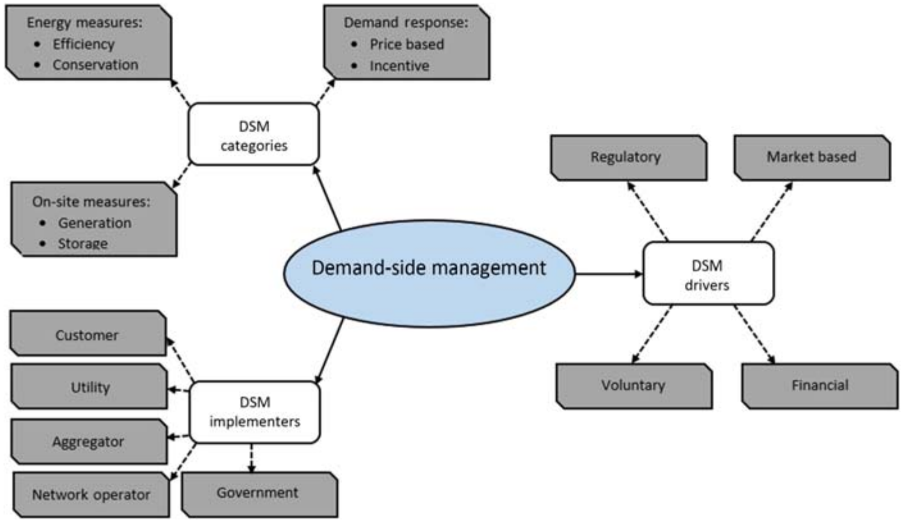

Figure 13.2 Demand-side management program architecture.

to promote efficient energy consumption and demand patterns [8]. These criteria can be grouped into three main categories: DSM categories, stakeholders, and drivers. In the following subsection, these categories will be developed in detail.

13.2.1 Demand-side management categories

DSM is a crucial component of any SG energy management system (EMS). Basically, DSM, or sometimes called energy demand management, is a set of interconnected programs that aim to encourage the end user to be more energy efficient. A DSM portfolio may include a variety of measures used to improve the consumer's load profile. These measures may include lighting retrofits, building automation upgrades, recommissioning, HVAC improvements, variable frequency drives, etc. [9]. Depending on the methodology used, the time of application, on-peak or off-peak, and the defined target, DSM mechanisms can be grouped into four main categories: DR, EE, virtual power plants (VPPs), and spinning reserve (SR) (Fig. 13.3).

A key objective of DSM projects is peak load power management [10] and thus expanding the capacity of the current network to accommodate more energy sources to be connected to the grid, minimizing losses due to standby power generation units, reduce GHG emissions, and provide a more comfortable and economic solution for customers. In an electrical system the load factor can be employed to judge the EE of a grid. The load factor is defined as the average load divided by the peak load in a specific time period, as shown in Eq. (13.1), where f_{load} is the load factor, P_{avg} is the average electrical load of a grid in the given time period, and P_{peak} is the peak electrical load of the grid in the given time period. A high load factor indicates a high EE. High load factors are always preferred by utility companies.

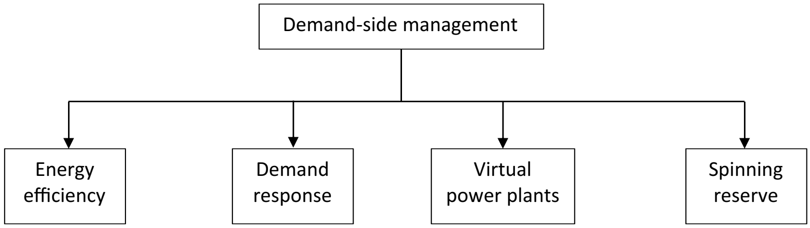

Figure 13.3 Demand-side management categories.

$$f_{load}(t) = \frac{P_{avg}(t)}{P_{peak}(t)} \tag{13.1}$$

Different methods can be used to improve the load factor. These methods are illustrated in Fig. 13.4. Peak clipping, load shifting, and flexible load shape are the most effective methods and are commonly adopted by the utility companies.

Hence, the main objective of a DSM project is to achieve peak load reduction. Nevertheless, it is noteworthy to highlight that the peak load of a grid may not be resulted by the individual peak loads of the end users. In other words, the peak hours of power demands may not fall in the same peak period for different end users. In such cases, the DR programs cannot achieve their original objectives but only affect the satisfaction of the consumers. To be effective in relieving network constraints, DSM measures must be capable of addressing the particular characteristics of these constraints. Network constraints have both timing and spatial dimensions.

In relation to timing, network constraints may be:

- *narrow peak related*: occurring strongly at the time of the system peak and lasting seconds, minutes, or a couple of hours;
- *broad peak related*: less strongly related to the absolute system peak, occurring generally across the electrical load curve and lasting several hours, days, months, years, or indefinitely.

In relation to the spatial dimension, network constraints can occur generally across the network in a particular geographical area or be associated with one or more specific network elements such as certain lines or substations.

Therefore factors that reflect prosumers' capabilities toward a certain DSM program are necessary to evaluate such a program. The load factor defined in Eq. (13.1) is one factor. Other defined factors are the diversity factor, coincidence factor, and the demand factor.

- *Diversity factor* is the ratio of the peak demand of a population of units to the sum of the noncoincident peak demands of all individual units.
- *Coincidence factor* is the fraction of the peak demand of a population that is in operation at the time of system peak. Thus it is the ratio of the population's demand at the time of the system peak to its noncoincident peak demand. The peak demand-use for given end users is typically not aligned exactly with the utility system peak, which is how the

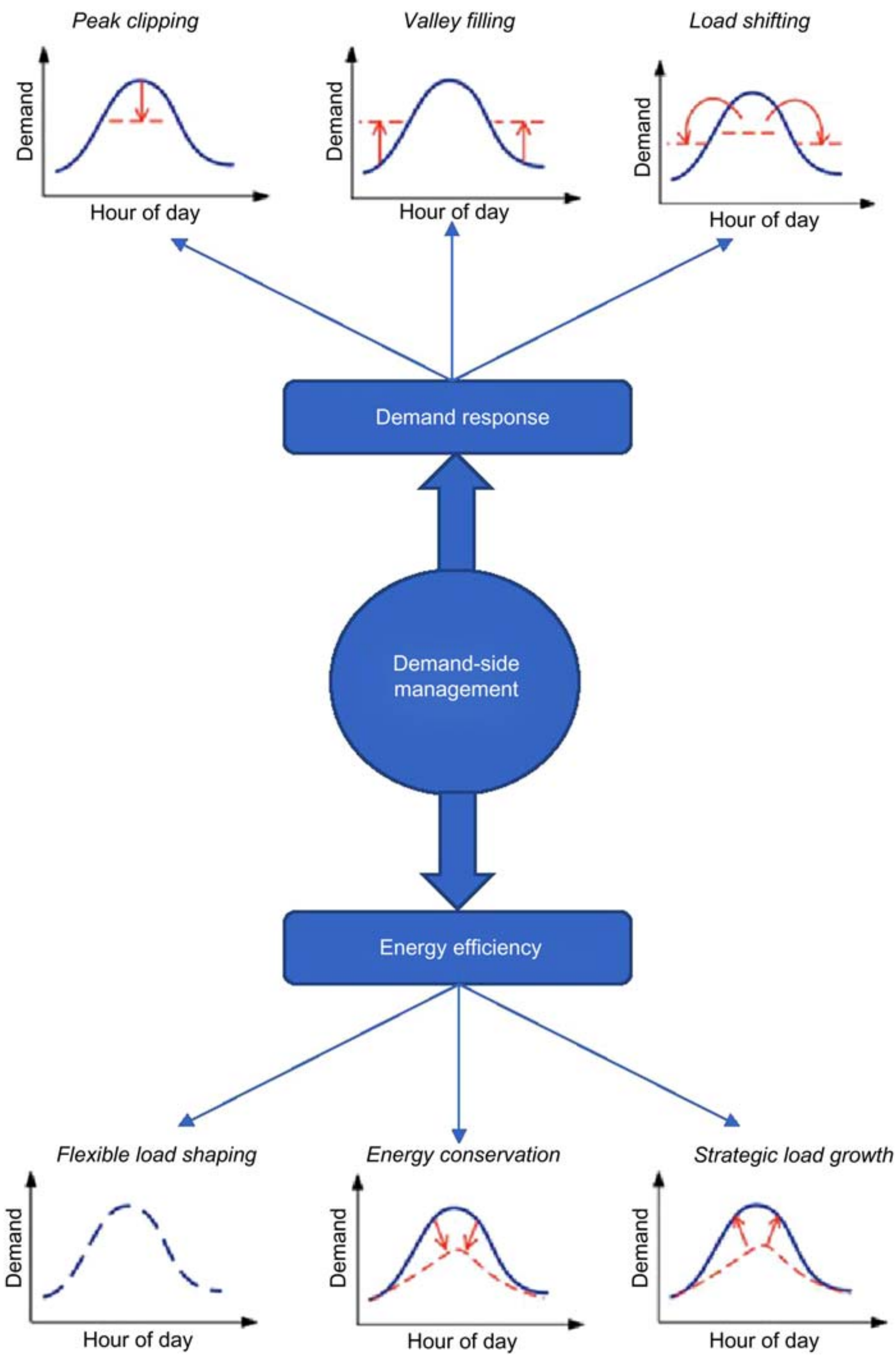

Figure 13.4 Methods for improving the load factor.

avoided peak demand is defined. The coincidence factor tells how likely the individual end users are peaking at the same time. DSM projects may reduce peak demand and consequently the need for investment in new generation, transmission, and distribution systems. This reduction in the need for new investment is called "avoided capacity costs."

- *Demand factor* is defined to represent the power demand characteristics of the end users, which can also be used as a factor indicating the potentials of the power DR. The demand factor is defined as the maximum power demand divided by the maximum possible power demand in a specific time period, as shown in the following equation [11]:

$$f_{Demand}(t) = \frac{P_{max}(t)}{P_{cap}(t)} \tag{13.2}$$

where P_{max} is the maximum power demand of an end user in the given time period and P_{cap} is the maximum possible power demand of the end user or, in other words, the total connected load of the end user, in the given time period.

Coincidence factor and diversity factor are often used for top-down forecasting in transmission and distribution planning. After the corporate level forecast is developed, the planning team would get a quota telling the sum of the peaks from various regions. This quota is usually calculated by dividing the forecasted system peak by the coincidence factor. The regional peak load forecasts can then be developed subject to the constraint of this quota [12].

13.2.1.1 Energy efficiency

According to the US Department of Energy (DoE), EE is defined as the use of a technology that requires less energy to perform the same function and such behavior is called energy conservation [13]. In the context of DSM programs, EE is defined as a long-term energy conservation measure (ECM), such as house-appliance efficiency enhancement and weatherization, that aims to save energy and reduce demand [14]. The implementation of EE programs can decrease energy demand for both on-peak and off-peak, limit energy demand growth, and postpone the need to expand the grid's capacity [15]. EE strategies may include:

- promoting energy-conscious behavior of users;
- taking advantage of wasted sources of energies, such as heat, to minimize the demand for energy by using cogeneration techniques;
- enhancing maintenance procedures and conducting regular or even continuous maintenance of equipment;
- replacing low-efficiency equipment with higher efficiency equipment;
- using advanced control systems for electrical equipment to regulate the voltage, achieve a three-phase balancing and improve the power factor; and
- using advanced control systems, such as EMSs and building management systems to properly control the use of energy and minimize the wasted energy.

Improving buildings or industrial facilities' EE begins with the acquisition and analysis of energy-related data [16]. This information is necessary to calculate or estimate the energy savings. Such calculation can be based on four approaches:

- Comparison to a baseline model: The new energy consumption achieved after the implementation of an ECM is compared to a baseline model constructed using historical data from the building or facility.
- Weekly comparison of time series: Most of the time systems such as lighting, ventilation, and air conditioning run through periods with no occupancy. By reducing the operational hours of these systems, considerable energy savings can be achieved.
- Benchmarking: Based on the comparison of the energy performance of your building or facility to similar buildings or facilities.
- Process correlation: Investigate if the energy performance of the system is correlating to independent variables such as outside temperature, occupancy, or production rate.

13.2.1.2 Demand response

DR is a term used for programs designed to encourage end users to make short-term reductions in energy demand in response to a price signal. Sometimes, energy professionals use the terms "demand response" (DR) and "demand-side management" (DSM) interchangeably, but they are not the same. While DSM targets to achieve a balance between energy production and energy consumption, since such an imbalance makes the price of energy even more expensive for the final consumer, DR programs pursue the temporary reduction of electricity consumption by the consumer, for a short period and in peak demand periods in exchange of economic incentives. Hence, DR encourages consumers to reduce their energy demand in the short term, while DSM includes not only DR but also long-term or permanent energy measures.

With the emergence of the SG concept and the advancement of two-way communication systems in electrical grids, DR is getting more attention and can be considered as the most crucial DSM mechanism. The fact that the consumer and the utility can exchange real-time information based on electricity pricing tariffs and energy demand allows to develop new models to schedule energy consumption offering not only a benefit to the consumer but also improving the electric grid's stability as well.

With the advancement and development of DSM programs, DR has proved to be a key DSM mechanism, and it is believed that DR is DSM's subset in a wider context. DR is described as a tariff scheme or program designed to incentivize the end users to change their energy consumption profile in response to electricity prices [17]. DR programs are further classified into two main categories: incentive based and price based. An incentive-based program provides monetary incentive to the end user on the base of load curtailment. Various incentive programs are discussed in Section 13.4, including direct load control (DLC), interruptible/curtailable load, demand bidding and buyback programs, emergency DR programs (EDRPs), capacity market programs, and ancillary services (AS) market programs. On the other hand, a price-based program is built upon different electricity tariffs during different time intervals. The aim of the price-based program is to minimize electricity usage in periods of high electricity cost and, thus, reduce demand during peak periods. Price-based programs are time-of-use (ToU), real-time pricing (RTP), inclined block rate, critical price peaking (CPP), and day-ahead pricing. DR programs are considered as a key feature in SGs, helping power markets set efficient energy prices, mitigate market power, improve economic efficiency, and increase security, thus improving the sustainability and reliability of power grids and at the same time offering a variety of financial and operational benefits to electricity customers, load-serving entities and grid operators [18,19].

On the other side, a successful DR program is completely dependent on DR enabling technologies since it is very difficult for energy consumers to track time fluctuating dynamic energy costs and amend their consumptions accordingly. In a residential sector, DR enabling technologies are available in the context of a smart home. The smart home features a home EMS (HEMS) that intelligently controls household loads through an association between smart meters, smart appliances, electric vehicles (EV), small home power generation units, and storage systems. Smart meters provide important information for both utilities and customers such as home load profiles and dynamic price signals. Rooftop solar panels and small wind turbines are now widely used. In addition, the market of plug-in EVs is growing fast. Emerging technologies pushing DSM projects, and specifically DR programs, to the next level are discussed in Section 13.5.

13.2.1.3 Virtual power plants

During the last decade, energy systems have metamorphosed from centralized form and hierarchically structured systems to a decentralized distributed system characterized by an increase of complexity in both terms of the number and type of resources and of the different stakeholders involved in the energy supply chain. The main driver behind this change is to meet market expectations of a decentralized, decarbonized, and digitized electric grid and respond to fast market changes as the exceptional growth of DERs. The integration of DSM and DERs into a VPP concept was made possible by recent advancements in the information and communications technology (ICT) field and modern power system issues. Together DSM and DERs bring important synergies in the form of a VPP. VPP management means that electricity suppliers can offer their prosumers the opportunity to save money if the overall power production and distributed generation capacities are intelligently meeting the instant demand. Nevertheless, this can only be feasible if the energy value chain is fully optimized by allowing remote management of the distributed generation and loads for brief periods of time. Power suppliers can use aggregated capacity to optimize the electricity schedule and minimize imbalance costs or to trade on AS market [20–22].

VPPs are considered as a cornerstone of the smart electricity networks of the future [23], and even though today they only exist on a megawatt scale, they will soon be deployed on a gigawatt scale at utility level as the underlaying ICTs are evolving exponentially specially with the emergence of new disruptive technologies such as blockchain, artificial intelligence (AI), and machine learning. Advanced IT systems allow electricity suppliers to manage their growing share of intermittent renewable sources, energy storage, and flexible consumption efficiently. Microgrids allow a better exploitation of the flexible and dispersed nature of DERs. This idea is further extended with the concept of VPPs and aggregators. Aggregation of different distributed resources, including load management, can efficiently replace or complement traditional peaking power plants and DR programs [24].

By definition, a VPP is an aggregation of power generation units, storage units, and controllable or flexible loads that form a virtual entity that interacts with a single central entity responsible for managing the electrical energy flow within the cluster and their exchange with the main network and monitoring and controlling functions over multiple DERs [25].

A VPP is considered a DSM mechanism since it has the potential to improve the integration of DERs by providing both demand- and supply-side flexibility services to the grid. Demand-side flexibility is provided by aggregating DR resources or energy storage units to act to grid requirements. Supply-side flexibility is provided by optimizing fast-response power generation units from flexible resources such as renewable energy generators, combined heat and power (CHP) plants, and biogas plants and energy storage units. Operation optimization is done based on historical data demand forecasted date, power generation data, and electricity prices.

VPPs contribution to DSM can be summarized as follows:

- *Load shifting:* VPPs can enable real-time shifting of residential, commercial, and industrial loads to provide DSM services to grid operators, based on price signals.
- *Balancing services:* VPPs can use optimization platforms to provide a range of AS, increasing the system's flexibility to integrate intermittent renewable energy resources. The aggregations of different DERs can mitigate the variations in renewable energy sources such as solar power or wind, the neck of the duck in the duck curve, or any other variable generation output. In addition to providing ramping requirements, VPPs can be used to provide AS such as voltage control, reactive power, frequency control, and energy imbalance.

By using VPPs to provide DSM and load shifting, investments in transmission and distribution grid reinforcements also could be minimized. However, real-time data acquisition from DERs is necessary for the creation and operation of a VPP. This would require a complete digitization of the electric network including smart meters, broadband communication infrastructure, network remote control, and automation systems.

13.2.1.4 Spinning reserve

On the generation side, SR refers to the available amount of online power generation capacity that exceeds the power required to supply the load and that can be used to respond to sudden load changes or loss of generators. In the DSM context, SR is a load management mechanism that involves supporting traditional AS by changing the loads on the demand side to maintain the frequency of the power generation system. Distributed SR tries to support the traditional providers of AS by imitating their behavior. On the demand side, this means that load can be reduced or increased when the grid frequency drops or rises.

Using demand-side resources to provide SR increases the total contingency reserve available to any system operator and might thus prevent situations in which operators would otherwise run short of generator-provided SR and have to call for rolling blackouts. The contingencies that trigger the need to call on SR typically occur once or twice a month, sometimes more or less often. However, because triggering contingencies are unpredictable, the system operator must have predetermined amounts of SR, among other contingencies, available continuously, to avoid rolling blackouts. SR is the fastest responding contingency reserve and thus the most critical for maintaining power system reliability.

Advanced communication and control technologies now make it possible to use aggregated groups of curtailable loads, such as air-conditioning units already equipped with load-cycling controls, as an SR resource that is potentially superior to relying on generators for this service. The natural response capabilities of these loads match the response speed, duration, and frequency required to support SR.

13.2.2 Demand-side management stakeholders

Over the past several decades, the energy sector has undergone a considerable transition taking advantage of different emerging technologies to provide wider capabilities to consumers and greater value to distributed resources. Traditional governance approaches, based on centralized decision-making techniques, are being upended to a decentralized more collaborative approach that awards edge stakeholders a greater role in governance [26]. A DSM project might include several stakeholders:

1. Government and policy makers
2. Power grid enterprises
3. Power generation enterprises
4. Third-party aggregators
5. End users
6. Energy service companies (ESCO)
7. Manufacturers and suppliers of energy conservation products
8. Financial institutions

- *Government and policy makers:* Energy security issues and environmental concerns are gaining most governments' attentions and increasingly moving to the forefront of political agendas. Energy production and consumption are the largest sources of GHG emissions and a major anthropogenic contributor to climate change. Global economy growth, demographic explosion, digitization, increased mobility, and greater demand for heating and cooling due to climate change in different areas of the world are the main drivers for the surge in energy demand. The increase in energy demand is also the basis of economic challenges for power companies alongside several socioeconomic problems in communities such as energy poverty, defined as the insufficient coverage of energy needs, especially in the residential sector. DSM is one of the tools that governments and policy makers could rely on to increase energy and environmental efficiencies, reduce CO_2 emissions, improve exchanges and generation allocations between interconnected countries, and meet international commitments and targets by increasing renewable energies penetration rate.
- *Power grid enterprises:* Power grid enterprises may include network service providers (NSP) and independent system operators (ISO). NSPs manage electricity networks and provide transport services for electrical energy through these networks. In addition, they may or may not carry out the technical operation of the electricity system and/or own

network assets. Independent system operators carry out the technical operation of electricity systems but they usually do not manage and provide transport services for electrical energy through electricity networks or own network assets. The application of DSM projects allows grid operators to balance intermittent generation from wind and solar units, particularly when the timing and magnitude of energy demand does not coincide with the renewable generation and to ensure grid reliability and reduce operational costs.

- *Power generation enterprises:* As the name suggests, power generation enterprises are responsible for the generation of electricity that is consumed by the end users. These are also considered the main promotor for DSM projects due to the value of DSM in balancing generation and demand. DSM can be beneficial to the power system thanks to reduced electric power peak demands, higher operational efficiency in production, lower investments for new power capacity, lower price volatility, lower electricity costs, and more cost-competitive power generation.
- *Third-party aggregators:* Increased digitalization and smart metering have created new business models. Aggregators are a new market player that can optimize the use of DERs. A third-party aggregator bundles several DERs together, creating a sizeable capacity similar to that of a conventional generator or a single load profile. Hence, in the DSM context, third-party aggregators manage and aggregate the provision of load reductions and DR by individual end users and receive direct payments from NSPs or ISOs.
- *End users:* By participating in DSM programs, end users may benefit from increased network reliability and lower network use of system charges—that would be the case without the implemented DSM, resulting in reduced electricity bills, increased choice about how their energy services needs are met, an increase in the variety, and number of customer services available and rebate payments from NSPs, ISOs, or third-party aggregators against the participation in the DSM program.
- *ESCO:* The ESCO model is an expanding industry throughout the energy world contributing to the improvement of EE and energy conservation. The models of offering these services can get various forms such as energy supply contracting or energy performance contracting, resulting in diverse contract models and financing arrangements. In many use cases, ESCOs have proven to be a powerful DSM instrument promoting performance-based EE measures.

Even though manufacturers and suppliers of energy conservation products and financial institutions are not considered as key players involved in any DSM program, they still can be looked at as fundamental actors of the new DSM financing schemes. Traditionally, program participants have funded the up-front cost of utility DSM projects through rebate programs or direct investment, or through loans from the utility to customers purchasing and installing various DSM measures. Alternative sources of financing based on a collaboration between ESCOs, suppliers of energy conservation products, and financial institutions have emerged in response to new market needs offering DSM participants immediate benefits with no or minimal up-front cost.

13.2.3 Demand-side management drivers and benefits

The success of any DSM program relies on some or all of the following levers: rates, incentives, access to information, communication and control, education and marketing, and measurement and verification (M&V).

- *Rates:* Electricity rates should be carefully tailored to achieve the desired objective taking into consideration the financial capabilities of the customers and reflecting in the best way the cost of power generation. Thus any DSM program must include a very well-designed tariff structure to yield the desired behavior while assessing the positively affected social classes and negatively impacted portions and making sure that any socio-economic class does not bear unnecessary costs.
- *Incentives:* Incentive is a key factor in engaging consumers to participate in a DSM program. Yet, incentives do not only apply to consumers but also power grid operates and utilities require to be incentivized to engage in a DSM project and cover for their DSM induced revenue losses. Moreover, DSM incentive mechanisms can encourage energy distribution utilities to play a major role in achieving more efficiency among their customers.
- *Access to information:* Access to real-time information may create an additional driver that pushes customers to be more aggressive in managing their energy consumption. Furthermore, the availability of comparative information about the true costs and benefits of the program greatly increases the prospects for the successful implementation of a DSM program.
- *Communication and control:* To fulfill their target, DSM programs require a two-way communication system, between the utility and the consumer, and load control mechanism to curb the demand. The communication system will allow the consumers to manage their own demand and distributed generation resources, based on electricity rates or other signals from the utility. On the other side, control systems could be integrated with programmable communicating devices, such as smart meters, thermostats, smart appliances, HEMSs, or other automation tools, to match consumers' preferences. This communication and control system commonly refer to the concept of SG, which aims to improve the reliability, quality, and efficiency of electricity services [27].
- *Education and marketing:* The purpose behind customer education and marketing of DSM programs is to increase perceived value of offered energy services, increase customer awareness of programs, and encourage greater customer acceptance of programs. Customer education is the most basic of the market implementation methods available and should be integrated in conjunction with other market implementation methods for maximum effectiveness of the program.
- *Measurement and verification:* To drive improvements and make sure that the DSM project has achieved its targeted goals, it is essential to verify the program results and collect feedback data from different sources. Such a process is conducted via a well-designed and defined M&V protocol.

Typically, DSM benefits can be grouped into two categories: benefits that accrue to a certain stakeholder and market-wide benefits. Stakeholder's specific benefits have been detailed in Section 13.2.2. Market-wide benefits include benefits that accrue to all participants, even if the DSM project was initiated by a specific stakeholder. The market wide−specific benefits from implementing DSM programs can be classified into four main categories:

- *Economic benefits:* Although DSM programs drivers are usually based on reasons other than high prices in the electricity market, the load reductions achieved, by these programs, may lead to reduced market prices. Therefore market-wide economic benefits from DSM projects may include reduction in the average price of electricity in the spot market, limited spot market prices' volatility, and reduced costs of wholesale long-term bilateral electricity transactions.
- *Reliability benefits:* Power system reliability, characterized by system security and system adequacy, is a crucial concern in any grid. DSM programs have the ability to help achieve

voltage stability in power systems. System adequacy is concerned with the existence of sufficient equipment and facilities in the system to fulfill consumer demand. System security is related to the capability of the system to respond to disturbances. The two main performance indicators of any electric grid's reliability are voltage and frequency stability. Voltage stability is important for alleviating transmission congestions that are otherwise limited by bus-voltage violations. On the other hand, DSM programs play a major role in maintaining the grid's frequency stability as well [28]. Moreover, as DSM aims to flatten the load profile as much as possible and minimize the peak load duration, the needed transmission capacity is thus reduced, and this effect indirectly relieves transmission congestion as well and therefore minimizing outage time and increasing grid's reliability [29].

- *Market operation benefits:* DSM measures implemented to achieve network-related objectives may also impact on the operation of the electricity market. Market operation benefits may include reduced market power (situational and behavioral) and improved overall market efficiency from better interaction of demand and supply.
- *Environmental benefits:* As previously detailed, the main objective of DSM projects is to reduce the need for additional power generation and mitigate further investments in grid expansion. This reduction in power generation allows to lower GHG emissions and thus decreases environmental damage [30].

13.2.4 Demand-side management cost-effectiveness

The question of how to define the effectiveness of any DSM program is a critical issue to address when advancing DSM as a key resource in balancing between supply side and demand side. Well, the cost-effectiveness test is the simplest way to measure whether an investment's benefits exceed its cost. Several factors should be taken into consideration when conducting a DSM cost-effectiveness test. First, a stakeholder perspective should be defined. The cost-effectiveness test can be conducted from the DSM program participant's perspective as well as from the utility's perspective. Both perspectives represent a valid viewpoint and contribute toward assessing DSM programs. The second key element to be considered is the defined costs and benefits and how well they reflect the aimed at program targets. Moreover, the final factor involved is the baseline against which the costs and benefits are measured. Five cost-effectiveness tests that are commonly used for DSM programs are listed next. A comparison between these five cost-effectiveness tests is shown in Table 13.1.

- Participant cost test: Comparison of the costs and benefits of the customer participating in the DSM program
- Program administrator cost test: Comparison of program administrator's costs to supply-side resource costs
- Ratepayer impact measure test: Comparison of administrator costs and utility bill reductions to supply-side resource cost
- Total resource cost test: Comparison of program administrator and customer costs to utility resource savings
- Societal cost test: Comparison of society's energy-related costs to resource savings and nonmonetary costs and benefits

Each test provides unique information about the impacts of the DSM program from different vantage points in the energy system. On its own, each test provides

Table 13.1 Cost-effectiveness tests comparison.

Component	PCT	PACT	RIM	TRC	SCT
Energy and avoided capacity cost		Benefit	Benefit	Benefit	
Additional resources savings				Benefit	
Nonmonetized benefits				Benefit	
Incremental equipment and installation costs	Cost				
Program overhead		Cost	Cost	Cost	
Incentive payments	Benefit	Cost	Cost		
Bill savings	Benefit		Cost		

PACT, Program administrator cost test; *PCT*, participant cost test; *RIM*, ratepayer impact measure test; *SCT*, societal cost test; *TRC*, total resource cost test.

a single stakeholder perspective. Together, these multiple tests provide a comprehensive approach for assessing the program's overall effectiveness while providing additional information on the program's balance, on the effect of rates and on adjustments that might be required to improve the program's alignment. The basic structure of each cost-effectiveness test involves a calculation of the total benefits and the total costs in dollar terms from a certain vantage point to determine whether or not the overall benefits exceed the costs. A test is positive if the benefit-to-cost ratio is greater than 1, while negative if it is less than 1. The results are reported either in net present value (net present value) or as the ratio of the benefits over the costs. The results of cost-effectiveness test compare relative benefits and costs from different perspectives. A benefit−cost ratio above 1 means the program has positive net benefits, whereas below 1 indicates the costs exceed the benefits.

13.3 Demand response

As previously described, DR has proved to be a key DSM mechanism and it is believed that DR is DSM's subset in a wider context. By definition, DR is a term used for programs designed to encourage end users to make short-term reductions in energy demand in response to a price signal. Hence, while DSM programs aim at long-term energy demand reduction, DR programs focus on reducing demand temporarily in response to a price signal or other type of incentive, particularly during the system's peak periods. Consumers receive compensation, in the form of an incentive or rate design, to reduce nonessential electricity use or to shift electric load to a different time, without necessarily reducing net usage. DR is dispatchable in both space and time, providing the ability to stabilize transmission grids, reduce wholesale market price volatility, dilute market power of wholesale generators, and provide AS. Depending on the price-scheme used, some DR programs may operate in real-time, whereas others may work on a day/hour-ahead scheduling basis. Different DR programs have been developed and applied for encouraging the end users to change their energy usage behaviors expected by the grid. Generally, consumers are able to limit and/or shift the power demands according to their own considerations under the specific incentives. In general, the optimization model is as follows:

$$Minimize\left(\sum_{t\in T}\gamma_t \cdot E_t\right) \tag{13.3}$$

where γ_t is the energy rate in \$/kW h at time t and E_t is the energy consumed in kW h at time t.

Under a DR program, utilities may call customers to serve needs such as reducing costly on-peak power purchases and diffusing market power of wholesale generators or to respond to emergency events. To alleviate customer concerns, utilities often design into the program flexibility options to allow for relative degrees of customer participation. Such flexibility options might include a set of operating constraints such as user comfort levels, priority and operating patterns of appliances, and weather conditions, data uncertainty, and user behavior considerations as shown in Fig. 13.5. The formulation of a DR algorithm or a load control strategy depends on the type of loads, typical usage patterns, working cycles, uncertainty considerations, behavior modeling, technical constraints and distributed renewable generation, and storage facilities available. Hence, DR potential of various services needs to be assessed for designing a proper DR algorithm [31].

However, DR mechanisms might have some undesirable effects in some cases such as peak rebound problem, blackout or brownouts, disturbing the load diversity if not properly coordinated. In DR programs, electricity consumers play a significant role in power system operations in terms of reducing their electricity usage during system peak load in response to a time-based rate or incentive payment [32]. Nevertheless, when energy consumption strategies such as response (DR) programs

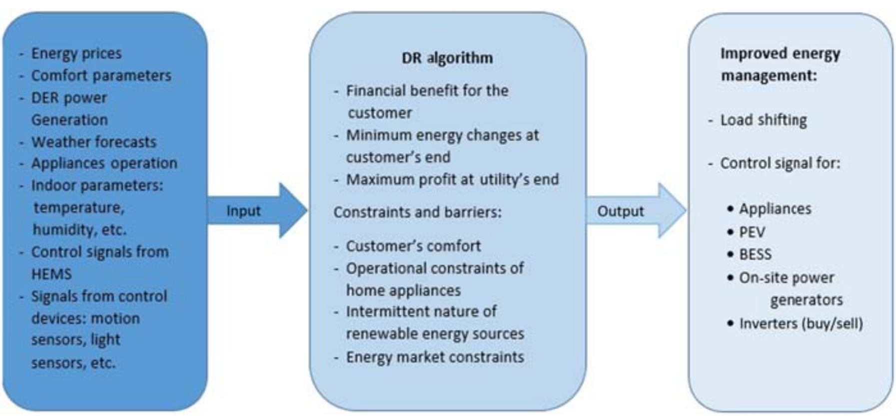

Figure 13.5 Inputs and outputs for a typical residential DR algorithm. *DR*, Demand response.

are considered, the economic problem of free riding arises [33]. Free riding is considered when a person benefits from certain goods or services without expending effort or paying for it. In other words, free riders are those who utilize goods without contributing their fair share and even end up consuming excessively. In DSM programs, free riding occurs when consumers get incentives without really reducing their loads. In general, people profit from energy consumption but seldom pay for it as for other public goods which may eventually lead to the destruction of this public good or service [34]. On the other hand, an important barrier to overcome when considering the desired and designed impact for DR load shifting projects is the so-called rebound effect. In conservation and energy economics the rebound effect, or take-back effect, is the reduction in expected gains from new technologies that increase the efficiency of resource use, because of behavioral or other systemic responses [35]. This is a significant outcome of DR programs, which is commonly underestimated. It characterizes the negative relationship between technology and consumption [36]. Thus it is essential to develop a DR program that can achieve the ultimate targets of reducing the overall energy demand and shaving the peak load while avoiding the free riding and rebound effects.

DR programs are broadly classified based on the applied customer motivation method. DR mechanisms can be divided into two groups: time or price based, and incentive based. The idea behind the time based, or price based, DR is that a customer changes his electricity usage in response to changes in electricity prices. The incentive-based DR program refers to incentives separated from the retail electricity rate and can be offered by the grid operator or utilities [37].

13.3.1 Price-based demand-response programs

In a price-based DR model, or sometimes referred to as price-responsive demand, the price is controlled to induce customers to decrease demands as occasion arises. Time- or price-based DR mechanism is applicable with dynamic rate structures such as ToU, RTP, and CPP. In systems where a dynamic rate structure is applied, the electricity price depends on both the energy demand and power generation resulting in high electricity rates when the electricity demand is high and/or when there is a shortage in production or the used power generation systems have a high levelized cost of energy. For different hours or time periods, if the price varies significantly, customers can respond to the price structure with changes in energy use. Their energy bills can be reduced if they adjust the time of the energy usage taking advantages of lower prices in some periods and reducing consumption when prices are higher. In contrast to fixed pricing is dynamic pricing, where rates of energy for certain time periods can be changed daily, in RTP rate structure the customers have access to the hourly fluctuations in energy rates. In a ToU program the price of electricity varies on a daily and yearly basis. The ToU can be seen as an RTP tariff with a very long-time lag. The idea of CPP is to offer customers reduced electricity rates under normal circumstances, while the retailer or the utility company has the possibility to increase the electricity rates for some periods of the year when the total power demand is high [37]. Dynamic pricing enables more accurate adjusting of consumption. Price-based DR model can be classified as follows:

- *ToU:* ToU pricing schemes mean that when customers use energy, not only the quantity consumed, but also the time when the energy is consumed influences the applied rate of the energy portion of the bill. ToU typically applies to usage over broad blocks of hours that vary by season, on weekdays versus weekends and holidays, and across multiple periods over the course of an individual day. The goal of ToU pricing is to better align the price for electricity paid by consumers with the actual cost of electricity production electricity. In most cases, utilities update the residential electricity rates, under a ToU scheme, once or twice a year.
- *RTP:* An RTP scheme has the same objective as a ToU pricing scheme but is defined for shorter periods of time, usually 1 h, reflecting the changes in the wholesale price of electricity. Customers usually receive information about price adjustments on a day-ahead or hour-ahead notice.
- *CPP:* It is a hybrid of the ToU and RTP schemes and is harder to implement. Within a CPP scheme, a ToU pricing is in effect all the time with the exception of certain peak periods when electric prices may reflect the costs of generating or purchasing electricity at the wholesale level. Thus when utilities observe or anticipate high wholesale market prices or power system emergency conditions, they may call critical events during a specified time period and raise electricity rates considerably during these time periods. The number of critical events within a well-defined time period (i.e., a year) is usually predetermined in advance and consumers are typically informed about the critical event a day ahead.
- *Critical peak rebate (CPR):* A CPR scheme is similar to CPP with a difference that consumers are paid to reduce consumption during critical peak tariffs. As in the case of CPP, here as well, consumers are informed about the critical events in advance, usually a day ahead.
- *Inclining/declining block rates:* Inclining block rates provide customers with an incentive to reduce the total usage, whereas declining block rates provide customers with an incentive to increase the total usage. Usually, a declining block rate is applied in cases where generation capacity is abundant. However, these rates do not provide price signals that reflect current market conditions. An inclining block rate may provide a relatively high energy price to customers at higher usage levels **and** can lead to **a modest** reduction in the amount of energy consumed.

13.3.2 Incentive-based demand-response programs

In the incentive-based model, also known as the reward-based model, if customers reduce energy consumption, they will be given financial incentives. Some of the applied incentives are AS program, capacity demand program, demand-side bidding, emergency programs, interruptible programs, and DLC.

- *AS program:* The US Federal Energy Regulatory Commission (FERC) defines the AS as "those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system." Some of the AS are voltage control, reactive power, frequency control, and energy imbalance. Thus the AS DR program provides incentives for costumers to interfere on the grid to

control one or more AS. AS market programs allow customers to bid load curtailment in the spot market as operating reserve. When bids are accepted, participants are paid the spot market price for committing to be on standby and are paid spot market energy price if load curtailment is required. Traditionally, AS have been provided exclusively by generators. Over the past decade, alternative resources such as DR have become increasingly capable of providing such bulk power systems. Conceptual studies have proven that DR resources are well suited to provide AS to the grid due in part to their fast response, distributed nature, and the statistical reliability of large number of smaller resources [38].
- *Capacity demand program:* In a capacity DR program, the system operator is given the right to call upon the end user to reduce his demand during reliability emergencies; typically, on hot days during summer season. Capacity demand programs, also known as capacity market programs, are offered to customers who can commit to provide prespecified load reductions when system contingencies arise. Participants usually receive a day-ahead notice of events and are penalized when not responding to load reduction call.
- *Demand-side bidding:* Also called buyback program. The concept of demand bidding is that the customer is free to choose a bidding value in terms of their availabilities in load reduction quantities and the expected cost benefits in advance. The bid is accepted if it is less than the market price. When a bid is accepted, the customer should curtail his load by the amount specified in the bid. If the actual amount of energy saving is met, the customer will be rewarded. On the other hand, the end user will be penalized if he cannot accomplish the declared load reduction.
- *Emergency programs:* The EDRP allows utilities or wholesale electrical retailers in deregulated markets to subscribe retail end users able to provide load reduction by curtailing load or by shifting load onto a local generator when called upon during emergency conditions.
- *Interruptible/curtailable program:* The interruptible program is intended to provide load reduction on the gird on a specific period of time when the utility operator issues a curtailment notice. In return, the customers enrolled in this program are given up-front payments or rate discounts and are warned in advance prior to any curtailment. This type of DR mostly targets big commercial and industrial customers.
- *DLC:* As the name indicates, the utility or the power provider has the right to control the appliances or equipment of the end users to shave the peak load. For the indirect load management the utility or power provider sends the price signals to incent the end users to reduce their energy demand. Using remote control devices, the grid operator can remotely monitor and control the consumer's appliances. Mostly, this type of program is suitable for residential customers.

DLC and interruptible/curtailable programs are classified as classical incentive-based DR programs, whereas demand bidding, emergency DR, capacity market, and AS programs are classified as market-based DR programs. Also, it is worth mentioning that the price-based DR can contribute to the daily peak load reduction, while incentive-based DR can contribute to either the daily peak load reduction or the real-time power balance [39]. Fig. 13.6 shows the classification of power DR corresponding to the grid power management. Finally, the DR is considered as an essential component of the SG playing a key role in reducing the peak demand and improving the EE and the stability of the power system. Nevertheless, a successful DR implementation requires both the DR enabled technologies and the DR policies and regulations.

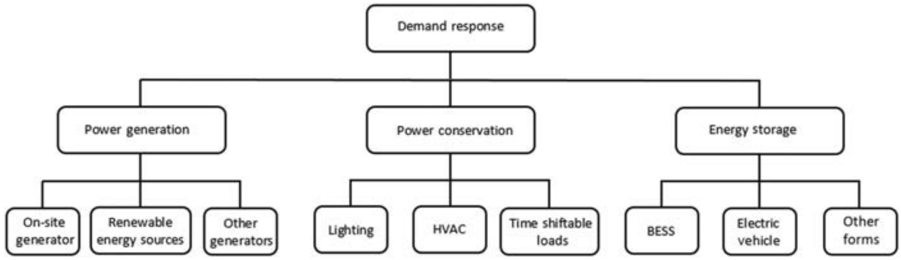

Figure 13.6 Demand-response mechanisms at power demand side.

13.3.3 Potential benefits

One of today's most effective tools for improving energy management is DR. This provides financial incentives for businesses to reduce or shift electricity use in response to power grid reliability needs or, in some cases, high electricity prices. DR enables grid operators and electric utilities to relieve stress on the electrical grid by compensating commercial and industrial customers, and, to an increasing extent, residential customers, for curtailing electricity use at times of peak demand or in the event of an emergency. Due to a closer alignment between the electricity prices of customers and the value they place on electricity, the most important benefit of DR is increased resource-efficiency of electricity production. This improved productivity produces a number of benefits, falling into four groups:

- DR eliminates the need to run standby generators or use SR.
- DR eliminates the problem of integration of renewable energy sources to the grid.
- DR eliminates the problem of frequency instability and keeps the balance between demand and supply.
- Customers can reduce the electricity bill by shutting down or shifting high load devices during peak periods.

13.3.4 Limitation and barriers

Besides the financial incentives, a successful DR program relies on DR enabling technologies since it is very difficult for energy consumers to track time fluctuating dynamic energy costs and amend their consumptions accordingly. In a residential sector, DR enabling technologies are available in the context of a smart home. The smart home features a HEMS that intelligently controls household loads through an association between smart meters, smart appliances, EV, small home power generation units, and storage systems. Smart meters provide important information for both utilities and customers such as home load profiles and dynamic price signals. Therefore despite all the benefits offered by DR programs, the lack of advanced metering infrastructure (AMI) remains a major barrier preventing the full realization of DR.

Moreover, today's energy billing systems are not designed for a bidirectional energy market in which customers produce and consume energy at the same time. For example, individual bills are still issued for every point-of-delivery, rather than one aggregate bill per customer, who might own several apartments, illustrating that these systems do not apply a user-centric system hierarchy. As a result, retailers do not have any information about customers who own multiple locations and therefore are unable to offer personalized products. Moreover, billing constitutes between 5% and 15% of retailers' total operating costs. This results from the fact that the industry still relies on expensive and outdated legacy software that have high setup and maintenance costs, without providing the necessary functionalities that are needed to compete in a more customer-centric energy market. Moreover, the current data collection, processing, and financial settlement processes are highly inefficient and error-prone, resulting in significant time delays in value settlement and the need for costly reconciliation processes. Thus the need to develop an automatic decentralized energy trading system that can automatically collect energy consumption offers a user-centric approach and ensures a simple settlement for energy transactions in a bidirectional way. This is where blockchain, Internet of Things (IoT), and AI can revolutionize the current energy trading models by providing energy companies with the possibility to incorporate thousands data points per day per smart meter, enabling them to offer customers a variety of innovative, dynamic tariffs, services, and products, while running on an efficient, fully automated, and process-assured billing system.

13.4 Advanced demand-side management technologies

The modern power system is more and more penetrated by DERs and it is evolving into the SG model. More interaction between different energy sectors, new storage possibilities and new loads like electrical vehicles, heat pumps, and CHP units are expected. Most utilities are focusing on integrating SG technologies in energy systems to achieve system adequacy, EE, low-carbon and sustainability, circular economy, and user comfort while enabling energy flexibility and efficiency for economic savings in integrated energy systems using advanced technologies tools and Big Data from AMIs. Intelligent energy systems for smartening active distribution grids are highly essential. Intelligent integrated solutions are regarded as a key to developing new and smarter DSM programs toward sustainability, CO_2 emissions reduction, high integration of renewable energy sources, improvement of the energy system efficiency, and increased energy independence.

13.4.1 Smart loads and smart grids

The essential problems that microgrids are meant to solve are those of limited backup energy or the excess of electrical power over the amount used at any moment, and the increasing integration of intermittent sources, such as wind and photovoltaic that are unpredictable and controllable, on the grid. The first adopted solution was based on the usage of fast start technologies such as diesel or gas generators. The problem with this type of power generation systems is that these systems have a low efficiency and sometimes can be very expensive. The second adopted solution was based on the DR. DR is technically based on both increasing as well as reducing the energy demand in everyday usage controlling by this the load profile via signals sent by the utility operator.

The SG combines advanced communications and control technologies and practices to improve reliability, efficiency, and security that are key ingredients in the ongoing modernization of the electricity delivery infrastructure. The latest technologies contributing to the development of the SG systems can be grouped as follows:

- AMI: AMI is an integrated system of smart meters, communications networks, and data management systems that enables two-way communication between the utility and the prosumer. The core element of AMI is smart meters, which provide a number of functions, including measuring customer electricity consumption on prefixed intervals, measuring voltage levels, and monitoring the on/off status of electric service. Smart meters communicate these readings to utilities for processing, analysis, and recommunication back to customers for billing, energy feedback, and time-based rates. The AMI system enhances the operational efficiency of the utility operator and provides the prosumers with the necessary information to better manage their energy usage.
- Users' smart technologies such as programmable thermostats and building EMSs for commercial and industrial applications and HEMSs for residential applications. The combination of these technologies with the AMI can contribute toward controlling the peak demand and shaving new investments in the utility grid. Nevertheless, when dealing with the consumer's smart technologies, the issue of the customer's privacy should be addressed.
- The integration of sensors, communication systems, and control technologies in the transmission and distribution network to improve the reliability and efficiency of the power supply system. SG applications enable utilities to automatically locate and isolate faults to reduce outages, dynamically optimize voltage and reactive power levels for more efficient power use, and monitor asset health to guide maintenance.

A new emerging component of DSM programs, that also plays a major role in improving SG's power quality, is smart loads. Smart loads differ from any other conventional load by having the following characteristics:

- Smart loads can be remotely controlled.
- Can perform and report state examination. The state of a smart load can be examined automatically and fed back to the network.
- Can perform power quality examination: Voltage sag, three-phase voltage imbalance, etc. When the power quality cannot meet the need of loads, the information is uploaded and the power is cut to guarantee the safe of loads.

Smart loads represent the convergence of energy-efficient, controllable appliances and real-time access to energy usage data. This integration of smart devices and SG enables customers to proactively manage energy use in ways that are convenient, cost effective, and good for the environment. Automated household appliances, controlled based on the user's preferences and adapted to his daily lifestyle, along with advanced intelligence that enables the consumer to use real-time energy budgeting to manage the dollars spent on energy in any given day, allow smart loads to fine-tune the consumer's energy consumption to match his usage habits.

Smart loads are a new enabler of residential DR programs. Even for traditional DR programs, smart loads may offer greater aggregate response while offering wider acceptance and attracting greater engagement from the end users. On the other side, autonomous load shaping may be a key developer of smart load. Autonomous load shaping is valuable not only to SGs, but to future microgrid energy models, including site-based storage and generation. A well behaved and more predictable load is a more valuable load. Smart loads satisfy customers through more efficient and cost-effective DR programs.

13.4.2 Internet of Things

Modern smart devices allow building systems to communicate and interact with each other, sometimes without any human intervention. This development, enabled by the revolution of the IoT, is starting to have an impact on the way facilities or prosumers communicate with electric utilities. In fact, the IoT is essential to automating DR programs as the utilities industry tries to move closer to a national SG. The IoT is the concept of basically merging the physical and digital worlds by connecting any device to the Internet and/or to each other. The IoT is a giant network of connected devices. When combined with distributed power generation such as renewable energy sources, microgrids have to deal with variable power generation output levels. For example, clouds can reduce the solar generation level very quickly. Therefore the local generation level, power drawn from the power grid, local power storage, and demand load need to be monitored, coordinated, and controlled rapidly to maintain stability in a microgrid. Moreover, the integration of SG components, such as smart metering and smart technologies implemented on the generation, transmission, and distribution levels, all require advanced communication and control techniques. None of the above will be possible without a highly reactive, real-time data layer that controls and reacts to every sensory input on the system. The IoT is a key component in this framework and provides the link for microgrid integration. Furthermore, the ability of microgrids to operate autonomously from larger grids could prove to be a major driver of IoT adoption in smart cities of the future. Microgrids are becoming more efficient as sensors improve and faster communication protocols will pave the way for better grid and source control. The integration of IoT with microgrids will offer the following advantages:

- predicting renewable energy resource availability and near-term local generation levels in advance to allow enough time for the utility to adjust power generation;
- analyzing supply, consumption, price, cost, generation resource availability, and asset conditions in real-time to create optimal DR plan under constraints and optimal generation plan balancing local generation level, drawing from/feeding to the grid and drawing from/storing in local storage; and
- operating independently of the power grid—dynamic switching between connected, transitioning and island modes based on physical data about the grid.

IoT-based DSM could potentially achieve intelligent energy management through information network platform and Big Data analysis, planning, and administration. IoT devices have the capability to distinguish any failure in the operation or abnormal decrease in EE, alarming the need for maintenance or adjustments, thus increasing the reliability and efficiency of the system, in addition to reducing the cost of maintenance. Therefore the integration of IoT devices in DSM projects lessens the risk borne by the end user, hedging the chances of noncompliance with the program requirements, avoiding penalties, and making the most of the offered incentives.

13.4.3 Blockchain-based demand-side management programs

Real-time control and supervision play an important role in the smart energy grids management. Due to the rapid growth in the deployment of DERs, the SG management problems can no longer be efficiently addressed using centralized approaches. Hence, the need for visionary decentralized approaches and architectures is widely recognized. Blockchain technology could facilitate a fully decentralized energy system. Demand-side response would be a clear beneficiary.

A blockchain is a distributed chronological ledger that is hosted, updated, and validated by several peer nodes, rather than by a single centralized authority. By eliminating the central authority and having immutable transaction records that are validated by several peers, the blockchain increases the simplicity, speed, and transparency of transactions between two peers. An example of the implementation of blockchain is the cryptocurrency Bitcoin. While credit card transactions require validation from a bank and require time, blockchain does not require central validation and two-party transactions happen immediately [40].

Since blockchain is a secure peer-to-peer trading platform, it has gained the interest of businesses and industries in energy markets. The blockchain promises a transactional platform that is fast, highly secure, has lower incidents of error, and can often reduce capital requirements [41]. It allows companies to automate more while processing greater volumes of data with fewer people at lower cost and risk. Energy companies are dealing with greater requirements for reporting, transparency, and security of data, which increases energy trading process costs and the need for personnel and resources. Energy blockchain provides solutions for these challenges. The energy sector is one of the industries where blockchain can have substantial impact.

Traditional transactional models are based on a centralized structure. Transactions between network nodes occur only through an intermediary third party who maintains the ledgers. Involvement of an intermediary is often necessary because it creates trust when transaction partners are unacquainted. Intermediaries usually charge fees for their services. The involvement of intermediaries increases the processing time required for transactions. Since all transactions are linked and stored on a central server or infrastructure, centralized structures have the disadvantage of a single point of failure. Alternatively, decentralized systems, such as the one offered by blockchain, have different network nodes that can interact directly with each other without an intermediary. There are many ways that transaction ledgers can be maintained. With a secure P2P distributed ledger technology, problems associated with centralized structures can be resolved.

So, blockchain technology has the potential to deliver more efficient, transparent, and near real-time transaction platforms that will unlock new business models. In the energy industry, this promise is particularly compelling when applied at the grid edge, as greater market participation and transparency are sought. An interesting feature of DSM projects is that multiple parties can benefit simultaneously from a single action. The forecasting of power generations and power demands is the essential premise for generation arrangement and power management. The use of blockchain technology for delivering a transparent, secure, reliable, and near real-time energy model, under the form of energy demand profiles management, is something to look at. Such a model can be based on a blockchain-enabled distributed tamperproof ledger where the energy prosumption data, collected from smart meters, is stored, while self-enforcing smart contracts programmatically define the expected energy flexibility at the level of each prosumer, the associated rewards or penalties, and the rules for balancing the energy demand with the energy production at the grid level. Another potential use case is the model of a DSM aggregator, as a key player in managing the demand during the peak hours by acting as an energy manager between the utility and the consumer.

13.5 Conclusion

Energy systems are on the threshold of a new transition era as policies and measures targeting energy supply took off over the last decades. The main dilemma confronted by all energy utility companies is how to maintain an equilibrium between the supply and demand. Large-scale deployment of DERs and microgrids combined with the need for efficient use of energy call for system-wide integrated approaches to minimize the socioeconomic-environmental impacts of energy systems. Besides, concerns about the sensitivity of economies to energy prices, oil dependency and more recently climate change, contributed to the development of EE policies. Demand-related policies that aim to influence quantities or patterns of energy use have traditionally been referred to as DSM programs. DSM and specifically DR can play a vital role in balancing the supply and demand without introducing more generation capacity and threatening environment. In addition, the implementation of DSM programs is likely to introduce improvement in the efficiency of power systems, reduce financial burdens on utilities, improve the environmental situation and lower the cost of delivered energy to consumers, thus lowering operation and maintenance costs as well as consumer bills, enhance system reliability by reducing power shortages and power cuts, improve the national economy by improving the value added of the electricity sector, and advance the national energy security.

Moreover, new emerging technologies such as blockchain, IoT, AI, machine learning, and Big Data will heavily disrupt the energy sector and change it from a central, hierarchical supply chain to a decentralized, decarbonized, and decentralized smart platform. Energy suppliers are in a continuous quest to reap greater productivity and improve safety. Digitalization of the energy sector can improve safety, increase productivity, and reduce costs. Digitalization is essential to integrate DERs, to unlock load flexibility, to increase variability in the system, to enable people to participate in the management of their energy supply, or help them become active participants in the energy system with their own projects, with their own resources. From the utility perspective, digitalization allows them to monitor the system, detect failures, and procure the services and solutions that they need to keep the system running.

Finally, a better integration of flexible DR programs with distributed generation, energy storages, and SGs could lead to an increase of the value of DSM and DERs and a decrease of problems caused by the intermittent nature of distributed renewable energy-based generation in the electric network and at the electricity market level.

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6.3 ARTICLE: BLOCKCHAIN-ENABLED ENERGY DEMAND SIDE MANAGEMENT CAP AND TRADE MODEL

Cet article, intitulé « *Blockchain-Enabled Energy Demand Side Management Cap and Trade Model* », a été publié dans sa version finale en décembre 2020 par les éditeurs du journal *MDPI – Energies.*

Référence: Aoun, A.; Ibrahim, H.; Ghandour, M.; Ilinca, A. Blockchain-Enabled Energy Demand Side Management Cap and Trade Model. Energies 2021, 14, 8600. https://doi.org/10.3390/en14248600

En tant que premier auteur, j'ai contribué à la conceptualisation et au développement du modèle, à l'essentiel de la recherche sur l'état de la question, à la collecte et l'analyse des données et à la rédaction du manuscrit. Les professeurs Adrian Ilinca, Mazen Ghandour et Hussein Ibrahim en tant que co-auteurs, ont participé à la direction du projet, à la supervision du travail, validation des résultats, à la révision de l'article et à la revue de la littérature.

Résumé : La croissance économique mondiale, l'explosion démographique, la numérisation, l'augmentation de la mobilité et l'augmentation de la demande de chauffage et de refroidissement due au changement climatique dans différentes régions du monde sont les principaux moteurs de l'augmentation de la demande d'énergie. L'augmentation de la demande d'énergie est à l'origine de défis économiques pour les compagnies d'électricité, ainsi que de plusieurs problèmes socio-économiques dans les communautés, tels que la pauvreté énergétique, définie comme la couverture insuffisante des besoins en énergie, en particulier dans le secteur résidentiel. Deux stratégies principales sont envisagées pour répondre à cette demande accrue. La première stratégie se concentre sur de nouveaux modes de production d'électricité durables et respectueux de l'environnement, tels que les sources d'énergie renouvelables et les ressources énergétiques distribuées. La seconde stratégie est axée sur la demande plutôt que sur l'offre. Les programmes de gestion de la demande, de réponse à la demande et d'EE entrent dans cette catégorie. D'autre part, la décentralisation et la numérisation du secteur de l'énergie, accompagnées par l'émergence de nouvelles

technologies telles que la chaîne de blocs, l'IdO et l'IA, ont ouvert la voie à de nouvelles solutions pour résoudre le dilemme de la demande d'énergie. Parmi ces technologies, la chaîne de blocs a fait ses preuves en tant que plateforme commerciale décentralisée entre des pairs non fiables, sans l'intervention d'un tiers de confiance. Le modèle d'échange P2P est utilisé pour créer un nouveau concept de contrôle de la charge de la demande. Dans cet article, le concept d'un modèle DSM par plafonnement et échange (Cap and Trade, C&T) d'énergie est introduit et simulé. Le modèle DSM introduit est basé sur le concept de plafonnement de la consommation d'énergie mensuelle des consommateurs et sur la récompense des consommateurs qui réduisent leur consommation d'énergie. Le modèle présenté est basé sur le plafonnement de la consommation mensuelle d'énergie des consommateurs et de récompense des consommateurs qui ne dépassent pas ce plafond avec des crédits d'énergie échangeables qui peuvent être échangés en utilisant le commerce d'énergie P2P basé sur la chaîne de blocs. Un modèle basé sur 200 maisons est utilisé pour simuler le modèle proposé et prouver que ce modèle peut être bénéfique à la fois pour les fournisseurs et les consommateurs.

Contexte et Objectifs : Dans cet article, un nouveau programme DSM, basé sur le concept "Cap and Trade" fusionné avec un mécanisme d'échange d'énergie P2P basé sur la chaîne de blocs, est proposé. La deuxième section de l'article passe en revue les recherches les plus récentes sur le commerce de l'énergie de pair-à-pair, la gestion intelligente de l'énergie et les mécanismes innovants utilisés pour atténuer les défis et les limites des modèles traditionnels de gestion de la demande. Ce modèle va servir comme composant du système de contrôle des PADs pour gérer la demande durant les heures de pointe et à long terme dans les micro-réseaux.

Méthodologie : En premier, la technologie de chaîne de blocs et ses composants sont présentés. Dans une seconde partie, le modèle Cap and Trade de gestion de la demande d'énergie basée sur la chaîne de blocs est défini, ainsi qu'un modèle d'échange proposé qui met en évidence sa fonctionnalité. Le modèle DSM proposé combine les caractéristiques de l'échange d'énergie P2P par la chaîne de blocs et le mécanisme bien connu de plafonnement et d'échange utilisé pour l'échange de droits d'émission de carbone. Ainsi, pour expliquer clairement le mécanisme DSM proposé, le mécanisme de plafonnement et d'échange est d'abord présenté, puis l'importance de l'adoption d'une plateforme d'échange d'énergie P2P basée sur la chaîne de blocs est soulignée. Enfin, un modèle de simulation utilisant les données historiques de 200 maisons est mis en œuvre pour tester l'efficacité du mécanisme de DSM.

Résultats et Contributions : Le programme DSM proposé a été testé en utilisant 200 ménages comme banc d'essai, et le modèle a été simulé sur quatre mois pour tenir compte de tout effet saisonnier. En outre, trois scénarios différents, soft, intermédiaire et agressif, ont été pris en considération pour valider les critères les plus appropriés à appliquer pour obtenir les meilleurs résultats équilibrés à la fois pour l’entreprise de service public et pour le consommateur. Les résultats obtenus ont prouvé l'efficacité du modèle, en particulier pour les scénarios doux et intermédiaire, dans lesquels l'entreprise de services publics peut obtenir une réduction de 6,04 % à 7,8 % de la consommation mensuelle totale d'énergie, sans changement considérable de son chiffre d'affaires mensuel total et sans incidence importante sur les factures mensuelles moyennes des consommateurs. En outre, l'analyse de sensibilité a montré l'importance de bien choisir la valeur du plafond pour obtenir un résultat optimal à la fois pour l'entreprise de services publics et pour les consommateurs. Cette valeur doit être modifiée toutes les quelques années pour tenir compte des nouveaux besoins du marché et contrôler la demande d'énergie.

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Article

Blockchain-Enabled Energy Demand Side Management Cap and Trade Model

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Abstract: Global economic growth, demographic explosion, digitization, increased mobility, and greater demand for heating and cooling due to climate change in different world areas are the main drivers for the surge in energy demand. The increase in energy demand is the basis of economic challenges for power companies alongside several socio-economic problems in communities, such as energy poverty, defined as the insufficient coverage of energy needs, especially in the residential sector. Two main strategies are considered to meet this increased demand. The first strategy focuses on new sustainable and eco-friendly modes of power generation, such as renewable energy resources and distributed energy resources. The second strategy is demand-side oriented rather than the supply side. Demand-side management, demand response (DR), and energy efficiency (EE) programs fall under this category. On the other hand, the decentralization and digitization of the energy sector convoyed by the emersion of new technologies such as blockchain, Internet of Things (IoT), and Artificial Intelligence (AI), opened the door to new solutions for the energy demand dilemma. Among these technologies, blockchain has proved itself as a decentralized trading platform between untrusted peers without the involvement of a trusted third party. This newly introduced Peer-to-Peer (P2P) trading model can be used to create a new demand load control model. In this article, the concept of an energy cap and trade demand-side management (DSM) model is introduced and simulated. The introduced DSM model is based on the concept of capping consumers' monthly energy consumption and rewarding consumers who do not exceed this cap with energy tradeable credits that can be traded using blockchain-based Peer-to-Peer (P2P) energy trading. A model based on 200 households is used to simulate the proposed DSM model and prove that this model can be beneficial to both energy companies and consumers.

Keywords: energy; cap and trade; blockchain; demand-side management; energy policy; energy trading

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1. Introduction

Electric utility companies worldwide deal with severe and recurring power crises caused by a combination of supply-side problems, including fuel supply challenges, maintenance requirements and unplanned outages, and a continuous increase in energy demand, driven by global demographic growth, electrification of the transportation sector, and greater need for heating and cooling. The dilemma of equilibrating the energy supply with energy demand can be targeted using two principal methodologies. The first way is to meet the demand by increasing the power supply, using fast-acting, low energy cost power generators. The second method to equilibrate the supply with the demand is to act on the demand side by managing the load to minimize the overall energy demand and clear the gap between the supply power and demand power [1]. This second methodology relies heavily on the participation of electricity consumers to reduce their electrical energy consumptions during peak times in exchange for an incentive compensation [2].

Nevertheless, when energy demand-side management (DSM) strategies are considered, the economic problem of free-riding emerges [3]. Free-riding usually refers to users who benefit from conservation subsidies without really contributing to decreasing energy consumption or paying for it. In demand-side management programs, free-riding occurs when consumers get incentives without really reducing their loads [4]. On the other hand, the rebound effect is another challenge when assessing the long-term goals and impacts of energy efficiency projects. In energy efficiency projects, the rebound effect, also known as the take-back effect, is the reduction in anticipated energy savings from the applied energy conservation measures or technology caused by a change in consumer's energy consumption behavior due to the applied measure itself [5]. This is a significant outcome of energy efficiency, which is commonly underestimated. Moreover, it characterizes the negative relationship between technology and consumption [6]. Thus, it is essential to develop a demand-side management program that can achieve the ultimate targets of reducing the overall energy demand and shaving the peak load while avoiding the free-riding and rebound effects. The model proposed in this article is a demand-side management model based on the cap-and-trade system, empowered by a peer-to-peer (P2P) blockchain-based credit trading platform that aims to limit the increase in energy demand.

On the other hand, new emerging technologies such as blockchain, Internet of Things (IoT), artificial intelligence (AI), machine learning, Big Data, etc. have the potential to disrupt the energy sector heavily and change it from a centralized, hierarchical supply chain to a decentralized, decarbonized and decentralized smart platform. Energy suppliers are in a continuous quest to reap greater productivity, improve safety and reduce energy costs. The digital transformation of the energy sector offers the means to achieve those goals. Furthermore, the digitalization of the energy sector is the cornerstone of the broad integration of distributed energy resources (DERs) in any electric grid, which aims to increase load flexibility and diversity in the power generation systems. This digital transformation also unlocks new potentials for users to manage their energy consumption and supply while offering them the possibility to become active stakeholders in electricity grid management. For electric utilities, digitalization permits better monitoring of the grid, faster detection of failures supplemented by an autonomous diagnosis and response to those faults, thus reducing power failures, grid downtime, and higher quality of service [7]. Additionally, the accelerated expansion of DERs, as a fundamental part of smart grids, can no longer be efficiently addressed using conventional centralized methods but instead requires a decentralized real-time control and supervision of all grid assets. Hence, new innovative management systems relying on decentralized networks are becoming a necessity. Blockchain technology could facilitate a fully decentralized energy system [8].

A blockchain is a decentralized network that relies on a distributed chronological ledger, hosted, updated, and validated by several peer nodes rather than a single centralized authority, acting as an immutable record of all transactions. The fact that blockchain substitutes the trusted third parties makes this technology a simple, fast, safe, and transparent means of transaction between peers. An example of the implementation of blockchain technology is the famous cryptocurrency Bitcoin. While conventional wire transfers require validation from a bank and take several days to be completed, Bitcoin transactions can be achieved in near real-time directly from peer to peer [9]. Since the appearance of Bitcoin in 2008 as a peer-to-peer (P2P) electronic cash system, blockchain, its underpinning technology, has gained broad interest from different businesses and industries. Blockchain technology promises a secure, near real-time, and low-cost method for conducting digital assets transactions [10]. It increases process automation while managing more significant volumes of data with limited human intervention at lower cost and risk. Meanwhile, energy companies are grappling with increased reporting, transparency, and security regulations, which incurs additional costs to the energy trading process and greater demand for personnel and resources. Blockchain technology can help target those challenges and have a significant positive impact on the energy sector [11]. Traditional transactional models rely on centralized, server-client-based architectures. Transactions between network nodes occur only through an intermediary third party required to establish trust, especially when unknown parties are involved. Nevertheless, the involvement of intermediaries induces additional commission fees in exchange for their services and increases the processing time required for transactions. Furthermore, since all transactions are managed and recorded using a central server, centralized networks suffer from a single point of failure. Alternatively, decentralized architectures, such as blockchain's P2P platform, offer a network of interconnected nodes that can interact directly, preserving the integrity of the grid even if several nodes are jeopardized or disconnected. Thus, P2P decentralized networks allow bridge or mitigate most of the problems associated with centralized networks [12].

Blockchain can transform the energy sector in harmony with the natural laws of growth. It provides an incremental, sequential, highly integrated approach to developing the energy sector's effectiveness and efficiency. This new technology can move the energy market progressively from a dependent market to an independent market to an interdependent market. The existing market is an entirely dependent market where consumers rely on utility companies and service providers. With the development of DER technologies, the market can evolve into an independent market where off-grid isolated micro-grids can survive. But with the integration of blockchain, the energy sector has the potential to metamorphose into an interdependent market ruled by the paradigm of we-we can do it, where people can cooperate and combine efforts, abilities, and resources to create something greater together.

In this article, a new demand-side management (DSM) program, based on the "Cap-and-Trade" concept merged with blockchain-enabled peer-to-peer (P2P) energy trading mechanism, is proposed. The second section of the article provides a review of the most recent researches on peer-to-peer energy trading, smart energy management, and innovative mechanisms used to mitigate challenges and limitations faced with traditional demand-side management models. In Section 3, blockchain technology and its components will be introduced. In Section 4, the proposed blockchain-enabled energy demand-side management Cap and Trade model is defined along with a proposed trading model that highlights its functionality. The proposed DSM model combines the features of blockchain P2P energy trading and the well-known Cap and Trade mechanism used for carbon emissions trading. Thus, to clearly explain the proposed DSM mechanism, at first the Cap-and-Trade mechanism is introduced, and secondly, the importance of adopting a P2P blockchain-based energy trading platform is highlighted. Finally, in Section 5, a simulation model using historical data from 200 households is implemented to test the effectiveness of the DSM mechanism.

2. Related Works

The language of innovation is expected in sustainable development policy contexts and load reduction, resulting from demand-side management mechanisms, including energy efficiency programs and demand response models. This can be perceived as an innovative equivalent of sustainable power generation development. Thus, in this framework, several works have already been developed to respond to challenges faced by existing demand-side management projects. The work conducted in [3] offers a two-step model to address the free-rider issue resulting from demand response programs. The first step focuses on predicting the customer's baseline load using a regression-based estimation model. The second step proposes an incentive paid to the consumer based on load reduction for a specific baseline rate. The proposed two-step method outperformed other approaches in terms of payment rule improvement.

Additionally, demand-side management is considered the central pillar of smart grids and distributed energy resources. Conversely, as presented in [13], the emergence of new technologies in smart grid settings has led to the advancement of the communication and control infrastructure, enabling a better exchange of information and data necessary to implement any demand-side management program properly. Similarly, article [14] proposes, in the frame of smart grids, a methodology to implement an active demand-side management model for households equipped with solar photovoltaic (PV) systems and battery energy storage systems. Nevertheless, the development of innovative demand-side management models is not just limited to the smart grid outline. Advanced technologies such as Artificial Intelligence (AI), machine learning (ML), blockchain, etc., have disrupted conventional demand-side management practices. As presented in [15], AI and ML have emerged as new enablers of demand response programs by tackling various challenges, limitations, and barriers. Among these barriers are the consumers' behavioral characteristics and preferences, a pricing model that responds to the consumers' expectations, the management of the demand load, and connected devices. They also contribute to setting an incentive reward program in a fair and economically efficient manner. In the same vein and as highlighted in [16], data analytics and ML can be employed to forecast energy demand, understand customer behavior, and tailor power generation solutions required in the future to respond to increasing demands.

However, recently blockchain has emerged as a new technology that can play an important role in smart grids and more specifically in advanced demand-side management mechanisms. As presented in [17], blockchain technology, especially when merged with advanced metering infrastructure (AMI), can deliver a transparent, secure, reliable, and timely energy flexibility to adapt consumers' energy load profiles to existing energy value chain stakeholders' capabilities. The work conducted in [18] suggests a blockchain-based DSM model using the Ethereum platform that matches energy demand and energy production at a smart grid level to validate this concept. The model improves feedback from DR enrolled consumers and aggregates and forecasts available DR loads while reducing the amount of energy flexibility needed for convergence. Similarly, article [19] uses a micro-grid with various residential load profiles to test a blockchain enhanced demand-side management mechanism that reduces peak-to-average ratio and smoothens the dips in the load profile caused by supply constraints.

Additionally, the proposed model optimizes the pay-off of both the energy provider and the consumer. Equally, Ref. [20] introduces a distributed demand-side management interconnecting, using a network of IoT smart meters, multiple households equipped with renewable energy sources in a single micro-grid. The proposed system minimizes the individual electricity cost for each household and the total cost of energy consumption for the entire micro-grid. The consumers aim to optimize their daily energy consumption in addition to their source of energy: self-generated energy from renewable energy sources, shared energy on the community microgrid, and energy provided by the utility. Each participant applies the best strategy that minimizes his energy consumption cost while maintaining his privacy of energy consumption.

On the other side, the application of blockchain technology in demand-side management is not restricted to the relationship between the energy service provider and the consumer but can cover machine-to-machine (M2M) interaction in the context of demand response. The work presented in [21] provides an example of M2M interaction where a power management system and a generator will cooperate to adjust the power generation trading over the blockchain. But then again, demand-side management is not only limited to demand response programs, and it also includes energy efficiency mechanisms. Even at this level, blockchain can play a major role in advancing energy conservation measures, as shown in [22].

Based on those above and even though only a little work has been conducted on applying advanced technologies, such as AI, ML, and blockchain in the field of DSM, the potential of these technologies in disrupting conventional DSM models is obvious and worthy of further investigation. Hence, the work presented here offers a new perspective for implementing the renowned emissions trading scheme known as Cap-and-Trade, as a demand-side management mechanism in the energy sector. It uses blockchain technology as a trading platform to limit the continuous increase in electricity demand faced by most utilities worldwide, as shown in Figure 1.

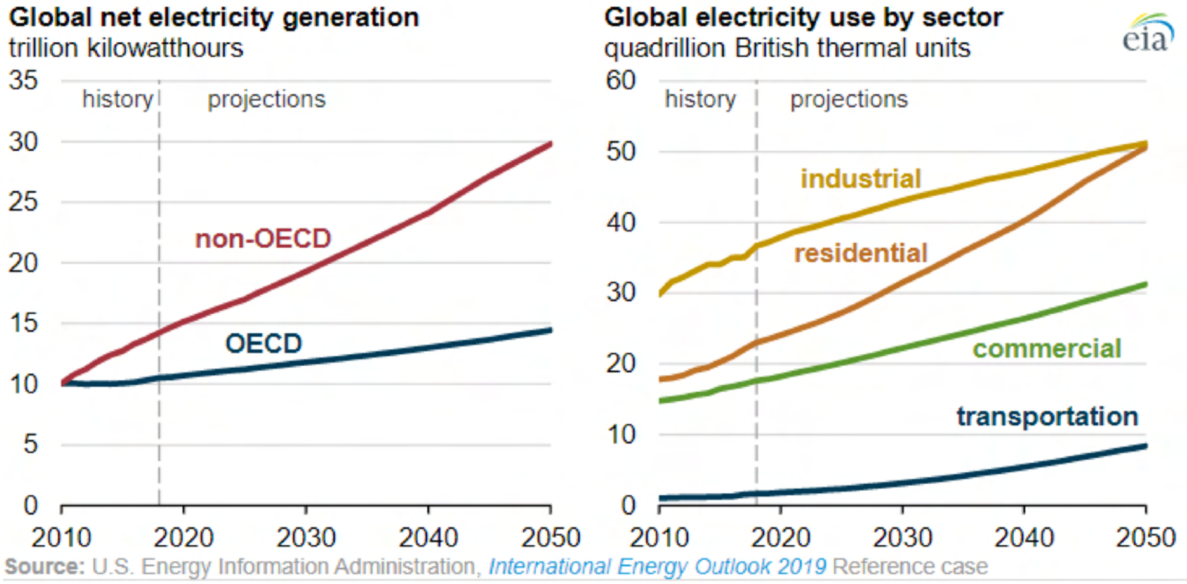

Figure 1. Global electricity generation and use.

3. Blockchain and Smart Contracts

3.1. Blockchain Technology

Satoshi Nakamoto first proposed the concept of blockchain in 2008 [23]. Blockchain technology is an additional layer on top of the internet. It is defined as the "internet of assets" as opposed to the world wide web that is recognized as the "internet of information" [24]. Blockchain offers the great potential of digitizing assets such as records, deeds, bonds, copyrights, currencies, art, real estate, carbon credits and energy while enabling a P2P trading system that doesn't rely on third parties. This process is known as tokenization. By converting physical assets to digital tokens, blockchain unlocks new values for real-world assets and enables trading them in real-time.

The value of the global market for blockchain technology is growing. Governments, utilities to academia, and civil organizations are accommodating a digital era in which blockchain is best known by cryptocurrencies like Bitcoin [25]. The blockchain has indeed based its reputation on the Bitcoin revolution, but the blockchain is not only about transferring token ownership. Blockchain technology can have significant social and economic impacts on established business practices. It offers an alternative means of transacting, sharing value, storing data, and doing business by eliminating the need for centralized entities. It is a decentralized trusted network, enabling anyone to digitize and save or transact data, assets, contracts, or value in a secure manner. Global revenues of blockchain technology are forecasted to grow in the coming years to more than $23 billion (U.S.) by 2023. The largest shares will come from the financial and energy sectors [26].

Traditional transactional models are based on a centralized structure. Transactions between network nodes occur through an intermediary third party. Intermediaries are most often required to establish trust between unknown involved parties. On the other side, one of the most notable features of blockchain is its decentralized structure (Figure 2). With blockchain, the trust between peers is empowered by mathematical algorithms and cryptography, and transactions are conducted from peer-to-peer, which makes blockchain most suitable for applications that meet the following criteria:

- Decentralized problems
- Peer-to-peer transactions
- Beyond boundaries of trust among unknown peers
- Require validation, verification, and recording of a time-stamped immutable ledger
- Autonomous operations guided by a rule structure and policies

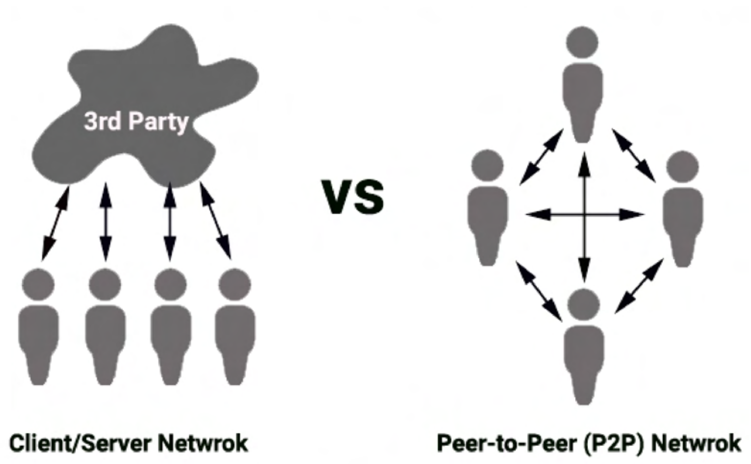

Figure 2. P2P network vs Client/Server network.

3.2. What Is a Smart Contract?

The concept of smart contracts refers to autonomous, self-enforcing programming codes that run on a blockchain network to simplify, govern and enforce agreements and transactions between untrusted peers without the need for a trusted intermediary [27].

The main problem with traditional client-server coded contracts is that when any of the parties involved has root access to the server, they can change the rules and conditions of the contracts. This is why in traditional contract models, a trusted third party or government is required. Intermediaries usually charge fees and can be considered a source of risk that potentially jeopardizes the confidentiality of any contract. This is a problem that blockchain and smart contracts can solve by offering a platform that enables parties to reach a consensus on the required set of rules or business policies and to jointly control the information. Hence, what blockchain and smart contracts offer is an evolution of the internet with immutable shared rules.

Bitcoin was the first blockchain to support basic smart contracts, providing a network capable of transferring value between participants. Its programming language enabled limited transaction features to be created (e.g., payment channels, escrows, multi-sign accounts, and time locks). Ethereum introduced the new feature of smart contracts. Its programming language enabled developers to build their decentralized applications (Dapps). At present, it is the most widely used smart contracts platform.

Smart contracts aim to make legal agreements self-executable by using computer code. Unlike conventional contracts drafted by lawyers, signed by stakeholders, and enforced by law, a smart contract establishes a relationship with cryptographic coding. Unlike a client-server-coded contract, smart contracts are immutable and unstoppable once deployed on the blockchain. Smart contracts offer the following benefits:

- Smart contracts are cryptographically secured, immutable, and enforced.
- Smart contracts are fast and inexpensive.
- They offer a multi-sig feature, which means that transactions are executed only when all approvals or signatures are provided.
- They are capable of managing agreements between users without human interruption.
- They may serve as part of other contracts (similar to how a software library works). Smart contracts can run independently and can automatically interact with other smart contracts.
- They store information, such as records, prices, energy consumption, etc., generated by the smart contract itself, fed by another smart contract or an outside oracle.

A smart contract is made up of two main parts: smart contract code and smart legal contracts. The smart contract code is the code that is stored, verified, and executed on the blockchain. A smart legal contract is a digital representation of a legally binding agreement using a smart contract code. A smart contract is created and signed by parties using their digital signatures. The terms of the agreement and the obligations of each participant are established and limited by program code instructions and functions. Once the agreement terms are satisfied, transactions are automatically executed as defined in the smart contract code.

Smart contracts are capable of redefining business relationships. Smart contracts offer viable solutions with lower transaction costs and risks [28]. Smart contracts' autonomous and self-enforcing nature makes business operations faster, safer, and less prone to human errors. Additionally, the fact that smart contract-managed processes require less human intervention allows reducing the overhead. Finally, since all transactions are recorded on a distributed ledger, it would be very difficult to tamper with the relevant data.

4. Blockchain-Enabled Energy Cap and Trade DSM Mechanism

4.1. Concept

The concept of sustainable consumption was first used on a global scale in Agenda 21, the action plan for sustainable development adopted by 179 heads of state at the Rio Earth Summit in 1992. For the first time, overconsumption in industrialized countries was identified as a direct driver of unsustainable development, and the idea of sustainable degrowth was introduced. Basically, the wished-for solution involved short-term and long-term market means to shift consumption patterns in an eco-efficient manner [29]. One way to achieve sustainable consumption is to use economic tools, such as subsidies, taxes, and charges, to impact the price of goods or services and directly alter consumers' choices [30]. Such market-based mechanisms minimize the impact of adverse market externalities and play an essential role in influencing purchasing patterns [31].

Nevertheless, economic tools can only impact consumers' preferences if the offered financial incentive is strong enough to overcome the threshold of the decision-making process. In other words, taxes should be adequately scaled to sway consumer-purchasing decisions. As a result, economic tools can be seen as mechanisms to render eco-friendly products financially appealing for consumers while making ecologically detrimental ones more expensive with the aim of discouraging their consumption. However, subsidies and taxes are not the only forms of economic tools. Trading or purchase schemes can also be used as financial strategies. The energy cap and trade scheme presented in this article falls under this category.

Often, prices of certain goods or services are increased to reflect their environmental cost. Primarily, these additional costs are determined by the price elasticity of the products in question. In other words, it depends on the percentage of consumers willing to decrease their consumption when prices increase at a certain rate. The price elasticity depends on the product or service itself and the household's income group. The cost of environmental policy initiatives is thus determined by users' willingness to alter their consumption and sacrifice some of their well-being in exchange for their environmental contribution. As a result, these increasing costs, which may not necessarily be evenly dispersed, have significant consequences for households [32,33]. Therefore, any economic tool needs to achieve a balanced distribution of the repercussions of the increased cost. One example of such behavior, is the Fuel Poverty Strategy, a UK effort that targets environmental policy distributional challenges [34]. This plan aims at all households whose energy use surpasses 10% of their income to meet their heating demands, with a special focus on disadvantaged groups.

People's habits in consuming energy should be altered to fight against energy demand increase. Habits are defined as the intersection of knowledge (what to do), skill (how to do), and desire (want to do) [35]. Any plan that aims to change people's habits or their energy consumption patterns should combine all three. Thus, considering these criteria, the proposed energy cap and trade scheme penalizes heavy electricity consumers and compensates low energy consumers. The work conducted in [36,37] reveals that as one's income rises, so does one's energy use. This growth, however, is not uniform. Energy consumption growth remains flat as income grows at the lowest end of the income spectrum. Energy consumption begins to rise only after a particular low-income threshold is reached. Therefore, indirectly the suggested energy cap and trade targets consumers with high income without impacting households majorly with relatively low income, which respects the equitability concept in the distribution of the increased costs.

The Cap-and-Trade mechanism is well known in the greenhouse gases emissions reduction and carbon credit markets. A cap-and-trade scheme allows governments to issue a limited number of carbon dioxide emission permits each year, essentially putting a "cap" on overall pollution. Companies that are part of the program can acquire and sell permits amongst themselves [38]. Because the overall supply of permits is limited, some businesses may determine that reducing their emissions is more cost-effective than purchasing permits. For example, investing in more efficient technology, reducing energy waste, or switching to renewable energy are all options that are less expensive than buying permits. The cap is then reduced each year, resulting in fewer and fewer permits available each year. As permits become more expensive, many businesses opt to minimize their emissions rather than purchase allowances. Cap-and-Trade is considered more flexible than flat regulations since they simultaneously combine sustainability goals, covered by the cap, and economic efficiency, covered by the trading feature, and offer the potential to achieve both [39].

In a Cap-and-Trade scheme, allocation is the process of distributing allowances to participating or involved entities. The allocation process should be governed by rules to ensure the fair distribution of allowances. There are three basic ways of allocation; allocating based on historical data (grandfathering), allocating based on benchmarking, and auction [40]. Grandfathering offers participating entities allowances based on their historical data from a pre-defined base year or period. Grandfathering increases the scheme's feasibility by avoiding significant upfront costs. However, grandfathering as a mechanism of allocation tends to reward historically high consumers and necessitates additional allowances for future entrants. Comparatively, using a benchmarking allocation method, allowances are distributed based on performance metrics. Benchmarking rewards efficient and innovative solutions and makes it easier for newcomers to fit in [40]. The third allocation method is selling allowances, usually by auction. The auction method is advantageous in reflecting the real requirement of installations for allowances and offers participating entities an equal chance to procure allowances. Furthermore, it generates revenue for the regulator, which may then be used to fund additional initiatives. Therefore, the choice of the allocation method has a significant impact on the cost-efficiency of any Cap-and-Trade mechanism.

Therefore, analogously to the mechanism applied to fight against the increase in greenhouse gas (GHG) emissions, we propose a cap-and-trade model to limit the increase in energy demand while combining both the goals of sustainability and cost-effectiveness. The proposed model is based on a benchmarking allowance system. Each category of users or each sector, residential, commercial, healthcare, industrial, etc., is allocated a cap for the monthly energy consumption based on a benchmark study of the relevant market. Suppose the monthly energy consumption of the involved entity is below the monthly cap value. In that case, the entity will pay the usual energy rate, but the entity will have to pay an incremented rate for each energy unit consumed above the cap value. Nevertheless, efficient energy consumers might have a total monthly energy consumption way below the energy cap. Thus, the difference between their anticipated monthly energy consumption and the cap value can be tokenized and sold to heavy energy consumers at any rate between the usual rate and the incremented rate (Figure 3). Thus, the proposed model generates two incentives for consumers. The first incentive is for consumers to lower their energy consumption not to exceed the set cap value. The second incentive is to improve their energy efficiency to maximize the number of energy tokens traded and thus lower their monthly energy bill. The suggested selling algorithm is defined in Algorithm 1.

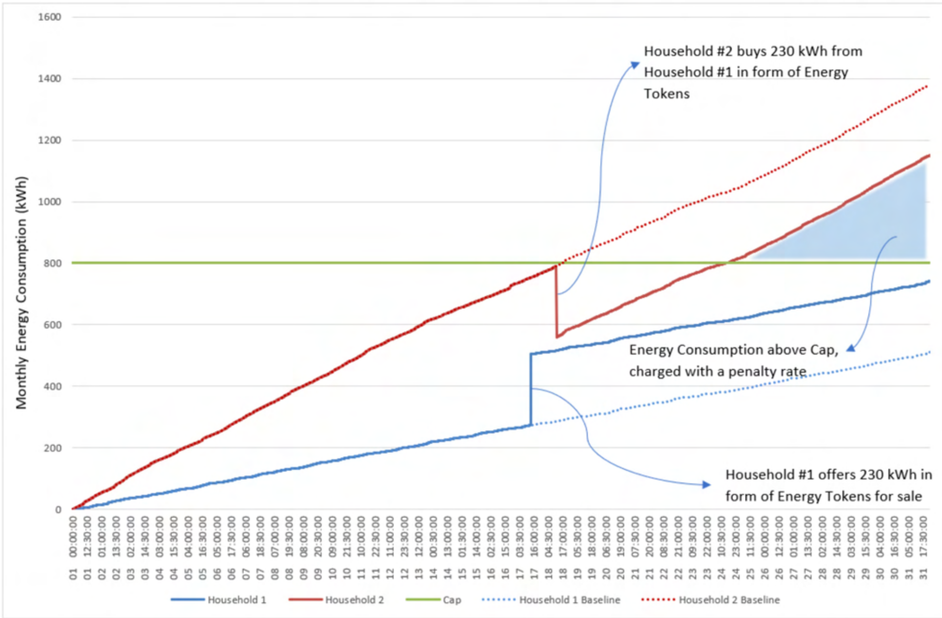

Figure 3. Energy Cap and Trade Energy Consumption Model.

However, the application of such a model can be very complex for utility companies and energy providers. Applying a cap-and-trade model for GHG emissions at the national level or large-scale companies might be feasible. Still, its implementation on a small retail scale with thousands and millions of consumers will undoubtedly prove to be a time-consuming, labor-intensive, challenging, and sophisticated process. For this reason, we propose using blockchain as a distributed ledger to govern the tokenization of traded energy. It handles payments, keeps an immutable record of all transactions, and manages the relationship between stakeholders: selsumers (consumers who are selling excess energy tokens), pursumers (consumers buying energy tokens), and the utility company.

The adoption of a blockchain P2P architecture for our energy cap-and-trade model offers several advantages. The anonymity of peers and security guaranteed by blockchain are among the most important features. Additionally, blockchain's greatest feature derives from the transparency of its distributed ledger shared by all participating nodes. It provides an unprecedented layer of accountability to any financial or business model, forcing all involved stakeholders to be accountable towards other involved parties. Moreover, the fact that each exchange of tokens is recorded on a blockchain creates an auditable trail of all transactions, which can improve security, prevent fraud, and verify the legitimacy of the traded asset. Finally, blockchain will help make the process more efficient and less costly by eliminating intermediaries or third parties.

Hence, the proposed blockchain-enabled energy Cap-and-Trade DSM mechanism is based on creating a monthly cap for consumers' energy consumption, allowing them to tokenize any unused energy, not exceeding the cap limit, and trading them with other interested buyers using a blockchain P2P energy trading platform.

Algorithm 1 Energy Cap and Trade

1: Initiate algorithm at time t
2: **If** t = end of billing period **then**
3: $\mathrm{R}(m, n) = 0$
4: $t = 0$
5: $i - 1$
6: **Goto** 1
7: **Else Goto** 9
8: **end if**
9: **If** User = Seller **then**
Step 1: Seller Registration
10: Check if Seller Smart Meter is registered
11: Seller set γ_S^i and E_S^i
12: Offer is stored in matrix:$\mathrm{R}(1, i) = \gamma_S^i$ and $\mathrm{R}(2, i) = E_S^i$
13: Arrange matrix R from lowest to highest γ_s^i
14: $i = i + 1$
End Seller Registration
15: **Else**
Step 2: Buyer Registration
16: Check if Buyer Smart Meter is registered
17: Seller set γ_B and E_B
18: Initialize $j = 1$
19: If $j = i$ **then**
20: $t = t + 1$
21: **Goto** 2
22: **Else**
23: If $\mathrm{R}(1, j) \leq \gamma_B$ **then**
24: If $\mathrm{R}(2, j) \geq E_B$ **then**
24: Buy from Seller the quantity E_B for γ_S^j
25: $\mathrm{R}(2, j) = \mathrm{R}(2, j) - E_B$
26: $t = t + 1$
27: Goto 2
28: **Else**
29: Buy from Seller the quantity E_S^j
30: $\mathrm{R}(2, j) = 0$
31: $E_B = E_B - E_S^j$
32: $j = j + 1$
33: Goto 19
34: **end if**
35: **Else**
36: $j = j + 1$
33: Goto 19
34: **end if**
End Seller Registration
35: **end if**
36: $t = t + 1$
21: **Goto** 2

4.2. System Architecture and Functionality

To better understand how the proposed blockchain-enabled energy Cap-and-Trade DSM mechanism works, the architecture of the system, including all soft and hard components functionalities are detailed in this section.

The main target is to enable electric end-users to exchange electric energy tokens securely, in near real-time, and transparently. To achieve this, a Dapp will allow energy consumers and prosumers to participate easily and create their own decentralized and deregulated open P2P energy market.

A public decentralized virtual machine will operate as an autonomous agent that connects and matches selsumers (consumers willing to sell energy tokens) to pursumers (consumers willing to buy energy tokens) and conducts the financial settlement between them without the need for an aggregator, broker, or any type of intermediary. The decentralized virtual machine is nothing more than several smart contracts that take over the two major functions of today's energy retailers: billing and trading while keeping a transparent record of all executed transactions. These smart contracts are then paired with a user-friendly front-end application programming interface (API) that allows selsumers and pursumers to interact directly with the virtual machine. Thus, the virtual machine collects data, processes it, charges the pursumer for the bought electricity based on an agreed-upon rate, and pays the selsumers for the sold energy tokens. It manages the financial settlement between the two parties' digital wallets in an autonomous, secure, and completely transparent manner that doesn't require the intervention of any trusted third party. The proposed architecture is shown in Figure 4.

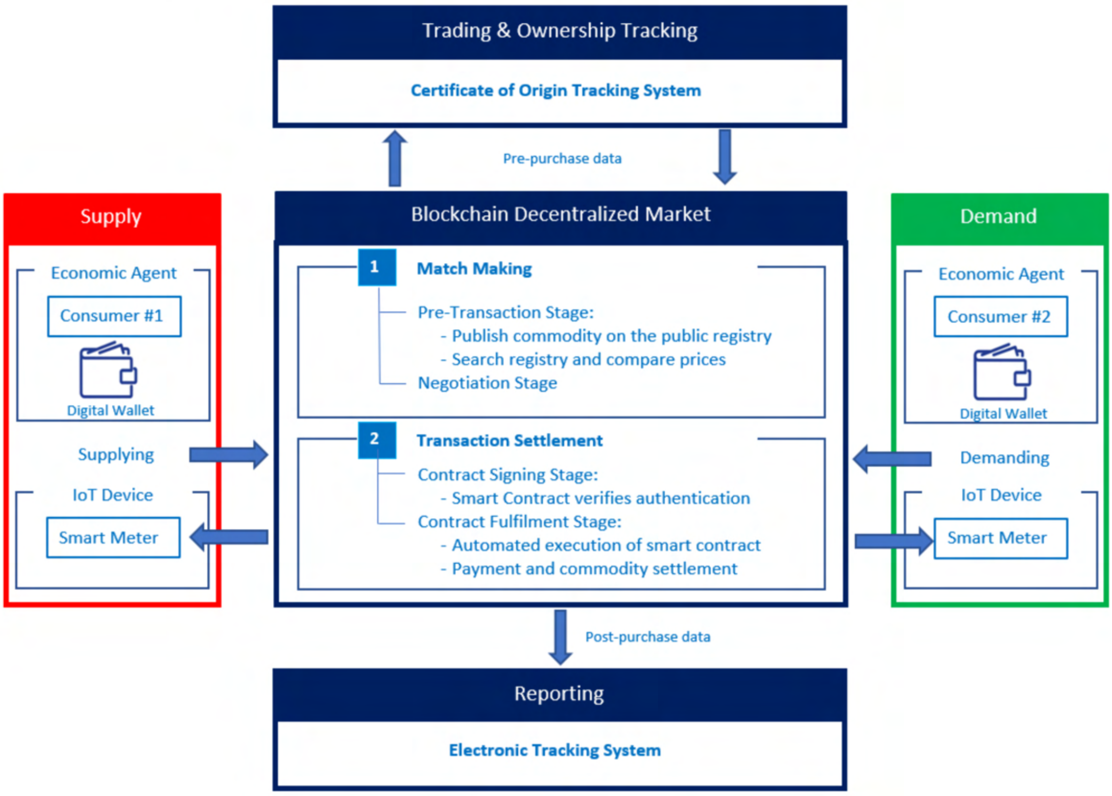

Figure 4. Trading model architecture.

The functionality of the model and the different steps of the process can be summarized as follows:

- Data collection is provided by IoT devices connected to Smart Meters
- Smart contracts manage the processing and storage of data on the blockchain network in an autonomous way
- Transactions between selsumers and pursumers are conducted in near real-time using smart contracts and via the Dapp itself.
- Data is recorded and encrypted using cryptography, guaranteeing its immutability and authenticity.
- Smart Contracts automate and ensure that all system functionalities, i.e., billing, trading, and reporting, are carried out correctly without the risk of human error.

The Solidity code, included in the Appendix A, represents the smart contract trading.sol that allows to create buy/sell orders and log them. In addition, this smart contract calls for another smart contract called Registeredusers.sol that governs the registration of smart meters for consumers who are willing to participate in the program and allocate an address for each smart meter.

5. Case Study

To test the functionality and effectiveness of the proposed DSM mechanism, we propose using a simulation model based on historical data from two hundred households and applying the proposed DSM's logic, outlined in Algorithm 1, to the adopted use case. However, to achieve that, the proposed selected use case model is defined in the first part of this section. In the second part, the simulation model and algorithm are transformed into a mathematical model that allows one to test the DSM mechanism under several scenarios. The ECT DSM mechanism is tested under different scenarios to evaluate its dynamicity and how the outcome will change when the system variables are modified. Finally, the simulation results, under different scenarios, are presented and analyzed.

5.1. Selected Model

Two hundred (200) households, randomly taken from a sample of housing units in the Residential Energy Consumption Survey in the United States' Midwest region, are considered to test the proposed energy demand-side management model. The chosen sample is part of the work conducted in [41]. The curves shown in Figure 5 represent the total monthly energy consumption of the 200 households registered over four months of the year (January, May, July, and October).

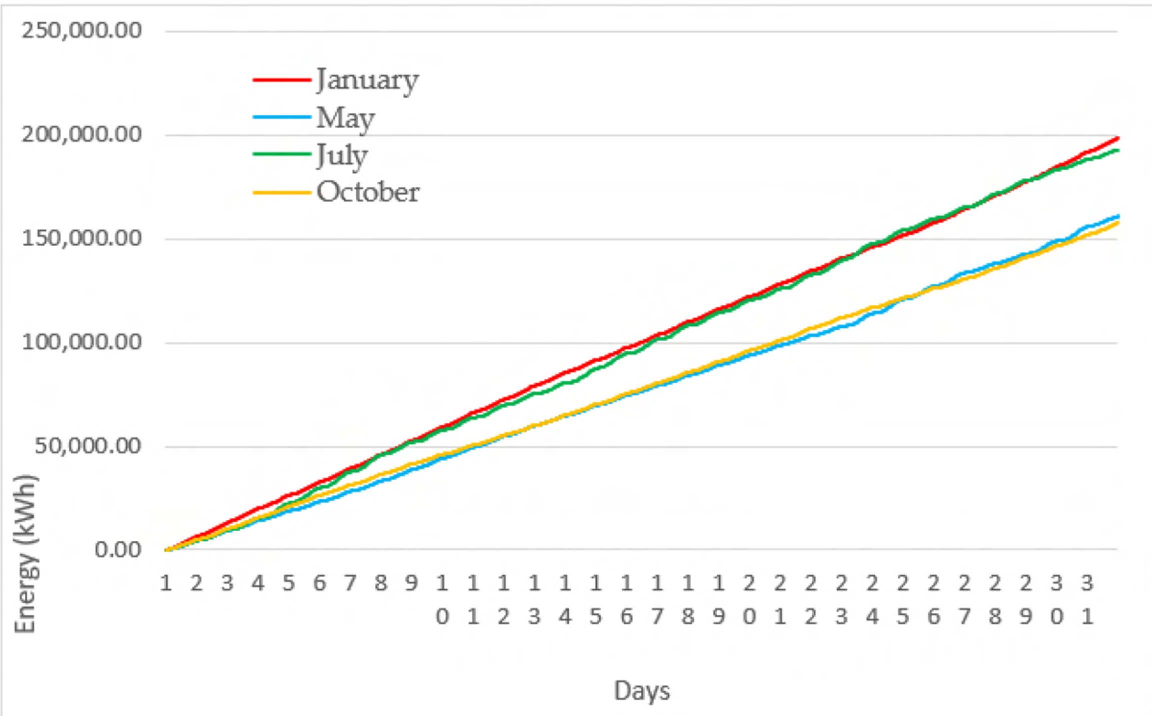

Figure 5. Daily cumulative total energy consumption of the 200 households.

The proposed Cap-and-Trade demand-side management model is verified for the above-defined energy consumption capping applications under different scenarios. In addition, the blockchain-enabled Cap-and-Trade DSM model is tested over four months of the year (January, May, July, and October), each representing a season to account for the energy seasonal variations. Table 1 shows the distribution of the households' monthly energy consumption for the selected months of the year.

Table 1. Distribution of households' monthly energy consumption.

Monthly Energy Consumption (kWh)	Number of Households			
	January	May	July	October
0–600	29	31	17	43
601–800	61	80	53	71
801–1000	54	59	58	60
1001–1200	11	21	32	14
1201–1400	9	6	22	6
1401–1600	15	1	9	3
1601–1800	9	0	5	1
1801–2000	3	2	2	1
2001–2200	2	0	2	1
>2200	7	0	0	0

The considered cases are validated according to three different strategies: aggressive, intermediate, and soft. The three strategies differ in the set cap value, cap charge rate, and average energy tokens selling price. The defined values for each simulation strategy are given in Table 2.

Table 2. Defined values for simulation strategies.

Parameter	Aggressive Strategy	Moderate Strategy	Soft Strategy
Cap Value as percentile of the Population's Monthly Energy Consumption	15 percentiles	30 percentiles	45 percentiles
Cap Charge	\$0.50	\$0.20	\$0.12
Average Energy Token Price	\$0.20	\$0.15	\$0.10

The outcomes of the simulation models are evaluated based on three criteria:

- The variation of the consumer's monthly electricity bill between the baseline period and under the cap-and-trade DSM program
- The variation of the total consumed monthly electric energy of the 200 households between the baseline period and under the cap-and-trade DSM program
- The variation of the total collected monthly electric bills by the utility between the baseline period and under the cap-and-trade DSM program

An average price for the traded energy tokens was considered to simplify the simulation. Optimization of the transactions between the selsumers and the pursumers is applied, which means that they sold energy tokens are equally distributed among all pursumers. Additionally, it is assumed that all available excess energy tokens are sold. Such an assumption is justified because, in the case of a large grid, there will always be a pursumer willing to buy the offered energy token at a lower price than the electricity tariff per kWh. In other words, if the supply in energy tokens is higher than the demand, all pursumers are served, and in case the demand is higher than the supply, all selsumers are served. This hypothesis defines the optimal case of the considered model.

Furthermore, it is considered that a certain percentage of the population will reduce their energy consumption in response to the applied cap and the surcharge for energy consumed above the monthly cap value. This assumption is defined by two the factors α and β, respectively the percentage of households reducing their energy consumption and the percentage by which the monthly energy consumption of these households is reduced. For simulation purposes, α is set at 20% and β at 25%.

5.2. Energy Cap and Trade Formulation

A mathematical model serves to test the above-defined algorithm. Accordingly, as previously described, after the application of the Energy Cap and Trade (ECT) demand-side management (DSM) program, it is expected that a certain percentage $\propto$ of the households will automatically respond to the program and reduce their energy consumption by a certain ratio defined as β_i. Moreover, it is assumed that the households that will respond to the applied ECT DSM program are part of the households whose monthly electrical energy consumption E_i exceeds the set cap value K. Households with $E_i < K$ will not have any interest in decreasing their monthly electricity consumption. For simulation purposes and to keep track of the number of households reducing their monthly electrical energy consumption, a counter n was created. The counter n will be increased by 1 at each iteration if the subject household i have a benchmarked monthly electrical energy consumption above the set cap and if the maximum number of expected households to reduce their energy consumption, defined by the percentage $\propto$, is not reached. The counter n will continue to increase until it is equal to the round down of $\propto \times N$ which represents the total number of households to reduce their monthly electrical energy consumption in response to the ECT DSM program.

$$n_i = q_i \times \left[\frac{[\alpha N] - n_{i-1}}{[\alpha N]} \right] + n_{i-1} + q_i \tag{1}$$

Hence, to identify the households that have decreased their monthly electrical energy consumption E_i, in response to the ECT DSM program, the index p_i is defined. This index equals 1 if the subject household i has reduced its monthly energy consumption and 0 if not. The index p_i is calculated using Equation (2):

$$p_i = \left(1 + \left[\frac{[\alpha N] - n_i}{[\alpha N]} \right] \right) \times q_i \tag{2}$$

$i \in N$ set of all households
$t \in T$ set of time intervals
$\begin{cases} q_i = 1 \; if \; E_i \leq K \\ q_i = 0 \; Else \end{cases}$
$\begin{cases} p_i = 1 \; if \; Household \; i \; reduced \; his \; electrical \; energy \; consumption \\ p_i = 0 \; Else \end{cases}$
N: Population (in our case, the 200 households)
E_i: Household monthly electrical energy consumption in kWh
K: Defined electrical energy cap value in kWh
$\propto$: Percentage of households to respond to the new rate structure and reduce their monthly electrical energy consumption

The simulation aims to analyze the energy demand and economic impacts of the proposed ECT DSM program on the consumer and the utility company or energy provider. Two factors assess the effects on the electricity distribution company. The first one is the total energy consumed by the 200 studied households, and the second factor is the sum of the collected electricity bills from the 200 households. As for the consumers, the main criteria used for the evaluation of the model is the new monthly electric bill U_i'.

The new total energy demand E_T' at the utility-scale is given by Equation (3):

$$E\prime_T = \sum_{i \in N} (1 - p_i).E_i + \sum_{i \in N} p_i.\beta_i.E_i \tag{3}$$

The reduction in energy demand at the utility-scale is given by Equation (4):

$$R_E = \frac{E_T - E\prime_T}{E_T} \tag{4}$$

E_T: Baseline total monthly electrical energy consumption of the population in kWh
$E\prime_T$: Total monthly electrical energy consumption of the population in kWh after implementation of the Cap-and-Trade scheme
β_i: Percentage of monthly electrical energy reduction for each household
R_E: Total monthly electrical energy consumption reduction

The baseline monthly electric bill for household i, is given by Equation (5):

$$U_i = \gamma_U \times E_i^C \tag{5}$$

The new monthly electric bill for household i, is given by Equation (6):

$$U\prime_i = \gamma_U \times \left[q_i.K + (1 - q_i).E_i^C + E_i^S\right] - \gamma_S.E_i^S + \gamma_B.E_i^B + \gamma_C.a_i.\left(E_i^C - K - E_i^B\right) \tag{6}$$

U_i: Baseline total monthly electricity utility bill for household i
$U\prime_i$: Total monthly electricity bill after implementation of the Cap-and-Trade scheme for household i
γ_U: Utility electricity rate ($/kWh)
γ_S: Rate for sold electrical energy tokens ($/kWh)
γ_B: Rate for bought electrical energy tokens ($/kWh)
E_i^C: Total monthly electrical energy consumed by household i in kWh
E_i^S: Total monthly electrical energy sold by household i in kWh
E_i^B: Total monthly electrical energy bought by household i in kWh
$$\begin{cases} a_i = 1\ if\ E_i^C - K > E_i^B \\ \quad a_i = 0\ Else \end{cases}$$

The reduction in the monthly electric bill for household i, is given by Equation (7):

$$R_i^B = \frac{U_i - U\prime_i}{U_i} \tag{7}$$

R_i^B: Total monthly reduction or increase on electricity bill of household i.

5.3. Simulation Results

As previously detailed, the simulation is conducted over four different months of the year to account for the seasonal effect on the energy demand. The obtained results are analyzed considering two different perspectives. The first is the utility company's perspective, and the second one is the consumer's perspective. From a utility perspective, the main target is to reduce the monthly electric energy consumption without heavily impacting the monthly turnover. The obtained results show that even when incorporating the selsumers as energy sellers and competitors to the utility company in terms of selling electricity at a lower rate to penalized pursumers, the monthly turnover of the utility is either comparable to the baseline (period without implementation of any DSM program), for the soft and moderate scenario, or exceeding the baseline for the aggressive scenario (refer to Figure 6).

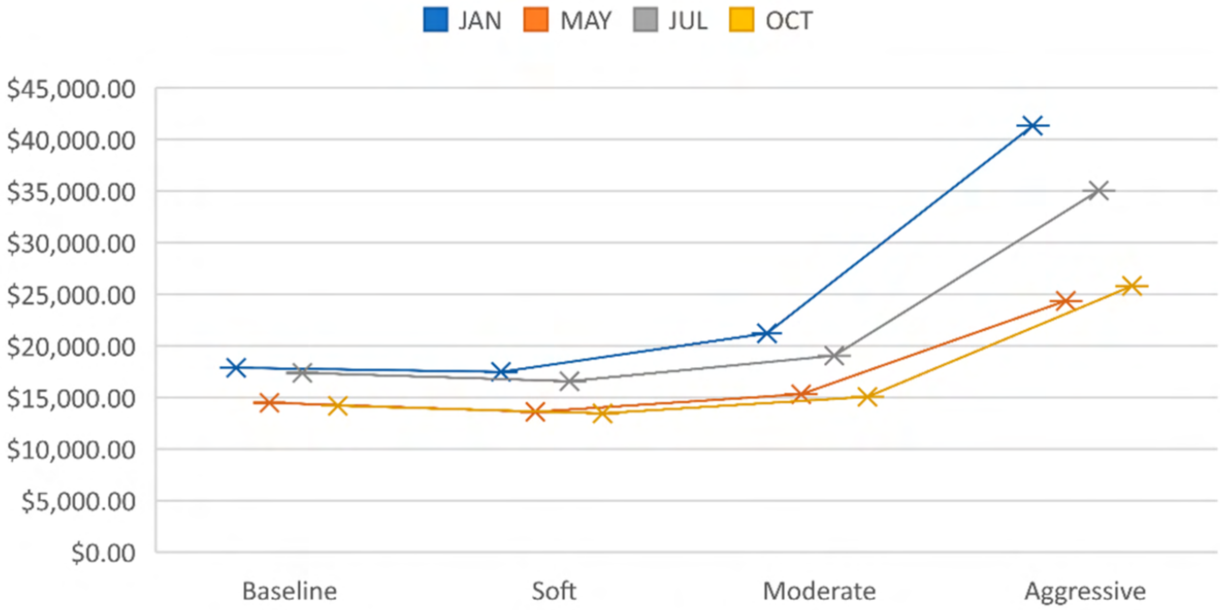

Figure 6. Utility monthly turnover in USD.

From the consumer's perspective, the simulation results show that the seasonal effect lightly affects the cap value (refer to Figure 7). Still, the same cannot be said for the traded energy tokens. Figure 8 shows a remarkable increase in the number of traded kWh during January and July. The main reason for this development in the number of traded kWh during January and July is the increase in heating and cooling loads during those two months. The high demand for heating and cooling energy is directly reflected in the monthly electric bills, which means that under a Cap-and-Trade scheme, heavy consumers will exceed the monthly cap value and consequently be penalized for the excess energy consumed. Thus, in the proposed ECT DSM program, those heavy consumers will try to buy energy tokens to minimize the additional charge applied to their monthly bills, which verifies the increase in the number of traded energy tokens.

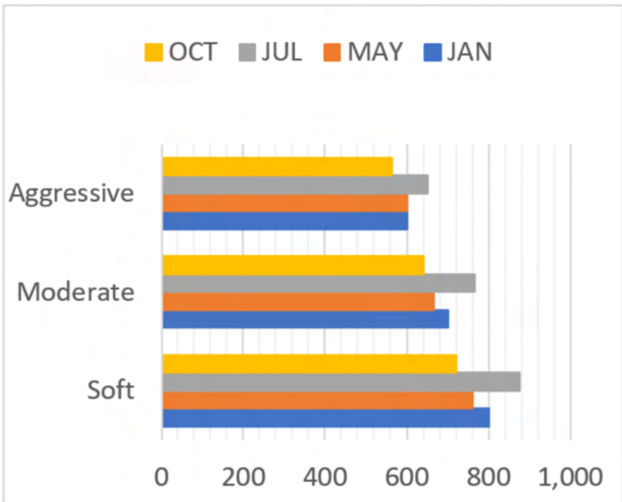

Figure 7. Monthly Cap Values in kWh.

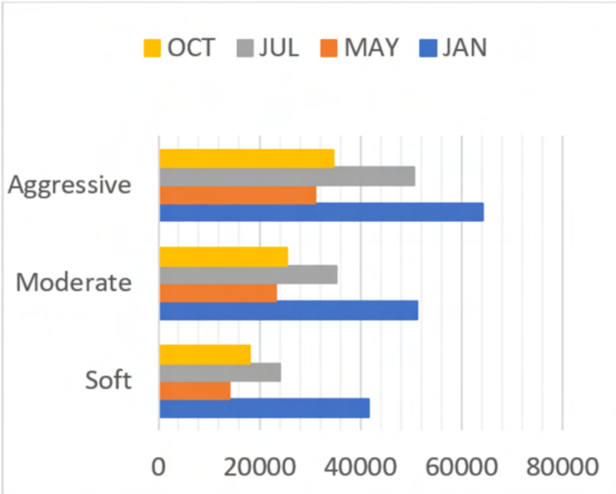

Figure 8. Total traded monthly Energy Credits in kWh.

Besides that, it is entirely reasonable to see that the number of selsumers is high in a soft scenario, where the cap value is relatively high, allowing consumers to earn a considerable number of tradeable energy credits. On the other hand, identically, the number of pursumers is low, whereas these numbers are reversed under the conditions of an aggressive scenario, as shown in Figures 9 and 10. Additionally, the proposed ECT DSM model minimizes the impact of free riders while rewarding efficient consumers and penalizing heavy consumers. Figures 11 and 12 show respectively the average monthly reductions on the selsumers' electricity bills and the average monthly increase on the pursumers' electricity bills. Under the conditions of the soft scenario, selsumers can achieve a reduction of approximately 9% on their monthly bills whereas the increase on pursumers' monthly bills is between 3% and 7%. With an intermediate scenario, the selsumers' reduction is between 16% and 18.6%, whereas the pursumers' increase is between 23% and 32.7%. Subsequently, the aggressive scenario allows selsumers to achieve higher reductions on their monthly electric bills and imposes higher penalties on heavy consumers where the increase on the monthly electric bill can reach 140% during January. On the other side, the applied ECT DSM, based on the previously detailed assumptions, can achieve a 6.04% to 8.79% reduction in the total monthly electrical energy consumption (refer to Figure 13).

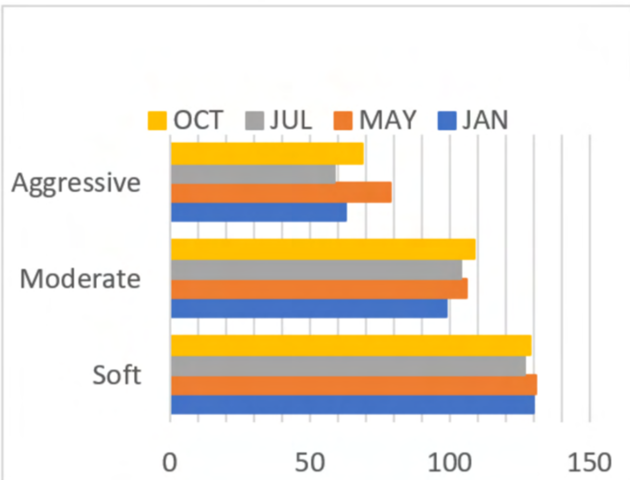

Figure 9. Number of Selsumers per month.

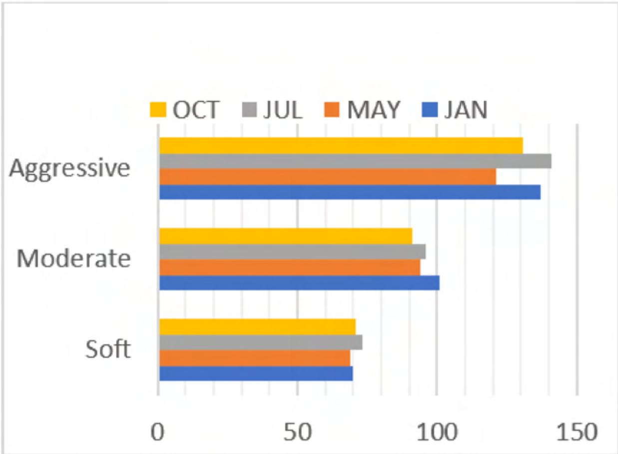

Figure 10. Number of Pursumers per month.

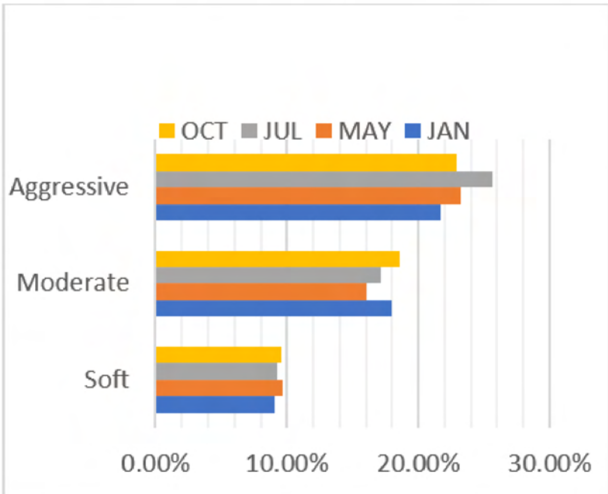

Figure 11. Average monthly reduction on selsumers' bills.

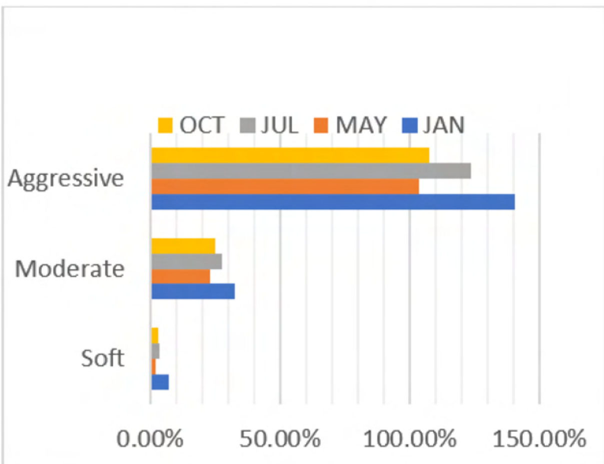

Figure 12. Average monthly increase on pursumers' bills.

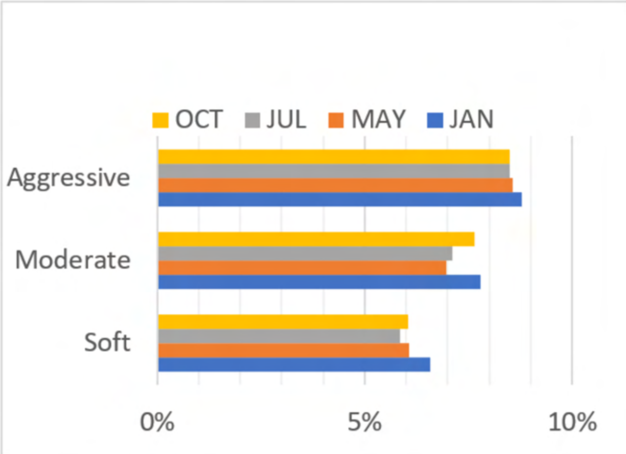

Figure 13. Total monthly energy reduction.

Lastly, Figure 14 compares the average monthly bills of prosumers under the different scenarios that the utility can adopt to minimize the yearly increase in electricity demand. The baseline scenario is the business-as-usual scenario where no demand-side management program is applied. The second scenario is the "Baseline + Cap" scenario. This scenario simulates the application of a cap value for the monthly energy consumption and penalizes consumers that exceed this cap without offering them any trading option. In that case, even though it is assumed that 20% of households will automatically reduce their monthly electricity consumption by 25% in response to the application of the cap value, the average monthly electricity bills have nearly doubled. This proves that such a model can have a severe negative impact on consumers and can be considered an unembellished DSM model. The other three scenarios represent the implementation of the ECT DSM program with respectively aggressive, intermediate, and soft conditions. As shown in Figure 14, the aggressive scenario can have similar adverse outcomes as the "Baseline + Cap" scenario. In contrast, the intermediate and soft scenarios can maintain an average monthly bill comparable to the baseline model to decrease the overall monthly energy demand, which can be considered a win-win situation for both the utility company and the consumers.

5.4. Sensitivity Analysis

As defined in Section 5.1, several parameters are considered in the proposed blockchain-enabled C&T energy trading model design. Thus, it is essential to determine and analyze the set of independent variables or inputs that affect the outcomes of our model. The parameters or variables identified as having an impact on the outcome of our model are defined as follows:

- Cap value
- Energy rates
- Percentage of people reducing their energy consumption
- The energy consumption reduction rate

Indeed, the set cap value is the most critical variable that can significantly impact the performance of the presented model. Hence in this context, Figure 15 represents the sensitivity analysis or the "What if" analysis that illustrates the impact of the set cap value on the model's outcomes.

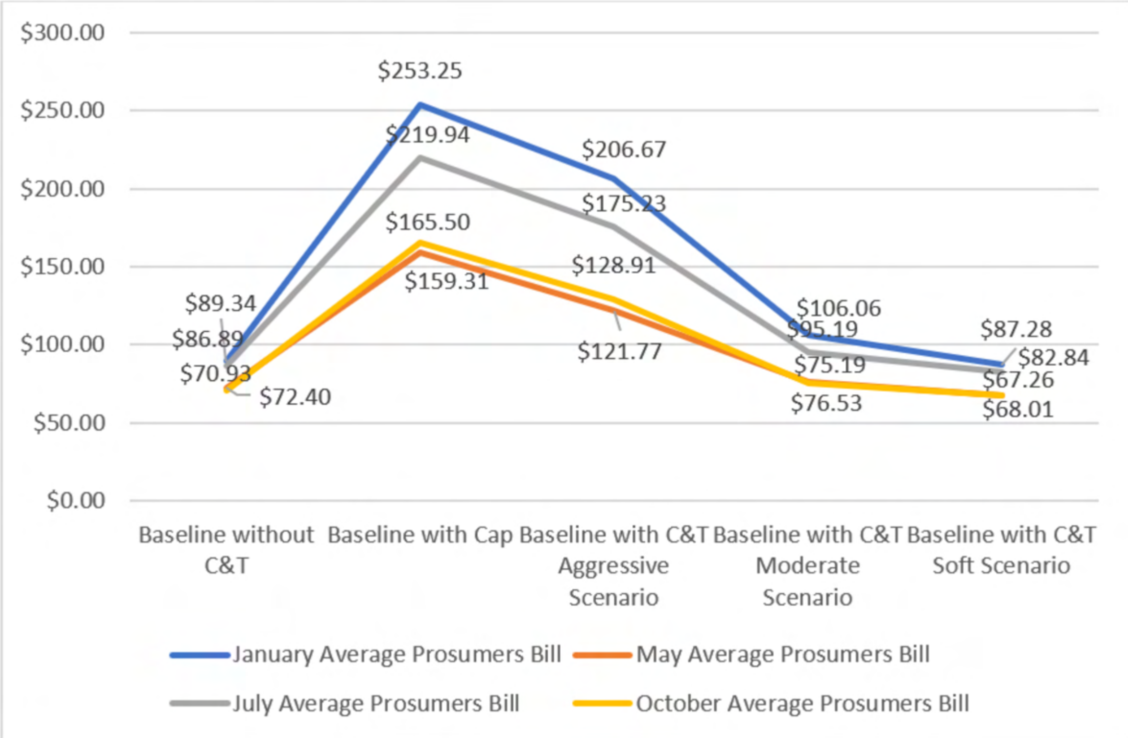

Figure 14. Average prosumer monthly bill in USD.

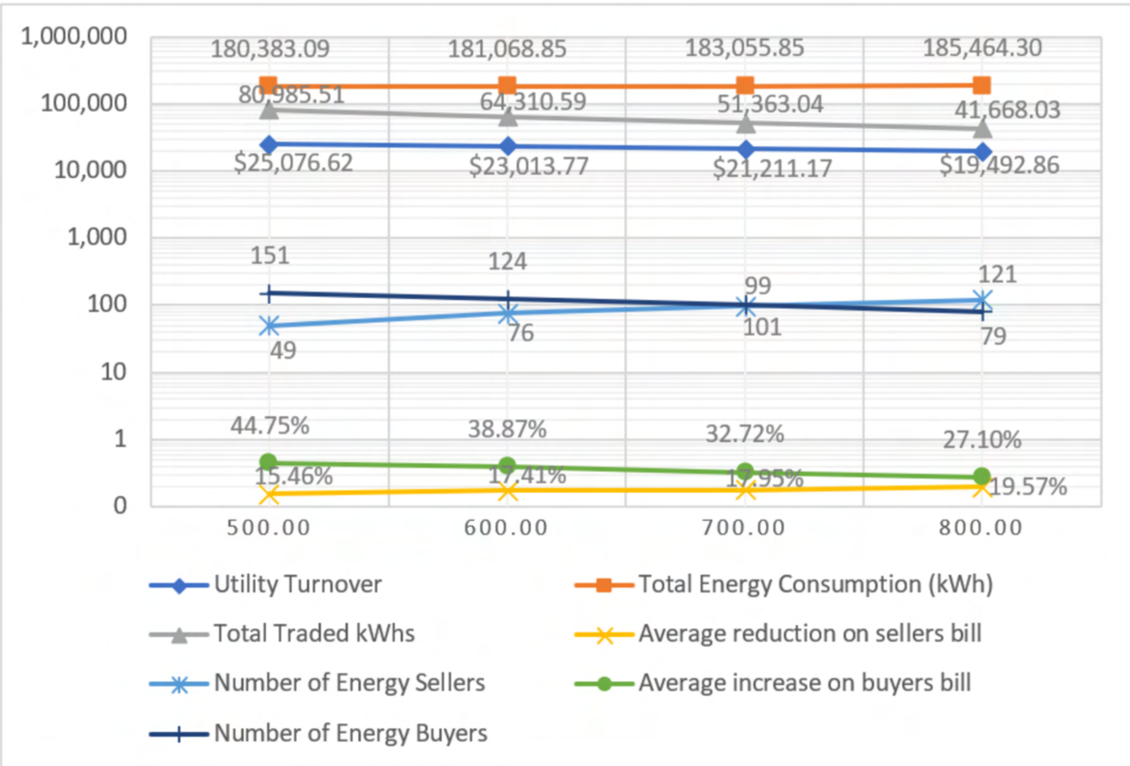

Figure 15. Energy Cap's impact on the model's outcomes.

5.5. Other Application: Peak Load Shaving Use Case

The presented and simulated model, in Section 5, is not the only application for the proposed blockchain decentralized application. The developed blockchain-enabled C&T

energy trading model can also be used for peak load shaving. The suggested peak load shaving model can operate as follows:

- Based on historical data of at least two complete cycles for each household, a cap value will be defined for the peak power during the peak time for every billing cycle
- When the power during the peak period for each household is lower than the set cap, the consumer earns energy tokens equivalent to the amount of energy reduction below the set cap value (as shown in Figure 16)
- The earned tokens can be exchanged with the utility company or the independent system operator (ISO) to pay the monthly energy bill or can be sold to other consumers
- Pursumers can benefit from the bought tokens to pay for the extra charge applied to their energy consumption during on-peak periods
- The complete energy trading process will be similar to the one detailed in Section 4.2

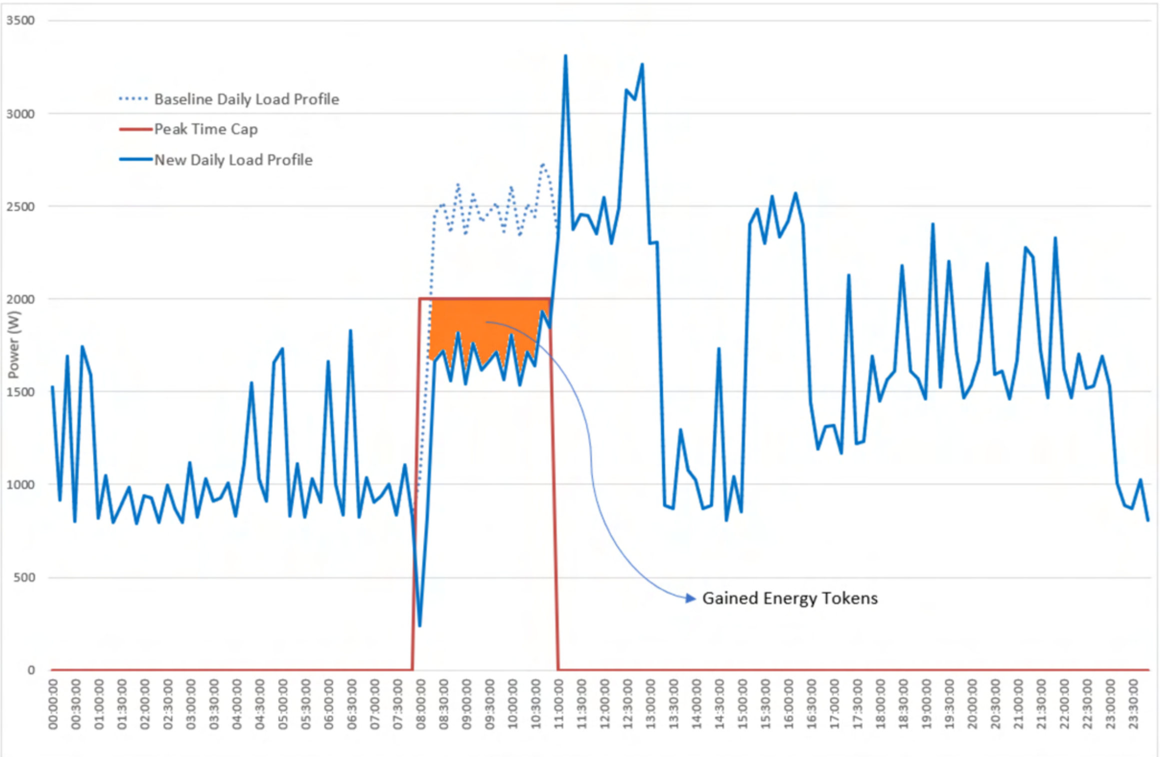

Figure 16. Energy Cap and Trade Peak Load Shaving Model.

Such a model can be used as a demand response program to incentivize consumers to lower their power peak demand during peak-time periods in exchange for tradable energy tokens and thus to contribute to the reduction of the daily peak load and minimizing the need for alternative means of power generation or a large spinning reserve.

6. Conclusions

This article presents a new DSM model that can help minimize the yearly increase in electricity demand, inspired from the concept of Cap and Trade previously applied to fight against the rise in carbon emissions, and benefiting from the emergence of blockchain technology and the tokenization of energy assets. The suggested ECT DSM concept minimizes the free-rider and rebound effects usually faced with conventional DSM programs. It is fundamentally based on integrating consumers as the main stakeholders in the energy supply and procurement process. It rewards efficient consumers and penalizes heavy consumers. Furthermore, it creates an open market for energy trading based on P2P energy trading. The prices are not controlled by a central entity, i.e., the utility company, but instead governed by the general rules of a deregulated supply and demand. The central concept is that the average energy consumer no longer acts as a passive user, located at the end of the energy supply chain, but rather as an integral part of a future smart digital grid, where more and more distributed energy resources (DERs) are being integrated. Such a consumer-driven energy system can benefit all stakeholders, as proven by the presented ECT DSM model.

The proposed DSM program was tested using 200 households as a test bank, and the model was simulated over four months to account for any seasonal effect. Moreover, three different scenarios, soft, intermediate, and aggressive, were taken into consideration to validate the most appropriate criteria to be applied to get the best-equilibrated outcomes for both the utility and the consumer. The obtained results proved the effectiveness of the model, especially for the soft and intermediate scenarios where the utility company can achieve a reduction between 6.04% and 7.8% on the total monthly energy consumption, without any considerable change in its total monthly turnover and without highly affecting the average monthly bills of the consumers. Furthermore, the sensitivity analysis showed the importance of properly selecting the cap value to achieve an optimal result for both the utility company and the consumers. This value has to be modified every few years to account for new market needs and control the energy demand.

Nevertheless, cash incentives alone are not sufficient to create a good DSM program. Still, they should be complemented by real-time feedback from energy meters and an updated billing system that considers an aggregate bill per consumer rather than individual bills based on single points of delivery (PoD). Such a model can help to protect the system against free riders. For example, a person or a family owning and occupying more than one household will not benefit from a double quota of energy credits and can be billed fairly for their aggregated monthly energy consumption as any other family who owns just one household.

The presented blockchain-enabled energy Cap-and-Trade model can be applied to several applications such as peak load shaving. Moreover, it can offer a new perspective for the utility's relationship with its customers, specifically for DSM projects. However, this model might be confronted by several challenges, such as the need for new legislation and regulations. Additionally, it is crucial to create awareness amongst people to embrace this change and appropriately interact with the system and the new technological innovation to extract the maximum benefits from the program. Otherwise, such a model might backfire and lead to negative results.

The work conducted in this article can serve as a test-bed to evaluate the proposed DSM mechanism for new applications, commercial or industrial, and various microgrids, to optimize the model's outcome especially by combining the impact of other distributed energy resources. Additionally, it will be beneficial to test the ECT DSM model under different rate structures such as Real-Time Pricing (RTP) and Time of Use (ToU), as well as applying the rules of open market demand and supply on the actual price of the traded energy tokens.

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Appendix A

The following code is written using Solidity a programming language used for coding smart contracts on the Ethereum platform. The smart contract trading.sol allows to create buy/sell orders and log them on the blockchain's shared ledger. In addition, this smart contract calls for another smart contract called Registeredusers.sol that governs the registration of smart meters for consumers who are willing to participate in the program and allocate an address for each smart meter.

Energy Trading Smart Contract—Solidity Code

```
Pragma solidity >=0.4.22 <0.6.0;
import "./Registeredusers.sol";
// Contract Registeredusers.sol registers a wallet address for each smart meter to enable the
registered user to trade energy on blockchain
// Contract trading.sol manages and records energy buying or selling transactions
contract trading is Registeredusers {
    struct SellOrder {
    address seller;
        uint32 price;
        uint64 energy;
    uint64 timestamp;
}
struct BuyOrder {
    address seller;
    uint32 price;
    uint64 energy;
    address meterAddress;
    uint64 timestamp;
}
// Add registry address
address public utilityreg = 0x89205A3A3b2A69De6Dbf7f01ED13B2108B2c43e7;

SellOrder[] public sellOrders;
BuyOrder[] public buyOrders;

//stores the amount of energy supplied by the seller
BuyOrder[] public sellerEnergy;
mapping(address => uint) public sellIndex;
mapping(address => uint) public buyIndex;
event sellEvent(address indexed seller, uint32 indexed price, uint64 energy);
event buyEvent(address indexed seller, uint32 price, uint64 energy, address meterAddress);

function sellEnergy(uint32 aprice, uint64 aenergy, uint64 atimestamp) onlyRegisteredUsers public
{
// record the sell order
uint idx = sellIndex[msg.sender];
sellOrders.push(SellOrder({
    seller: msg.sender,
    price: aprice,
    energy: aenergy,
    timestamp: atimestamp
    }));
emit sellEvent(sellOrders[idx].seller, sellOrders[idx].price, sellOrders[idx].energy);
}
```

```
function buyEnergy(address aseller, uint32 aprice, uint64 aenergy, address mAddress, uint64
atimestamp) onlyRegisteredUsers public {
// find offer by seller (aseller)
uint idx = sellIndex[aseller];
require(0x0 != idx);
// check if any matching offer is available
if ((sellOrders.length > idx) && (sellOrders[idx].seller == aseller)) {
// check if price is matching
    require(sellOrders[idx].price == aprice);
    buyIndex[msg.sender] = buyOrders.length;
// record the buyer's choice
    buyOrders.push(BuyOrder({
        seller: aseller,
        price: aprice,
        energy: aenergy,
        meterAddress: mAddress,
        timestamp: atimestamp
        }));
emit buyEvent(aseller, aprice, aenergy, mAddress);
//checks if the consumer bought from the seller and stores it
// The array sellerEnergy in trading.sol stores the energy transaction
require(buyOrders[idx].seller == utilityreg);
sellerEnergy.push(BuyOrder({
    seller: aseller,
    price: aprice,
    energy: aenergy,
    meterAddress: mAddress,
    timestamp: atimestamp
    }));
} else {
revert();
}
}
}
```

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6.4 ARTICLE: BLOCKCHAIN APPLICATION IN ENERGY PERFORMANCE CONTRACTING

Cet article, intitulé *« Blockchain Application in Energy Performance Contracting »*, a été accepté en tant qu'article-conférence dans la conférence « Association of Energy Engineers World Energy Conference à Washington. (É.-U.) en octobre 2019. L'article a été publié dans le journal « International Journal of Strategic Energy & Environmental Planning ».

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En tant que premier auteur, j'ai contribué au développement de l'idée générale, à l'essentiel de la recherche sur l'état de la question et au développement du modèle, à la collecte et l'analyse des données et à la rédaction du manuscrit.

Résumé : Alors que l'efficacité énergétique dans les bâtiments et les projets est normative, les contrats de performance énergétique (CPE) gagnent en popularité en tant que mécanisme de financement pour réaliser des économies d'énergie. Néanmoins, la mise en œuvre du CPE est confrontée à des défis majeurs. L'un des obstacles au CPE est qu'il implique plusieurs parties pour réaliser une transaction : une société de services énergétiques (ESCO), le client et l'institution de financement. Les relations multiformes entre ces parties nécessitent un processus administratif complexe qui induit des coûts opérationnels élevés, des frais de transaction et des problèmes de confiance entre les parties. Un risque pour les ESCOs est la défaillance possible de l'hôte après l'achèvement du projet.la chaîne de blocs et les contrats intelligents fournissent une plateforme commerciale qui permet l'exécution et l'application d'accords entre des parties non fiables sans impliquer un tiers de confiance. Cet article explore le potentiel d'intégration de la chaîne de blocs et des contrats intelligents dans le processus de CPE en collectant automatiquement les données des mesures de conservation de l'énergie (MCE) mises en œuvre, en calculant leurs économies d'énergie et en gérant les paiements et les pénalités. Une fois que les processus de mesure et de vérification (M&V) sont terminés et que les conditions du contrat sont satisfaites, les contrats intelligents appliquent

automatiquement le déblocage des paiements du portefeuille électronique du client à l'ESCO. Cette configuration résout les problèmes rencontrés dans le processus EPC, tels que la confiance, l'exécution des paiements, les frais de transaction et les risques financiers, ce qui lui permet de servir les petites organisations et les nouvelles ESCO.

Contexte et Objectifs : Les CPE sont des accords entre les fournisseurs de services énergétiques et les consommateurs, garantissant des améliorations en matière d'efficacité énergétique avec des résultats mesurables et vérifiables. Dans le contexte des DSM, les CPE facilitent l'implémentation de mesures d'efficacité énergétique en offrant un mécanisme financier pour couvrir les coûts initiaux des projets. Ainsi, l'intégration de la technologie de la chaîne de blocs permet de sécuriser et d'automatiser les processus de mesure et de vérification des performances énergétiques, réduisant ainsi les risques de fraude et d'erreurs. Les contrats intelligents, éléments clés de la chaîne de blocs, facilitent l'exécution automatique des termes du CPE, en garantissant que les économies d'énergie prévues sont correctement mesurées et que les paiements sont effectués de manière transparente et fiable. Dans le cadre de notre projet, ce modèle peut être intégré dans les fonctionnalités des PADs. Ainsi, le PAD peut gérer les CPEs, mesurer les économies d’énergie et récompenser les consommateurs pour leurs réductions énergétiques dans le cadre des programmes de gestion de la demande.

Méthodologie : La méthodologie est basée sur l'intégration de la chaîne de blocs et des contrats intelligents au processus EPC en collectant les données des M&V mis en œuvre, en calculant les économies d'énergie, en gérant les paiements et en imposant des pénalités. Une fois que les processus de M&V sont terminés et que les exigences du contrat sont satisfaites, le contrat intelligent libère automatiquement le paiement du portefeuille électronique du client à l'ESCO. La chaîne de blocs fournit un moyen de paiement en temps réel entre pairs qui ne nécessite pas d'intermédiaire tiers de confiance qui facture des frais de transaction et de commission.

Résultats et Contributions : Le modèle, présenté dans cet article, vise à révolutionner la gestion de l'efficacité énergétique en intégrant des contrats intelligents pour automatiser les processus de mesure, de vérification et de paiement. Grâce à la transparence et à la sécurité inhérentes à la chaîne de blocs, le modèle proposé réduit les risques de fraude et les erreurs de mesure, garantissant ainsi des transactions fiables et vérifiables. En facilitant l'implémentation des mesures d'efficacité énergétique, le modèle de CPE basé sur la chaîne de blocs permet une gestion décentralisée et optimisée des ressources énergétiques, renforçant la confiance entre les parties prenantes et minimisant les coûts de transaction.

Blockchain Application in Energy Performance Contracting

Alain G. Aoun

ABSTRACT

While energy efficiency in buildings and projects is normative, energy performance contracting (EPC) is gaining popularity as a financing mechanism to achieve energy savings. Nevertheless, the implementation of EPC faces major challenges. A barrier to EPC is that it involves several parties to complete a transaction: an energy services company (ESCO), the client (host) and the financing institution. The multifaceted relationships among these parties requires a complex administrative process that induces high operational costs, transaction fees, and issues of trust among the parties. A risk for ESCOs is the possible default of the host after project completion. Blockchain and smart contracts provide a trading platform that enables the execution and enforcement of agreements between untrusted parties without involving a trusted third party.

This article explores the potential of integrating blockchain and smart contracts in the EPC process by automatically collecting data from implemented energy conservation measures (ECMs), calculating their energy savings and managing payments and penalties. Once the measurement and verification (M&V) processes are completed and contract conditions are satisfied, the smart contracts automatically enforce the release of payments from the host's electronic wallet to the ESCO. This configuration resolves challenges confronted in the EPC process such as trust, payment enforcement, transaction fees and financial risks, enabling it to serve smaller organizations and new ESCOs.

INTRODUCTION

In a world that seeks energy efficiency (EE) technologies and climate mitigation, massive investments are required to achieve targets and comply with local standards and codes. As EE in buildings and projects grew more popular, energy performance contracting (EPC) gained a reputation as an appealing financial mechanism to achieve energy savings. EPC provides a means of addressing demand side energy issues in existing buildings, particularly older structures and industrial facilities [1]. Nevertheless, many energy investments are made without a clear financial understanding of their values, risks and volatilities. Despite over 20 years of experience with EPC, the demand for new projects has remained below expectations [1].

The energy sector is changing from an analog world of highly centralized, fossil fuel-based generation and transmission systems to a new paradigm of decarbonization, decentralization, and digitalization (the 3Ds). This transition is possible to the extent that available technologies allow it. Blockchain, the internet of asset transfer, might be the solution. It is a digital, decentralized network formed by network-connected distributed computers. These computers are called nodes and each blockchain transaction is recorded among all nodes and accessible to those with permission. New entries (transactions) are validated by special nodes (miners) and uploaded to the blockchain after a consensus is reached. Data recorded on the blockchain is protected by cryptographic encryption. Blockchains are a union of several technologies, such as digital databases, peer-to-peer (P2P) networks and cryptography. This combination of digital technologies brings far-reaching changes to the energy sector.

Investigating the potentials of blockchain technology in EPC makes sense. The key financial risk to ESCOs is the possibility of host payment default after project completion. Blockchain and smart contracts offer a transaction platform that enables the execution and enforcement of an agreement between untrusted parties without involving a trusted third party.

This article provides guidelines for the design, development and implementation of a blockchain based EPC prototype. The methodology is based on integrating blockchain and smart contracts with the EPC process by collecting data from implemented ECMs, calculating the energy savings, managing payments and exacting penalties. Once the M&V processes are completed and the contract requirements are satisfied, the smart contract automatically releases payment from the host's electronic wallet to the ESCO. Blockchain provides a means of real time payment between peers that does not require a trusted third-party intermediary who charges transaction and commission fees. Next, the advantages, disadvantages, and limitations of the proposed configuration will be considered and recommendations for future investigations offered.

ENERGY PERFORMANCE CONTRACTING

Energy performance contracting is an important concept for financing EE. It is based on an energy services company implementing an investment to reduce a host's energy cost, and accepting the financial and technical risks for a specified contract term. The host might be a hospital, educational facility, governmental entity or campus of buildings. The host uses the project's future avoided costs to amortize the invested capital. These funds may be supplied by the ESCO or a third party. At the end of the performance contract term and after the investment has been amortized, the host often continues to benefit from lower energy costs. When the capital is sourced from the ESCO, the financing mechanism is the energy performance contract and the collection mechanism is through invoices and payments. There are two types of energy performance contracts:

- Contracts with shared savings
- Contracts with guaranteed savings

Performance contracting financial structures are tailored for each specific host and application. A typical structure would follow these stages:

- A preliminary analysis is undertaken to determine the host's energy consumption and costs and identify ways to maximize energy savings.
- A detailed energy analysis (known as an investment grade audit) is performed to determine energy savings and costs associated with the improvement measures.
- Improvements are selected for implementation.
- Facility improvements are implemented and the new equipment associated with the project is installed.
- Periodic M&V of savings determines the savings that is achieved.

EPC providers will usually arrange financing for the set-up and installation period, starting payments from the time when the enhanced ECM or facility begins to generate verifiable savings.

Energy performance contracts are helpful in situations when funding sources are elusive, maintenance is lacking, or new equipment and technology is needed and requires unique skills. Energy performance contractors use future energy savings to finance present improvement measures and generally guarantee the savings to lower the risks of the host.

Under a shared savings scheme the ESCO or a third party finances the costs of the EE interventions and is paid by the host using a negotiated portion of the future cost avoidance. The host benefits by receiving the balance of the cost savings beginning at the outset of the performance obligation period and ending at the conclusion of the contract term.

In a guaranteed savings scheme, the host or a third party provides the upfront investment for the energy efficiency measures. The ESCO financially guarantees that the energy savings projected from the improvements will be achieved. Alternatively, when the negotiated savings are not achieved the ESCO is contractually required to reimburse the host the value of the difference between the actual and agreed savings. The ESCO also accepts the design and performance design risks associated with the improvements. The guaranteed savings scheme functions best in countries with established banking structures, greater familiarity with project financing, sufficient technical expertise, and with hosts who understand EE projects. The guaranteed savings concept is more difficult to introduce in developing markets as it requires customers to assume investment repayment risk. However, it fosters long-term growth for the ESCOs and finance industries. Newly-established ESCOs with no credit history and limited resources are often unable to invest in the projects they recommend; market entry is limited to contracts in situations when they can guarantee the savings but the host secures the financing [2].

Energy savings cannot be directly measured because it represents the absence of consumed energy. M&V is used to assess the quantitative outcomes of the EE plans implemented as part of an EPC program. An M&V protocol is the cornerstone of an energy performance contract. According to the International Performance Measurement and Verification Protocol (IPMVP) Core Concepts book, published by the Efficiency Valuation Organization (EVO), M&V is the "process of planning, measuring, collecting and analyzing data" to verify and report "energy savings within an individual facility resulting from the implementation ECMs." The IPMVP was developed over many years to provide guidance and standards for M&V procedures. An M&V protocol is used in EPC because the entity hosting a project depends on the savings to meet its financial obligations and the ESCO is guaranteeing the value of the energy savings. Therefore, M&V design is the foundation of the long-term success of an EPC project.

The aim of EPC is to improve the energy efficiency of the host facility to achieve energy savings by reducing the host's energy costs. The energy consumption of existing facilities prior to implementation is used for baselining. The first step in an M&V plan is to establish a model for the baseline period representing the host facility's historical energy consumption. The baseline model is denoted as $f(X)$, that explicitly defines the relationship between the energy consumption $E(t)$ and a set of independent variables $X(t)$.

$$E_B(t) = f\,[X(t)] \tag{1}$$

Post-project completion conditions establish the post-installation case or performance period. Savings are determined by comparing baseline energy use to performance period energy use. If necessary, regression analysis is used to correlate energy use with relevant independent variables (e.g., weather conditions and occupancy data). If we denote $E_B(t)$, the baseline energy consumption of the facility, and $E_P(t)$, the performance period energy consumption, where t is the discrete time, then savings can be calculated using Equation 2.

$$S(t) = \sum_{t-T}^{t} E_B(t) - E_p(t) \pm \text{Adjustments} \qquad (2)$$

Proper determination of savings includes adjusting for changes that affect energy use but are unrelated to equipment performance. Such adjustments may be caused by changes in weather, occupancy or other factors. The savings are generally computed monthly and financial transactions (payments) occur annually.

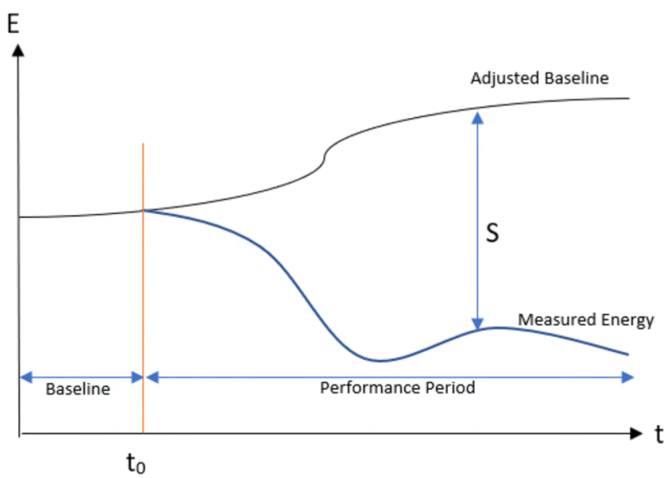

Figure 1. Graph of a performance contract (*E* = energy, *t* = time).

Identifying Risks and Limitations in EPC Projects

Despite the advantages of EPC projects, their providers and customers face legislative, administrative and financial barriers.

When compared with traditional methods of delivering EE projects (e.g., fixed-fee for services, or design-bid-build), EPC projects accept long-term performance and financial risks [3]. EPC procedures seem comparatively complex. For both public and private institutions, disadvantages of EPC include the need for a more sophisticated contract and the calculation of the energy consumption baseline. Mills et al. identified the threats associated with EE projects and classified them as economic, contextual, technological, operations and M&V risks [4]. Hu and Zhou proposed that for EPC projects, risks could be classified as political, legal, market, technology, management, financial project quality and client risks [5]. Here, the barriers and risks are classified in four main categories as shown in Figure 2.

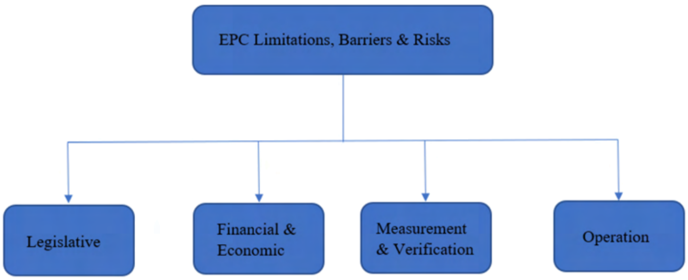

Figure 2. EPC limitations, barriers and risks.

Legislative Barriers and Risks

A country's stable political system and consistent governmental policies are propitious to the development of a market for EPC. Policy instability is a major risk to the implementation of performance contracts since they usually require considerable time for completion. A nation's economic development, planning, regional and industrial development greatly affects the market for energy efficiency [5]. The absence of legislation to force the implementation of ECMs and lack of incentives, such as credits and tax supports, limit the development of the EPC sector. When enabling legislation is in place and incentives are available, lengthy administrative procedures for approval and permitting create additional barriers.

Economic Barriers and Risks

Economic barriers and risks can be divided into two subcategories: market and financial. Market risk is due to market uncertainties, client demand, energy costs, demand charges, material costs, equipment costs, labor costs and industry competition. Most standard EPC contracts stipulate that both contracting parties bear the risk of variations in energy costs and demand charges; the baseline of those costs are adjusted accordingly when they occur [6]. However, in the guaranteed savings model, the ESCO bears those risks. The ESCO also accepts risks associated with variations and increases in material, equipment and labor costs [5].

Financial risks and barriers are mainly linked to the financing mechanisms for EPC projects. The two main financing forms are self-financing and third-party financing. With self-financing, the host provides the upfront capital for project implementation, and the ESCO bears the performance risk by guaranteeing the energy savings for the proposed ECMs. With third-party financing, the ESCO or the host obtains a loan for the project from a third-party financial institution. These loans can be from commercial banks, governments, international capital or a combination. Key financial risks related to financing are associated with macroeconomic factors such as inflation or interest rate variability during contract term. Other financial challenges may arise from a third-party financing institution's lack of awareness of the risks in EPC projects which may result in higher interest rates.

Measurement and Verification Risks

A poorly developed M&V plan can create additional risks for an EPC contract. In practice, M&V often encounters difficulties with lack of clarity, the availability of relevant data, or inadequate resources for follow-up assessments. Moreover, a poorly designed M&V sampling plan or inaccurate metering may distort the performance of the implemented ECMs.

M&V plans often fail to capture the non-energy benefits of EPCs causing system performance to be understated. Furthermore, when O&M procedures are not properly defined in an M&V plan, savings might not be recognized.

A new generation of M&V programming is needed to monitor and verify operational savings, environmental emissions reductions credits, and the energy system capacity credits that EPC projects produce. Newer M&V plans will make fuller use of the metering and communications technologies that did not exist when the IPMVP was written in the mid-1990s, but are now widely available in utility re-metering programs, advanced building automation systems and the expanding internet of things [7].

Operational Risks

Operational limitations and risks are associated with the design, construction, commissioning, operation, maintenance and management of an EPC contract including all related human, financial and technical factors. An accurate estimate of the energy savings from proposed ECMs is crucial to the success of EPC projects. Apart from proper engineering design, project design risks may arise from insufficient facility information, inaccurate surveys, or improper designs or design faults. Such risks can lead to inaccurate energy baseline models or shortfalls in guaranteed energy savings.

Technology risks arise from issues with project feasibility, evolutionary changes, and the technical effects of energy-saving technologies. Such risks are often linked to poor equipment or system performance or sizing. Typically, the ESCO bears all technology risks during the contract term. These risks can be limited with correct system design and equipment selection. Management risks include lack of experience and management failures. Failure to adopt life-cycle based management approaches may result in not meeting important project objectives.

EPC projects often involve the replacement of old equipment and systems with newer, higher efficiency equipment. In practice, this process might encounter considerable delays caused by the restriction of work to specific hours, shortage of labor, or delays in permit issuance. Delays in materializing the actual energy savings will be induced. Successful projects must be completed on time and properly commissioned before use. Poor commissioning leads to missed opportunities, the inability to verify ECMs performance and lower system performance. Proper system commissioning should include validation of equipment performance, and documentation of calibration, O&M procedures, with information reported to the concerned parties.

Human risks in EPC contracts should not be underestimated. EPC projects may require a long period of time for completion. During this period, the host may modify the occupancy or operation of the facility. Another human risk factor is the possibility of inconsistent activity regarding the approved M&V plan.

The payments in EPC projects are linked to verifiable energy savings achieved by the ESCO during the performance period. Defining a suitable payment arrangement is important for the ESCO to maintain a stable cash flow during the project term. Often fixed payment schedules are adopted in EPC contracts. The ESCO receives the fixed amount of payment from the host when the actual savings are determined to be equal to or greater than the guaranteed amount in each M&V period. Deductions are applied when performance shortfalls occur. M&V performance reporting periods could be monthly, quarterly or annually. It is not uncommon for the host to dispute the energy savings achieved by the ESCO, which may result in possible payment defaults by the host. Also, a payment default may occur from the host's inability to fulfill its payment responsibilities. In a worst-case scenario, the host might go out of business before full contract payment.

The multifaceted relationships between involved parties in an EPC contract induces operational risk associated with the complex project administrative process. Such risk causes higher operational costs and transaction fees and reduces the trust among the different parties. The existing EPC models rely heavily on traditional payment methods that necessitate trusted third-party intermediaries. The problems with the third-party intermediaries are that they charge considerable transaction and commission fees, and fail to offer real time payment processing. Plus, the forced bureaucratic process can be complicated and time consuming.

BLOCKCHAIN AND SMART CONTRACTS

In contrast to the world wide web being the internet of information, blockchain technology is an "additional layer of technology on top of the internet" that is defined as the "internet of things" [8]. Blockchain is a distributed chronological ledger that is hosted, updated, and validated by several peer nodes, rather than by a single centralized authority. Eliminating the central authority and having immutable transaction records that are validated by several peers, blockchain increases the simplicity, speed, and transparency of transactions between two peers. An example of the implementation of blockchain is the cryptocurrency Bitcoin. While credit card transactions require validation from a bank and require time, blockchain doesn't require central validation and two-party transactions happen immediately [9].

The value of the global market for blockchain technology is growing. Governments, utilities to academia, and civil organizations are accommodating a digital era in which blockchain, best known for cryptocurrencies, is a cornerstone [10]. While the blockchain has based its reputation on the Bitcoin revolution, it is not only about transferring token ownership. The blockchain can have profound social and economic impacts on traditional models. It offers an alternative means of transacting, sharing value, storing data and doing business by eliminating the need for centralized entities. It is a decentralized trusted network, enabling anyone to digitize and save or transact data, assets, contracts, or value in a secure manner [11]. Global revenues of blockchain technology are forecasted to grow in the coming years to more than $23 billion (U.S.) by 2023. The largest shares will come from the financial and energy sectors [10].

Traditional transactional models are based on a centralized structure. Transactions between network nodes occur directly or through an intermediary third party. Involvement of an intermediary is often necessary because it creates trust between unacquainted transaction partners. With blockchain, trust between peers is empowered by mathematical algorithms and cryptography.

Blockchain is most suitable for applications that meet the following criteria:

- Decentralized problems
- Peer-to-peer transactions
- Beyond boundaries of trust among unknown peers
- Require validation, verification and recording of time stamped immutable ledger
- Autonomous operations guided by a rule structure and policies

Figure 3. P2P money transaction.

Smart Contracts

The term *smart contract* refers to self-executable code that operates on the blockchain to facilitate, execute and enforce an agreement between untrusted parties without involving a trusted third party [12].

The main problem with traditional client server coded contracts is that when any of the parties involved has root access to the server, they can change the rules and conditions of the contracts. This is why in traditional contract models, a trusted third party or government is required. Intermediaries usually charge fees and can be considered a source of risk that potentially jeopardizes the confidentiality of any contract. This is a problem that blockchain and smart contracts can solve by offering a platform that enables parties to reach a consensus on the required set of rules or business policies and to jointly control the information. Hence, what blockchain and smart contracts offer is an evolution of the internet with immutable shared rules.

Bitcoin was the first blockchain to support basic smart contracts, providing a network capable of transferring value between participants. Its programming language enabled limited smart contracts to be created (e.g., payment channels, escrows, multi-sign accounts and time locks). Ethereum was conceived with smart contracts in mind. Its programming language enabled developers to build their own decentralized applications. It is currently the most prominent smart contracts framework.

The main goal of a smart contract is to provide a superior system for contractual agreements based solely on computer code. Unlike a normal contract, which is drafted by a lawyer, signed by stakeholders, and enforced by law, a smart contract establishes relationships with cryptographic code. Unlike a client server coded contract, smart contracts are unstoppable once deployed on the blockchain. Smart contracts offer the following benefits:

- Smart contracts are cryptographically-secured, immutable and enforced.
- Smart contracts are fast and inexpensive.
- They function as multi-signature accounts, so that funds are spent only when a required percentage of people agree.
- They are capable of managing agreements between users without human interruption.
- They provide utility to other contracts (similar to how a software library works). Smart contracts can run independently and can automatically interact with other smart contracts.
- They store information about an application, such as domain registration information or membership records.

A smart contract has two primary components: smart contract code and legal contracts. The *smart contract code* is the code that is stored, verified and executed on the blockchain. A *smart legal contract* is a legally binding agreement that is embodied in a digital form using the smart contract code as a complement or substitute for legal contracts. A smart contract is created and signed by parties using their discreet public keys. Smart contracts are framed and restricted by the terms set in the agreement and the obligations of each party through code instructions. They include all information about the agreement, price, closing date, etc. Upon the set date, ownership automatically transfers to the buyer with terms securely registered in the public ledger. Conflict resolution instructions automatically resolve inconsistencies.

Smart contracts have the potential to change the way business is transacted, and offer viable solutions with lower transaction costs [13]. The automated and real-time update of smart contracts reduces transaction time, and is less susceptible to manual errors. Additionally, these processes require less human intervention and reduce the payroll costs. Due to the decentralized nature of the execution process, nonperformance or manipulation risks are reduced.

Contributions to the EPC Model

The EPC sector faces many challenges, barriers and risks. Some of these risks are uncontrollable and others are resolved by stakeholder awareness or by the implementation of the M&V plan. While legislative and economic risks are beyond the control of the involved parties, other risks such as design, technology, management and commissioning risks, can be mitigated by the involved parties. When barriers and risks are related to trust between parties, payment defaults, human errors, process complexity, delays and high processing cost, blockchain technology and smart contracts offer a platform that helps solve these challenges.

PROPOSED MODEL

The aim of this prototype is to develop a blockchain based energy performance contract that uses a multivariate linear predictive model. It obtains data from installed sensors to adjust the baseline and compare it to the performance period energy consumption to calculate the savings and process the payments accordingly. The implementation of this prototype requires an underlaying blockchain technology that has built-in smart contract support. To this end, the Ethereum blockchain platform is chosen.

Model

Smart contracts in Ethereum are written in the Solidity language. The use of the blockchain occurs once a baseline model has been established and fit to historical data. The development of the blockchain based energy performance contract has four phases:

Agreement on the baseline model: Stakeholders agree on the proposed predictive model, define frequency of data collection, outline the accepted accuracy, set the energy data and mode of payment.

Programming of the corresponding smart contract: The conditions defined in the first phase are hard coded inside different smart contracts (in this case three or four).

Deployment on the blockchain: A unique address is generated for each stakeholder and hard coded inside the smart contract to allow controlled access to the smart contracts. Then the smart contracts are deployed to the blockchain and their corresponding unique addresses are generated.

Execution inside the blockchain: At this phase, the smart contracts are executed and called through their addresses.

Blockchain is a technology that exists only in digital form. Interfacing the real world with its digital representation is challenging. To overcome this, external services to process transactions are required; oracles are used to bridge the gap between the digital and physical worlds. In blockchain, oracles are used to push the information to the blockchain. Oracles allow blockchain contracts to interact with the outside world, by allowing smart contracts to request external information. *Oracles* are digital agents that automatically locate and verify real world data, and then submit the information to the querying smart contract to initiate one or several transactions based on the encoded logical conditions. The hereafter "Solidity code for sensor data logging" is a smart contract that permits data accessed from a physical sensor to be logged into the smart contract. To further elaborate the potentials of the blockchain based EPC, an example is used in which an old chiller gets replaced by a higher efficiency chiller. For this case, the defined independent variable is the *cooling degree day* (CDD) and assumes constant occupancy. The predictive model is based on a regression formula given by the following equation:

$$y = 3{,}317x + 53.505 \tag{3}$$

Where y is the chiller's consumed energy in kWh and x corresponds to the CDD.

In our case, three oracles are needed to obtain real-world data and log it into the blockchain and smart contracts. The *Energy Meter Oracle* is responsible for obtaining the chiller's daily energy consumption. The *Temperature Sensor Oracle* provides the hourly temperatures to the relevant smart contract where the temperature will be processed to represent a CDD. The *Time Oracle* is a software entity that provides precise time information to the blockchain (e.g., end of the day or month). Additional oracles can be added to verify that the client's static

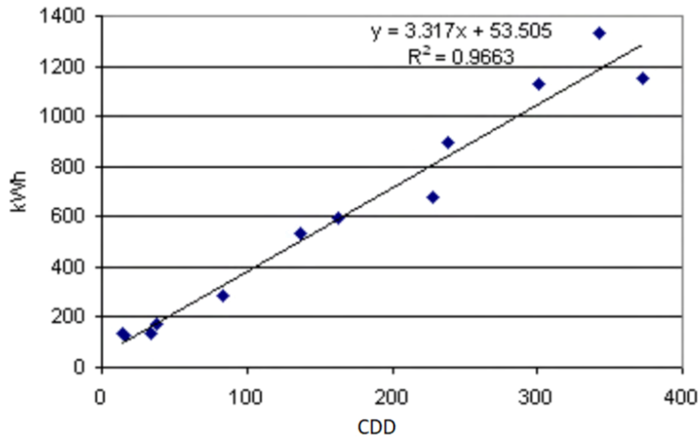

Figure 4. Regression model.

facility data have not been compromised (i.e., an oracle for the facility occupancy, operation or the air conditioning system set temperature).

In this example, the blockchain based energy performance contract is represented by three smart contracts with the possibility of adding a fourth. The first smart contract is the *Data Logger*. Its purpose is to store information collected from the different oracles, convert temperature data into CDD and initiate the daily prediction process.

The data storage and calculations are performed using dedicated transactional functions hardcoded within the smart contract, such as the *StoreIntegerValue* and *getSensorData* functions. At the end of each day, the *Data Logger* smart contract is triggered by the *Time Oracle* and logged data (e.g., the CDD value and daily energy consumption) are passed to the *Adjustments* smart contract. The aim of this smart contract is to predict the daily adjusted baseline energy consumption using the logged daily data and defined regression equation. Moreover, the *Adjustments* smart contract calculates the daily savings and the output of this calculation is then passed to the *Savings* smart contract. The role of the *Savings* smart contract is to aggregate savings from a daily into a monthly time stamp. When a daily saving is added, it increments the total savings by the amount of the current date. Eventually, when the *Time Oracle* declares the month's end, the *Savings* smart contract calculates the monthly saving in kWh and translates it into a financial flow using the *Contract Payment* smart contract. If needed, an additional smart contract can be added to validate the static variables of the facility.

The last piece is the front-end section which provides a human machine interface between the authorized users and the prototype. For this purpose, two

Solidity code for sensor data logging

```
pragma solidity ^0.4.10;

contract StoreIntegerValue {
      address owner;
      int sensorData;

      function StoreIntegerValue() {
      owner = msg.sender;
      }

      function              getSensorData()
constant returns (int) {
      require(msg.sender == owner);
      return sensorData;
     }
```

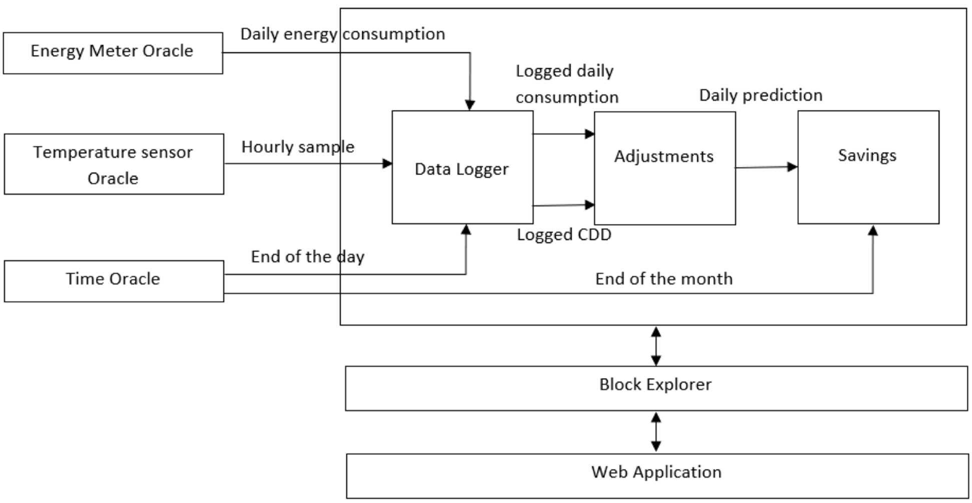

Figure 5. Functional system architecture.

application programming interfaces (APIs) are defined: *Block Explorer* and *Web Application*. The Block Explorer API provides information on blockchain data and allows developers to access and integrate the functionality and data from *Block Explorer* with other applications. It also allows access to charts and block information, listing charts, blocks and managing transactions. The Web Interface API displays the obtained results to the end-users via a user-friendly interface. It shows all results together with their corresponding block numbers. The authorized users may then check the information details by using these block numbers through *Block Explorer*. The architecture of this system is illustrated in Figure 5.

Limitations and Barriers

Blockchain based solutions and smart contracts are not a panacea but help solve specific business problems. This proposed prototype shows the approach's feasibility; however, there are several limitations and barriers. While the blockchain guarantees data immutability, data veracity is not guaranteed since false data can be stored in the blockchain. Moreover, adopting a regression model for an energy performance contract might require the use of float numbers. Unfortunately, floating-point numbers are not supported in Solidity or the Ethereum Virtual Machine (EVM). For example, the operation $2.9 * 2$ truncates the result to 5. The obvious reason is that floats are unpredictable, which would make the outcome of operations variable over nodes. Nevertheless, any number can be converted into an integer with some degree of accuracy. In practice, this means that a minimum unit and maximum divisibility should be applied for case applications. For example, if the MWh is the unit for energy in a certain calculation, hundreds of kWh can be added or lost. In some cases, this means that thousands of dollars are being overpaid or deducted. Therefore, in such applications it might be appropriate to store values in kWh or Wh when additional accuracy is required.

Another limitation that arises from the use of the Solidity language for smart contract coding is the lack of standard mathematical libraries such as arrays and matrix operations. In Solidity, a library is a different type of contract that lacks storage. Sometimes it is helpful to think of a library as a singleton in the EVM, a piece of code that can be called from any contract without the need to deploy it again. Solidity libraries are similar to contracts, but they are deployed only once at a specific address with its code being reused by various contracts. Whenever a mathematical operation is not available as a library, the operation will be implemented as a function. The problem with functions is that they enlarge the size of the contract and thus more *gas* is required to execute the contract. *Gas* is defined as the execution fee for operations made on Ethereum. Therefore, using functions instead of libraries means that the fees paid to execute a smart contract on the blockchain will increase. This is counter to the goal of reducing transaction costs.

In Solidity, the maximum size of a contract is restricted to 24KB and there is an approximate 8 million gas limit per block on the Ethereum blockchain. The total amount of gas for all the transactions in a block including contract deployment cannot exceed this limit. When executing a smart contract, global variables are stored or persist in the contract's state on the blockchain. This is perhaps the most expensive operation in terms of gas for a transaction. It is imperative to have the minimum memory footprint for the stored global variables. This is why our model uses a daily (instead of a monthly) predictive model since it is costly or impossible to store one-month hourly temperature data inside a smart contract.

Being a blockchain element, smart contracts have the same feature in terms of immutability as blockchain. Thus, even the slightest coding error can be expensive and time-consuming to correct once the executable smart contract is deployed. To prevent this from occurring, it is important to develop test scenarios and test the smart contract prior to deploying it on the blockchain.

CONCLUSION

In this article, guidelines for the design, development and implementation of a blockchain based energy performance contract prototype were introduced with the aims of improving trust between the ESCO and the host, avoiding possible conflicts or payment defaults, and reducing process time and fees. The suggested process uses blockchain technology along with smart contracts and oracles to automatically collect data from implemented ECMs, calculate the energy savings, and manage payments and penalties when based on a well-defined M&V plan.

The multiple advantages and opportunities of blockchain technology hold potential to revolutionize business transactions. Besides its technological capabilities, the blockchain shifts power and trust from a central control entity to all participants. The introduced blockchain based contract model provides an example of the added value that this technology brings to the energy sector and highlights the model's feasibility. Though limitations must be addressed, once the changes are embraced, blockchain will improve energy sector transaction capabilities.

This article represents a beginning that will hopefully spawn future investigations to overcome the barriers and limitations of energy applications for blockchain technology. It points to the need for additional research that focuses on the development of blockchain components or modules that serve the EPC market and can create plug-and-play applications. Such components have the potential to enhance wider adoption of blockchain based energy performance contracts.

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CHAPITRE 7CHAPITRE 7
LE ROLE DE LA CHAÎNE DE BLOCS DANS L'ELECTRIFICATION DU TRANSPORT ET L'INDUSTRIE

7.1 INTRODUCTION

L'électrification du transport a un impact significatif sur les réseaux électriques. Cette transformation représente un changement radical par rapport aux modèles traditionnels de consommation d'énergie et introduit de nouveaux défis et opportunités pour les gestionnaires de réseau. Premièrement, l'adoption croissante des véhicules électriques entraîne une augmentation substantielle de la demande en électricité. Selon les prévisions, les VEs pourraient représenter une part importante de la consommation électrique mondiale d'ici 2030. Cette hausse de la demande nécessite une adaptation de la capacité de production et de distribution d'énergie pour éviter les surcharges et les pannes. En particulier, les périodes de pointe de recharge, souvent en soirée lorsque les utilisateurs rentrent chez eux, peuvent coïncider avec les heures de consommation maximale résidentielle, exacerbant les contraintes sur le réseau. Pour répondre à cette demande accrue, les opérateurs de réseau doivent investir dans des infrastructures de réseau améliorées, telles que des transformateurs plus robustes et des lignes de distribution renforcées. Parallèlement, l'intégration de sources d'énergie renouvelable décentralisées devient essentielle pour fournir une énergie propre et durable aux VEs. Cependant, la nature intermittente de ces sources d'énergie renouvelable pose un défi supplémentaire pour l'équilibre et la stabilité du réseau.

Deuxièmement, la recharge intelligente (smart charging) émerge comme des solutions prometteuses pour gérer l'impact des VEs sur les réseaux électriques. La recharge intelligente permet de répartir la demande de recharge des VEs sur des périodes moins chargées, réduisant ainsi les pics de demande et optimisant l'utilisation des ressources disponibles. La gestion de la charge des VEs joue un rôle crucial dans le maintien de la stabilité et de l'efficacité des PADs. Avec l'augmentation rapide de l'adoption des VEs, une charge non coordonnée et simultanée pourrait entraîner des pics de demande énergétique, mettant ainsi à rude épreuve les infrastructures électriques existantes. Les PADs, conçues pour améliorer la résilience et la flexibilité du réseau, doivent intégrer des stratégies de gestion de la charge pour éviter ces nouveaux pics de demande. En optimisant la charge des VEs, il est possible de répartir uniformément la demande énergétique sur la journée, réduisant ainsi les risques de surcharge et les coûts associés à la mise à niveau des infrastructures. De plus, une gestion intelligente de la charge peut permettre d'utiliser les VEs comme des sources d'énergie distribuées, participant activement à l'équilibrage du réseau et à la gestion des ressources énergétiques locales.

D'autre part, l'énergie et l'industrie sont inextricablement liées, formant un duo synergique qui alimente le développement économique et la croissance technologique à l'échelle mondiale. L'énergie, sous ses diverses formes, est le moteur essentiel de l'industrie, fournissant la puissance nécessaire pour alimenter les usines, les machines et les processus de production. L'industrie 4.0, caractérisée par l'intégration des technologies numériques avancées dans les processus industriels, transforme profondément les réseaux électriques à travers le monde. Cette quatrième révolution industrielle, marquée par l'IdO, l'IA, la robotique, la réalité augmentée, et l'analyse de données massives, modifie non seulement la manière dont les industries fonctionnent, mais aussi comment elles consomment et gèrent l'énergie. Tout d'abord, l'industrie 4.0 exige des réseaux électriques plus intelligents et flexibles. Les usines intelligentes et les systèmes de production automatisés reposent sur une alimentation électrique stable et fiable pour fonctionner de manière optimale. Pour répondre à ces besoins, les réseaux électriques doivent évoluer vers des réseaux intelligents ou smart grids. Ces réseaux sont capables de gérer de manière dynamique l'offre et la demande d'électricité grâce à l'utilisation de capteurs, de compteurs intelligents et d'algorithmes avancés. Les smart grids permettent une surveillance en temps réel et une gestion proactive des ressources énergétiques, réduisant ainsi les risques de pannes et augmentant l'efficacité énergétique. De plus, l'industrie 4.0 encourage l'intégration des sources d'énergie renouvelable et décentralisée. Les entreprises adoptent de plus en plus les énergies renouvelables, telles que l'énergie solaire et éolienne, pour alimenter leurs opérations. Cette transition vers des sources d'énergie plus propres s'accompagne souvent de l'installation de systèmes de stockage d'énergie, comme les batteries, qui permettent de gérer les fluctuations de production. Par conséquent, les réseaux électriques doivent s'adapter pour intégrer ces sources d'énergie décentralisées, ce qui nécessite des investissements dans l'infrastructure et la mise en place de systèmes de gestion de l'énergie sophistiqués.

L'industrie 4.0 implique également une demande croissante de flexibilité dans la gestion de l'énergie. Les processus de production modernes sont souvent plus modulaires et peuvent s'adapter rapidement aux changements de la demande. Cela signifie que les besoins en énergie peuvent fluctuer de manière significative en fonction des cycles de production. Les réseaux électriques doivent donc être capables de répondre rapidement à ces variations de demande. Les technologies de gestion de la demande jouent un rôle crucial en permettant une meilleure coordination entre la production et la consommation d'énergie. Les systèmes de gestion de l'énergie industriels, basés sur l'analyse de données en temps réel, permettent d'optimiser la consommation d'énergie en fonction des besoins précis des processus de production. Par ailleurs, l'utilisation de l'IoT et de l'IA dans l'industrie 4.0 améliore considérablement l'efficacité énergétique. Les capteurs IoT collectent en continu des données sur la consommation d'énergie et les conditions opérationnelles des équipements. Ces données sont ensuite analysées par des systèmes d'IA pour identifier des opportunités d'amélioration de l'efficacité énergétique, prévoir les besoins en maintenance et optimiser les opérations. Par exemple, l'IA peut anticiper les pannes d'équipement et recommander des actions de maintenance proactive, réduisant ainsi les interruptions non planifiées et les pertes d'énergie.

L'industrie 4.0 transforme également les modèles économiques liés à l'énergie. Avec la numérisation, de nouvelles opportunités émergent pour les services énergétiques, tels que les CPEs et les micro-réseaux. Les CPEs permettent aux entreprises de financer des améliorations de l'efficacité énergétique sans coûts initiaux, en remboursant les investissements à partir des économies réalisées. Les micro-réseaux, quant à eux, permettent aux entreprises de produire, stocker et gérer leur propre énergie, offrant ainsi une plus grande résilience et l'indépendance énergétique. Ainsi, l'industrie 4.0 a un impact profond et multidimensionnel sur les réseaux électriques. Elle nécessite des réseaux plus intelligents, flexibles et capables d'intégrer des sources d'énergie renouvelable décentralisées. Les technologies de gestion de la demande, l'IdO et l'IA jouent un rôle crucial dans cette transformation en améliorant l'efficacité énergétique et en permettant une gestion proactive des ressources. Les nouveaux modèles économiques et les innovations technologiques qui en résultent renforcent non seulement la résilience des réseaux électriques, mais contribuent également à la durabilité et à l'efficacité énergétique globale.

Ainsi, ce chapitre présente deux articles qui traitent les sujets de l'électrification du transport et l'industrie. Dans le premier article, les auteurs explorent l'optimisation de la charge des VEs en développant un algorithme dynamique pour gérer efficacement la demande énergétique. Cette étude met en lumière les défis actuels liés à l'intégration des VEs dans le réseau électrique. Le second article se concentre sur l'application de la technologie de la chaîne de blocs dans l'industrie 4.0, mettant en évidence son potentiel pour révolutionner la gestion des données, la traçabilité des produits et la sécurité des transactions.

7.2 ARTICLE: DYNAMIC CHARGING OPTIMIZATION ALGORITHM FOR ELECTRIC VEHICLES TO MITIGATE GRID POWER PEAKS

Cet article, intitulé « *Dynamic Charging Optimization Algorithm for Electric Vehicles to Mitigate Grid Power Peaks* », a été publié dans sa version finale en juillet 2024 par les éditeurs du journal *MDPI – World Electric Vehicule Journal*.

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En tant que premier auteur, j'ai contribué à la conceptualisation et développement du modèle, à l'essentiel de la recherche sur l'état de la question, à la collecte et l'analyse des données et à la rédaction du manuscrit. Professeur Mehdi Adda a participé à la direction du projet, à la supervision du travail, validation des résultats ainsi qu'à la révision de l'article et à la revue de la littérature. Les professeurs Adrian Ilinca, Mazen Ghandour et Hussein Ibrahim en tant que co-auteurs, ont participé à la révision de l'article et à la revue de la littérature.

Résumé : La prolifération rapide des VEs présente à la fois des opportunités et des défis pour le réseau électrique. Alors que les VE constituent un moyen prometteur de réduire les émissions de gaz à effet de serre et la dépendance à l'égard des combustibles fossiles, leur comportement de charge non coordonné peut mettre à rude épreuve l'infrastructure du réseau, créant ainsi de nouveaux défis pour les exploitants du réseau et les propriétaires de VE. La nature non coordonnée de la recharge des véhicules électriques peut conduire à l'émergence de nouvelles charges de pointe. Les gestionnaires de réseau planifient généralement les périodes de pointe et déploient des ressources en conséquence pour assurer la stabilité du réseau. La recharge non coordonnée des VE peut introduire de l'imprévisibilité et de la variabilité dans les schémas de charge de pointe, ce qui complique la gestion efficace des charges de pointe par les opérateurs. Cet article examine les implications de la charge non coordonnée des VE sur le réseau électrique pour relever ce défi et propose un nouvel algorithme d'optimisation dynamique conçu pour gérer efficacement les programmes de charge des VE, en atténuant les pics de puissance du réseau tout en garantissant la satisfaction de l'utilisateur et les exigences de charge du véhicule. L'algorithme PoN calcule un indice de priorité pour chaque VE et coordonne la charge de tous les VE connectés à tout moment de manière à ne pas dépasser la capacité de puissance maximale allouée. L'algorithme a été testé dans différents scénarios, et les résultats offrent une comparaison de la demande de puissance de charge entre un scénario de base de charge de VE non coordonnée et le modèle de charge coordonnée proposé, prouvant l'efficacité de notre algorithme proposé, réduisant ainsi la demande de charge de 40,8 % sans impact sur le temps de charge total global.

Contexte et Objectifs : L'algorithme d'optimisation de la charge dynamique PoN (PONDCOA) représente un changement de paradigme dans les techniques de charge intelligente des VE, offrant une solution holistique aux défis complexes posés par un comportement de charge non coordonné. PONDCOA s'appuie sur un algorithme d'optimisation, un mécanisme de consensus, un protocole de communication avancé et des données en temps réel pour ajuster dynamiquement les programmes de charge en fonction de la demande en temps réel et des conditions du réseau. Contrairement aux approches traditionnelles qui reposent sur des programmes de charge prédéterminés ou des modèles de tarification statiques, PONDCOA évalue en permanence les besoins des véhicules individuels et les capacités du réseau, en optimisant les décisions de charge à la volée. En gérant intelligemment le temps et la répartition des charges des VE, l'algorithme proposé vise à répartir les charges des VE sur différentes périodes afin d'éviter les pics de demande et d'équilibrer la charge sur le réseau électrique. En répartissant la demande de charge, l'algorithme aide à prévenir la congestion du réseau et les fluctuations de tension, garantissant ainsi la stabilité et la fiabilité du réseau. L'efficacité de PONDCOA repose sur sa capacité à hiérarchiser la charge en fonction des besoins immédiats des propriétaires de VE, tout en équilibrant les objectifs généraux de stabilité et d'efficacité du réseau. En analysant des facteurs tels que l'état de charge de la batterie, les caractéristiques de charge et le nombre de VE connectés par ménage, PONDCOA garantit que chaque véhicule est chargé simultanément sans surcharger le réseau ou causer des retards importants pour l'utilisateur final. Les résultats de la simulation démontrent l'efficacité de l'algorithme dans l'atténuation des pics de puissance et la promotion de la durabilité de l'infrastructure de charge des VE.

Méthodologie : La méthodologie de développement et de simulation adoptée suit une approche systématique et intégrée. Premièrement, une revue approfondie de la littérature existante, ciblant les impacts de la charge non coordonnée des VEs sur le réseau électrique et les techniques d'optimisation de charge des véhicules électriques, est réalisée pour identifier les meilleures pratiques et les lacunes. Ensuite, le modèle algorithmique est conçu en intégrant le mécanisme PoN, qui privilégie les besoins réels des utilisateurs et la disponibilité des ressources énergétiques distribuées. Le modèle prend en compte divers paramètres, tels que l'état de charge des batteries des VEs, les prévisions de demande énergétique, et le nombre de VE par maison. Et finalement le modèle est simulé et comparé au modèle de base.

Résultats et contributions : L'algorithme PONDCOA peut gérer la charge simultanée de plusieurs VE en utilisant la méthodologie PoN sans avoir d'impact sur le temps total de charge des véhicules ni provoquer de pic de demande de charge. Les résultats de la simulation démontrent une réduction significative de la demande de pointe sans avoir d'impact sur le temps de charge total tout en respectant les préférences de l'utilisateur final. Un tel algorithme peut être utilisé non seulement pour gérer la charge des VE au niveau de la sous-station électrique locale, mais aussi pour gérer la charge des flottes de VE pour n'importe quelle entreprise ou installation.

World Electric Vehicle Journal

Article

Dynamic Charging Optimization Algorithm for Electric Vehicles to Mitigate Grid Power Peaks

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Abstract: The rapid proliferation of electric vehicles (EVs) presents both opportunities and challenges for the electrical grid. While EVs offer a promising avenue for reducing greenhouse gas emissions and dependence on fossil fuels, their uncoordinated charging behavior can strain grid infrastructure, thus creating new challenges for grid operators and EV owners equally. The uncoordinated nature of electric vehicle charging may lead to the emergence of new peak loads. Grid operators typically plan for peak demand periods and deploy resources accordingly to ensure grid stability. Uncoordinated EV charging can introduce unpredictability and variability into peak load patterns, making it more challenging for operators to manage peak loads effectively. This paper examines the implications of uncoordinated EV charging on the electric grid to address this challenge and proposes a novel dynamic optimization algorithm tailored to manage EV charging schedules efficiently, mitigating grid power peaks while ensuring user satisfaction and vehicle charging requirements. The proposed "Proof of Need" (PoN) charging algorithm aims to schedule the charging of EVs based on collected data such as the state of charge (SoC) of the EV's battery, the charger power, the number of connected vehicles per household, the end-user's preferences, and the local distribution substation's capacity. The PoN algorithm calculates a priority index for each EV and coordinates the charging of all connected EVs at all times in a way that does not exceed the maximum allocated power capacity. The algorithm was tested under different scenarios, and the results offer a comparison of the charging power demand between an uncoordinated EV charging baseline scenario and the proposed coordinated charging model, proving the efficiency of our proposed algorithm, thus reducing the charging demand by 40.8% with no impact on the overall total charging time.

Keywords: energy management; electric vehicle; charging optimization; smart charging; dynamic optimization algorithm; state of charge; efficiency; peak load management; grid modernization

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1. Introduction

Amid a global transition towards sustainable transportation, the electrification of transportation has gained significant momentum in recent years [1], driven by advancements in battery technology, supportive government policies, and growing consumer demand for sustainable mobility solutions. EVs offer numerous benefits [2], including reduced greenhouse gas emissions, improved air quality, and decreased reliance on finite fossil fuel resources. EV sales have experienced exponential growth over the last decade, with significant increases observed in many regions worldwide. This growth has been particularly pronounced in countries with supportive policies and incentives for EV adoption, such as Norway, China, and the United States [3–5]. Automakers have significantly expanded their EV offerings, introducing a wide range of models across various vehicle segments. This increased variety has made EVs more accessible to a broader range of consumers, catering to different preferences and needs. However, the widespread adoption of EVs also introduces new challenges for the electrical grid, particularly concerning the management of charging infrastructure and its impact on the stability and efficiency of the electrical grid [6]. The uncoordinated charging of EVs can create new peak demands in the electric grid's typical load profile. As EV ownership continues to grow, particularly in urban areas, the simultaneous charging of vehicles during peak periods can exacerbate existing grid congestion and strain infrastructure capacity. Unlike traditional loads, such as residential and commercial buildings, EV charging patterns exhibit high variability and unpredictability, driven by user behavior, vehicle characteristics, and charging infrastructure availability. During peak periods, the simultaneous charging of numerous EVs can overwhelm local distribution networks, necessitating costly upgrades and increasing the risk of grid outages. This uncontrolled influx of demand increases the risk of grid overloads and hampers efforts to integrate renewable energy sources effectively. Moreover, without coordinated charging strategies, utilities face heightened operational costs and may resort to fossil fuel-based generation to meet sudden surges in demand, undermining sustainability objectives. Addressing these issues necessitates developing and implementing intelligent charging management systems capable of optimizing EV charging schedules, smoothing out demand peaks, and ensuring grid reliability amidst the accelerating transition to electrified transportation.

Moreover, numerous other obstacles are associated with electric vehicle charging, spanning technical, economic, and infrastructure aspects. In many areas, there is a shortage of charging stations, particularly in rural and suburban locations, which can discourage the adoption of EVs. Additionally, the lack of standardized charging connectors and communication protocols can result in compatibility issues between EVs and charging stations [7]. Similarly, varying payment systems and access methods across different charging networks can make it difficult for EV drivers to locate and pay conveniently for charging services. These factors can limit the use of EVs for long trips, hindering the rapid transition from traditional gas and diesel vehicles to EVs.

Furthermore, while fast chargers are available, many charging stations offer slower charging speeds, resulting in longer wait times for drivers. Even with fast chargers, the time required to recharge an EV can still be significantly longer than refueling a traditional vehicle, which may inconvenience some drivers. At the grid level, concentrated EV charging in specific locations or during peak hours can strain the electricity grid, causing voltage fluctuations and potential instability. Expanding and upgrading the electricity grid to accommodate the increase in demand from EV charging can be costly and time-consuming. At the end-user level, some consumers may still hold misconceptions about EVs, such as concerns about battery life, safety, and performance, which can impede adoption. Increasing public awareness and understanding of EV technology, benefits, and charging options is crucial to overcome these barriers. Addressing these challenges requires collaboration among governments, utilities, automakers, charging infrastructure providers, and other stakeholders to invest in infrastructure, develop supportive policies, and promote the adoption of EVs.

On the other hand, advancements in smart charging technologies and communication protocols show potential for optimizing EV charging schedules and improving grid integration. These technologies utilize data analytics, artificial intelligence (AI) algorithms, and Internet of Things (IoT) devices to manage EV charging in real time and counter its unpredictable nature. By coordinating charging schedules across multiple EVs and optimizing resource allocation, smart charging systems can enhance grid stability, maximize renewable energy utilization, and minimize utility costs. This paper proposes a novel dynamic optimization algorithm designed to manage EV charging schedules efficiently, mitigating grid power peaks while ensuring user satisfaction and meeting vehicle charging requirements. Through load balancing and smart scheduling, the algorithm utilizes real-time data on grid load and EV charging demand to intelligently coordinate the simultaneous charging of all connected EVs without creating a peak demand at the level of the local distribution grid.

The proposed optimization algorithm is based on the Proof of Need (PoN) mechanism, which we introduce and detail in this article. This mechanism is a consensus among all end-users to identify which EVs require charging more urgently than others. It draws inspiration from consensus mechanisms in other areas, such as peer-to-peer (P2P) networks, blockchain, and Internet of Things (IoT) systems. These mechanisms are utilized in different distributed systems and protocols to reach agreement among multiple participants on transaction validity, network status, or event sequencing. Consensus mechanisms are crucial in ensuring distributed systems' integrity, reliability, and security by coordinating actions, validating data, and preventing malicious activities. In our scenario, the PoN determines a specific value that reflects the need for an EV to be charged. This value is then incorporated into our dynamic optimization algorithm to arrange the sequence of events, or in other words, the charging of EVs, in a manner that avoids any peak load or disruptions on the local electric distribution network.

The PoN dynamic charging optimization algorithm (PONDCOA) represents a paradigm shift in EV smart charging techniques, offering a holistic solution to the complex challenges posed by uncoordinated charging behavior. At its core, PONDCOA leverages an optimization algorithm, a consensus mechanism, an advanced communication protocol, and real-time data to dynamically adjust charging schedules based on real-time demand and grid conditions. Unlike traditional approaches that rely on predetermined charging schedules or static pricing models, PONDCOA continuously evaluates individual vehicles' needs and the grid's capabilities, optimizing charging decisions on the fly. By intelligently managing the timing and distribution of EV charging loads, the proposed algorithm aims to distribute EV charging loads across different periods to avoid peak demand spikes and balance the load on the electricity grid. By spreading out charging demand, the algorithm helps prevent grid congestion and voltage fluctuations, ensuring grid stability and reliability. Central to the effectiveness of PONDCOA is its ability to prioritize charging based on the immediate needs of EV owners while balancing the overarching goals of grid stability and efficiency. By analyzing factors such as battery state of charge, charging characteristics, and number of EVs connected per household, PONDCOA ensures that each vehicle is simultaneously charged without overburdening the grid or causing remarkable delays to the end-user. Simulation results demonstrate the algorithm's effectiveness in smoothing out power peaks and promoting the sustainability of EV charging infrastructure.

This article is divided into three parts. In the first part, we review the current challenges associated with uncoordinated EV charging and the existing methodologies used to solve this issue. Then, we introduce the methodology adopted to develop our proposed dynamic smart charging algorithm and the PoN consensus mechanism. In the final part, we introduce our simulation scenarios and the results we achieved compared to the uncoordinated EV charging baseline model.

2. Related Works

Addressing the challenges associated with uncoordinated EV charging requires a multifaceted approach that integrates technological innovations, regulatory reforms, and consumer engagement strategies. Article [8] emphasized the potential grid stability issues arising from simultaneous high-demand EV charging. Uncoordinated charging of EVs can lead to new peak load periods, where multiple vehicles charge simultaneously during high-demand hours [9]. Figure 1 illustrates the demand load peak caused by the uncoordinated charging of 500 EVs in the evening (between 4:00 and 8:00 PM) when drivers usually arrive back home from work and connect their vehicles to charge.. This sudden increase in demand can strain the grid infrastructure and lead to voltage fluctuations and reliability issues. The sudden influx of EVs plugging in for charging during peak hours can lead to grid congestion and voltage fluctuations. This phenomenon, known as "charging stress," poses challenges for grid operators, requiring careful management to avoid disruptions. In addition to charging stress, EVs can impact voltage regulation within distribution networks. As article [10] discussed, unmanaged EV charging can cause voltage drops, particularly in areas with high EV concentrations. This necessitates the development of smart charging solutions that consider voltage constraints and optimize charging schedules accordingly.

Similarly, the integration of EVs also affects grid frequency response. The work conducted in [11] highlighted the potential for EVs to provide frequency regulation services through Vehicle-to-Grid (V2G) technologies. V2G allows EVs to discharge stored energy back to the grid during periods of high demand, enhancing grid stability and reducing reliance on traditional power plants for frequency support. The continued development of V2G technologies holds promise for grid integration. Article [12] discussed the potential for EVs to act as mobile energy storage units, providing grid services such as peak shaving and frequency regulation. V2G can transform EVs into valuable assets for grid operators, enhancing grid stability and reliability. In article [13], the authors presented a home energy management system that allows residential households to reduce their yearly energy bill in a dual tariff scheme using the EV's battery as a power shiftable load. However, financial incentives for V2G technology are essential to compensate for the potential degradation of battery life while still ensuring profitability for EV owners. By providing monetary rewards, utility companies, and governments can encourage EV owners to participate in V2G programs, where their vehicles' batteries are used to supply power back to the grid during peak demand periods. These incentives help offset the costs associated with the wear and tear on batteries caused by frequent charging and discharging cycles. Additionally, well-structured compensation schemes ensure that EV owners can achieve a net financial gain, making participation in V2G economically attractive. This approach not only promotes the wider adoption of V2G technology but also supports grid stability, energy efficiency, and the integration of renewable energy sources [14].

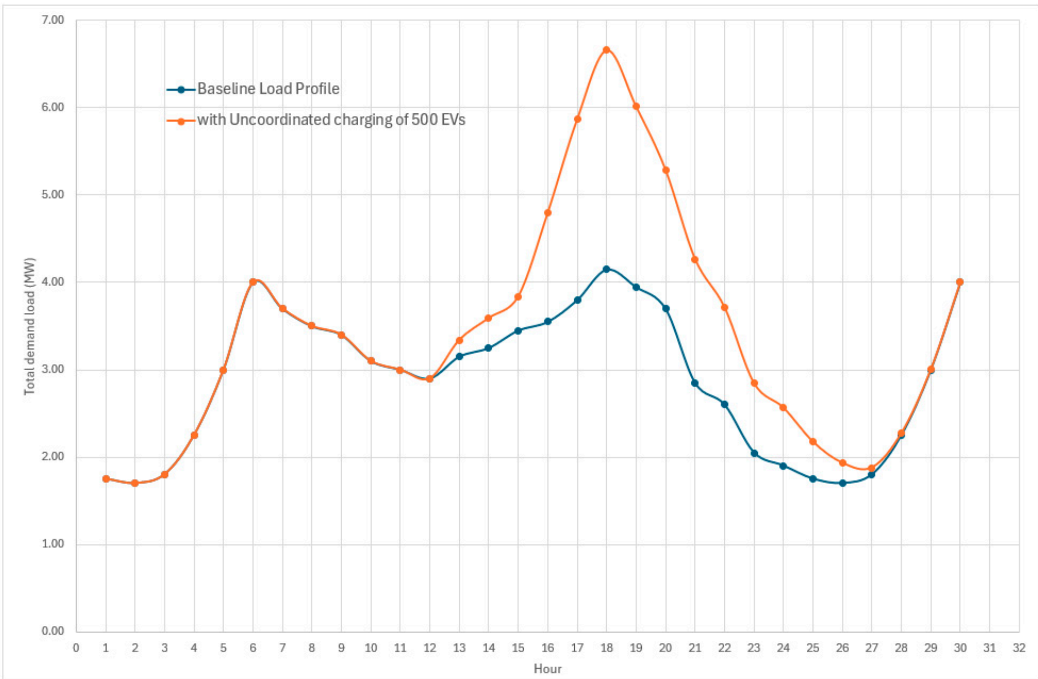

Figure 1. The increase in load demand caused by the uncoordinated charging of 500 EVs

On the other hand, the authors of article [15] discussed the challenges of grid congestion during peak EV charging hours. Without proper management, the simultaneous charging of EVs can strain local distribution networks, leading to voltage drops and increased line losses. This congestion not only affects EV owners but also impacts other electricity consumers connected to the same grid. Demand response strategies have been proposed to address peak load management challenges. One promising avenue for grid management is the implementation of time-of-use pricing schemes [16], which incentivize EV owners to shift their charging behavior away from peak periods, thereby reducing grid stress and lowering electricity costs. The work presented in article [17] explored the effectiveness of time-of-use pricing and incentive-based programs to encourage off-peak EV charging. By offering lower electricity rates during non-peak hours, EV owners are incentivized to shift their charging schedules, reducing stress on the grid during peak times. Additionally, demand response programs enable utilities to actively manage EV charging loads in real time [18], leveraging price signals and demand-side incentives to modulate charging rates and alleviate congestion on the grid.

In article [19], the authors investigated the role of smart charging algorithms in optimizing EV charging schedules. These algorithms consider factors such as grid conditions, electricity prices, and user preferences to determine the most cost-effective and grid-friendly charging times. By coordinating charging activities, smart algorithms can smooth out demand peaks and improve overall grid efficiency. Moreover, the convergence of EVs and smart grid technologies offers new opportunities for grid optimization. The authors of article [20] proposed the concept of an "EV-integrated smart grid," where EVs are seamlessly integrated into the grid's demand response and energy management systems. This holistic approach maximizes the benefits of EV grid integration while minimizing its impact on the electricity network. Additionally, as EV adoption grows, the demand for charging infrastructure increases accordingly. Article [21] discussed the challenges and opportunities of expanding EV charging infrastructure. Public charging stations, workplace chargers, and residential charging solutions are all essential components of a comprehensive EV charging network. However, deploying these charging points requires careful planning to ensure adequate coverage and accessibility for EV owners.

Furthermore, the authors in article [22] highlighted the need for grid upgrades to accommodate the growing EV fleet. Upgrading distribution transformers, power lines, and substations is crucial to prevent overloads and ensure reliable electricity supply to EVs and other consumers. Additionally, integrating fast-charging stations along highways and major routes requires significant infrastructure investments. EV grid integration also enhances energy diversification. The work conducted in article [23] discussed how EVs can serve as distributed energy resources, storing renewable energy during times of surplus and discharging it back to the grid when needed. This flexibility helps integrate variable renewable energy sources like wind and solar power, making the grid more resilient and sustainable. Furthermore, renewable energy-based charging stations contribute to energy independence and resilience, ensuring a more stable and reliable energy supply for the growing number of EVs on the road. By harnessing energy from renewable sources such as solar, wind, and hydropower, these stations reduce the reliance on fossil fuels and minimize the carbon footprint associated with EV charging [24]. This not only supports the global transition to clean energy but also enhances the appeal of EVs by aligning their use with eco-friendly practices.

Nevertheless, despite the benefits, grid upgrades pose a significant challenge for EV grid integration. Article [25] emphasized the need for investment in grid infrastructure to support the increased demand for EVs. This includes upgrading distribution networks, installing smart meters, and deploying advanced grid management systems. However, with the increasing connectivity of EVs and charging infrastructure, cybersecurity is a significant concern. Article [26] highlighted the potential vulnerabilities of EVs to cyber-attacks, emphasizing the need for robust cybersecurity measures. Secure communication protocols and encryption technologies are essential to protect EVs from unauthorized access and ensure data privacy.

One of the primary benefits of EV grid integration is reducing greenhouse gas emissions. The environmental and economic implications of EV charging management are also significant considerations. In article [27], the authors conducted a life cycle assessment to compare the environmental footprints of various EV charging scenarios, including home, workplace, and public charging. The results indicated that home charging with renewable energy sources had the lowest environmental impact. Article [28] offered a life cycle assessment of EVs and found that they emit significantly fewer greenhouse gases than gasoline vehicles, even when accounting for electricity generation emissions. The grid can mitigate climate change by promoting EV adoption and clean energy generation. Similarly, the work presented in [29] examined the economic feasibility of public EV charging infrastructure investments, highlighting the importance of cost-effective solutions to encourage widespread adoption.

On another level, interoperability and standards are critical for the seamless integration of EV charging infrastructure. The work presented in article [30] discussed the importance of standardized communication protocols between EVs, charging stations, and the grid. Common standards ensure compatibility and interoperability, allowing EV owners to easily access charging facilities across different networks. ISO 15118 [31] is an international standard that defines a communication protocol for the exchange of information between EVs and charging stations. This protocol is a key component in the development of smart charging infrastructure, enabling features such as Plug & Charge, where authentication and billing are seamlessly managed without user intervention. By standardizing the communication process, ISO 15118 facilitates interoperability between different manufacturers' EVs and charging stations, promoting a more user-friendly and efficient charging experience [32]. Additionally, it supports advanced functionalities like bi-directional power transfer, enabling V2G services that can enhance grid stability and energy management. As the adoption of electric vehicles continues to grow, ISO 15118 plays a crucial role in ensuring that the necessary infrastructure is both reliable and scalable. Also, wireless EV charging can be a solution to address the issue of incompatibilities between EVs and charging stations. By standardizing wireless charging protocols and ensuring compatibility across different manufacturers, interoperability eliminates the need for multiple, often incompatible charging systems. Wireless power transmission (WPT) can become an important development trend due to its greater flexibility, convenience, safety, and intelligence compared with traditional contact charging [33]. This seamless integration enhances the user experience, making it more convenient for EV owners to charge their vehicles without worrying about connector types or specific charging station compatibility. Moreover, it promotes widespread adoption of EVs by simplifying the infrastructure requirements and reducing the barriers to entry for new users. Interoperability also supports the development of smart cities and advanced transportation systems, where consistent and efficient wireless charging is essential for the smooth operation of diverse EV fleets. Ultimately, achieving wireless charging interoperability is a vital step toward a more sustainable and user-friendly electric mobility ecosystem. Moreover, effective policy and regulation play a crucial role in facilitating EV grid integration. The work presented in [34] emphasized the importance of supportive policies such as tax incentives, rebates, and mandates for EV adoption. Clear regulatory frameworks for EV charging tariffs and grid connection standards are also necessary to create a favorable environment for EV deployment.

Finally, integrating EVs into the grid presents challenges and opportunities for the energy sector. This comprehensive review has highlighted the impacts of EV charging on grid stability, peak load management, infrastructure requirements, and the broader benefits of EV grid integration. While challenges such as grid upgrades, interoperability, and cybersecurity persist, strategic planning and innovative solutions can leverage these challenges into opportunities for a more resilient and sustainable energy system. In this article, we present and test a new dynamic EV charging algorithm capable of balancing grid requirements with user needs, such as charging speed and time, to create a sustainable and efficient EV charging ecosystem.

3. Methodology

The decentralized nature of EV charging infrastructure makes it challenging to achieve a centralized EV charging management system. A decentralized and distributed methodology is needed to better suit the nature of EV charging and support electric mobility's diverse and evolving landscape. Our dynamic smart charging methodology is applied at the level of the end-of-line electric distribution networks, which are distributed by nature. Controlling the EV charging dilemma at a small modular level offers a systematic approach that can help address this complex issue effectively. Managing the coordination of EV charging at the level of substations involves implementing strategies to ensure that the increasing demand for EV charging does not overwhelm the distribution grid, leading to grid congestion, voltage instability, or other operational challenges. Deploying a smart charging infrastructure, equipped with communication and control capabilities at the substation level, allows for dynamic control of charging stations to optimize charging patterns based on grid conditions, energy needs, and the user's charger capacity, as well as balancing EV charging loads in real-time to maintain grid stability. By implementing an intelligent charging strategy and leveraging advanced technologies, it is possible to effectively manage the coordination of EV charging at the substation level while ensuring the electric grid's reliability, efficiency, and sustainability.

Advanced control and communication networks are vital for maximizing the potential of EV smart charging systems. These networks enable grid integration, load management, demand response, grid services, user interaction, and data-driven optimization. A robust communication network is essential as it facilitates real-time data exchange and seamless coordination among EVs, charging stations, grid operators, and available energy resources. This connectivity allows for dynamic load management by conveying crucial data, such as the connectivity of the EV to the charger, the current state of charge of the EV, and the number of charging EVs per household, from the chargers to the substation EV charging management system and, in return, the communication system will transmit the control signals to turn the charging on or off at each charging station (Figure 2).

The PONDCOA dynamic charging optimization algorithm, presented in this article, addresses the dynamic and rapidly evolving nature of EV charging. It efficiently allocates and utilizes available resources by applying the proof of need concept. This concept fundamentally shifts the resource allocation paradigm by prioritizing and validating needs in real time. Unlike traditional methods that rely on static or predefined criteria, the PoN-based algorithm dynamically assesses the urgency and significance of each energy or resource allocation request. This ensures that resources are directed where they are most critically needed, enhancing overall system efficiency and reliability.

Proof of need for electric vehicle (EV) charging refers to the evidence or criteria used to prioritize charging sessions based on the urgency or necessity of the charging requirement. This concept is important in scenarios with limited charging infrastructure or during periods of high demand, where prioritization is necessary to ensure equitable access to charging resources. The PoN for each EV is calculated based on different decision factors:

- State of charge;
- Number of charging EVs per household;
- The charging capacity of the EV's charger.

The *PoN* is calculated using the following equation:

$$PoN = \frac{n \times Q \times k}{C} \tag{1}$$

where:

n: Priority index
Q: Maximum state of charge index
k: Number of charging EV index

C: Charger's capacity index

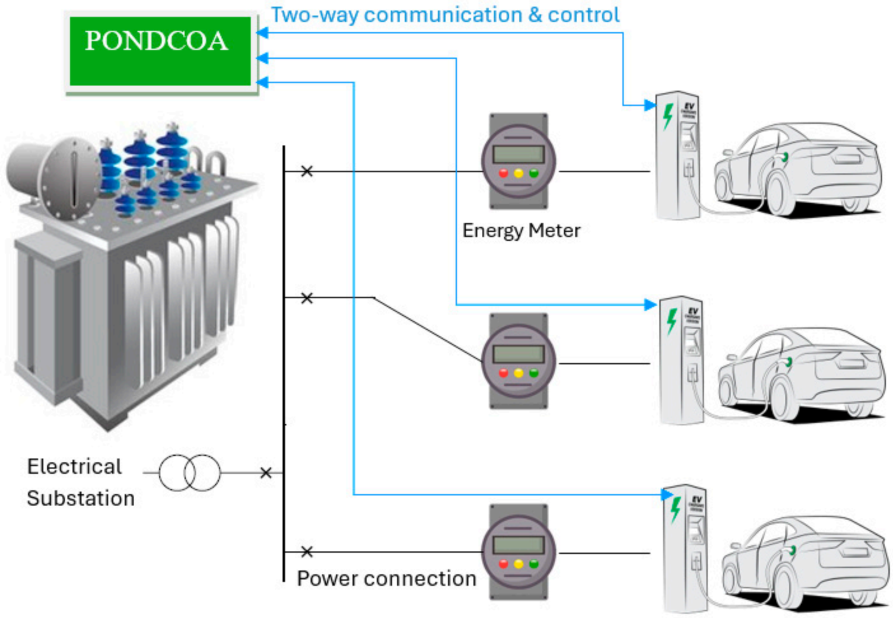

Figure 2. PONDCOA schematic single line diagram.

The description and utility of each factor is detailed hereafter:

1. Priority index n: EVs with low battery levels require immediate charging to ensure continued operation. Proof of need could be based on the remaining state of charge (SOC) of the vehicle's battery, with priority given to vehicles with lower charge levels. The priority index n expresses the need to charge the EV battery according to its current SOC status. Since the priority index is directly proportional to the priority value, this will ensure that the EV with the higher priority index, which means with a lower SOC, will have the advantage of having a higher priority value and may start to charge before another EV with a lower priority index. Several methods exist to measure the SOC of a battery, each with its strengths and limitations. Voltage measurement is straightforward but can be inaccurate due to its non-linear relationship with the SOC and susceptibility to temperature and load variations. Coulomb counting, or Ah counting, tracks the current flow over time, providing decent accuracy but being prone to cumulative errors and requiring periodic recalibration. Impedance spectroscopy offers high accuracy by analyzing the battery's impedance at different frequencies but demands sophisticated equipment and analysis. Kalman filtering combines voltage and current data with a predictive model, enhancing accuracy through continuous adjustments. Machine learning algorithms leverage extensive datasets to predict the SOC with high precision, yet they depend on the quality and diversity of the training data. Among these, temperature compensation stands out as a critical factor for accuracy, as battery performance and voltage significantly vary with temperature [35]. By integrating temperature compensation with other methods, such as coulomb counting and voltage measurement, one can achieve the most reliable and accurate SOC estimation. As shown in Figure 3, the priority index can take only four values ranging from 1 to 4 based on the following conditions:
   - If $SOC \leq SOC_{min}$, then n = 4, where SOC_{min} is the minimum state of charge of the EV battery as recommended by the manufacturer,
   - If $SOC_{min} \leq SOC < SOC^*_{min}$, then n = 3, where SOC^*_{min} is the minimum state of charge desired by the user.

- If $SOC^*_{min} \leq SOC < SOC^*_{max}$, then n = 2, where SOC^*_{max} is the maximum state of charge desired by the user.
- If $SOC^*_{max} \leq SOC \leq SOC_{max}$, then n = 1, where SOC_{max} is the maximum state of charge of the EV battery as defined by the manufacturer.

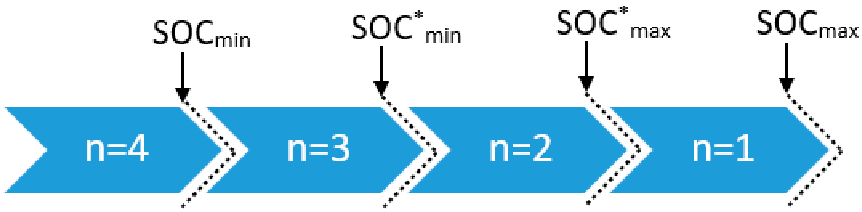

Figure 3. Distribution of the priority index n.

2. Maximum state of charge index: The maximum state of charge index level Q is the difference between SOC_{max} and the current SOC of the EV battery, as shown in Equation (2). It expresses the remaining SOC until the battery reaches its maximum full charge status, as defined by the manufacturer.

$$Q = SOC_{max} - SOC \tag{2}$$

Since the maximum state of charge index level is directly proportional to the priority value, the EV with a higher difference between SOC and SOC_{max} has the advantage of having a higher priority value and may start to charge before another EV with a lower maximum state of charge index level.

3. Number of charging EVs index: The number of EVs factor k is defined as the penalty of having many EVs plugged in for charging simultaneously and in the same house. It is calculated using various conditions and may return multiple values for the same house if more than one EV is plugged in for charging. The preset value and the formula used to find the different values of the number of EVs factor k are as follows:
   - k = 1

This value applies to each house where a single EV is plugged in for charging. Also, this applies to the case where a single house has multiple EVs plugged in, but this value is only given for the EV with the lowest SOC in the house.

$$k = \frac{1}{Total\ number\ of\ charging\ EVs\ per\ household} \tag{3}$$

This formula applies for a single house with multiple EVs plugged in, but this value is only given for the EV that doesn't have the lowest SOC in the house.

The assigned index k is directly proportional to the proof of need. This means a higher k value should be assigned to the EV that needs charging the most, i.e., having the lowest SOC. In simpler terms, if two EVs are simultaneously plugged into the same house, the EV with the lowest SOC is assigned a k value of 1, while the second EV has a k value equal to ½.

4. Charger's capacity index: The capacity of EV chargers plays a critical role in the optimization of electric vehicle (EV) charging, influencing not only the speed and efficiency of charging sessions. The higher the charger's capacity is, the higher the power levels it can deliver, thus significantly reducing the time required to charge an EV. This is particularly beneficial in scenarios where quick turnaround times are essential. Hence, because more time should be allocated to lower-capacity chargers, we consider the charging capacity inversely proportional to the priority value. Therefore, the charger capacity index—equal to the charger's nominal power ($P_{charger}$) multiplied by its efficiency $\eta_{charger}$ —was included in the denominator of the PoN

formula. As a result, an EV with a lower charging capacity has the advantage of receiving a higher priority value and may begin charging before another EV with a higher charging capacity.

$$C = P_{charger} \times \eta_{charger} \tag{4}$$

The algorithm below (Algorithm 1) summarizes the PoN calculation method for each EV connected to a charging station:

Algorithm 1: PoN Algorithm

```
Initiate algorithm at time t
n_{i,t} = 0, k_{i,t} = 0, Q_{i,t} = 0
For i = 1 to |R| do   (|R| is the set of connected EVs for charging)
    if SOCi ≤ SOC_min then
    n_{i,t} = 4;
        else if SOC_min ≤ SOC < SOC*_min then
        n_{i,t} = 3;
            else if SOC*_min ≤ SOC < SOC*_max then
            n_{i,t} = 2;
                else if SOC*_max ≤ SOC ≤ SOC_max then
                n_{i,t} = 1;
                end if;
            end if;
        end if;
    end if;
if Number of EV plugged-in for the same house = 1 then
k_{i,t} = 1;
    else if Number of EV plugged-in for the same house > 1 then
        for j = 1 to |S| do (|S| is the set of connected EVs for charging
          in the same house)
        If SOC_i < SOC_j then
        k_{i,t} = 1 ;
        else
        k_{i,t} = 1/Number of EVs per house
        end if;
    end if;
end if;
Q_{i,t} = SOC_max - SOC_{i,t} ;
PoN_{i,t} = (n_{i,t} × k_{i,t} × Q_{i,t}) / C_i;
p.insert (PoN_{i,t});
Repeat for t = t + 1
```

Applying the PoN concept to EV charging aims to ensure that charging resources are allocated efficiently and fairly based on the urgency and importance of the charging request. This ultimately optimizes simultaneous EV charging without significantly impacting the overall duration of the process or increasing congestion at electrical substations. However, including the grid power constraint as a main factor in the formula is essential. Our dynamic optimization model considered the available spare power capacity at the substation level as the lead indicator. This ensures that the additional power required for EV charging does not overload the substation. Therefore, in each iteration, the EVs that need to be charged are prioritized using the calculated PoN of each vehicle. The EVs with the highest PoN that satisfies the condition of Equation (5) are enabled for charging. The entire process is illustrated in the flowchart in Figure 4.

$$\sum P_{i,charger} + P_{Load} \leq P_{Sub,max} \quad (5)$$

where:

$P_{i,charger}$: The power in kW of the enabled EV charger i

P_{Load}: The total demand load in kW (excluding the charging of EVs)

$P_{Sub,max}$: The nominal power capacity of the substation in kW

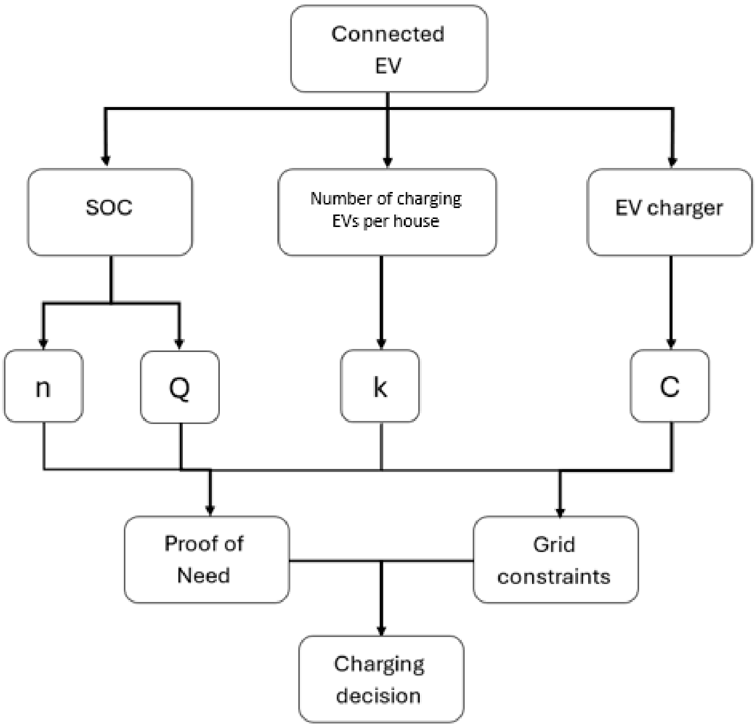

Figure 4. Proof of need flow chart.

4. Simulation Model and Test Conditions

To test and validate the proposed dynamic EV charging optimization algorithm based on the PoN, a set of data, assumptions, and scenarios has been defined. For the simulation of the PONDCOA, we selected a set of EVs with different battery capacities that were equally distributed among different charger capacities. The combinations of selected EVs and chargers are presented in Appendix A. The selected 30 EVs used in the simulation have been randomly chosen by the algorithm from a list of 180 EVs. Also, the initial SoC of each EV's battery was randomly set by the algorithm as well.

Additionally, to define the priority index defined in the PoN equation, SOC^*_{min} and SOC^*_{max} must be defined for each EV. Hence, the following assumptions were made:

- SOC_{min}: Although it is usually defined by the manufacturer, in this study, it is considered 30% of the SOC_{max} of the EV battery.
- SOC^*_{min}: This is the minimum SoC defined by the user. In our simulation, SOC^*_{min} is assumed to be the round-up of SOC_{min} to the nearest multiple of 5.
- SOC^*_{max} (or SOC*): This is an SoC defined by the user according to his needs and his range anxiety. EV range anxiety refers to the fear or concern that an EV will run out of battery power before reaching its destination or a suitable charging point. Hence SOC^*_{max} can take different values depending on the user's needs. To simplify the simulation, SOC^*_{max} is considered the energy needed to ensure a travel distance of 100 km without discharging the EV below SOC^*_{min}.

Another factor to be defined in our simulation is the grid power constraint. A grid capacity limitation should be defined to reduce the challenges imposed on the power grid by the uncoordinated charging of EVs. This study aims to reduce the power demand resulting from uncoordinated EV charging. Therefore, the grid constraint is defined as the percentage (factor j) of the total power of all chargers connected to the substation at a time t, as given by Equation (6).

$$Grid\ Capacity = j \times \sum_{i=1}^{N} C_i \tag{6}$$

where:

C: Charger's capacity

j: Grid constraint factor in percentage

N:Total number of charging EVs at time t

$i \in N$

On the other side, to assess the impact of the PONDCOA algorithm, a scenario including 30 EVs in 28 houses—i.e., 2 houses are considered to have 2 EVs each—has been considered. The connection schedule of the 30 EVs to the grid is defined as follows:

- At t = 1, 10 EVs are connected for charging;
- At t = 2, 5 EVs are connected for charging;
- At t = 3, 10 EVs are connected for charging;
- At t = 4, 5 EVs are connected for charging;
- For the 2 houses with 2 EVs each, in one case, the 2 EVs are connected for charging both at the same time, and in the second case, the EVs are connected at different times.

In this scenario, t is the time in hours and t = 1 indicates the first hour of the peak period as defined by the grid operator.

In each algorithm iteration, connected EVs for charging are prioritized using the PoN methodology. Once prioritized, the algorithm adds EVs to the charging list in descending order of priority. With each addition, the charging power of the EV is added to the total demand of all previously selected cars. This total is then compared with the grid's maximum allowed charging power. If the addition of an EV causes the total demand to exceed the grid's limit, that EV is removed from the list of selected EVs, and the next prioritized EV is considered. This process continues until all EVs have been assessed. This methodology maximizes the number of EVs charging simultaneously without violating the grid's limitations. It may also allow lower-priority EVs to charge if their power demand does not exceed the grid's available power, thus utilizing the available power to the maximum. Once the list is finalized, the PONDCOA controller sends signals to the selected EVs' chargers, thus enabling those EVs to charge. The procedure's logic diagram is presented in Figure 5.

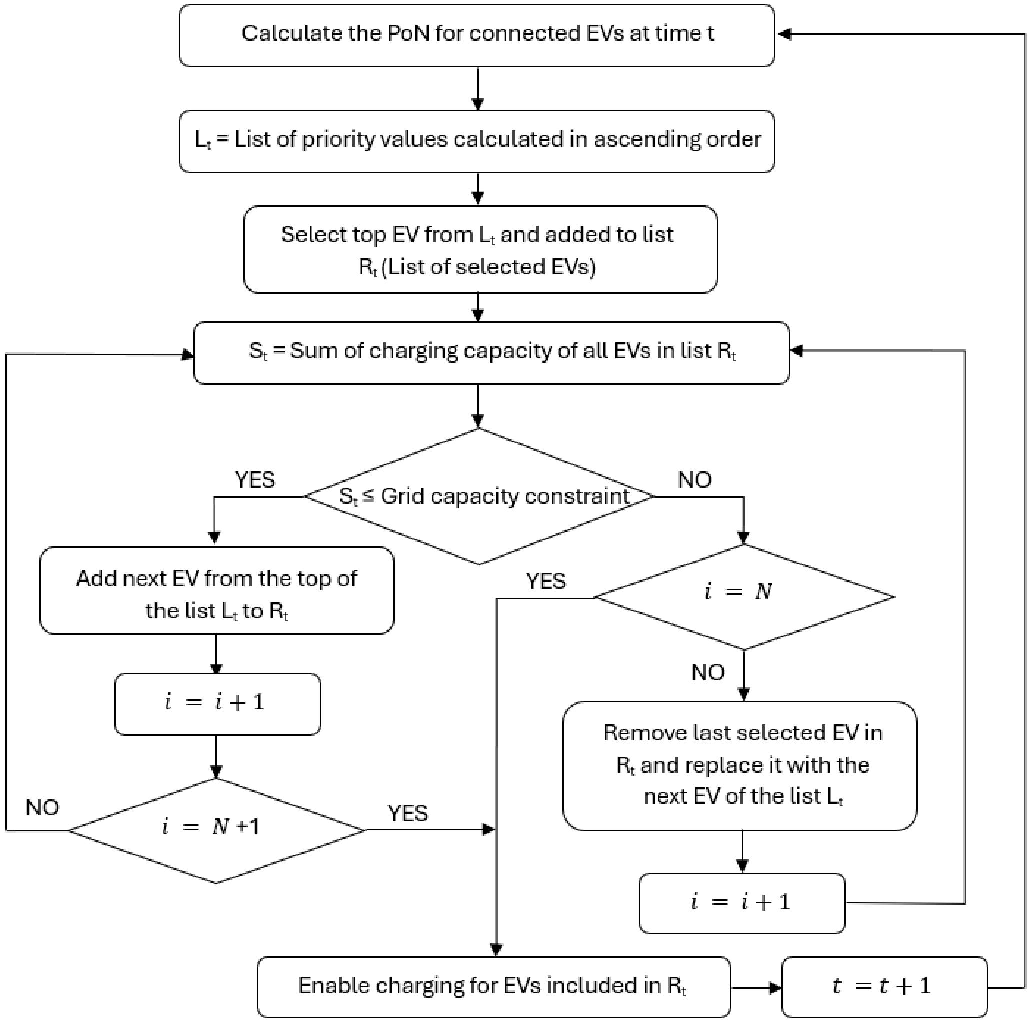

Figure 5. PONDCOA flow chart diagram.

5. Simulation Results and Analysis

The performance of the PONDCOA algorithm has been compared to two basic scenarios. The first scenario is an uncoordinated EV charging model. Here, an EV begins charging immediately upon connection and continues until its battery is fully charged. This model doesn't consider any grid constraints, allowing us to simulate the impact of uncoordinated charging on the grid for a specific set of EVs. The second scenario considers a specific grid constraint. Therefore, at each iteration, only a portion of the connected EVs can charge to avoid exceeding the maximum allocated charging power. This scenario employs the same grid constraint formula as defined in Equation (6). However, it doesn't apply the PoN prioritization algorithm. Instead, the EVs allowed to charge are selected based on a First Come, First Served (FCFS) methodology. These scenarios are evaluated based on two criteria: the maximum charging power demand in kW and the total time required to charge all vehicles.

Figures 6 and 7 illustrate the comparison of the PONDCOA algorithm to the two baseline scenarios: the uncoordinated charging and the FCFS scenario with a grid constraint. The j value for the grid constraint, as defined in Equation (6), has been set to 0.35 (or 35%) for both the PONDCOA algorithm and the FCFS with the grid constraint model.

Both the PONDCOA and the FCFS models show a reduction in peak charging demand compared to the uncoordinated charging model. In both cases, this peak has been reduced from 115 kW to 68 kW (a reduction of 40.8% at t = 4). However, the main difference between the PONDCOA and the FCFS models is the time required to charge the 30

EVs fully. This can be seen in Figure 7, which shows the number of EVs charging simultaneously at each time. In the case of the FCFS with grid constraints, it took 12 h to fully charge the 30 EVs, whereas the PONDCOA algorithm was able to charge all vehicles in 10 h without exceeding the maximum set charging power demand.

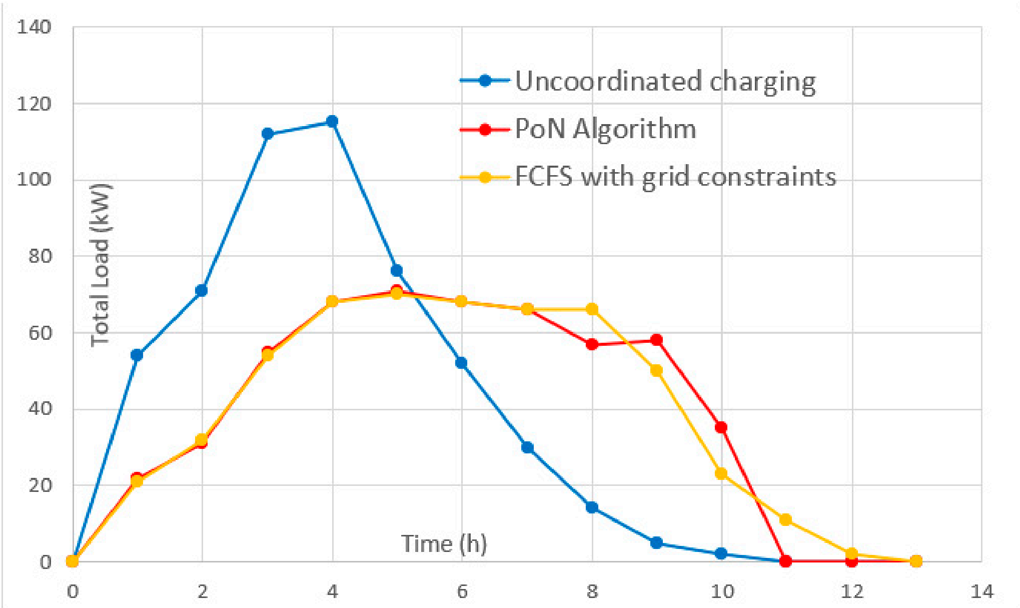

Figure 6. Comparison between uncoordinated charging vs. FCFS scenario with grid constraints vs. PONDCOA at j = 0.35.

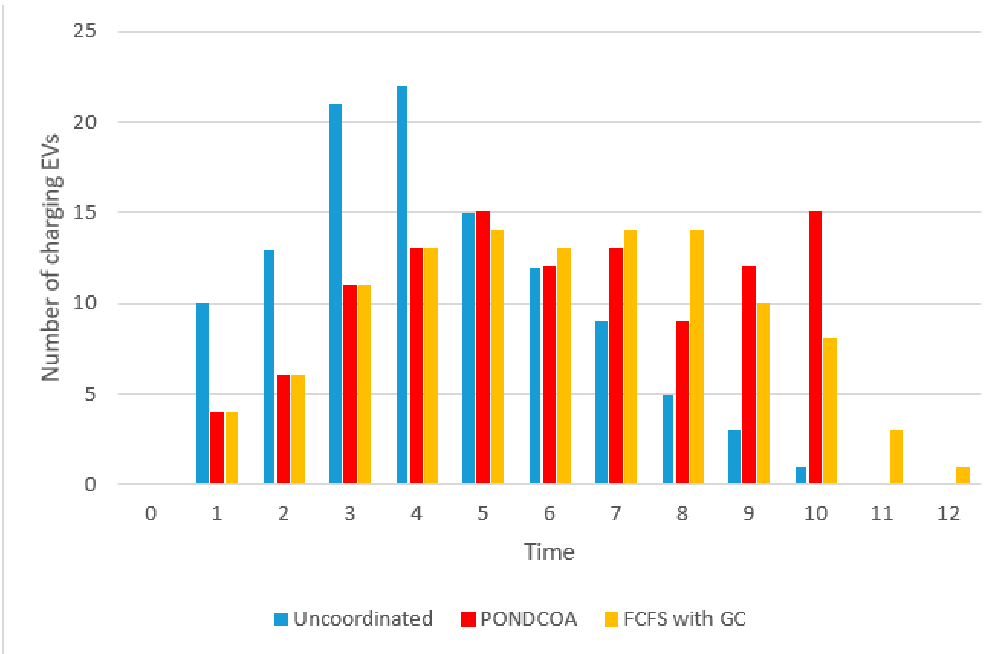

Figure 7. Comparison between the total number of charging EVs at each time t, for uncoordinated charging vs. FCFS with grid constraints vs. PONDCOA at j = 0.35.

The FCFS algorithm considers grid constraints but does not include the PoN prioritization function. Therefore, while it can limit the simultaneous charging of EVs, it takes more time to fully charge all EVs, as shown in Figure 7. With the PONDCOA algorithm, we can charge all vehicles in a shorter time, similar to uncoordinated charging, but without exceeding the grid constraint limit. In terms of driver satisfaction, all EVs are fully charged within the time limits originally required by the baseline model (uncoordinated charging).

Additionally, several simulations have been conducted to assess the impact of the grid constraint's index j on the performance of the proposed algorithm. Figure 8 shows that the lower the value of j, the greater the reduction of the peak charging demand. However, a very low j value can lead to a longer time to fully charge all vehicles (in the cases of j = 0.35 and j = 0.275). On the other hand, a high value of j can have a minimal impact on reducing the peak charging demand, such as in the case of j = 0.55. In the case of the considered 30 EVs, the optimal value of j is 0.35, where we achieved a 40.8% reduction of the peak charging demand while charging all vehicles in 10 h (same time as the uncoordinated scenario).

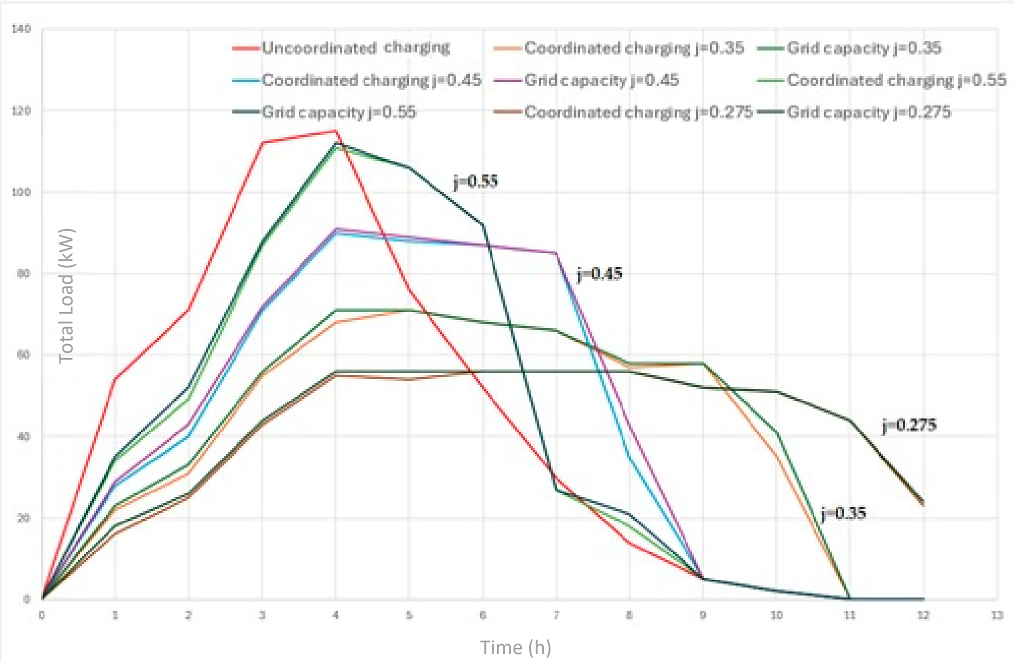

Figure 8. PONDCOA simulation with 30 EVs at different grid capacity factors.

The analysis of the simulation results for the PONDCOA algorithm designed to coordinate the charging of EVs while respecting grid constraints and driver preferences reveals promising outcomes. The algorithm successfully balances the electricity demand, ensuring that the grid operates within its capacity limits while accommodating the individual charging needs and preferences of EV drivers. The simulations demonstrate that the algorithm can dynamically adjust charging schedules based on the PoN of each EV, preventing overloads and reducing peak demand. Additionally, it respects driver preferences such as charging time and required energy levels, achieving a high level of user satisfaction. The results indicate that this coordinated approach not only enhances grid stability but also optimizes the overall charging process, paving the way for more efficient and driver-friendly EV charging solutions.

6. Conclusions

The electrification of transportation presents a transformative opportunity to decarbonize the transportation sector and build a more sustainable energy future. However, realizing this vision requires proactive measures to manage the grid impacts of EV charging, especially the peak charging demand caused by uncoordinated charging patterns, to ensure the electrical infrastructure's reliability and resilience. The presented work offers a robust solution to mitigate the risk of peak charging demand caused by uncoordinated charging of EVs. The PONDCOA algorithm can manage the simultaneous charging of several EVs by using the PoN methodology without impacting the overall time to fully charge the vehicles or causing a peak charging demand. Simulation results demonstrate a significant reduction in peak demand without impacting the overall total charging time while respecting the end-user's preferences. Such an algorithm can be used not only to manage the charging of EVs at the local power substation level but also to manage the charging of EV fleets for any company or facility.

Moreover, the algorithm's adaptability to varying grid conditions and user preferences makes it a versatile tool for future smart grid applications. As the adoption of EVs continues to rise, such a dynamic management system will be crucial in maintaining grid reliability and efficiency. Further research could explore the integration of the PONDCOA algorithm along with other V2G or vehicle-to-vehicle (V2V) strategies to unlock the full potential of electric vehicles as a catalyst for grid modernization and sustainable development. Overall, this work contributes to the sustainable evolution of EV infrastructure, promoting a more resilient and responsive energy system. The practical implementation of this algorithm can support utilities and stakeholders in navigating the challenges of increasing EV penetration, paving the way for a cleaner and more efficient energy future.

Continued research and innovation are essential for overcoming the technical, economic, and regulatory barriers to effective EV grid integration. Critical areas for future investigation include the development of interoperable charging standards, deploying vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) technologies, and integrating EV charging infrastructure with renewable energy systems and energy storage solutions. Moreover, policymakers must enact supportive regulations and incentives to encourage the adoption of grid-friendly charging practices and foster collaboration between stakeholders across the transportation and energy sectors.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Selected EVs for the 30 EV simulations.

EV Brand and Model	SOC_{max}	Charger Capacity (kW)	SOC_{min}	SOC^*_{min}	SOC^*_{max}	kWh/100 km Consumption	Initial SOC
Renault Megane E-Tech EV40 130hp	40	6	12	15	32	16.3	27
Volkswagen ID.3 Pro S—5 Seats	77	6	23.1	25	43	17.1	56
Opel Ampera-e 58 kWh	58	10	17.4	20	38	17.3	52
Renault Megane E-Tech EV60 220hp	60	6	18	20	37	16.7	29
Polestar 2 Long Range Dual Motor	75	3	22.5	25	44	19	71
Nissan Ariya e-4ORCE	63	3	18.9	20	40	19.4	39
Audi e-tron GT RS	85	10	25.5	30	51	21	23
Sono Sion	47	10	14.1	15	34	18.1	42

Volvo XC40 Recharge Pure Electric	67	6	20.1	25	47	21.3	43
Hyundai IONIQ 5 Long Range 2WD	73	3	21.9	25	44	18.9	44
Nissan Ariya e-4ORCE	63	6	18.9	20	40	19.4	58
Peugeot e-Rifter Long	45	6	13.5	15	39	23.1	31
Opel Corsa-e	46	10	13.8	15	32	16.4	32
Ford Mustang Mach-E ER RWD	88	6	26.4	30	50	20	68
MG Marvel R	65	3	19.5	20	40	19.1	43
Volkswagen ID.3 Pro-Performance	58	6	17.4	20	37	16.6	28
Opel Zafira-e Life M	45	10	13.5	15	40	25	31
Hyundai Kona Electric	64	10	19.2	20	37	16.2	59
Tesla Model Y Performance	76	6	22.8	25	43	17.7	73
Polestar 2 Standard Range Single Motor	75	3	22.5	25	43	17.6	56
Tesla Model 3 Standard Range Plus LFP	53	6	15.9	20	35	15	28
Citroen e-SpaceTourer M	45	6	13.5	15	40	25	35
Toyota PROACE Verso L	45	10	13.5	15	40	25	32
MG Marvel R	65	6	19.5	20	40	19.1	57
Peugeot e-Traveller Compact	45	3	13.5	15	40	24.3	28
Volkswagen ID.4 Pure 52 kWh	52	10	15.6	20	39	18.2	40
Renault Megane E-Tech EV60	60	10	18	20	37	16.7	43
Peugeot e-Traveller Long	45	10	13.5	15	40	24.3	23
Toyota PROACE Verso M	45	6	13.5	15	40	24.3	21
Nissan LEAF (40 kWh battery)	37	6	11.1	15	32	16.4	19

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7.3 ARTICLE: A REVIEW OF INDUSTRY 4.0 CHARACTERISTICS AND CHALLENGES, WITH POTENTIAL IMPROVEMENTS USING BLOCKCHAIN TECHNOLOGY

Cet article, intitulé « *A review of Industry 4.0 characteristics and challenges, with potential improvements using Blockchain technology* », a été publié dans sa version finale en décembre 2021 par les éditeurs du journal *ELSEVIER – Computers & Industrial Engineering Journal.*

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En tant que premier auteur, j'ai contribué au développement de l'idée générale, à l'essentiel de la recherche sur l'état de la question et au développement de la méthode, à la collecte et l'analyse des données et à la rédaction du manuscrit. Les professeurs Mazen Ghandour, Adrian Ilinca et Hussein Ibrahim en tant que co-auteurs, ont participé à la supervision du travail, ainsi qu'à la révision de l'article et à la revue de la littérature.

Résumé : L'industrie 4.0 fait principalement référence aux usines dans lesquelles les machines utilisent des systèmes intelligents et autonomes améliorés par l'IdO, l'IA, l'apprentissage automatique et les systèmes cyber-physiques. Mais ce qui révèle le véritable potentiel de l'industrie 4.0, c'est la connexion et la communication établies entre les ordinateurs et les machines qui permettent de prendre des décisions sans aucune intervention humaine. Le réseau formé par ces machines interconnectées, et la quantité considérable de données générées, marque la valeur réelle de l'industrie 4.0. En examinant les principales caractéristiques de l'industrie 4.0, nous trouvons de nombreuses similitudes avec la technologie de la chaîne de blocs. Les principaux moteurs de l'industrie 4.0 et de la chaîne de blocs sont la gestion des données, la connectivité et la numérisation.

En outre, la décentralisation et la distribution sont considérées comme des caractéristiques architecturales communes. Cet article cherche à ouvrir de nouveaux horizons sur le potentiel de la technologie de la chaîne de blocs en tant qu'outil d'autonomisation pour la quatrième ère industrielle. Nous étudions tout d'abord les fondements de l'industrie 4.0, ses défis, ses obstacles et ses limites, et nous explorons enfin les domaines dans lesquels la technologie de la chaîne de blocs peut apporter de nouvelles fonctionnalités et ajouter de la valeur au déploiement de l'industrie 4.0.

Contexte et Objectifs : Cet article offre une revue des caractéristiques de l'industrie 4.0. Il étudie les différents défis et obstacles techniques, économiques et sociaux auxquels se heurte l'adoption à grande échelle de cette nouvelle révolution industrielle et explore la manière dont la technologie de la chaîne de blocs peut transformer et faire progresser l'industrie 4.0. Cet article est divisé en deux parties principales. Dans la première partie de l'article, les quatre caractéristiques de ce nouveau cadre industriel sont détaillées, ainsi que les différentes limites et barrières techniques, économiques et sociales qui entravent l'adoption de l'industrie 4.0. Dans la deuxième partie, la technologie de la chaîne de blocs est étudiée en tant que plateforme de données possible pour gérer, enregistrer et sécuriser les données générées par les différentes technologies qui sous-tendent la quatrième révolution industrielle.

Méthodologie : La méthodologie adoptée dans cet article s'appuie sur une approche analytique et systématique pour examiner les caractéristiques et les défis de l'Industrie 4.0 et explorer comment la technologie de la chaîne de blocs peut apporter des améliorations potentielles. Tout d'abord, une revue de la littérature exhaustive est réalisée pour identifier les principaux éléments constitutifs de l'Industrie 4.0, notamment l'IdO, les systèmes cyber-physiques (Cyber-physical system, CPS), et l'IA. Cette étape permet de comprendre les fonctionnalités, les applications et les défis inhérents à ces technologies. Ensuite, l'article procède à une analyse critique des défis actuels de l'Industrie 4.0, tels que la sécurité des données, l'interopérabilité des systèmes, et la gestion des données massives. Pour aborder ces défis, l'étude explore l'intégration de la technologie de la chaîne de blocs, en mettant en lumière ses caractéristiques uniques telles que la décentralisation, la transparence, et la sécurité cryptographique. Des cas d'utilisation spécifiques de la chaîne de blocs dans des contextes industriels sont identifiés et évalués. La méthodologie comprend également des études de cas et des exemples pratiques où la chaîne de blocs a été mise en œuvre avec succès pour améliorer les processus industriels. Les résultats sont synthétisés pour proposer un cadre théorique et pratique sur l'amélioration des systèmes de l'Industrie 4.0 grâce à la technologie de la chaîne de blocs.

Résultats et contributions : Cet article offre une synthèse exhaustive des caractéristiques de l'Industrie 4.0, clarifiant les interconnexions entre les technologies clés telles que l'IdO, les CPS, et l'IA. Cette synthèse aide à structurer la compréhension des innovations actuelles et des défis associés à leur mise en œuvre. En outre, l'article met en lumière les défis critiques de l'Industrie 4.0, en particulier ceux liés à la sécurité des données, à l'interopérabilité des systèmes, et à la gestion des données massives. En identifiant ces obstacles, l'étude prépare le terrain pour des solutions ciblées. Enfin, l'article explore de manière approfondie comment la technologie de la chaîne de blocs peut répondre à ces défis, en soulignant ses avantages uniques comme la décentralisation, la transparence, et la sécurité cryptographique. Les contributions de cet article sont doublement académiques et pratiques, offrant un cadre robuste pour l'intégration de la chaîne de blocs dans l'Industrie 4.0 et ouvrant de nouvelles voies pour des recherches futures et des innovations technologiques.

A review of Industry 4.0 characteristics and challenges, with potential improvements using Blockchain technology

Abstract- Industry 4.0 mainly refers to factories in which machines use smart and autonomous systems enhanced by the Internet of Things (IoT), Artificial Intelligence (AI), machine learning and cyber-physical systems. But what reveals the true potential of Industry 4.0 is the established connection and communication between computers and machines that allow making decisions without any human intervention. The network formed by these interconnected machines, and the generated considerable amount of data, marks the actual value of Industry 4.0. Looking at the main features of Industry 4.0, we find many similarities with blockchain technology. The key drivers for Industry 4.0 and blockchain are data management, connectivity and digitization.

Additionally, decentralization and distribution are considered as shared architectural features. This paper seeks to open new horizons on the potential of blockchain technology as an empowering tool for the 4th industrial era. We are first investigating the fundamentals of Industry 4.0, its challenges, barriers and limitations, and finally exploring areas where blockchain technology can bring new features and add value to the deployment of Industry 4.0.

***Keywords*-** Industry 4.0, Smart Factories, Blockchain, Internet of Things, Artificial Intelligence, Machine Learning

I. Introduction

The fourth industrial revolution, or Industry 4.0, mainly refers to the concept of factories in which machines are augmented with smart and autonomous systems enhanced by the Internet of Things (IoT), 3D printing, Artificial Intelligence (AI), machine learning, big data, augmented reality, etc. [1]. Thus, industry 4.0 represents the revolutionary age of computers, machines and human interconnectivity and interaction for higher manufacturing efficiency, larger production scale, sustainable environmental outcomes and improved quality of life. But what reveals the true potential of Industry 4.0 is the established connection and communication between computers and machines that allow making decisions without any human intervention[2]. Hence, the network formed by these interconnected machines and the generated big amount of data marks the true value of Industry 4.0 [3].

The main criterion that defines the fourth industrial revolution is its capability to automate decision-making and problem-solving processes. It enables both operation and asset real-time performance management [4] while equally engaging all stakeholders through vertical and horizontal integration. Vertical integration quickly responds to unexpected order changes resulting from demand fluctuations, equipment failure or stock shortage. It relies on an interconnection network of the digital and physical processes throughout the different departments or sections of the industry. In comparison, horizontal integration is achieved by networking the different processes, entities and services forming the global value chain of any product [5]. The recording, real-time availability and assessment of data generated by the different physical and machines processes like inbound logistics and warehousing, research and development, production, marketing and sales to downstream services enable a transparent flow of information across the complete value chain. It allows a faster response to market fluctuations and production failures. This new paradigm transforms data generated from the network of interconnected machines and computers into valuable assets for all underlying Industry 4.0 technologies. It contributes to improving manufacturing efficiency on multiple levels. It achieves visibility, transparency and traceability between all value chain involved parties, including the raw material supplier, the logistics company, the manufacturing and storing facility, the retailer, the end customer or any other stakeholder or intermediary that might be involved in the process [6].

Nevertheless, this extreme automation of factories does not come without limitations. Driving organization-wide innovation is a challenging process that requires a solid foundation, which most organizations lack. Furthermore, the implementation of a vertical or horizontal integration requires a high level of coordination between all involved entities and stakeholders and an integrated administration that are not always available [7]. Moreover, big data, being a central pillar of this new industrial revolution, lays the foundation for data ownership worries, mainly when relying on a third-party service provider to host and operationalize this data, thus representing a real apprehension to most industrial facilities shifting towards the adoption of Industry 4.0. An additional barrier is the lack of know-how to implement and maintain Industry 4.0 measures successfully and the absence of courage at the upper management levels to launch this radical digitalization plan. Furthermore, data integration from various sources to enable initial connectivity can be challenging, considering the diversification of existing communication protocols and data exchange formats [8].

On the other hand, and in most Industry 4.0 definitions, blockchain technology is overlooked as a driver of this industrial revolution. The main focus is on technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning and cyber-physical systems (CPS). Even though, just by looking at the challenges faced by Industry 4.0, it can be found that blockchain has the answer to most of them. Security and privacy preservation are essential concerns for Industry 4.0 applications [9,10]. In contrast, blockchain technology is renowned as a distributed consensus scheme that allows peer-to-peer (P2P) transactions of digital currencies, digital assets, and any other type of data in a pseudo-anonymous and secure manner. It ensures that these transactions are immutably stored and verified without the need for any centralized authority. Henceforth, trust, immutability, security and privacy are fundamental features of blockchain technology [11] that can be of great value for the new Industry 4.0 framework

Moreover, data management, connectivity, decentralization, distribution and digitization are shared key drivers between Industry 4.0 and blockchain [12]. The fourth industrial revolution will have to be founded on trust between all value-chain involved stakeholders without the need for third-party intermediaries that might jeopardize the integrity and safety of information [13]. This feature can be ensured with blockchain technology. Additionally, blockchain's smart contracts allow handling simple manual and segregated industry processes in a fully automated integrated manner.

This paper offers a review of Industry 4.0 characteristics. It investigates the different technical, economic and social challenges and barriers facing a wide adoption of this new industrial revolution and explores how blockchain technology can transform and advance Industry 4.0. This article is divided into two main parts. In the first part of the article, the four characteristics of this new industrial framework are detailed, together with the different technical, economic and social limitations and barriers challenging the adoption of Industry 4.0. In the second part, blockchain technology is investigated as a possible data platform to manage, record and secure data generated by the different technologies underpinning the fourth industrial revolution.

II. INDUSTRY 4.0 CHARACTERISTICS

By the end of the 18th century, the industrial sector, mainly the chemical manufacturing and iron production processes in Britain, witnessed a transition from hand production to mechanized techniques driven by steam and water power [14]. This transition will be next identified as the first industrial revolution. This evolution lasted till the mid-1800s. Following the economic recession from the late 1830s to the early 1840s [15], the adoption of the original innovations that drove the first industrial revolution was no longer powerful enough to drive high growth rates. Thus, it was time for a new revolution. Groundbreaking techniques such as new steel-making processes and innovative production management systems such as mass-production and assembly lines, alongside the development of electrical grids and increased use of steam-powered machines, marked the second industrial revolution [16]. In the second half of the 20th century, a new industrial revolution emerged and brought forth the rise of some new technologies such as electronics, telecommunications and computers. This technological advancement opened the doors for two major inventions: Programmable Logic Controllers (PLCs) and Robots [17]. These inventions helped rise to an era of high-level automation of industrial processes, also known as the third industrial revolution. Nowadays, the world is in the midst of a significant industrial transformation driven by Web 3.0 and a massive digital transformation blurring the physical and cyber digital divide [18]. Industry 4.0 refers to integrating Cyber-Physical Production Systems (CPPSs) intending to configure better and efficiently manage the entire value chain process of any manufacturing industry [19].

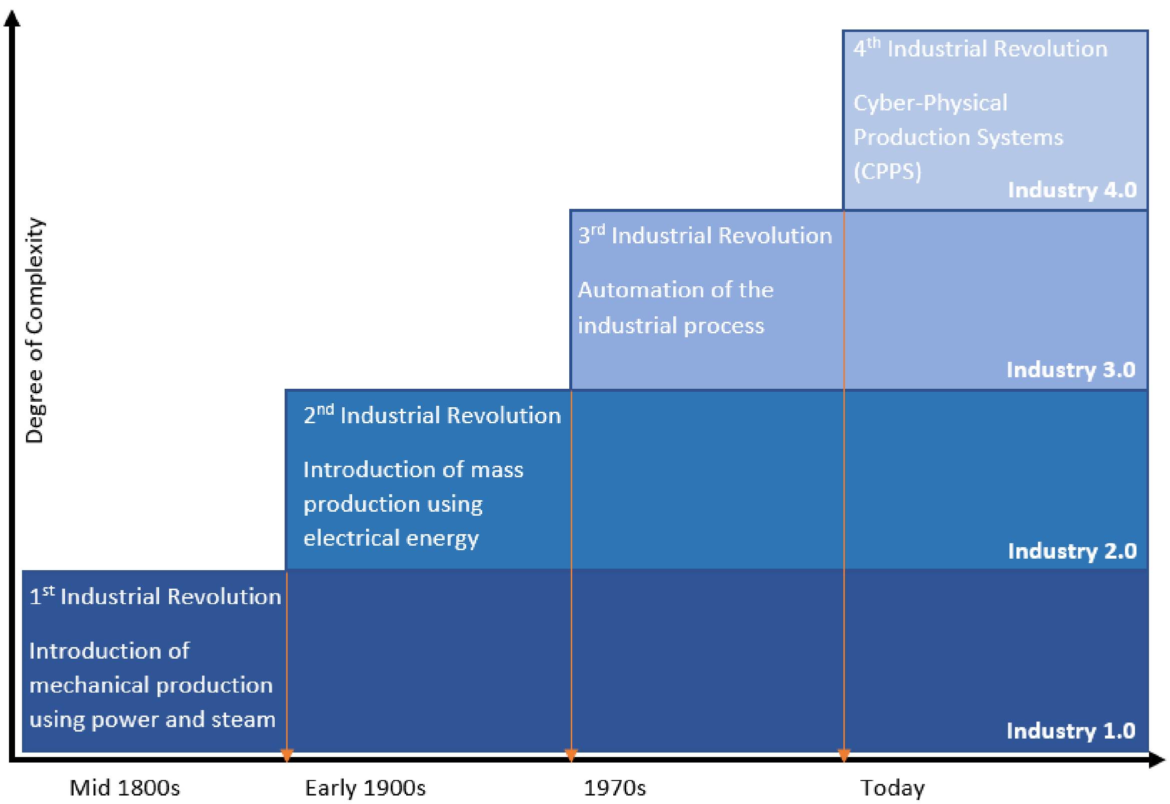

Fig.1- Industrial revolutions through time

The main evolution from traditional manufacturing toward Industry 4.0 summarizes into four primary characteristics: 1) vertical networking of smart production systems; 2) horizontal integration via a new generation of global value chain networks; 3) through-life engineering across the entire value chain and 4) the impact of exponential technologies [20] (see Figure 2).

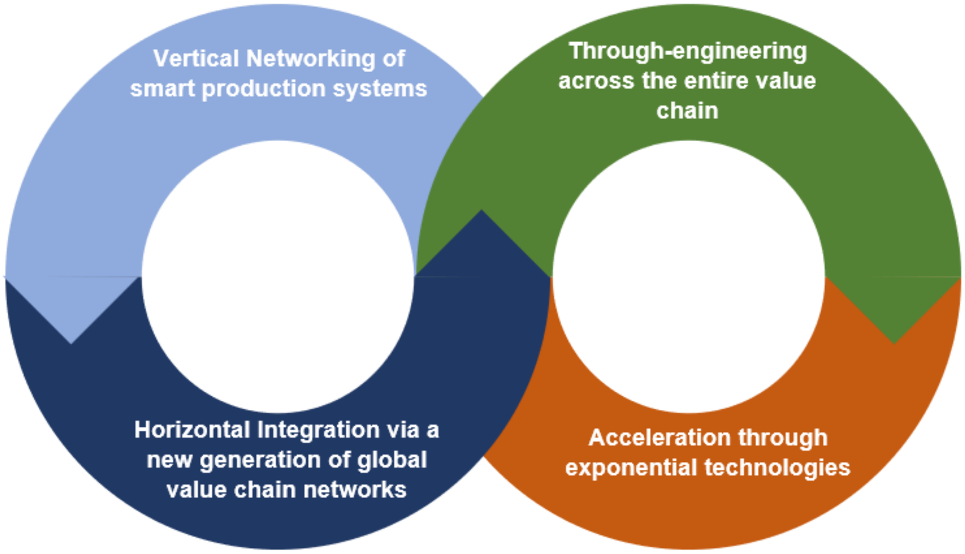

Fig.2- The four characteristics of Industry 4.0

A. Vertical Networking

Industry 4.0's first main characteristic is the vertical networking of smart production systems. Vertical integration in Industry 4.0 creates a link between the different levels of the industry from the production floor up through the monitoring, control and supervision of the production, research and development (R&D) department, quality management, operations, product management and processing …etc. (see Figure 3). This interconnection between all company layers enables a smooth, transparent circulation of data which allows strategic and tactical decisions to be data-driven. Hence, the main target behind vertical networking is to use Cyber-Physical Production Systems (CPPSs) to enable industries to quickly respond to unexpected order changes resulting from demand fluctuations, equipment failure or stock shortage [21].

The vertical networking increases the enterprise's ability to agilely and adequately adapt to changes in market demands and respond to new opportunities. Moreover, under the vertical networking of smart production systems, smart factories manage their production in a customer-specific and individualized manner [22]. As well as providing an autonomous arrangement for production management, CPPSs provide a tool for maintenance management [23], shifting the mode of operation from a reactive or even predictive into a prescriptive mode of operation. Predictive data serves not only to monitor wear and tear on materials and anticipate any failure but also to issue recommendations to optimize any asset's operation and even maximize its business potential.

Additionally, it helps to connect the resources to the products and locate materials and parts at any time [24]. Similarly, processing data, anomalies and faults from different processing stages of the production line are automatically logged and registered, thus enabling a fast response to order amendments, fluctuations in quality or even machinery breakdowns [25]. As a result, waste is reduced, and resource efficiency is optimized, particularly material use, energy consumption and human resources.

Nevertheless, this extreme adaptation in the production process to achieve a complete vertical integration is not feasible without an extensive integration of data systems and smart sensor technologies to manage the monitoring and automation processes [26].

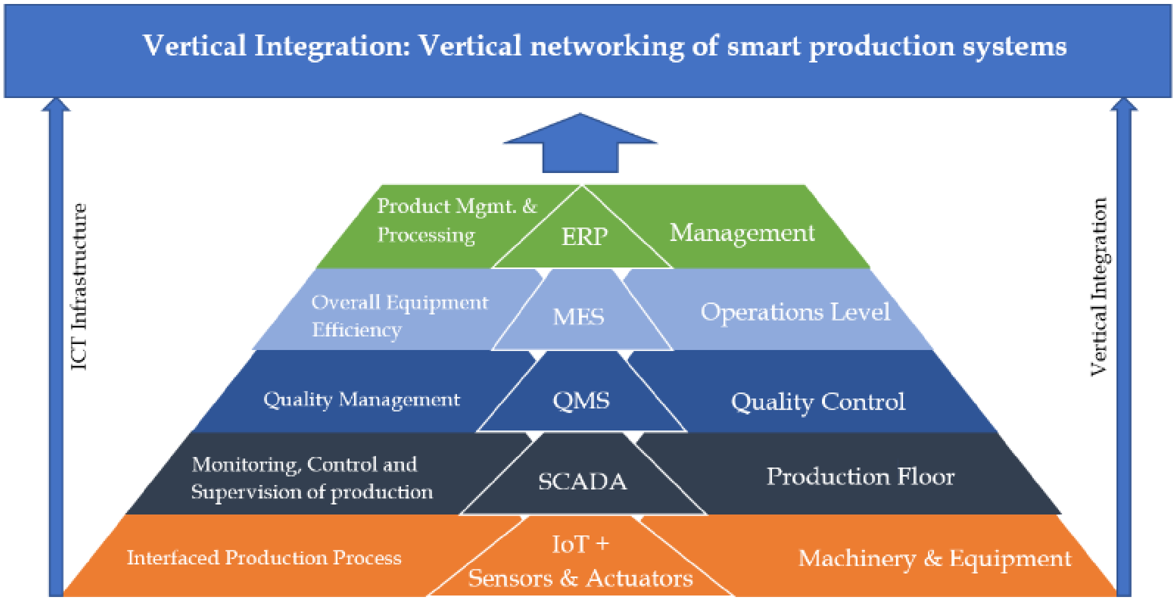

Fig.3- Industry 4.0 Vertical Integration

B. Horizontal Integration

The horizontal integration in the Industry 4.0 framework is the network of the different processes, entities and services forming the global value chain of any product [27]. At the production level, this can be interpreted as a complete consolidation of all involved manufacturing processes. In contrast, vertical integration refers to a high level of coordination between production and upper management layers such as production control, quality management, and product management [28]. The horizontal integration in an Industry 4.0 enterprise occurs at different levels: production floor, multiple production facilities, and entire value chain. Each connected machine or production unit becomes a node with well-defined properties within the production network [29]. These nodes continuously communicate their status to respond autonomously to dynamic production requirements cost-effectively and reduce system downtime through predictive maintenance.

If an enterprise owns several production facilities, the horizontal integration enables to share inventory levels and unexpected delays and possibly redistribute work among owned facilities to respond to market demand fluctuations rapidly or increase the efficiency and speed of the production process (see Figure 4). However, the most critical and global horizontal integration remains the integration across the entire value chain. Industry 4.0 offers a highly automated and transparent collaboration across the complete value chain, using CPPSs, from the inbound assembly, packaging, storing, production, quality control, marketing and sales, to outbound distribution, logistics and retail services. The horizontal integration across all these activities creates a transparent value chain that is updated in real-time. Hence this feature provides a high level of flexibility to respond more quickly to changing market demands, shortcomings and problems, facilitates the optimization of the production process, increases its efficiency and reduces the generated waste [30]. Additionally, the fact that any part or product's history is logged and can be accessed at any time ensures constant traceability, also known as "product memory" [31].

Fig.4- Industry 4.0 Horizontal Integration

C. *Through-Life engineering across the entire value chain*

Industry 4.0's third main characteristic is adopting a through-life engineering approach over the entire value chain of any product and covering its complete life cycle [32]. Through-life engineering is based on the concept of expanding the manufacturing design beyond the production process to cover all aspects of the value chain from the cradle to the grave by considering a product's entire life cycle as part of its production process. Therefore, this approach creates a collaboration between the production process of any product and the diverse processes and services included in its value chain, such as raw material procurement, product delivery, retail services, etc. The main feature enabled by adopting the through-life engineering approach is the availability of data collected throughout the complete life cycle of a product, from modelling to prototyping and through production. This data creates more efficient and more flexible production cycles, develops integrated delivery systems and maximizes the availability and value of products [33].

D. *Acceleration through exponential technologies*

Across different sectors and as a result of implemented digital transformation strategies, increased adoption of exponential technologies, such as artificial intelligence (AI), machine learning, 3D printing, blockchain, Internet of Things (IoT), etc., is disrupting conventional businesses management approaches and creating not only new business models but also new sources of revenue. Industry 4.0 is powered, at a nonlinear pace, by those exponentially growing disruptive technologies that instate fast changes in industrial processes [34]. They increase autonomy and speed up individualization and flexibilization by enabling tailored solutions while contributing to waste reduction and thus allowing additional cost savings. The pace of change in Industry 4.0 is no longer just incremental but substantially quicker, nonlinear and more disruptive than ever before. The integration of some, if not most, exponential technologies is essential to overcome Industry 4.0 challenges and barriers and bring this transformation to the next level.

III. Industry 4.0 Challenges

Industry 4.0 appears as a breakthrough in industrial development, making extensive use of the Internet and other technologies. It witnesses an exponential adoption of automation across manufacturing processes while increasing productivity and reducing manufacturing costs. The fourth industrial revolution can be characterized by the convergence of computing, networking and integrating cyber-physical processes. Nevertheless, the challenges, barriers and limitations faced by Industry 4.0 are not only limited to applying new technologies, but they also cover the economic and social aspects and outcomes of this transformation.

A. Technical Challenges

Industry 4.0 uses new technologies such as the Internet of Things (IoT) to improve industrial settings' operations and management [35]. Nevertheless, the fourth industrial revolution doesn't come without challenges and limitations due to the complex nature of the accompanying technologies. The digital transformation of the industrial sector imposes new constraints on companies who have to deal with new requirements as reporting, transparency, and data security. Generally, the increased implementation of new technologies at the core of the fourth industrial revolution and the wide dependence on the Internet has opened the door to new operational issues and vital concerns for Industry 4.0. For example, because of the increased reliance on the Internet as an infrastructure, data security has become a significant concern for new factories [36]. Likewise, the collection, management, analysis and storage of big data is also a significant challenge [37]. Industry 4.0 big data originates from processes such as product or equipment design, operation and control systems, product processing and quality control, records of manual operations carried out by staff, manufacturing systems, management and operational costs, system-monitoring data, logistics and customer information [38].

Moreover, big industrial data has "5V" characteristics [39]. That is, volume, velocity, variety, veracity and value, which challenge the utilization of traditional signal processing techniques to analyze big industrial data. Thus, networks, infrastructures, data processing systems, data storage devices and data analytics platforms have to withstand this avalanche of data and ensure proper transmission, storage and protection of all the IoT data. In other words, networks have to adapt to an IoT and Big data world. Along with demands for increased capacity within networks, there is also a new Information and Communications Technology (ICT) infrastructure paradigm due to digital transformation. The integration of new technologies such as IoT pushes the computing power and connectivity closer to the devices themselves, closer to the network's edge, shifting the conventional ICT model into a more distributed architecture [40].

Like any other application in the cyber world, IoT data represent a significant security concern. Data security is a major nightmare to all Industry 4.0 settings. The integration of IoT solutions poses uncommon privacy issues, many of which go beyond the current data privacy issues [41] and may extend to industrial espionage concerns. On the other hand, the accuracy of artificial intelligence and machine learning algorithms is directly related to the amount of data used to train them [42]. Consequently, data sharing between different applications is fundamental to improve the accuracy of such algorithms. Thus, an equilibrated coexistence of transparency and privacy is a crucial driver to the development and growth of Industry 4.0.

Every time a new technology is integrated into a business model, the concern of employees' qualifications arises. The industrial digital transformation imposes new employees' capabilities across the different activities, entities, services of the value chain, from procurement, to production, distribution and retail [43]. Processes and services shifting towards a new data-based model will undoubtedly require, in most cases, unavailable employee skills and qualifications. In addition, new skills such as software development and data analysis will certainly be needed in future industrial settings.

B. Economic Challenges

Two of the significant and most critical economic challenges facing the adoption of Industry 4.0 techniques are uncertain economic gains and the accompanying prohibitively high investment. The increasing digitization of production processes provides several financial benefits, including a significant reduction in the cost of human resources, inventory management and operations. However, the considerable amount of financial resources required to shift towards Industry 4.0 may hinder the whole process and raise concerns about profitability and investment return. In addition, limited access to financial resources is also an obstacle. The work conducted in [44] proved that the lack of financial resources in Industry 4.0 is a more significant issue than the absence of conscious planning and confirmed that the limited availability of financial resources represents a more substantial obstacle to the digital transformation of the studied companies compared to employees' resistance.

C. *Regulatory and Social Challenges*

The emergence of new technologies might provoke, in various cases, general policy concerns. The ability of governments to develop and implement appropriate regulations and policies is a critical key to a successful adaption of new technologies [45]. In response to emerging technologies disruption of existing conventional business models, governments must swiftly act to create, amend, and enforce policies, regulations, codes, standards and even certification programs. In addition, they need to build a legal framework that protects people, ensures fair competition, and creates a fertile environment for innovation and entrepreneurship to thrive.

A significant apprehension to be targeted by regulations is the indistinct legal state concerning the use of external data. Furthermore, concerns such as providers, manufacturers and other stakeholders' data protection and confidentiality are essential topics to be also considered. As big data continues to transform industries, organizations across all industries recognize its value and seek to harness its potential. But equally, big data-related privacy problems are rising, and current laws are not firmly designed to deal with the exponential nature of this transition [46].

Furthermore, the fourth industrial revolution provokes significant social issues that could escalate, making policy intervention crucial to guarantee that this technological transformation will benefit society and that induced damages are limited and controlled. The exponential increase in automation in industrial facilities can lead to the loss of millions of jobs [47]. Nevertheless, employees are differently affected by this transition, depending on their qualifications, tasks and positions. Jobs related to process data management, manual labor and product packaging, storage and transfer, are highly endangered by the automation process. On the other hand, communicative and intellectual jobs that require a certain level of high education are less exposed to the automation risk. Such tasks cannot be easily reduced to codes and algorithms.

A different expected outcome of the adoption of Industry 4.0 is the aggravation of the income inequality gap. The acceleration of the technological disruption, in various sectors, through exponential technologies, combined with a weak regulated financial integration and rising competition in product and service markets, may enlarge the income inequality gap [48]. Highly qualified people have all that it takes, from ability and skills, to embrace and benefit from this transformation. But, low-skilled workers, especially those whose jobs require moderate skills, will eventually lose their jobs to artificial intelligence and thus suffer from a drastic income reduction.

IV. Blockchain's Impact on industries and economy

The Internet is now over four decades old. Started as a military experiment in the Cold War context, this technology has changed global industry [49]. This technology disrupted almost all industry sectors [50]. Even though some of these sectors, i.e., agriculture, have seen little change, they are not free from the Internet's influence. The Internet saw its first commercial booming with Web 1.0 or what is known as the "read-only web," where websites were pure information-based and made up entirely of static content. A decade later, the world witnessed the emergence of Web 2.0, the Internet of communication and convenience or the "read-write web." Web 2.0 is the era of dynamic websites, online payments, smartphones, applications and social media [51]. This advancement in technology has allowed individuals and businesses to exploit the web for their financial gain and control. The concept of web 2.0 has played an essential role in reviving the old business strategies into newer ones, shedding light on the importance of data as a commodity.

The third and current web form is Web 3.0, a model that heavily relies on machine learning and artificial intelligence (AI). Web 3.0, also known as semantic web, describes the transformation of the web into a database serving the enhancement of the web usage and user's experience [51]. Its main objective is to reshape websites and web applications into a new user-oriented, connected and intelligent form. Beneficiating from the advancement of the Internet and relying on cyber-physical systems and other supporting technologies, Industry 4.0 stands on the frontline of the new digital transformation era. This established framework enables the interconnection of computers and equipment, the design of more intelligent machines and the optimization of the complete production process, forming an intelligent, networked value chain known as a "smart factory." Thus, Web 3.0 is a complementary element of the fourth industrial revolution as it establishes the platform that supports and links all the exponential technologies [52]. At the core of the third web generation, a new technology, blockchain, has emerged, bringing incredible value to Web 3.0's main features while dealing with many undermining issues and limitations in Web 2.0 [53]. Blockchain technology can be considered a foundation protocol for Web 3.0, which supports peer-to-peer transactions and communications, thus eliminating most of the functions that existed with Web 2.0 and relied on third-party intermediaries.

As an answer to the 2008 global financial crisis, Bitcoin emerged as an online-based digital, decentralized, independent currency system that operates outside conventional banking and financial institutions [54]. Soon, the actual value of its backing technology (i.e., blockchain) emerged as a solution to online data privacy concerns, anonymity, security, transparency, immutability, and an enabler of peer-to-peer transactions. Blockchain is a decentralized network of peer nodes. Anyone can securely transfer any digital asset at a low transaction cost and without the need for a trusted third-party intermediary. Additionally, blockchain's adopted consensus mechanism allows to validate transactions, authenticate created data values, and verify the state of the network in a fault-tolerant manner. Global revenues of blockchain technology are forecasted to grow in the coming years to more than $23 billion (U.S.) by 2023. The most significant shares will come from the financial and energy sectors [55]. Although blockchain technology was initially based on applications in finance, the world witnessed far more potential in other industries such as intellectual properties, real estate, retail, agriculture, healthcare, energy, industry, supply chains and logistics. Blockchain technology can disrupt conventional business models by introducing innovative organizational forms and groundbreaking work processes and changing the way people transact digital assets and store data. It transforms enterprises' traditional top-down hierarchical structure into a decentralized form where mid, and low-level managers are given more authority in making decisions [56]. As a result, the global market value for blockchain technology is ramping up [57]. This technology will soon become the cornerstone of the new digital era in the private and public sectors [58].

Data transparency is one of the main features of blockchain technology. The blockchain's transparency stems from the fact that all digital transactions on a blockchain are recorded on a private, public, or semi-private distributed tamper-proof ledger, shared across multiple devices. Thus, the transparency of blockchain allows users to look through all transactions' history, thus creating an auditable trail of transactions. Nevertheless, the transparency level is conditional and depends on the type of blockchain network. For example, in a permissionless blockchain, where any participant can join the network, transactions data is shared publicly. But in the case of permissioned blockchain, where a participant requires permission to join the network, transaction data remain confidential and only visible to the authenticated participants [59].

On the other hand, privacy concerns may arise from the transparency feature of networks [60]. However, in a blockchain, privacy and confidentiality concerns are mitigated by end-to-end asymmetrical encryption based on the two keys concept: a private key and a public key. A public key is how an account is identified in the crowd, similar to the email address. The private key enables the account holder to decrypt received transactions, identical to the password. Thus, Blockchain proved that transparency and privacy could coexist.

Another prominent feature of blockchain technology is smart contracts. A smart contract is a self-directed, self-executable, self-enforcing digital contract between two untrusted peers, written in code and running over a blockchain network. With smart contracts, the workflow execution can be automated, and it will become simpler to report and track necessary data, verify enforcement and approval processes. The automated and real-time nature of smart contracts allows to speed up complicated business processes that are usually conducted manually and being prone to human errors, thus reducing nonperformance or manipulation risks. Moreover, eliminating the need for a trusted third party to monitor and facilitate the execution of the contract reduces the paid transactions cost considerably.

Today, blockchain applications are available for different sectors, industries and societies [61]. For example, in the financial sector, this can be translated into simplifying the business processes without jeopardizing the trustworthiness and transparency of agreements and transactions [62]. A good example is the Ripple consortium, a global network of more than 300 financial institutions across more than 40 countries that provides an automatic, reliable, cheaper and near real-time money transfer platform [63]. Similarly, blockchain technology can help create an end-to-end value chain that mitigates counterfeiting and fraud risks in the supply chain in the food industry [64].

As detailed in the previous paragraph, most of the technical challenges facing a wide adoption of the Industry 4.0 framework concentrates on data management and data infrastructures. Even though blockchain technology might not be able to solve economic and social challenges, the integration of blockchain as a P2P decentralized network to govern the interconnection of different CPSs, at the core of any Industry 4.0 setting, may be of great importance to respond to existing technological barriers and unlock new potentials. To survive through this fourth industrial revolution, manufacturing facilities must identify the impacts of this new digital transformation, driven by emerging technologies such as IoT, AI, blockchain, etc., on their business model and reframe their core value drivers accordingly. By adopting Industry 4.0 practices such as smart factory and smart supply chain, industrial companies can increase their production process efficiency and explore new opportunities through innovation, customized services and new business models [65].

At the foundation of this digital transformation, blockchain can have a higher impact on Industry 4.0 by creating the required underlying platform that interconnects CPS to exponential technologies, such as the Internet of Things (IoT), Robotics, 3D Printing, Augmented Reality and Smart Sensors. Moreover, it can manage data accessibility, provide transparency to the process and secure exchanged information. Hence, the role that blockchain technology can play in enabling new potentials at the core of Industry 4.0 and overcoming data-related technical challenges is detailed in the article's next section.

V. Blockchain supporting Industry 4.0 strategy

A. Blockchain Enablement for Industry 4.0

Blockchain technology can play a significant role in advancing and enabling Industry 4.0, not as a substitute for the existing technology but rather as a fundamental platform capable of interconnecting technologies together and securely managing the information flow. It can bridge some of the gaps, overcome the limitations, and offer solutions to many inherent challenges. For example, the significantly expanding scale of IIoT networks suffers from high connectivity and maintenance costs [66]. Moreover, conventional centralized network architectures are vulnerable to single point of failure and cyber-attacks, especially denial-of-service DoS attacks [67,68]. As a result, the new IT paradigm shifts the network computational power closer to the devices themselves, closer to the network's edge [69]. Blockchain technology offers a decentralized, secure, immutable data platform for IIoT systems without high maintenance and communication costs. Blockchain enables industrial companies to automate more while processing more significant data volumes with fewer human resources at lower costs and risks. Blockchain can contribute to Industry 4.0 by automating and integrating the different phases of the production process, tracking and tracing the products' life cycle, and finally sharing and securing IIoT data.

An additional significant challenge in IIoT networks is the provisioning of authenticated, trusted data sharing and authorized access control among IIoT devices, taking into account the limited capability of IIoT devices to handle large data computations. Any access control scheme for IIoT should guarantee scalability, dynamicity, and low overhead communication and computation [70]. However, the existing access control of centralized systems suffers from scalability limitations. Consequently, centralized access control management is a considerable challenge to be addressed in future networks. Nevertheless, this limitation can be avoided by the decentralized system, where each device independently controls itself. The work conducted in [71] proposes a blockchain-based data sharing and access control system for IoT devices to achieve authentication, authorization, and trustfulness. The decentralized system offered by blockchain networks also improves the fault tolerance [72] and communication speed of the system [73].

Furthermore, blockchain technology eliminates any third-party centralized routing entity conventionally required in any communication protocol and substitutes it with a distributed network of peer nodes. Consequently, it reduces any induced routing cost since the distributed ledger establishes all routes at negligible or even no cost. Furthermore, it increases security and data transfer speed. Moreover, blockchain's decentralization of data allows only authorized users to access any data set using asymmetrical encryption that relies on a set of private-public key combinations.

Additionally, blockchain technology can disrupt the communication industry with its speed, security, and low transaction cost, thus overcoming the traditional bottlenecks and limitations of conventional ICT infrastructures in most industrial facilities. Additionally, globalization in manufacturing industries requires a broad implementation of IIoT devices in different remote locations, making the transmission of data between geographically distributed locations the primary concern. Blockchain offers an advanced platform for content delivery networks (CDNs) [74]. A content delivery network (CDN) refers to a geographically and highly distributed platform of servers that work together to minimize delays in loading web content and guarantee fast delivery of internet content. CDNs are considered a vital component of global information transfer on the Internet, an intrinsic cost for data transfer, and a weak point of security risk [75]. Blockchain can optimize the operation of CDNs and minimize the unused bandwidth from servers worldwide by linking them together into an intricate mesh of servers capable of smoothly and continuously transferring data to any place in the world. Therefore, blockchain can allow industrial settings to automate more while minimizing the concerns related to the transmission of large amounts of data, especially for manufacturing facilities with entities located in different locations.

Furthermore, since data transferred over the blockchain is encrypted with an asymmetrical pair of keys and all transactions are recorded on a distributed ledger shared with all nodes, the integration of CDNs over blockchain will provide an increased level of security for users. Similarly, by reducing the costs of decentralized exchange networks, blockchain technology allows for networking and shared digital infrastructure levels without offering platform operators excessive market influences or data accessibility control. This reduction in networking costs has significant impacts on the current markets structure, as it facilitates the proliferation of open-source projects and start-ups. Consequently, the implementation of blockchain technology for Industry 4.0 applications creates a secure, fast and reliable data sharing system that can solve the operational challenges of big data and IIoT, especially with manufacturing industries operating in different geographical locations.

Besides, the main advantage of decentralized networks is their insusceptibility to a single point of failure. For example, centralized IoT architecture, currently used by most modern industrial facilities, can suffer a single point of failure due to connection problems, power issues, or even denial of service attacks [76], resulting in increased downtimes and induced financial losses. On the other hand, in a blockchain network, all participating nodes share data, which creates a data system highly resistant to technical failures and malicious attacks since any node can replicate and store a copy of the ledger. Thus, there is no single point of failure: a single node offline does not affect the network's availability or security.

Moreover, to control a blockchain network, the attacker should control 51% of the nodes. This is known as the 51% attack [77]. A 51% attack is a cyber-attack on a blockchain network, where the attacker controls more than half of the network's hashing power and acts maliciously to disrupt the network's operation. In such a situation, the attacker would have enough computing power and, therefore, mining power to ignore or modify the ordering of transactions. Moreover, by controlling the majority of the nodes, the attacker could also reverse any executed transaction, allowing himself to double spend.

Additionally, a successful 51% attack would enable the attacker to control or deny the validation of new transactions, also known as transaction denial of service. He can also prevent other miners from mining, resulting in what is known as a mining monopoly. However, considering the large number of nodes participating in a blockchain platform, a 51% attack is rather unlikely. Hence, as blockchain networks grow larger and the number of miners and participating nodes becomes considerable, the probability of an attacker acquiring sufficient computational power to overtake all other participants becomes very low. Furthermore, since in a blockchain network, nodes are pseudo-anonymous and represented only by their addresses, privacy and security are better ensured, showing great potential in overcoming data security and privacy problems and offering a solid equilibrium between privacy and transparency. Hence, blockchain technology is increasing security and network reliability. It can help to target industrial espionage concerns while minimizing cybersecurity risks for Industry 4.0 facilities.

B. Improved Predictive Maintenance through Digital Twin Technology

The maintenance concern and resulting downtimes are a primary challenge to industrial facilities. With the third industrial revolution and the increase in process automation and installed electric and electronic detectors and actuators, maintenance procedures have shifted from a reactive mode of operation to a predictive mode. And today, the fourth industrial revolution requires a prescriptive mode of operation capable of using predictive collected data to issue recommendations to optimize the operation of any asset and even maximize its business potential. Alternatively, blockchain can achieve this prescriptive mode of maintenance by creating a digital twin for every piece of equipment or machinery and updating it continuously [78]. The compiled set of collected data can be used to create a real-time trail of the equipment's condition, from the day it was manufactured till the day it is salvaged or decommissioned years later. By offering data access control and identity management, blockchain could simultaneously encourage stakeholders' participation by increasing their visibility into their businesses, thus increasing their revenues while protecting their data from competitors. Additionally, this auditable real-time trail of the equipment's condition can be used to feed fault detection and diagnosis tools to reduce routine inspection and maintenance time. It enables engagement in a more predictive maintenance procedure and potentially heads problems off before affecting operations [79].

From a manufacturing point of view, the manufacturer's access to this updated ledger could detect fabrication defects early and reduce impacts from equipment callouts. Also, a large amount of shared data from similar equipment or machinery operating in different locations can improve machine learning algorithms and improve equipment efficiency, operation and maintenance. This complete setup can encourage the implementation of new, more intelligent and customized service models such as "power-by-the-hour" or "performance-based contracting" service arrangements where the customer only pays for the time the equipment operates. In such configurations, it is the supplier's responsibility to guaranty the supply, repair, and overhaul of the components and systems it provides to every piece of equipment. Such future service arrangements wouldn't be possible without real-time operation and maintenance data being collected. It allows the suppliers or manufacturers to forecast the current mode of operation, usage and status of the equipment and assess the life span of parts to ultimately manage the production processes of required spares and make sure they are available in due course when needed. This "just-in-time" configuration for spare parts manufacturing enables manufacturers to improve their customer services while cutting their inventory costs. The latest example of this blockchain transparency across interactions is launched by Renault [80]. The French automaker launched a proof-of-concept digitized car maintenance program, which uses blockchain to record cars' historical repair and maintenance data. The adopted car maintenance book using a blockchain distributed ledger allows customers to digitally, securely and immutably log all their vehicle information. Through its ability to provide verifiable real-time updated maintenance records, another extractable feature of this digital twin identity is that it allows buyers in the secondary market to have greater confidence in their purchases. They can select from the best-maintained machinery, hence raising the equipment's end-of-service value.

C. Blockchain can maximize the use of IIoT

The IIoT technology is powering the fourth industrial revolution and plays a significant role in interconnecting cyber to physical systems. However, the usage of IIoT devices for industrial applications, using conventional client-server platforms, faces several technical constraints (i.e. security and connectivity) as previously detailed. The potential of blockchain technology in maximizing the use of IIoT relies upon the definition of the technology itself. Blockchain is a distributed, timestamped, immutable digital ledger that creates trust between unknown peers using mathematical algorithms. The deployment of IIoT devices can be very complex, especially when connecting hundreds or thousands of IIoT devices to a centralized server. Conventional IIoT ecosystems involving data streaming from sensors to a centralized server may generate privacy concerns due to third-party management of Cloud servers, single points of failure, bottlenecks in data flow and difficulties in regularly updating firmware for millions of smart devices. The blockchain's distributed nature provides IIoT devices identification, authentication and guarantees seamless, secure data transfer. On the other side, immutability is another crucial feature of blockchain technology. Consequently, blockchain offers the necessary framework to protect IIoT devices' data from tampering and provides an immutable historical trail of data, resistant to malicious data duplication, that can be used to diagnose and detect faults in connected devices [81].

Blockchain eliminates the need for trusted third-party intermediaries by empowering peer-to-peer trust via mathematical algorithms. So, instead of relying on a trusted third party to securely manage the flow of information, IIoT sensors can exchange data through the blockchain platform by providing a unique identity for reach device and protecting data integrity. The absence of intermediaries will reduce the deployment and operation costs of IIoT and remove technical bottlenecks and system inefficiencies [82]. Moreover, blockchain's smart contracts ensure devices autonomy and processes automation and therefore limit the reliance on human intervention and, alternatively, the risk from human error and malicious.

D. Blockchain-enabled digital supply chain

In essence, Industry 4.0 enables increased automation across the complete life cycle of products, thus affecting the way supply chains are designed and operated. Proper supply chain management is a critical factor of Industry 4.0 horizontal integration and production process optimization. Nevertheless, the complexity of modern supply chains is continuously increasing, thereby rendering a sound management system a complex task that may affect companies' competitiveness [83]. Global supply chains are influenced by several external and internal factors [84]. World trends, such as globalization and global connectivity, are part of the external factors contributing to increasing global supply chains complexity. An example of internal factors is the constant struggle to achieve a more efficient production process and reduce the operating cost.

Furthermore, rapid market fluctuations require manufacturers to react to frequently occurring demand changes. Hence, building an effective supply chain management system is crucial to accurately monitor and predict risk to respond appropriately [85]. A typical supply chain may involve several stakeholders, and it can be very challenging to track the production and information flow efficiently. The information flow relies on the data being efficiently collected and shared between the different stakeholders. Hence an ideal supply chain would include the following:

- Visibility and Transparency: An end-to-end visibility of the supply chain can be achieved by monitoring, in real-time, the integrated services and processes to identify weak points and problems and, therefore, correct them and improve the efficiency and traceability across the supply chain.
- Flexibility: It is characterized by the ability to adapt and respond to frequent and fast market fluctuations without affecting the company's ability to compete in the market
- Trust: Trust between the different stakeholders is based on the confidence in the management system to assemble and provide accurate and immutable data
- Control: Through policies, management and monitoring mechanisms

Conventional supply chains face several challenges and barriers: continuity of information, accessibility to information [86], linking the digital world to the physical one, and code of conduct and fraud violations. Digitalized supply chains integrating IoT devices, such as tracking instruments and intelligent sensors, and blockchain technology can answer these challenges and provide more efficient manufacturing processes. Such digitalized supply networks will have to rely on blockchain technology as the primary network platform for data logging and data management systems, backed by IoT technology for data measurement and gathering and by AI or machine learning for high-performance analytical capabilities.

Additionally, the immutability of blockchain transactions or, in the case of industry, the data shared between the different supply chain stakeholders creates an auditable trail. It reduces inherent risk, thus guaranteeing a proper continuity of information. Moreover, the transparent and near real-time nature of blockchain transactions can provide immediate access to information in any digital supply chain and maximizes the value of data collected along the supply chain. Furthermore, IoT technology and oracles can help to link the data to the materials and products throughout all stages of the supply chain, connecting the digital world to the physical one. And finally, it is a must to ensure that human rights and codes of conduct are respected adequately along the chain to lower reputation damage risk. Effective fraud detection processes supported by appropriate technologies will be increasingly essential to reduce business risk. At this level, blockchain traceability and transparency will serve to fight code of conduct and fraud violations.

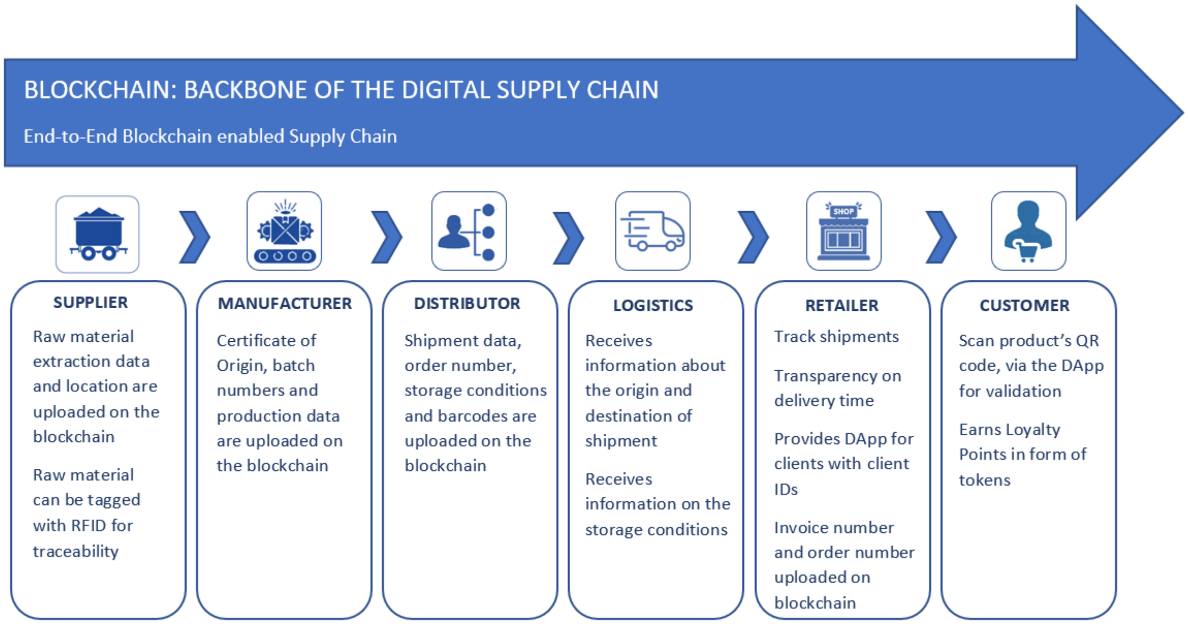

Fig.5- End-to-End Blockchain-enabled supply chain model

Consequently, blockchain smart contracts provide the possibility to automate a significant portion of the digital value chain processes and data transmissions between system-wide assets. Moreover, it creates a continuous physical-to-digital-to-physical fully connected and trusted cycle resulting in a new digitalized supply network, far more advanced than conventional networks. A typical end-to-end blockchain-based digital supply chain model appears in Figure 5.

VI. Conclusion

The Internet, Social Networking and e-Commerce brought the third industrial revolution. Emerging and essential technologies such as the Internet of Things, Artificial Intelligence, machine learning and blockchain are the key drivers of Industry 4.0. And there is no doubt that blockchain-based Industry 4.0 solutions can simplify business models and business processes, improve system efficiency, and achieve significant cost reductions. Blockchain's capability to securely and immutably log transactions data, increase the data transfer speed, and decrease transaction costs will encourage industrial facilities to automate more and remove any manual activities. The integration of blockchain technology as part of the Industry 4.0 framework can create a more flexible and efficient environment for manufacturing facilities to grow and become more productive as the world shifts towards an interconnected distributed ecosystem where more power is transferred to the peripheries. The fourth industrial revolution is redefining the value and innovation in manufacturing structures by establishing a new level for modern manufacturing characterized by smart factories that merge cyber and physical systems. Thus, industry stakeholders should restructure their business model and investigate the actual value of IoT technology combined with blockchain solutions to stay competitive and push innovation into their businesses and services. Thus, there is no doubt that soon, blockchain technology will become a fundamental pillar of Industry 4.0.

There are, however, several unexplored areas for the implementation of blockchain technologies on a large scale across the complete spectrum of the supply chain. Equally, it is essential to define the scope of blockchain ecosystems and their mode of operation. On the other hand, the regulatory framework that will allow enterprises to integrate blockchain with other emerging technologies, such as the Internet of Things and Artificial Intelligence, is still unclear. Therefore, regulators should embrace and drive blockchain technology adoption and develop appropriate standards and certification practices.

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CHAPITRE 8
PERSPECTIVES

Le concept des PADs représente une avancée significative dans le domaine de la gestion des réseaux électriques. Une fois cette technologie déployée et optimisée, les horizons de recherche s'élargissent considérablement. Cette perspective de thèse se concentre sur les futures recherches et innovations qui pourraient émerger suite à l'adoption généralisée des PADs. Ces nouvelles avenues de recherche non seulement amélioreront davantage la résilience et l'efficacité des réseaux électriques, mais ouvriront également des possibilités dans divers domaines tels que la gestion intelligente de l'énergie, la cybersécurité, les interactions homme-machine, et la durabilité environnementale.

Avec la mise en place des PADs, il devient crucial d'explorer des techniques d'apprentissage automatique plus avancées, telles que l'apprentissage renforcé. Ces techniques permettront aux sous-stations de s'adapter en temps réel aux variations de la demande et de l'offre d'énergie, en optimisant leur fonctionnement de manière autonome. Les recherches futures pourraient se concentrer sur le développement d'algorithmes capables d'apprendre et de s'adapter continuellement, améliorant ainsi la résilience et l'efficacité des PADs face aux perturbations et aux changements environnementaux.

Une autre perspective de recherche importante est l'intelligence artificielle explicable (eXplainable Artificial Intelligence, XAI). Avec des systèmes de contrôle de plus en plus autonomes, il devient essentiel de comprendre et de justifier les décisions prises par les algorithmes d'IA. Les recherches futures devraient se pencher sur le développement de modèles d'IA transparents et explicables, permettant aux opérateurs humains de comprendre les processus décisionnels des PADs et d'intervenir lorsque nécessaire.

Avec l'augmentation de la connectivité et de l'autonomie des PADs, la cybersécurité devient une préoccupation majeure. Les futures recherches devront se concentrer sur le développement de protocoles de sécurité avancés pour protéger les PADs contre les cyberattaques. Cela inclut l'utilisation de techniques de cryptographie avancées, la détection et la prévention des intrusions, ainsi que le développement de systèmes de réponse rapide aux incidents de sécurité.

Outre la cybersécurité, la résilience globale des PADs face aux perturbations physiques et techniques est cruciale. Les recherches futures devraient explorer des stratégies pour améliorer la résilience des PADs, telles que la redondance des systèmes, l'utilisation de technologies de stockage d'énergie avancées, et le développement de systèmes efficaces de reprise après sinistre.

À mesure que les PADs deviennent plus autonomes, l'interaction entre les opérateurs humains et les systèmes de contrôle devient plus complexe. Les recherches futures devront se concentrer sur le développement d'interfaces utilisateur intelligentes, permettant aux opérateurs de surveiller et de contrôler efficacement les PADs. Cela inclut l'utilisation de technologies de réalité augmentée et de réalité virtuelle pour fournir des visualisations intuitives et immersives des données de réseau.

Une autre perspective de recherche importante est la collaboration homme-machine. Les PADs autonomes ne doivent pas être complètement indépendants des opérateurs humains, mais doivent plutôt travailler en collaboration avec eux. Les recherches futures devraient explorer des méthodes pour améliorer cette collaboration, en intégrant des systèmes de recommandation basés sur l'IA, des outils de formation interactifs, et des mécanismes de rétroaction en temps réel.

L'une des principales motivations derrière les PADs est l'intégration efficace des sources d'énergie renouvelable. Les recherches futures devraient se concentrer sur l'optimisation de l'utilisation des énergies renouvelables dans les réseaux électriques décentralisés. Cela inclut le développement de modèles prédictifs pour la production et la demande d'énergie, l'intégration de systèmes de stockage d'énergie avancés, et l'utilisation de techniques de gestion de l'énergie basées sur l'IA pour équilibrer la production et la consommation en temps réel.

Les PADs sont une composante clé des micro-réseaux et des réseaux intelligents. Les recherches futures devraient explorer des stratégies pour la mise en œuvre et la gestion des micro-réseaux, en se concentrant sur la coordination entre les PADs, la gestion des flux d'énergie, et l'intégration de dispositifs IoT pour la collecte et l'analyse des données en temps réel. Cela inclut également l'étude des interactions entre les micro-réseaux et le réseau principal, afin de garantir une distribution efficace et fiable de l'énergie.

La transition vers des PADs nécessite l'acceptation et l'adoption par diverses parties prenantes, y compris les opérateurs de réseau, les régulateurs, et le grand public. Les recherches futures devraient se concentrer sur l'étude des facteurs influençant l'acceptabilité sociale des PADs, en utilisant des enquêtes, des études de cas, et des méthodes de modélisation sociale. Cela inclut également l'élaboration de stratégies pour sensibiliser et éduquer le public sur les avantages des PADs.

Le déploiement des PADs nécessite des investissements importants. Les recherches futures devraient explorer des modèles économiques pour évaluer la viabilité financière des PADs, en tenant compte des coûts initiaux, des économies à long terme, et des bénéfices environnementaux et sociaux. Cela inclut également l'étude des mécanismes de financement, tels que les partenariats public-privé, les subventions gouvernementales, et les modèles de tarification basés sur la performance.

La mise en place des PADs nécessite des cadres réglementaires adaptés pour garantir leur fonctionnement efficace et sécurisé. Les recherches futures devraient se concentrer sur l'élaboration de politiques et de réglementations pour soutenir le déploiement des PADs, en tenant compte des aspects techniques, économiques, et environnementaux. Cela inclut l'harmonisation des normes et des protocoles de communication, la réglementation de la cybersécurité, et la promotion de l'innovation dans le secteur de l'énergie.

Pour encourager l'adoption des PADs, les gouvernements doivent mettre en place des incitations et des programmes de soutien. Les recherches futures devraient explorer les meilleures pratiques en matière de politiques publiques pour soutenir les technologies d'énergie décentralisée, en utilisant des études de cas et des analyses comparatives. Cela inclut également l'évaluation des impacts économiques des incitations et des subventions sur le marché de l'énergie.

Le développement et le déploiement des PADs nécessitent une collaboration internationale entre les chercheurs, les industries, et les gouvernements. Les recherches futures devraient explorer des stratégies pour promouvoir la collaboration internationale, en se concentrant sur le partage des connaissances, la standardisation des technologies, et le financement conjoint de projets de recherche et de développement. Cela inclut également l'étude des meilleures pratiques en matière de collaboration et de partenariat.

Les partenariats public-privé sont essentiels pour le succès des PADs. Les recherches futures devraient explorer des modèles de partenariats efficaces pour soutenir le développement et le déploiement des PADs, en tenant compte des rôles et des responsabilités des différentes parties prenantes. Cela inclut également l'étude des mécanismes de gouvernance et de gestion des risques pour garantir le succès des projets de PADs.

Les PADs représentent une avancée significative dans la gestion des réseaux électriques. Cependant, leur adoption généralisée ouvre de nouvelles perspectives de recherche dans divers domaines. Les futures recherches devront se concentrer sur l'intégration avancée de l'intelligence artificielle, la cybersécurité, l'interaction homme-machine, la gestion intelligente de l'énergie, les technologies de stockage d'énergie, l'impact environnemental et la durabilité, les aspects sociaux et économiques, les politiques et réglementations, ainsi que la collaboration et les partenariats. En explorant ces perspectives, cette thèse espère contribuer à la réalisation d'un avenir énergétique plus résilient, efficace, et durable.

CHAPITRE 9
CONCLUSION GÉNÉRALE

La chaîne de blocs est considérée comme un facteur de changement majeur dans la plupart des secteurs économiques, mais son potentiel dans le domaine de l'énergie reste encore largement inexploité. Il a fallu près d'une décennie pour transformer la chaîne d'approvisionnement énergétique de sa forme centralisée initiale en une architecture décentralisée. Pourtant, cette transition n'a été possible que grâce à l'émergence de systèmes de production d'énergie renouvelable à faible coût et à l'application de nouvelles réglementations climatiques qui obligent les entreprises énergétiques à réduire leurs émissions de carbone. Ainsi, le réseau énergétique est passé d'un mode de fonctionnement unidirectionnel dépendant à un mode de fonctionnement indépendant bidirectionnel où des micro-réseaux hors réseau peuvent subsister. Aujourd'hui, la technologie de la chaîne de blocs offre la possibilité de faire évoluer le secteur de l'énergie vers un mode de fonctionnement interdépendant multidirectionnel où les utilisateurs peuvent effectuer des transactions entre eux et avec le réseau.

Le marché de l'énergie a énormément évolué au cours du siècle dernier, passant d'une forme décentralisée primitive, à une forme unidirectionnelle centralisée et enfin à une forme distribuée bidirectionnelle. Toutefois, cette évolution s'est ralentie au cours de la dernière décennie. Les investissements dans les projets d’énergie renouvelable sont plus ou moins stagnants alors que la consommation énergétique mondiale augmente à un rythme régulier. De plus, l'électrification du secteur des transports, sous-tendue par la nécessité de réduire les émissions de GES, va certainement accroître la pression sur les marchés de l'énergie et plus particulièrement sur le réseau électrique. Par conséquent, une nouvelle percée est nécessaire afin de perturber l'état statique du marché de l'énergie. De nouvelles incitations doivent être créées, une nouvelle forme de relation doit être établie entre les entreprises énergétiques et les consommateurs et les mesures nécessaires doivent être prises pour limiter la demande d'énergie.

De plus, les consommateurs d'aujourd'hui demandent une plus grande implication et une transparence dans la gestion et le suivi de leur consommation d'énergie. Les utilisateurs finaux sont déjà à l'origine d'investissements dans les énergies propres par le biais d'investissements privés ou en participant à des projets communautaires. Les consommateurs sont aujourd'hui considérés comme faisant partie intégrante de la nouvelle transition énergétique, non seulement en raison des ressources énergétiques qu'ils partagent avec le réseau, mais aussi en raison de la flexibilité de la charge qu'ils fournissent. Ainsi, un système énergétique axé sur les consommateurs s'avérera bénéfique pour toutes les parties prenantes.

D'autre part, une forte intégration des REDs dans le réseau électrique est considérée comme un cauchemar opérationnel et de gestion pour les opérateurs de réseau, en particulier parce que la plupart de ces REDs sont de nature intermittente et se trouvent à la périphérie du réseau. De plus, la révolution numérique qui touche le secteur de l'énergie exerce une forte pression sur les marchés de l'énergie en termes de gestion, d'analyse, de stockage et de sécurisation des big data générées. En outre, la question de la sécurité énergétique, et plus particulièrement de la cybersécurité de la chaîne d'approvisionnement énergétique, est une préoccupation fondamentale non seulement pour les entreprises du secteur de l'énergie, mais aussi pour les nations et les gouvernements du monde entier.

Afin de surmonter les défis et les obstacles auxquels est confronté le secteur énergétique actuel, de répondre aux dernières préoccupations environnementales, économiques et sociales, ainsi que de satisfaire les nouvelles attentes des utilisateurs finaux, un nouveau système énergétique est nécessaire. Le travail effectué dans cette thèse offre une nouvelle perspective pour un nouveau marché de l'énergie basé sur un modèle de sous-stations autonomes décentralisées, sur les échanges d'énergie P2P décentralisés et interdépendants et sur la chaine de blocs. Même si les scénarios présentés dans cette thèse se concentrent sur le réseau électrique, les concepts appliqués peuvent être facilement extrapolés pour couvrir le marché du pétrole et du gaz ainsi que le marché de l'eau.

Les solutions proposées couvrent les différents aspects de la chaîne d'approvisionnement énergétique : la production d'énergie et la gestion de la demande. Du côté de la production, cette thèse souligne la faisabilité économique du modèle d'échange d'énergie P2P comme mécanisme de financement alternatif aux systèmes d'incitation existants tels que FiT et Net Metering. Bien que le concept d'échange P2P ne soit pas nouveau sur le marché de l'énergie, cette thèse fournit une évaluation sans précédent de l'échange d'énergie P2P basé sur la chaîne de blocs comme mécanisme de financement pour les REDs. Les résultats de la simulation ont prouvé que le trading d'énergie P2P débloque de nouvelles incitations pour le déploiement de REDs, en particulier dans les zones rurales et éloignées. De plus, la chaîne de blocs offre une plateforme adéquate pour la gestion et la surveillance des REDs dans le cadre des PPVs, résolvant ainsi l'une des principales limitations à une large adoption des PPVs. Aussi, cette thèse offre un algorithme d'optimisations des REDs dans le contexte des VPPs afin de réduire le coût moyen de l'électricité, en tenant compte le coût des pertes techniques et le coût des émissions de GES. Aussi, cette thèse offre un modèle de régression dynamique à coefficients variables qui permet d'estimer l'impact des REDs sur les pertes techniques du réseau, ce qui permet de faire une optimisation dans les investissements de nouveaux projets de RED.

Du côté de la demande et dans le but de lutter contre la croissance de la consommation d'énergie, cette thèse propose un modèle de gestion de la demande basé sur la chaîne de blocs Cap and Trade qui non seulement récompense la réduction de la consommation d'énergie et pénalise les gros consommateurs d'énergie, mais fournit également une solution au free-riding et à l'effet rebond. En outre, un modèle de CPE basé sur la chaine de blocs et les contrats intelligents est présenté afin de surmonter les défis et limitations existants dans les modèles conventionnels et encourager les investissements dans les projets d'efficacité énergétique.

En outre, cette thèse a ouvert de nouveaux horizons sur le potentiel de la technologie de la chaîne de blocs en tant qu'outil d'autonomisation pour la 4e ère industrielle. Tout d'abord, les principes fondamentaux de l'industrie 4.0, ses défis, ses obstacles et ses limites ont été explorés, puis les domaines dans lesquels la technologie de la chaîne de blocs peut apporter de nouvelles fonctionnalités et une valeur ajoutée au déploiement de l'industrie 4.0 ont été présentés. Et enfin, l'effet de l'intégration de la chaîne de blocs dans le secteur de l'énergie en termes de sécurité et d'impacts environnementaux et sociaux a été exploré.

En conclusion, Les PADs basées sur la chaîne de blocs offrent une opportunité unique de transformer la gestion des réseaux électriques. Cette thèse a démontré que l'intégration de la chaîne de blocs et des technologies associées peut améliorer la résilience, la sécurité et l'efficacité des réseaux, tout en offrant des avantages économiques et environnementaux significatifs. Cependant, la réalisation de ce potentiel nécessite des efforts continus en recherche, développement et collaboration entre les différentes parties prenantes. En abordant les défis techniques, réglementaires et économiques, il est possible de créer des réseaux électriques plus robustes et durables, capables de répondre aux exigences croissantes de l'avenir énergétique. La transition vers des PADs représente une étape cruciale dans l'évolution des infrastructures énergétiques, alignée avec les objectifs de durabilité et d'innovation technologique. En adoptant une approche proactive et collaborative, nous pouvons exploiter pleinement les avantages de la chaîne de blocs et des technologies décentralisées pour bâtir un avenir énergétique plus résilient et équitable. Enfin, il est utile d'attirer l'attention sur le fait que plusieurs domaines inexplorés pourraient être considérés afin de compléter le puzzle. Le travail présenté devrait encourager d'autres personnes à poursuivre des travaux de recherche sur l'application des chaînes de blocs dans le secteur de l'énergie et à tester le concept de réseau énergétique décentralisé interdépendant en tant que modèle capable de débloquer de nouveaux potentiels pour l'ère de l'énergie 4.0.

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