AMÉLIORATION DE LA QUALITÉ DU SOUDAGE AU LASER DES ALLIAGES D'ALUMINIUM PAR UNE SURVEILLANCE EN TEMPS RÉEL DES DÉFAUTS POUR UN PROCESSUS DE SOUDAGE INTELLIGENT

Thèse présentée

dans le cadre du programme de doctorat en ingénierie de l’UQAC

offert par extension à l’UQAR

en vue de l’obtention du grade de Philosophiae doctor (Ph.D)

PAR

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Avril 2024

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Dépôt initial le 1 Novembre 2023 Dépôt final le 11 Avril 2024

À **mon père** et **ma mère**, qui m'ont toujours soutenu et encouragé à poursuivre mes rêves. Votre amour, votre soutien et votre guidance ont été inestimables tout au long de ma vie et ont joué un rôle crucial dans la réalisation de cette thèse.

Et à **mon amour Mahsa**, qui a toujours été présente, m'a soutenu dans les moments difficiles et encouragé à poursuivre mes passions. Ton amour inconditionnel a été la source de ma motivation et de ma persévérance tout au long de ce parcours.

Je dédie cette thèse à vous trois, avec une gratitude et un amour infini.

REMERCIEMENTS

Je tiens à exprimer ma profonde gratitude envers le professeur Noureddine Barka pour son soutien, ses conseils et pour l’opportunité qu'il m'a offerte pour développer mon projet de recherche. Je tiens à exprimer ma profonde gratitude envers le professeur Abderrazak El Ouafi pour avoir dirigé ce projet avec une compétence et un dévouement exemplaire. Je tiens à remercier chaleureusement mes collègues du groupe de recherche FI3 et mon ami Mostafa ainsi que les professeurs qui ont partagé leurs connaissances avec moi et ont contribué à améliorer mes compréhensions. Je souhaite également exprimer ma reconnaissance à François, Marc-Olivier, Siyu, Fatemeh du Centre National de Recherche du Canada avec qui j’ai travaillé pour développer mon projet de recherche. Je tiens à remercier l’UQAR et le département d’ingénierie, ainsi que leurs auxiliaires et techniciens : Suzie, Karel, Vianney, Richard, Jean-Charles et Denis pour l’aide précieuse apportée aux étudiants. Mes remerciements vont également à Farah et à Jacqueline.

Enfin, je tiens à remercier tous ceux qui ont contribué de près ou de loin à la réalisation de ce projet de recherche. Leur appui et leur expertise ont été inestimables pour la réussite de cette thèse.

RÉSUMÉ

La présente étude, inscrite dans le vaste contexte évolutif de l'industrie 4.0, s'intéresse à l'exploration et à l'exploitation de la technologie de soudage au laser pour la fabrication de structures en aluminium. Face à l'importance croissante de l'automatisation et de la digitalisation dans les processus industriels, la problématique de la surveillance des défauts des structures soudées au laser en aluminium se pose avec acuité, celle-ci étant identifiée comme un maillon critique dans un système de fabrication intelligent. Dans cette optique, le principal objectif de cette recherche est de mener une investigation approfondie et systématique de cette surveillance, afin de cerner les enjeux et les défis associés. La méthodologie adoptée pour aborder ce sujet complexe est résolument multidisciplinaire. Elle combine des méthodes expérimentales, des techniques de modélisation avancées, une analyse statistique rigoureuse, et l'exploitation de l'apprentissage automatique. Plusieurs chapitres de la thèse sont consacrés à détailler cette approche méthodologique. Par exemple, une analyse bibliométrique exhaustive est présentée, visant à cartographier l'état actuel des connaissances sur la surveillance en temps réel de la technologie de soudage. Par la suite, une approche novatrice d'inspection automatisée en temps réel est proposée, avec pour ambition de détecter avec précision les distorsions dans les assemblages soudés.

Les résultats obtenus dans le cadre de cette étude sont à la fois nombreux et significatifs. Ils démontrent, sans équivoque, que la surveillance en temps réel des défauts dans les structures en aluminium soudées au laser peut avoir un impact majeur sur la qualité du produit final. Ceci en améliorant non seulement la qualité intrinsèque de la soudure, mais aussi en augmentant la cadence de fabrication et, par conséquent, en réduisant substantiellement les coûts de production. Un des points saillants de l'étude concerne l'utilisation d'un modèle Random Forest pour la détection de la porosité. Cette approche a permis d'atteindre un niveau impressionnant de détection, avoisinant les 80%. Néanmoins, il est important de noter que la prédiction de certains défauts, tels que les pores microscopiques, demeure un défi de taille. En conclusion, cette recherche souligne le potentiel immense de l'approche basée sur l'apprentissage automatique pour améliorer de manière significative l'efficacité et la qualité du processus de soudage. Elle met également en lumière l'importance d'intégrer les principes de l'industrie 4.0 dans des domaines spécifiques tels que le soudage au laser, offrant ainsi une vision renouvelée et des perspectives prometteuses pour l'avenir de la fabrication industrielle.

Mots clés : Fabrication intelligente, soudage au laser des alliage d’aluminium, inspection automatisée, détection de défauts, traitement d'image, apprentissage automatique, algorithmes d'apprentissage avancés.

ABSTRACT

The current study, embedded in the vast evolving context of Industry 4.0, delves into the exploration and exploitation of laser welding technology for the fabrication of aluminum structures. Given the growing importance of automation and digitization in industrial processes, the issue of monitoring defects in laser-welded aluminum structures becomes particularly pressing, as it is identified as a critical link in an intelligent manufacturing system. With this perspective in mind, the main objective of this research is to conduct a thorough and systematic investigation of this monitoring to understand the associated challenges and stakes. The methodology adopted to tackle this intricate subject is decidedly multidisciplinary. It merges experimental methods, advanced modeling techniques, rigorous statistical analysis, and the utilization of machine learning. Several chapters of the thesis are dedicated to detailing this methodological approach. For instance, a comprehensive bibliometric analysis is presented, aiming to map the current state of knowledge on real-time monitoring of welding technology. Subsequently, a novel approach to real-time automated inspection is proposed, ambitiously aiming for accurate detection of distortions in welded assemblies.

The results obtained within this study are both numerous and significant. They unequivocally demonstrate that real-time monitoring of defects in laser-welded aluminum structures can have a major impact on the quality of the final product. This not only improves the intrinsic quality of the weld but also increases the manufacturing pace and, consequently, substantially reduces production costs. One of the standout points of the study concerns the use of a Random Forest model for porosity detection. This approach achieved an impressive detection level, nearing 80%. However, it is crucial to note that predicting certain defects, such as microscopic pores, remains a significant challenge. In conclusion, this research underscores the immense potential of the machine learning-based approach to significantly enhance the efficiency and quality of the welding process. It also highlights the importance of integrating Industry 4.0 principles into specific areas like laser welding, thus offering a renewed vision and promising prospects for the future of industrial manufacturing.

Keywords: Intelligent manufacturing, aluminum laser welding, process monitoring, automatic inspection, defect detection, image processing, machine learning, advanced learning algorithms.

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LISTE DES ABRÉVIATIONS, DES SIGLES ET DES ACRONYMES

AI	Artificial intelligence
IOT	Internet of things
AR	Augmented reality
M2M	Machine to machine
ICT	Information and Communications Technology
CNNs	Convolutional neural networks
RNNs	Recurrent Neural Networks
LSTMs	Long Short-term Memory
RF	Random Forests
GBMs	Gradient boosting machines
KNN	K-Nearest Neighbors
RLs	Reinforcement learning
SMF	Sheet Metal Forming
IWS	Intelligent Welding Systems
LDD	Laser Depth Dynamics
OCT	Optical Coherence Spectroscopy

NRC	National research council of Canada
ZDM	Zero-Defect Manufacturing
HRI	Human-Robot Interaction
FSW	Friction Stir Welding
WOS	Web of Science
CPS	Cyber-Physical Systems
RAMI 4.0	Reference Architectural Model Industry 4.0
GTAW	Gas Tungsten Arc Welding
GMAW	Gas Metal Arc Welding
DT	Digital Twin
CS	Cracking Susceptibility
VCFSW	Vertical compensation friction stir welding
YLS	Yterbium Fiber Lasers
3LS	3D Laser Scanning Inspection
CL	Cloud Mapping
DOE	Design of Experiences
DIC	Digital Image Correlation
SEM	Scanning Electron Microscope
LMP	Laser Material Processing

AA	Aluminum Alloys
ROC	Receiver Operating Characteristic
FPR	False Positive Rate
PMF	Programmable Motorized Focusing
SLJ	Laser-Welded Single Lap Joints
NDT	Non-destructive methods
CMOS	Complementary metal oxide semiconductor
ISO	International Organization for Standardization
SVM	Support Vector Machine/ Machine à vecteurs de support
PCA	Principal Component Analysis
TWBs	Tailor Welded Blanks
LWBs	Laser welded Blanks
CAD	Computer Aided Design
ANOVA	Analysis of Variance
DMAIC	Design Measure Analyze Improve Control
CAM	Computer Aided Manufacturing
CAI	Computer Aided Inspection
QA	Quality Assurance
P	Power

V	Welding Speed
A	Amplitude
CNN	Convolutional Neural Network
R^2	R squared, coefficient of determination
ML	Machine Learning
CPU	Central processing unit
GPU	Graphics Processing Units
Inline coherent imaging	ICI
Region Of Interests	ROI
Mean Squared Error	MSE
Random Forest	RF
Out Of Bag	OOB
MDA	Mean Decrease Accuracy

LISTE DES SYMBOLES

ms	Millisecondes
nm	Nanometer
Mg	Magnesium
Zn	Zinc
Cu	Cuivre
Al	Aluminium
kW	Kilowatts
mm	Millimetre
mm/s	Millimetre par second
Ɵ	Distortion angle
kW	Laser Power
m/min	Travel Speed
mm	Oscillation Amplitude
Hz	Oscillation Frequency

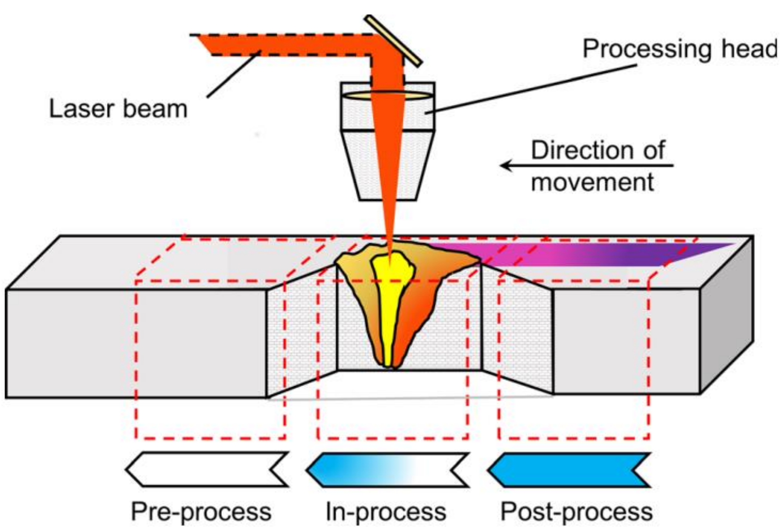
INTRODUCTION GÉNÉRALE

1. CONTEXTE ET GÉNÉRALITÉS

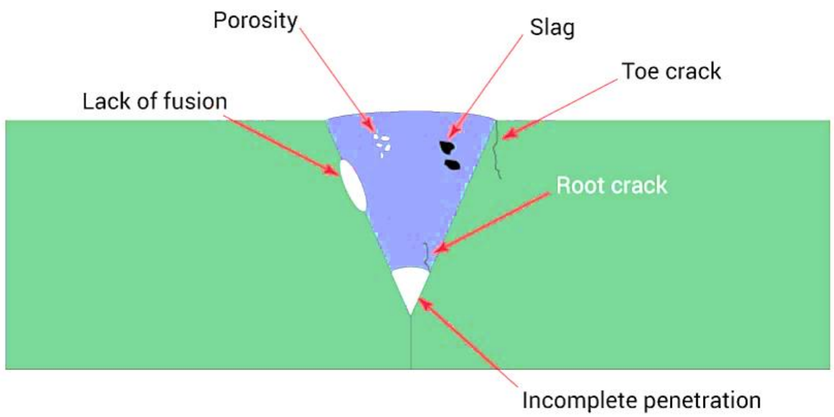
L'Industrie 4.0, considérée comme la quatrième révolution industrielle, a apporté une transformation significative dans le secteur manufacturier grâce à l'intégration de technologies avancées de l'information et de la communication (TIC) et à la connectivité Internet [1]. Cette révolution a permis aux entreprises de collecter, analyser et traiter des données pour produire des produits industriels de haute qualité. Cependant, il est nécessaire de mener des recherches approfondies pour comprendre les implications de cette nouvelle stratégie sur les systèmes de production centralisés [2]. L'émergence de systèmes décentralisés de production d'énergie a permis aux individus de générer de l'énergie verte et de partager des informations en ligne, ce qui a remodelé les pratiques de fabrication traditionnelles. La combinaison de l'intelligence artificielle (IA) et de l'Industrie 4.0 constitue un domaine de recherche fascinant qui explore de nouvelles approches pour modéliser le raisonnement humain et les émotions dans le contexte des activités industrielles. Pour s'adapter à ce paysage en évolution, les organisations doivent comprendre les principes et concepts fondamentaux sous-tendant la décentralisation et passer d'une fabrication traditionnelle axée sur les machines à un environnement numérique caractérisé par la connectivité, l'automatisation et la prise de décision centrée sur les données. Le transfert de technologies de pointe, telles que les systèmes de centralisation des données et les algorithmes d'apprentissage automatique intégrés, est en cours pour améliorer la collecte, l'analyse et l'optimisation des processus dans les entreprises manufacturières [3]. Le traitement des matériaux par laser a suscité beaucoup d'attention en raison de son potentiel pour réduire la consommation d'énergie et le gaspillage de matériaux, ce qui en fait un domaine de recherche crucial. Le soudage laser, réputé pour sa précision et sa rapidité, joue un rôle essentiel dans les chaînes de production industrielle modernes [4]. Cependant, l'optimisation du contrôle de la qualité et de l'analyse des défauts dans le soudage laser reste un défi. Les avancées récentes, telles que les systèmes de soudage laser cognitifs et les techniques d'inspection automatisées, offrent des solutions prometteuses pour relever ces défis [5]. Dans le contexte actuel marqué par l'ère des données massives, une collecte stratégique ainsi qu'un partage judicieux des informations s'avèrent cruciaux. Ces éléments sont essentiels pour optimiser les opérations internes et conduire des analyses approfondies du cycle de vie au sein des chaînes d'approvisionnement industrielles [6–8]. De plus, l'utilisation de flans soudés au laser (LWB), qui implique l'assemblage de feuilles individuelles à l'aide de techniques de soudage laser, permet l'adoption de méthodes de production personnalisées et améliore l'utilisation des matériaux [9]. Une surveillance efficace des défauts et une assurance qualité sont essentielles pour garantir les performances et la fiabilité des structures soudées au laser. Pour atteindre cet objectif, les chercheurs adoptent une approche multidisciplinaire comprenant une analyse rigoureuse, des méthodologies d'inspection avancées, des investigations expérimentales et une surveillance de la porosité basée sur l'apprentissage automatique, dans le but ultime d'améliorer l'efficacité et la qualité des processus de soudage laser dans le cadre de la fabrication intelligente. Cependant, la littérature existante manque d'investigations approfondies sur la surveillance intelligente en temps réel des défauts dans le soudage laser de l'aluminium, ce qui constitue l'objectif principal de la présente étude.

2. PROBLÉMATIQUE

Le soudage intelligent, également connu sous le nom de Soudage au Laser 4.0, est une approche qui vise à mettre en place des processus de production plus efficaces, automatisés et interconnectés. Cependant, la complexité de certains de ces processus pose des défis dans la détection et la correction des défauts lors du soudage au laser. La surveillance en temps réel des défauts est cruciale dans le soudage au laser 4.0 pour améliorer la qualité du produit final et réduire les coûts de production. Le soudage au laser est un des procédés les plus couramment utilisés dans la fabrication de structures en aluminium. Ce procédé peut dans certaines conditions entraîner des défauts importants tels que la porosité et les distorsions (Figure 1). Dans le domaine de la technologie de soudage, comprendre la diversité des défauts susceptibles de compromettre l'intégrité des assemblages soudés est primordial. Comme illustré dans la Figure 1.b, cette étude examine minutieusement six défauts de soudage prévalents : Le manque de fusion se produit lorsque le métal de soudure échoue à s'amalgamer adéquatement avec le métal de base ou le cordon de soudure précédent, conduisant à des joints affaiblis. La porosité, caractérisée par la présence de poches de gaz ou de vides dans le métal de soudure, compromet la robustesse structurelle de la soudure. Le laitier, un sous-produit non métallique résultant du flux dans les processus de soudage, peut obscurcir les efforts d'inspection et, s'il n'est pas méticuleusement éliminé, affaiblir la soudure. La fissure au pied, une fracture à la jonction où le métal de soudure interfère avec le métal de base, émerge en raison de concentrations de contraintes élevées et d'une fusion insuffisante. La pénétration incomplète, un défaut où le métal de soudure ne traverse pas entièrement l'épaisseur de l'assemblage, résulte en une région non fusionnée, diminuant ainsi la résistance de la soudure. Enfin, une fissure à la racine, initiée au point de départ de la soudure, est souvent attribuable à des contraintes élevées et à une fusion ou pénétration inadéquate.



(a)



(b)

Figure 1. Possible defects in laser welding. a) Process monitoring b) Welded structure [10]

Pour relever ces défis, cette étude propose un cadre multidisciplinaire pour la surveillance en temps réel des défauts dans les structures en aluminium soudées au laser, qui représente un aspect critique du Soudage au Laser 4.0. Les résultats de la recherche démontrent la faisabilité de la surveillance en temps réel de la porosité lors du soudage au laser de l'aluminium en utilisant une approche basée sur l'apprentissage automatique [11]. Cependant, prédire avec précision les pores microscopiques et profonds reste un défi [12]. L'apprentissage automatique à l'aide d'algorithmes avancés peut contribuer à l'amélioration de l'efficacité et de la qualité du processus de soudage au laser. De plus, l'intégration d'une inspection automatisée en temps réel pour identifier et corriger rapidement les distorsions dans les assemblages soudés apporterait une contribution décisive dans l'amélioration de la qualité globale du produit final (Figure 2).

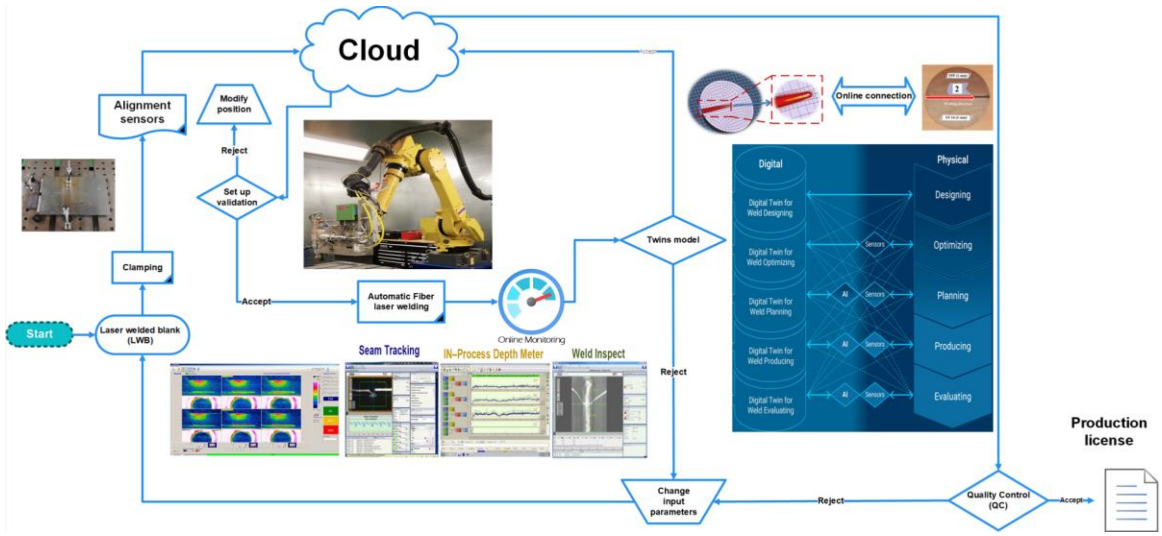


Figure 2. Cloud-based monitoring of laser welding defect [7]

Dans le cadre de cette recherche, une attention particulière est accordée à la surveillance basée sur le cloud des défauts de soudage au laser, en exploitant les techniques de vision par ordinateur et l'inspection automatique pour une analyse précise et en temps réel des anomalies. Cette approche innovante permet une collecte et un traitement décentralisés des données de soudage, offrant ainsi une plateforme flexible et scalable pour le monitoring des procédés de soudage au sein de l'Industrie 4.0. Grâce à l'utilisation de l'apprentissage automatique et des algorithmes de vision par ordinateur, la surveillance basée sur le cloud facilite l'identification automatique des défauts tels que la porosité, les fissures ou le manque de fusion, directement à partir des images capturées du bain de fusion et de la zone affectée thermiquement. Cette méthode de surveillance avancée s'intègre parfaitement dans les systèmes de fabrication intelligents, permettant non seulement une détection précoce et précise des défauts de soudure mais aussi une intervention corrective quasi-instantanée grâce à l'analyse des données recueillies en continu. En outre, l'inspection automatique via des techniques de vision par ordinateur réduit significativement le besoin d'inspections manuelles, accroissant l'efficacité du processus de contrôle qualité tout en minimisant les erreurs humaines. L'implémentation de cette surveillance en temps réel et basée sur le cloud représente une avancée majeure pour l'optimisation des paramètres de soudage, la garantie de la qualité des joints soudés, et l'amélioration de la productivité dans les environnements de production modernes. En somme, cette étude souligne l'importance de l'adoption des technologies de surveillance basées sur le cloud et de la vision par ordinateur comme composantes clés pour une stratégie efficace de surveillance et de contrôle des défauts de soudage au laser dans l'ère de l'Industrie 4.0. Dans le contexte du Soudage au Laser 4.0, plusieurs défis et aspects problématiques se posent:

(i) **Détection des défauts:** L'un des principaux défis est de détecter et d'identifier avec précision les défauts dans les structures en aluminium soudées au laser. Les défauts tels que la porosité et les distorsions peuvent affecter la qualité et les performances du produit final, et il est essentiel de développer des techniques de surveillance en temps réel et efficaces.

(ii) **Prédiction de la porosité:** Malgré les avancées dans la surveillance en temps réel de la porosité, prédire avec précision les pores microscopiques et profonds dans les structures en aluminium soudées au laser reste un défi majeur. Atteindre un niveau élevé de précision dans la prédiction de la porosité est crucial pour garantir l'intégrité des joints soudés.

(iii) **Paramètres de processus optimaux:** Déterminer les paramètres de processus optimaux pour le soudage au laser de l'aluminium pose un défi. Trouver la bonne combinaison de puissance laser, vitesse de soudage, forme du faisceau et autres paramètres peut influencer considérablement la qualité et la résistance des soudures.

(iv) **Distorsions de soudage:** Les distorsions induites par le soudage sont courantes dans le soudage au laser, en particulier dans les structures en aluminium. Gérer et réduire les distorsions pour maintenir la précision dimensionnelle et l'intégrité structurelle est une tâche difficile.

(v) **Optimisation du processus:** L'optimisation du processus de soudage au laser pour les structures en aluminium dans le contexte du Soudage au Laser 4.0 est un problème complexe. Atteindre le plus haut niveau d'efficacité, de qualité et de productivité tout en tenant compte de diverses contraintes telles que l'épaisseur du matériau, la conception de l'assemblage et les exigences de production nécessite des stratégies d'optimisation avancées et des algorithmes.

Aborder ces aspects problématiques est crucial pour faire progresser les capacités et la fiabilité du soudage au laser dans le contexte du Soudage au Laser 4.0 et atteindre des structures soudées de haute qualité dans l'industrie manufacturière.

3. OBJECTIFS

Le principal objectif de cette recherche est d'étudier l'utilisation de la technologie de soudage au laser pour la fabrication de structures en aluminium dans le contexte de l'industrie 4.0. Plus précisément, cette étude se concentre sur la surveillance en temps réel des défauts des structures soudées au laser en aluminium en tant que chaîne critique des systèmes de fabrication intelligents dans l'industrie 4.0. Les auteurs cherchent à examiner les facteurs critiques de la technologie de soudage au laser qui affectent la qualité et l'exactitude du produit final, ainsi que les approches de surveillance basées sur les capteurs (caméra et scanner à distance) pour assurer la qualité du produit final. De plus, cette recherche vise à proposer une approche novatrice d'inspection automatisée en temps réel pour détecter les distorsions dans les assemblages soudés. Les auteurs cherchent également à proposer une méthodologie expérimentale pour l'optimisation du processus de soudage pour les joints de recouvrement. Enfin, cette étude vise à proposer une approche de surveillance en temps réel de la porosité pour le soudage au laser de l'aluminium en utilisant l'apprentissage automatique. Les auteurs espèrent que cette recherche contribuera à améliorer l'efficacité et la qualité du processus de soudage, à réduire les coûts de production, à augmenter la cadence de fabrication et à réduire le temps de mise sur le marché dans l'industrie 4.0. Pour atteindre cet objectif, cinq objectifs spécifiques correspondant aux étapes du projet sont considérés. Plus précisément, il s’agit :

(i) Le premier objectif est de développer une approche intelligente pour l'usine de soudage des plaques d'aluminium (ALWBs) basée sur l'industrie 4.0. Cela implique une revue critique de la littérature sur les modèles intelligents existants et le développement d'un nouveau modèle intelligent pour améliorer l'efficacité et la qualité de la production. Un modèle intelligent, dans ce contexte, signifie un système qui non seulement apprend et s'adapte de manière autonome aux variations du processus de soudage pour prévenir les défauts, mais aussi optimise la qualité et l'efficacité de la production en fonction des données collectées, avec pour but ultime de minimiser les interventions manuelles et d'améliorer continuellement les opérations de production.

(ii) Le deuxième objectif est une analyse bibliométrique de l'intelligence artificielle et de la surveillance en temps réel de la technologie de soudage dans l'ère de l'industrie 4.0. Cette analyse permettra d'identifier les tendances et les développements dans le domaine de l'intelligence artificielle appliquée à la surveillance en temps réel de la technologie de soudage, ainsi que les défis et les opportunités actuelles et futures pour l'industrie. L'objectif est de saisir les progrès technologiques, les innovations méthodologiques, ainsi que les lacunes et les perspectives de recherche future dans le domaine, mettant en lumière les défis à surmonter et les opportunités d'amélioration de l'efficacité et de la qualité du soudage dans le contexte industriel actuel et futur.

(iii) L'objectif troisième consiste à effectuer une numérisation 3D en temps réel des plaques d'aluminium 5052-H32 soudées au laser, en mobilisant des technologies sophistiquées de capture d'images et de modélisation tridimensionnelle. Cette démarche emploie des scanners 3D de haute précision et des systèmes avancés de vision par ordinateur pour acquérir des données détaillées sur la géométrie de la soudure et les caractéristiques dynamiques du bain de fusion au cours du processus de soudage. Les données ainsi obtenues sont traitées à l'aide de logiciels dédiés pour créer un modèle tridimensionnel précis du cordon de soudure, offrant une analyse approfondie des distorsions thermiques et de la porosité. Cette méthodologie offre la possibilité d'ajuster les paramètres de soudage en direct, tels que la puissance laser, la vitesse de soudage et l'intensité de chaleur, afin d'affiner les conditions opérationnelles et de réduire les défauts. Ce processus vise à rehausser la qualité et la fiabilité des soudures, en assurant des assemblages de haute performance.

(iv) Le quatrième objectif englobe la conduite d'une étude exhaustive sur l'identification de la porosité dans les soudures d'aluminium à recouvrement, en s'appuyant sur une approche mixte d'expérimentation et d'analyse statistique. Les porosités sont mesurées grâce à des méthodes d'imagerie de pointe comme la radiographie X, permettant une visualisation précise et une quantification des défauts au sein de la soudure. L'analyse de ces images, réalisée à l'aide de logiciels spécialisés, facilite la détection, la mesure, et la classification des porosités selon leur taille, forme, et position. En complément, l'exploitation de techniques statistiques pour l'analyse des données recueillies aide à déceler les liens entre les conditions de soudage et l'apparition de porosités, identifiant ainsi les paramètres clés qui affectent la qualité de la soudure. Cette méthode intégrée enrichit la compréhension des processus de formation de porosité et soutient le développement de solutions pour réduire ces imperfections, optimisant ainsi la qualité des jonctions soudées.

(v) Enfin, le cinquième objectif de cette étude est axé sur l'élaboration d'un système de surveillance en temps réel de la porosité durant le processus de soudage au laser d'alliages d'aluminium, en exploitant l'apprentissage automatique qui analyse les caractéristiques morphologiques tridimensionnelles du trou de clé. Cette initiative vise à intégrer des méthodologies avancées pour la détection précise et instantanée des porosités, permettant ainsi une intervention immédiate et ciblée pour corriger les éventuelles imperfections. L'usage de l'apprentissage automatique pour analyser la morphologie en 3D du trou de clé ouvre des perspectives novatrices pour la surveillance et le contrôle de qualité en s'appuyant sur des données structurées issues du processus de soudage luimême. Ces objectifs contribuent ensemble à l'élaboration d'une stratégie intégrée visant à rehausser la qualité des soudures au laser pour les alliages d'aluminium, s'alignant ainsi avec les ambitions de l'industrie 4.0 pour une fabrication intelligente et optimisée.

4. MÉTHODOLOGY

La méthodologie de ce projet de recherche implique plusieurs étapes pour atteindre les objectifs spécifiques énoncés précédemment. Premièrement, une revue critique de la littérature sera effectuée pour identifier les meilleures pratiques et les approches récentes en matière de soudure au laser d'alliages d'aluminium. Cette revue permettra également d'identifier les lacunes dans la recherche actuelle et de proposer des solutions pour les combler. À la connaissance de l'auteur, il n'existe pas d'étude qui constitue une feuille de route complète pour l'utilisation d'un système de fabrication intelligent concernant le formage de flans soudés au laser en aluminium (ALWB) dans le concept de l'industrie 4.0 et qui propose un modèle efficace pour parvenir à une nouvelle solution à ce problème problématique. Dans ce domaine, le procédé ALWB est utilisé pour le formage à froid et permet d'alléger les pièces d'environ 15 à 20 % en fonction de leur conception. Étant donné que toutes les carrosseries en blanc semblent passer de l'acier à l'aluminium, l'utilisation des procédés ALWB présente un intérêt commercial majeur. En outre, le soudage laser autogène est utilisé en production chez Shiloh (le seul en Amérique du Nord) dans le cadre de sa ligne BlankLight®. L'entreprise utilise un système de soudage laser autogène bilatéral à diodes de 4 kW et a également mis au point une nouvelle technologie d'oscillation. Ils réalisent un joint bilatéral, car les contre-dépouilles dans les soudures unilatérales sont problématiques et ils soudent en mode conduction, ce qui lisse la surface. La prochaine étape pour les procédés ALWB est l'emboutissage à chaud, qui fait actuellement l'objet d'une attention particulière en ce qui concerne la qualification des soudures au laser dans l'emboutissage à chaud pour ce qui est de la formabilité et de l'effet des défauts sur la qualité.

Deuxièmement, une analyse bibliométrique sera réalisée pour étudier l'état de la recherche sur l'intelligence artificielle et la surveillance en temps réel de la technologie de soudage dans l'ère de l'industrie 4.0. Cette analyse permettra d'identifier les tendances actuelles dans la recherche sur l'application de l'intelligence artificielle et de la surveillance en temps réel pour améliorer la qualité de la soudure au laser. Cette étude apporte trois contributions principales. Tout d'abord, à la connaissance des auteurs, cette recherche est la première à étudier l'état d'évolution de la surveillance en temps réel de la technologie de soudage à l'aide d'une analyse bibliométrique. L'utilisation de cette dernière est importante, car il s'agit d'une analyse quantitative et objective qui permet d'éliminer les biais de l'examen systématique qui peuvent être induits par le jugement subjectif des chercheurs. Deuxièmement, cette recherche explore la structure des connaissances en étudiant les principaux auteurs, articles, revues, institutions et pays qui ont le plus influencé la surveillance en temps réel de la technologie du soudage. En outre, nous explorons la structure intellectuelle de la surveillance en temps réel de la technologie du soudage en effectuant une analyse de co-citation des auteurs et des revues. Enfin, nous évaluons la structure conceptuelle de la littérature sur la surveillance en temps réel de la technologie du soudage en explorant l'évolution thématique de ce concept et le réseau de cooccurrence des mots-clés des auteurs.

Troisièmement, des expériences de soudage au laser sur des échantillons d'alliages d'aluminium 5052-H32 seront menées. Les échantillons seront soumis à une numérisation 3D en temps réel pour caractériser la géométrie et les propriétés du cordon de soudure. L'objectif de cette étape est d'identifier les paramètres de soudage optimaux pour minimiser les distorsions thermiques et la porosité. L'analyse de la littérature confirme qu'aucun travail de recherche n'a proposé une inspection automatisée en temps réel des procédés LWB en aluminium par cartographie de nuages de points. Dans la présente étude, la distorsion des procédés LWB en alliage d'aluminium (5052-H32) est analysée à l'aide d'un balayage laser 3D afin d'exploiter les diagrammes de contribution à la distorsion pour analyser le retour élastique et les plis dans les processus de formage. Cette technique d'inspection en temps réel rejette automatiquement les pièces qui ont un effet négatif sur la conformité des pièces et la capacité de travail de la machine et de la chaîne de valeur dans l'industrie automobile. Ce faisant, non seulement les déchets de fabrication (défauts, surproduction, attente, non-utilisation, manutention, inventaire, mouvement, traitement excessif et temps de réglage) sont réduits, mais les temps préparatoires et auxiliaires sont également raccourcis et la correction du temps de réglage de l'outil, de réglage et d'assemblage en position d'exploitation sur la machine est maîtrisée.

Quatrièmement, l'étude se concentrera sur une analyse approfondie de la reconnaissance de la porosité dans les soudures au laser d'alliages d'aluminium, combinant des approches expérimentales et statistiques pour cerner les facteurs principaux contribuant à la porosité et élaborer des stratégies de mitigation. La mesure de la porosité s'effectuera par des techniques d'imagerie avancées, telles que la radiographie numérique, qui fourniront des visualisations détaillées permettant la quantification précise des défauts. En parallèle, une analyse statistique des données recueillies à partir de ces images permettra d'établir des liens entre les conditions spécifiques du processus de soudage et l'incidence de la porosité, offrant ainsi des perspectives pour ajuster les paramètres de soudage et améliorer la qualité des assemblages. L'objectif de l'étude était d'identifier les porosités et de déterminer les conditions appropriées. Les échantillons ont été fabriqués à partir d'un alliage d'aluminium AA6061-T6 dans une configuration de soudage par recouvrement, avec deux épaisseurs différentes (1,6 mm et 2 mm). L'alliage d'aluminium AA6061 est connu pour ses bonnes propriétés mécaniques, sa soudabilité et sa popularité pour un usage général. Ici, le processus de soudage au laser a été réalisé à l'aide de trois têtes laser différentes : 1) ScanLab remote, 2) Trumpf D70 et 3) Precitec YW52. Pour effectuer le soudage, un robot ABB à 6 axes, un dispositif laser à fibre (Precitec YW52), une table de travail pouvant fournir des champs magnétiques en changeant le courant et un équipement de gaz de protection à l'argon ont été utilisés. La forme du modèle d'oscillation linéaire avec une taille de spot nominale de 0,4 mm a été utilisée, et la tête de soudage compact YW52 a été utilisée pour toutes les machines laser à diode et à semi-conducteurs. Les pièces ont été polies et nettoyées avant le soudage pour garantir une qualité de surface constante. Les paramètres du processus de soudage au laser ont été choisis de manière à obtenir une porosité globale comprise entre 1 et 6 %. La source de soudage laser était une source Trumpf TruDisk de 10 kW, et la taille nominale du point était de 0,4 mm.

Enfin, la surveillance en temps réel de la porosité de la soudure sera réalisée en utilisant l'apprentissage automatique basé sur les caractéristiques de la morphologie 3D du trou de la clé. Cette méthode permettra une détection en temps réel de la porosité et une correction immédiate des paramètres de soudage pour améliorer la qualité de la soudure. L'analyse de la littérature indique qu'à la connaissance de l'auteur, il n'y a pas eu de recherche sur le développement d'un système automatisé de surveillance en temps réel pour le soudage au laser de l'aluminium par chevauchement qui incorpore des techniques de traitement d'images et d'apprentissage automatique pour l'analyse des caractéristiques des trous de serrure. La présente étude vise à combler cette lacune en proposant un système de surveillance de la porosité en cours de processus basé sur la classification pour le soudage au laser de l'aluminium. Le système de surveillance proposé fait appel à l'analyse par rayons X et à une caméra à grande vitesse pour prédire la probabilité de porosité en tant que fonction objective pour la classification. Cette technique d'inspection en temps réel peut automatiquement prendre des décisions sur l'estimation de la réussite ou de l'échec des pièces soudées, réduisant ainsi l'impact négatif sur la conformité des pièces et la capacité de travail de la machine et de la chaîne de valeur dans l'industrie automobile. La stratégie de traitement d'image implique la détection automatique des régions d'intérêt (ROI) par une caméra à grande vitesse (10,000 fps) et le logiciel ImageJ, qui est utilisé comme entrées pour définir des caractéristiques telles que la zone du trou de serrure et la caractérisation géométrique. En outre, la technologie des rayons X est utilisée pour valider et inspecter la reconnaissance de la porosité et la taille des défauts. Un modèle de classification Random Forest (RF) est formé pour détecter l'apparition de porosités lors du soudage laser en trou de serrure d'un alliage d'aluminium 6061. Cela démontre que le système de surveillance basé sur la radiofréquence peut prédire avec précision l'apparition de porosités. Enfin, un modèle intelligent basé sur l'apprentissage automatique est proposé, qui incorpore la fabrication intégrée par ordinateur (CIM) et l'intelligence artificielle (IA) pour une adaptabilité basée sur les données tout au long du cycle de production, de la conception du produit à la programmation, au contrôle et à l'optimisation du processus jusqu'à l'assurance de la qualité du produit.

5. ORGANISATION DE LA THESIS

La thèse présente une introduction générale suivie de 5 chapitres et d'une conclusion générale :

La première partie de la thèse s'ouvrira sur une introduction présentant le contexte général de l'étude. Cette section commencera par évoquer les problématiques liées à la soudure au laser des alliages d'aluminium, notamment les distorsions thermiques et la porosité qui peuvent altérer la qualité du cordon de soudure. Ensuite, les objectifs de la recherche seront exposés de manière détaillée, en précisant les cinq objectifs spécifiques correspondant aux différentes étapes du projet. Enfin, le plan de la thèse sera présenté pour donner une vue d'ensemble des aspects qu'elle aborde. Cette section aidera les lecteurs à se familiariser avec l'organisation globale de la thèse et à comprendre comment les différents chapitres s'articulent pour atteindre les objectifs de recherche.

Le chapitre 1 explore le soudage au laser des alliages d'aluminium, ses avantages et défis comme la porosité et les distorsions thermiques. Il introduit l'impact de l'Industrie 4.0, marquée par l'intégration de l'IoT, de la communication M2M, et de l'IA, dans l'amélioration des processus de fabrication. La contribution de l'IA, à travers l'apprentissage automatique pour l'analyse et la surveillance en temps réel des soudures, est soulignée comme un levier clé pour accroître la qualité des soudures et optimiser la production.

Le chapitre 2 réalise une analyse bibliométrique sur l'insertion de l'intelligence artificielle (IA) et de la surveillance en temps réel dans le soudage sous l'angle de l'Industrie 4.0. Cette analyse dévoile l'évolution des recherches, les innovations marquantes, et les défis à relever avec l'intégration de l'IA pour améliorer la détection des défauts et optimiser les paramètres de soudage. Le chapitre souligne l'apport des technologies de l'Industrie 4.0 pour une adaptation rapide aux variations du soudage, minimisant les défauts comme la porosité.

Il envisage également l'avenir de l'IA dans le soudage, notamment pour le développement de systèmes de surveillance autonomes capables d'apprentissage adaptatif.

Le chapitre 3 explore l'utilisation de la numérisation 3D en temps réel pour examiner les déformations des flans soudés au laser en aluminium 5052-H32 durant un formage automatisé. Cette méthode innovante d'inspection en temps réel est conçue pour améliorer la qualité du produit, réduire le temps de production, et diminuer les coûts. Les découvertes du modèle proposé révèlent un avantage significatif pour l'évaluation de la sensibilité à la fissuration dans les structures soudées en réduisant les distorsions nocives. Ce processus aide à prévenir le traitement des composants défectueux, surtout aux étapes clés de production, en offrant des avancées notables pour l'amélioration de la qualité et de l'efficacité des procédés de fabrication.

Le chapitre 4 examine la reconnaissance de la porosité dans le soudage laser d'alliages d'aluminium avec une méthode expérimentale et statistique, mettant en lumière les défis de la porosité interne malgré les avantages du soudage laser comme la précision et la rapidité. En analysant différentes configurations d'alliages d'aluminium et en appliquant la technologie des rayons X pour la détection de la porosité, ainsi qu'une analyse de la caractérisation du faisceau laser, l'étude révèle que les dimensions inappropriées du spot laser et les vitesses de déplacement influencent majoritairement la porosité, avec des risques de fissuration à chaud pour les spots trop grands. Cette recherche contribue à l'optimisation des paramètres de soudage pour améliorer la qualité des joints dans l'industrie automobile et des transports.

Le chapitre 5 présente l'application de l'apprentissage automatique pour surveiller la porosité en temps réel dans le soudage laser de l'aluminium, se concentrant sur l'analyse de la morphologie 3D du trou de serrure. Utilisant des caméras haute vitesse et un modèle Random Forest, cette méthode ajuste les paramètres de soudage pour minimiser la porosité, essentielle pour la qualité et la fiabilité des assemblages, spécialement dans l'automobile. Testée sur des alliages d'aluminium AA 6061-T6, elle démontre l'efficacité de l'apprentissage automatique pour prévoir et réduire la porosité, promettant moins de déchets et une meilleure qualité de production.

La conclusion souligne les progrès de la surveillance en temps réel de la porosité dans le soudage laser de l'aluminium grâce à l'apprentissage automatique et l'analyse morphologique 3D. Elle met en évidence l'amélioration de la qualité des soudures et la réduction des défauts, en particulier pour l'industrie automobile. Bien que des avancées significatives aient été réalisées, des défis demeurent, ouvrant des voies pour des recherches futures visant à affiner la méthodologie et à élargir les capacités prédictives, alignant ainsi le contrôle de qualité du soudage au laser avec les exigences de l'Industrie 4.0.

CHAPITRE 1
VERS UNE USINE INTELLIGENTE DE FLANS SOUDÉS AU LASER EN ALUMINIUM (ALWB) BASÉE SUR L'INDUSTRIE 4.0 ; EXAMEN CRITIQUE ET NOUVEAU MODÈLE INTELLIGENT

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Cet article a été publié dans The International Journal Optics and Laser Technology, Vol. 167, p. 109661. https://doi.org/10.1016/j.optlastec.2023.109661

1.1 RÉSUMÉ PREMIER ARTICLE

L'objectif de cet article de synthèse est de mener une enquête approfondie sur le soudage au laser et le processus de formage en tant que deux éléments essentiels de la fabrication intelligente et des systèmes intelligents de soudage dans l'industrie 4.0, en particulier pour le formage des flans soudés au laser en aluminium (ALWB). Dans l'ère moderne, les entreprises de fabrication et leurs modèles d'affaires ont un impact majeur sur le développement économique et les relations sociales. Depuis que l'industrie 4.0 est devenue un terme communément accepté par les centres de recherche et les universités, les entreprises

et les chercheurs sont intéressés par cette initiative. D'autre part, l'aluminium s'est révélé plus difficile à souder que les autres métaux, en raison notamment de sa tendance à former des porosités. À cet égard, la surveillance au moyen d'approches basées sur des capteurs (Tableau 4) qui centralisent les informations en temps réel gagne du terrain. En outre, cela permet de garantir la précision et la qualité du produit final. En fait, plusieurs facteurs critiques tels que la puissance du laser, la vitesse du laser, le point focal, le balayage du laser et la fréquence jouent un rôle clé dans la technologie laser, et il est important de les contrôler pour parvenir à un système de fabrication zéro défaut. D'autre part, la robustesse, prenant en compte les défauts géométriques tels que le volume et l'angle de sous-remplissage à la pointe, ainsi que le niveau acceptable de défauts de porosité dans la soudure en lien avec la formabilité, constitue les paramètres critiques du processus de formage. Cet article présente une revue complète de la fonction des différents capteurs en fonction des signaux provenant du processus de soudage et de formage. Enfin, un nouveau modèle a été proposé comme feuille de route pour l'application de l'idée de l'industrie 4.0 dans le formage des flans soudés au laser en aluminium (ALWB).

1.2 TITRE DU PREMIER ARTICLE

Toward an intelligent Aluminum Laser welded blanks (ALWBs) factory based on industry 4.0; A critical review and novel smart model

1.3 CONTRIBUTIONS

Les contributions scientifiques concrètes, explicites et détaillées de l'auteur de la thèse, Ahmad Aminzadeh, liées à la recherche sur la fabrication intelligente de blanks soudés au laser en aluminium (ALWBs) basée sur l'Industrie 4.0, peuvent être synthétisées comme suit :

Développement de la méthodologie de surveillance en temps réel : Ahmad Aminzadeh a joué un rôle central dans la définition et la mise au point d'une méthodologie innovante pour la surveillance en temps réel du processus de soudage au laser. Cette méthodologie intègre l'utilisation de l'intelligence artificielle pour analyser les caractéristiques morphologiques 3D du trou de serrure et identifier les défauts de porosité, un aspect crucial pour garantir la qualité des soudures dans les applications industrielles.

Recherche et expérimentation : L'auteur a conduit des recherches approfondies et réalisé des expérimentations pour valider l'efficacité de la méthode de surveillance proposée. Cela inclut la collecte et l'analyse de données à partir de séquences d'imagerie optique et de morphologie 3D, ainsi que l'application de techniques d'apprentissage automatique pour développer un modèle prédictif capable d'identifier la porosité en temps réel.

Création de contenus visuels (Tableaux, Figures) : Ahmad Aminzadeh a également été responsable de la création de tous les supports visuels nécessaires pour illustrer les résultats de la recherche, y compris des tableaux récapitulatifs et des figures explicatives qui démontrent l'efficacité de la surveillance en temps réel dans l'amélioration de la qualité du soudage.

Collaboration et révision : Bien que l'article ait bénéficié des conseils et de la révision des coauteurs et des experts du Centre National de Recherche du Canada (CNRC), la contribution principale en termes de recherche, de développement de la méthodologie et de rédaction de l'article incombe à Ahmad Aminzadeh. Sa collaboration avec Joys Silva Rivera, Pedram Farhadipour, Anas Ghazi Jerniti, Noureddine Barka, Abderrazak El Ouafi, Fatemeh Mirakhorli, François Nadeau, et Marc-Olivier Gagné a enrichi le travail, mais c'est Ahmad Aminzadeh qui a défini la trajectoire de la recherche et a apporté les contributions techniques essentielles.

En somme, les contributions d'Ahmad Aminzadeh à cette recherche s'étendent de la conceptualisation de la méthodologie à la conduite des expériences, en passant par l'analyse des données et la production du matériel visuel, démontrant un engagement profond dans le développement d'approches innovantes pour la surveillance en temps réel dans l'industrie du soudage au laser.

1.4 ABSTRACT

The aim of this review paper is a comprehensive investigation of laser welding and forming process as two critical parts of smart manufacturing and welding intelligent systems in industry 4.0, especially for forming of Aluminum Laser Welded Blanks (ALWB). In the modern era, manufacturing companies and their business models have a major impact on economic development and social relationships. Since industry 4.0 has become a commonly accepted term for research centers and universities, both businesses and researchers are interested in the initiative. On the other side, aluminum has proven more challenging to weld than the other metals accounting for the most part to its tendency to form porosity. In this regard, monitoring using sensor-based approaches that centralize the information in real-time is gaining ground. In addition, this ensures the accuracy and quality of the final product. In fact, there are several critical factors such as laser power, laser speed, focal point, laser scanning and frequency that play a key role in laser technology which is important to control them toward the zero-defect manufacturing system. On the other hand, robustness accounting for geometrical defects (ex. underfill amount / angle at toe as well as the amount of admissible porosity defects in the weld in relation with formability) are the critical parameters in forming process. Here, a comprehensive review paper is conducted insight into the function of different sensors (Table 4) to signals from the welding and forming process. Finally, a novel model has been proposed as a roadmap for applying the idea of Industry 4.0 in forming of Aluminum Laser Welded Blanks (ALWB).

Key words**:** *Industry 4.0, Smart manufacturing, Real time monitoring, Aluminum Laser Welded Blanks (ALWB), Sheet metal forming.*

1.5 NOMENCLATURE

AI	Artificial intelligence
IOT	Internet of things
AR	Augmented reality
M2M	Human machine interface
ICT	Information and Communications Technology
CNNs	Convolutional neural networks
RNNs	Recurrent Neural Networks
LSTMs	Long Short-term Memory
RF	Random Forests
GBMs	Gradient boosting machines
KNN	K-Nearest Neighbors
RLs	Reinforcement learning
SMF	Sheet Metal Forming
IWS	Intelligent Welding Systems
LDD	Laser Depth Dynamics
OCT	Optical Coherence Spectroscopy
NRC	National research council of Canada

ZDM	Zero-Defect Manufacturing
HRI	Human-Robot Interaction
FSW	Friction Stir Welding

1.6 INTRODUCTION

Nowadays, the digital communications, artificial intelligence (AI), internet of things (IOT), automated robots, sensors, augmented reality (AR), human machine interface (M2M), big data, and a slew of other game-changing technologies are widely expected to shape the global industrial environment in the modern world. Industry 4.0, or the fourth industrial revolution, provides a critical and valuable opportunity to accelerate social and technical progress [13]. Using advanced ICT (Information and Communications Technology) and the internet for the manufacturing of high-quality industrial products, industrial companies can collect, analyze, and process data. This revolution is having an enormous influence on today's existing production processes and the economy. Although the third industrial revolution is still continuing a cluster of radical innovations in communication and energy technologies merged into a new economic era was the first trigger less than a century later [14]. Here, as a comprehensive investigation of the fourth industrial revolution which is made a huge breakthrough in the centralized production systems. A decentralized energy production network is challenged by a decentralized system which engages hundreds of millions of people to generate their own green energy at home, at work, and even at factories and to share information online [15]. Figure 3 depicts the gradual revolution over the last few decades.

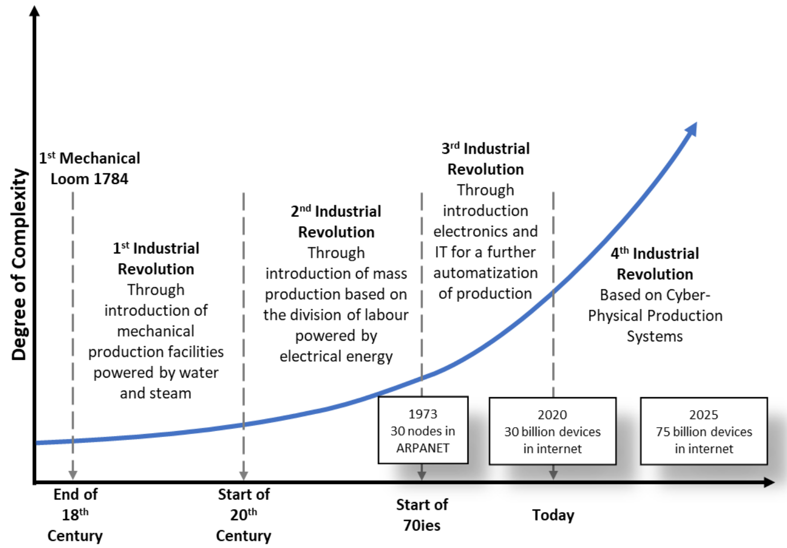

Figure 3. Trend of industrial revolution and connected devices to Internet

More precisely, the combination of Artificial Intelligence (AI), and Industry 4.0 is an exciting field of research and intellectual science that allows humans to find numerous innovative ways to model how humans reason and feel as they go about their activities [16–20]. On the other hand, industries are concentrating their efforts on the evolution of intelligent products, as well as the impact on potential customers. Therefore, it is critical that organizations understand what Industry 4.0 is and how it functions so that they can be prepared for potential shifts from machine-dominated manufacturing to digital manufacturing, which is now being researched by scholars and academic institutions. Now, a technological transfer is being made toward manufacturing companies that already start to use data centralization systems (ex. Scada/Ignition) and leverage machine learning embedded in data collection [21]. A major part of the AI method is symbolic learning and machine learning. Based on logical theories of computer science, symbolic learning is a precursor to smart systems. Compared to deep learning, which uses complex data and a variety of input factors, deep learning is the pinnacle of AI methods.

To design parameter distributions and determine the parameters one needs, convolutional neural networks (CNNs) [22], recurrent neural networks (RNNs) [23], long-short-term memory (LSTMs) [24], Random Forests (RF) [25], gradient boosting machines

(GBMs) [26], K-Nearest Neighbors [27] and reinforcement learning (RLs) [28] are the most effective strategies. A broad spectrum of artificial intelligence techniques is employed in manufacturing science, such as artificial neural networks, fuzzy logic systems, genetic algorithms, particle swarm optimization, colony optimization, simulated annealing, and evolutionary computing [29]. In the scope of ALWB manufacturing, several options are available based on the priority of production, limitation, and customer service. There are many factors that can impact the sheet metal forming (SMF), such as die deformation, tooling temperatures, material scatter, lubrication levels, and sheet properties. As a result of these variations, it is difficult to guarantee quality in the manufacturing process, despite the fact that a number of novel concepts have been developed to monitor and control the process. Control systems are one means of achieving control in manufacturing. The control system is composed of three basic components: a sensor that collects data (generally related to product properties), a predictive model that predicts the future state of the production system with the input of the current state, and a controller that proposes necessary changes to the production system (usually an input to the actuation mechanism) to make the product properties closer to the specifications desired. In order to achieve desired product specifications, sensors collect and analyze data. Controllers determine the necessary changes in production systems based on prediction models. After changing, the sensor will measure the effect again and the process will be repeated. Monitoring systems react to changing conditions (sensitivity, flexibility) as well as the robustness of the prediction mechanism (fidelity, timeframes, prediction models, knowledge management and reuse). Knowledge of how systems behave under various conditions is necessary to build a reliable prediction model. Through numerical SMF simulations, we can gain insight into how systems behave. Real-world data demonstrate the reliability of simulation models, so it is advisable to incorporate production data within models. As for unit connectivity, these technologies also bring about more robust, agile and consistent manufacturing systems with intelligent capabilities by linking IoT, M2M and CPS. The new manufacturing facilities require a philosophical change in setting up, leading to new concepts such as intelligence, products, communication, and information networks [30]. In summary, pioneer studies of the industry 4.0 method in aluminum alloys application and objective function are reviewed in Table 1.

Table 1. Research on the industrial 4.0 method and its objective function

Title	Input parameters	Objective function	Method	Reference
Green Activity-Based Costing Production Planning and Scenario Analysis for the Aluminum-Alloy Wheel Industry under Industry 4.0	Five possible scenarios: normal and material cost fluctuation, material cost discount, and carbon tax with the related cost function	the cost problem under Industry 4.0 and to be able to handle the environmental issues in making production decisions.	Numerical investigation	[31]
A Critical Review on the Trends Toward Effective Online Monitoring of Defects in Friction Stir Welding of Aluminum Alloys	A single sensor approach and the multisensory approach.	the use of multiple sensors has been demonstrated to give hope towards the development of robust detection of defects that will be able to cope with variations in material thickness and type of materials.	Critical Review	[32]
Sustainable manufacturing of ultra-fine aluminum alloy 6101 wires using controlled high levels of mechanical strain and finite	The manufacturing process of wires at SPD was controlled and monitored using additive manufacturing (AM) and	How the combination of smart manufacturing and simulations control represents the key to renew the traditional	Experimental study and numerical prediction	[33]

element modeling	numerical simulation.	manufacturing methods in the perspective of the industry 4.0		
Haptic-based touch detection for collaborative robots in welding applications	A robot is performing a multi-pass GTAW welding task, utilizing the 3-Sigma rule and the Hampel identifier, focusing on the keyhole area, intensity, and the plasma's electron temperature	Statistical analysis is conducted on the load-cell signals, employing a light and low-cost real-time algorithm for "touch" detection, complemented by porosity monitoring.	TCP/IP communication protocol for remote connection	[34]
SMEs can touch Industry 4.0 in the Smart Learning Factory	Physical and virtual simulation	Learning factory design and layout	Virtual simulation and Digital twin	[35]
A convolutional approach to quality monitoring for laser manufacturing	A raw Medium Wavelength Infrared coaxial images	Dilution estimation in Laser Metal Deposition, and location of defects in laser welding processes.	ConvLBM	[36]
A CPS platform oriented for Quality Assessment in welding	IR cameras and Imaging	Decision Support on the welding (Laser, resistance spot welding) process parameters.	Cyber-Physical System (CPS) and Quality Assessment (QA)	[37]
A three-stage quality diagnosis platform for laser-based	Image data collection from the weld pool to the module in which a statistical and	Weld defect detection and quality prediction.	Stage Quality Assessment (3SQA) method. Hidden Markov models. Cyber-	[38]

manufacturing processes	geometrical method is used		Physical Systems (CPS)	

1.6.1 Laser technology in intelligent industries and smart manufacturing

Laser material processing is one of the main subjects that support the reduction of wasted energy and materials, and it being as Green New Deals [39]. For this reason, it is one of the most important subjects for manufacturing researchers. Nowadays, welding processes and systems play an important role in modern industrial production lines and manufacturing processes, especially in laser welded blanks. Due to the fact that laser welding is a precise and very fast welding technique that can provide widespread applications in the industrial welding systems [40]. However, laser welding is a complex process that is often hard to optimize and perform the quality control and defect analysis. Recent research has demonstrated cognitive laser welding systems that perform well on a defined workpiece after setup to address control issues [41,42]. After decades of evolution, many hand-welding operations have been replaced by automated welding systems using industrial robots [43]. A number of parameters are involved in today's welding processes, and the mechanism of the process is not well understood. Also, customers and users have diverse welding requirements and the workplace is dynamic. In order to manage the changing nature of welding tasks while maintaining high quality, welding methods are moving towards more personalized production methods which utilize next-generation welding systems. Welding information should also be collected and shared smartly in the era of big data, both to improve operations internally and as a component of comprehensive life-cycle evaluations in industrial supply chains [44]. Largely, Laser Welded Blanks are made by joining individual sheets of different thicknesses, strengths, and coatings by means of laser welding [45,46]. Manufacturing in this manner enables flexible designs and ensures the correct materials are applied at the right places. In highly stressed areas, thicker or stronger materials can be used while thinner sheets and deep drawing grades can be utilized in other areas. Only the most expensive materials should be used in a highly stressed area. Cost reduction, weight reduction, and increased strength are among the benefits of this targeted approach. LWBs manufacturers drove the need to qualify the part at the source and eliminate costly post-qualification. This is one of the major drives for LWBs 4.0. Regarding the laser 4.0, this study is a trigger for making a clear route map to define intelligent laser welding and platforms for upgrading welding systems into higher levels of intelligence. Also, an automatic forming process is considered as forming operation to product a final part which is used in automobile structure. Finally, a license is defined for part each part which is passed all criteria of manufacturing. Table 2 summarizes the previous reviews on intelligent welding systems (IWS), which discussed several domains of IWS.

Table 2. Previous reviews on intelligent welding systems (IWS)

Application/scope	Objective	Reference
Literature review on the implications of Industry 4.0 for the plastics industry	Research trends and knowledge in Industry 4.0 using bibliometric analysis.	[47]
A state-of-the-art review and perspective on intelligent welding systems	A fundamental analysis of the components and methods required to make welding systems intelligent is presented in the paper, including sensing and signal processing, feature extraction and selection, modeling, decision-making, and learning. In addition, emerging technologies such as Industry 4.0, cyber-physical systems (CPS), digital twins, etc., and their application potential to IWS is discussed.	[43]
An overview of Industry 4.0 literature and related technologies	Interoperability, virtualization, local real-time talent, service orientation, modularity, and virtualization are six design principles.	[48]
Additive Manufacturing (AM) and Industry 4.0: A Relationship Analysis	Throughout this paper, the direct and indirect elements of Industry 4.0 are discussed in relation to additive manufacturing. The advantages of digital threat for AM are discussed as well as its impact on smart manufacturing.	[49]
A systematic review of the literature on sustainable industry 4.0: Current	How can Industry 4.0 be studied through different research approaches? Where does	[50]

trends and future perspectives	research stand in the areas of Industry 4.0 at the moment?	
The future of friction stir welding and a roadmap to Industry 4.0: A review of sensor-based monitoring and control	Industry 4.0 has been proposed as a roadmap for implementation in FSW.	[51]
An overview of Intelligent Manufacturing and Industry 4.0	The European Union, United States, Japan, and China all have strategic plans for intelligent manufacturing, as well as the United States government strategic plans. In addition, this paper outlines current challenges and future directions for research.	[52]
Review of Intelligent Manufacturing Systems	It describes recent advances in intelligent scheduling, process optimization, control, and maintenance. There is also a presentation of the concepts, requirements, applications, and methodologies used for each aspect.	[53]
The Role of Humans and Industrial Robots in a Smart Factory: Trends in Smart Manufacturing	The authors present an overview of humans and robots in smart factories, their relationship to Industry 4.0, and what progress they've made in terms of related technologies.	[54]

Laser welding has benefits like higher productivity values, deep welding penetration, high welding speeds values, adaptability, high power density these characteristics give better process results compared with other welding processes [55]. Thanks to its automation potential it is possible to implement controlled systems integrating artificial Intelligence, data science and machine learning that help to optimize each step of the process, predict, and control the parameters to operate the equipment to assure the best Quality/Cost/Delay balance for the product. Effective real-time monitoring technologies are essential for improving welding efficiency and ensuring joint product quality. For those reasons, applications in industries such as automotive, aerospace, shipbuilding, railways, and electronics have grown significantly [56–59]. Many established sectors, as well as newly emerging, fast-growing markets, use fiber lasers for advanced, high-volume welding applications. Fiber lasers' ability to produce large arrays of precise and consistent welds rapidly and accurately is a driving factor in the burgeoning e-mobility industry. It is well known that switching to lasers has many advantages in other established industries. The migration to modern industrial laser technology for metal joining is being driven by increased yields, design flexibility, and energy efficiency. An intelligent manufacturing process requires high-quality data collection online. In order to enable automated and decentralized decision-making, laser welding processes increasingly require technologies that can serve as the 'eyes and ears'. The different types of laser machines are listed as following table 3. Based on the characteristic's comparisons between major high-power industrial, fiber laser is more reliable (30%) not only in terms on quality but also for automation tasks.

Table 3. Characteristics comparisons between major high-power industrial lasers (Industrial Laser Solutions, 2005).

Characterization	**Fiber Laser**	**Nd:YAG**	**CO_2**	**Disc**	**Reference**
Wall Plug Efficiency	30%	5%	10%	25%	[60] [55]
Wavelength	1.07 µm	1.06 µm	10.6 µm	1.03 µm	[55]
Output Powers	to 100 kW	to 7 kW	to 15 kW	to 16 kW	[55]
BPP (4/5kW)	< 2.5	25	6	8	[61,62]
Diode Life times	100,000 h	10.000 h	N.A.	10,000 h	[63]
Cooling	Air/Water	Deionized	Water	Water	[63] [54]
Floor Space (4/5kW)	< 1 m^2	6 m^2	3 m^2	> 4 m^2	[61]
Operating Cost/hour	$21.31	$38.33	$24.27	$35.43	[64]
Maintenance	Not Required	Often	Required	Often	[63][62][54]

This review paper, which is divided into sections as shown in Figure 4, provides a handy library of Industry 4.0 to both academics as well as industrial practitioners. A comprehensive investigation is conducted in this study to bridge the gap between ALWB and tuning an intelligent model for TWB 4.0. To address the significant control challenges that prevent aluminum laser welding from reaching its full potential in process engineering and production, it is the objective of this study to investigate various welding features and defects and propose a machine intelligence architecture. Also, an intelligent model is proposed to define a valid part in terms of manufacturing criteria.

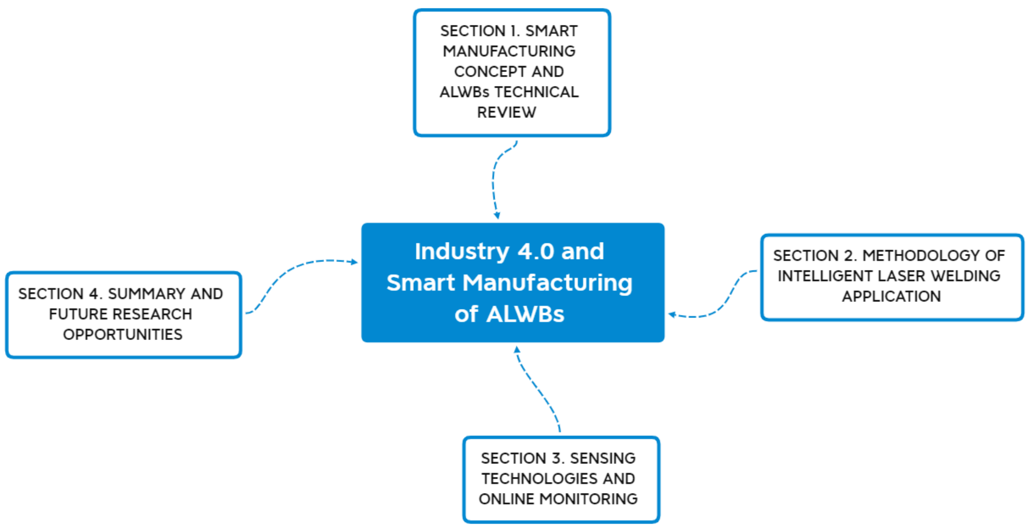

Figure 4. Scope and structure of the review

To the best of the author's knowledge, there is no study, which is a comprehensive road map in using an intelligent manufacturing system regarding forming of Aluminum Laser Welded Blanks (ALWB) in concept of industry 4.0 and proposed an efficient model to achieve a novel solution for this problematic problem. Working on this field, ALWB are used in cold forming and provides a lightweight around 15-20% depending on designs. As all body-in-white appears to shift from steel to aluminum, there is a major business case using ALWBs. Moreover, Autogenous laser welding is used in production at Shiloh (only one in North America) under their BlankLight® line. They use a two-sided 4kW autogenous laser welding diode system and developed a new wobbling technology as well. They do a two-sided joint as undercuts in one-sided weld are problematic and they weld in conduction mode which smoothen the surface. The next step for ALWBs is warm/hot stamping which is currently attention by qualification of laser welds in warm/hot stamping for formability and the effect of defect on quality.

1.7 METHODOLOGY

Aluminum laser welding is a challenging process in laser welding, mainly because of the fundamental problem of the low welding reliability of aluminum alloys in comparison with other industrial metals like steel. The namely reason is their physical properties notably the high thermal conductivity, high reflectivity and low viscosity [65] . Alloys of aluminum can be divided into two main categories: non-heat-treatable alloys and heat-treatable alloys. Alloying elements such as silicon, iron, manganese, and magnesium produce hardening effects that are primarily responsible for the initial strength of non-heat-treatable alloys. Alloys that cannot be heat treated are found primarily in the 1xxx, 3xxx, 4xxx, and 5xxx series. Alternatively, heat-treatable alloys are found most commonly in alloys 2xxx, 6xxx, and 7xxx. There are between 4 and 8 % zinc in the 7xxx series alloys, and between 1 and 3 % magnesium [66]. Both have high solid solubility in aluminum. Aluminum is one of the lightest engineering metals, having strength to weight ratio superior to steel. However, there are seven major types of weld defects in laser welding of aluminum: porosity [67], cracking [68], inclusions [69], lack of penetration or fusion [60], weld oxidation[70], loss of alloying elements [71]. Based on our investigation [55,72,73], the main process parameter such as laser power, power density, welding speed, type and shielding gas flow, beam shape on workpiece and the position of focal beam plane are shown in Ishikawa's diagram (Figure 5). Some of these variables have a greater impact on the laser welding process also easier to control and predict. The effects of speed and power have been studied in several articles and results indicate significant effects, although it’s far more possible to be controlled by artificial intelligence; in comparison with other parameters [74,75].

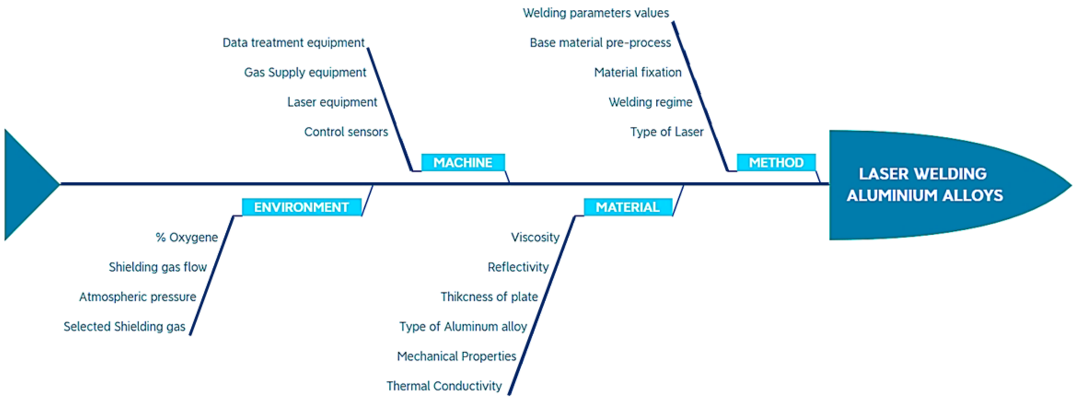

Figure 5. Classification of laser process parameters

To solve the catastrophic problems in aluminum laser welding, some literatures have been offered [76–78] real-time monitoring on intelligent techniques. In order to improve welding efficiency and guarantee joint quality, it is crucial to use real-time monitoring technologies. The findings and progress of research in the ten years prior to this study are critically reviewed, as is the state of the art for real-time monitoring of laser welding. Figure 6 is illustrated, schematic representation of Laser welding 4.0 process adding the main parameters that should be controlled to improve the quality of laser welding for aluminum alloys.

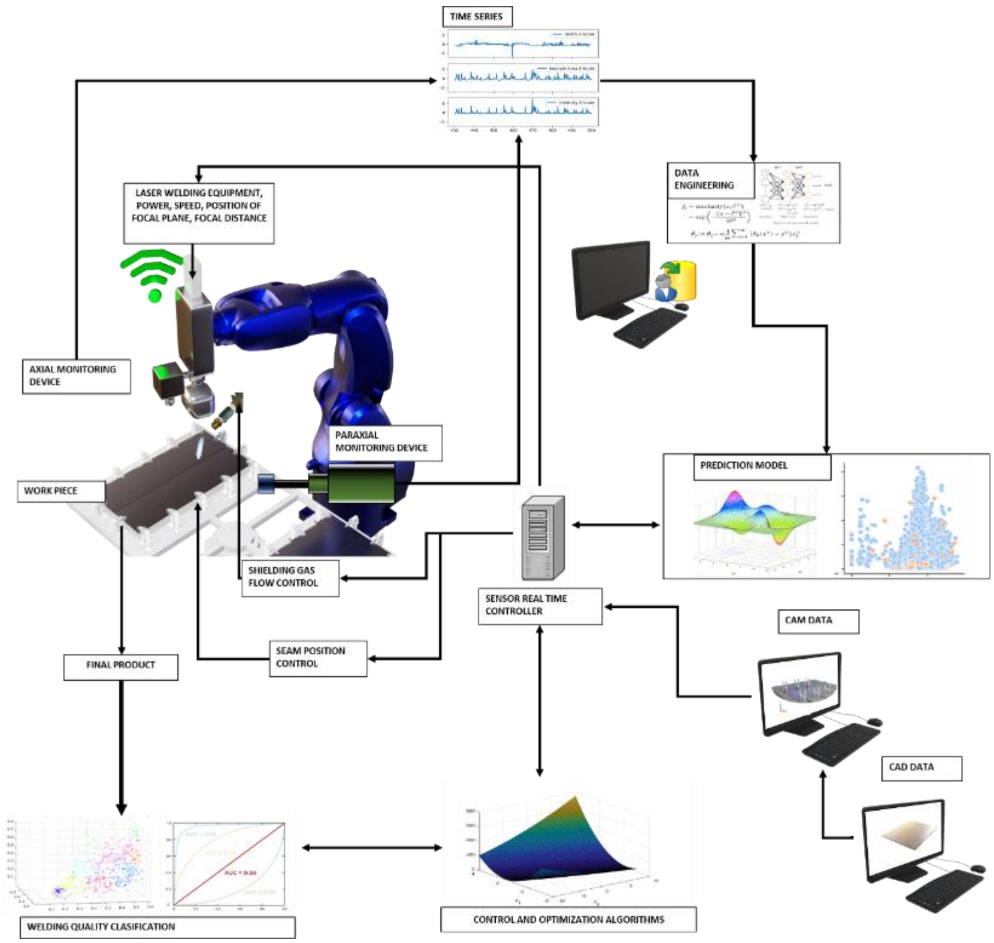

Figure 6. Schematic representation of intelligent Aluminum alloys Laser welding monitoring proposed based on industry 4.0 strategy

1.8 DISCUSSION

1.8.1 Real-time monitoring of laser welding

In terms of time, material losses, and productivity restrictions, off-line monitoring and welding characterization has traditionally been inefficient and costly. In order to efficiently regulate welding parameters, equipment responsiveness, and process quality requirements, real-time monitoring systems have been proposed and developed in this domain. As a result, a variety of real-time weld monitoring technologies have been developed to provide real-time data for welding process control [73]. In particular, high speed camera imaging [79], online x-ray [80], acoustic emission [81], audible sound[82], infrared detectors [83], ultraviolet detectors [84], Optical Coherence Tomography (OCT) systems [85], electromagnetic acoustic transducers [86], and so on can be mentioned. Proper parameters connected to the process itself, such as plasma, metal plume, spatters, seam geometry, keyhole, molten pool, laser back-reflection, and penetration hole, provide data from which signals such as optical, thermal, and acoustic can be obtained. The information provided allows welding settings for aluminum to be controlled based on key features such as strong reflectivity, high heat conductivity, and vapor plume particular chemical components released by the material [65,87]. A relatively new entrant to the sensor field, Laser Depth Dynamics (LDD). By doing so, real-time laser welding data collection finally solves a variety of long-standing challenges. Using this new method, a low-power infrared beam is used to measure distances more precisely than a welding laser. As a result of the measurement beam working during the process, the bottom of the vapor channel can be seen and directly measured. Basically, the Laser Depth Dynamics (LDD) from IPG as well as the IDM from Precitec systems that can control the depth of penetration. Concerning the experimental analysis, LDD system is used, and it works quite well in steel but in aluminum there are still challenges with the algorithms and it don't work with wobbling laser variants. The method used by these systems is based on OCT (Optical Coherence Spectroscopy). Moreover, the OCT-based systems were developed to control the penetration depth. The laser power is adjusted in real-time at very high frequency to modify the laser power achieving an equal depth of penetration. Also track the geometry just before the weld or after the weld for quality inspection, but it is purely geometric, not internal defects. This method cannot work actually on wobbling laser variants which are proved very effective in autogenous laser welding of aluminum to stabilize the keyhole, thus reducing porosity [88]. As much information is stored in the results as in a section along the entire weld. However, the information is available within milliseconds instead of having to destroy the part. A second advantage of the method is its versatility. By pointing the measurement beam ahead of the weld site, the amount of material feeding in can be measured. To check the surface quality of the final weld, it can also be pointed behind the melt pool. The part can even be scanned to create a 3D image, providing unprecedented precision and ease of setup. Different data types can be collected quasi-simultaneously by switching between measurements. Through one measurement system, controlled by one software package, it is possible to extract five different measurement modes comprising more than 20 different metrics from the welding process simultaneously. In figure 7, the main parameters that can be measured in the laser welding process are shown. Those parameters are related to welding conditions and help to predict and control the final product quality [89,90].

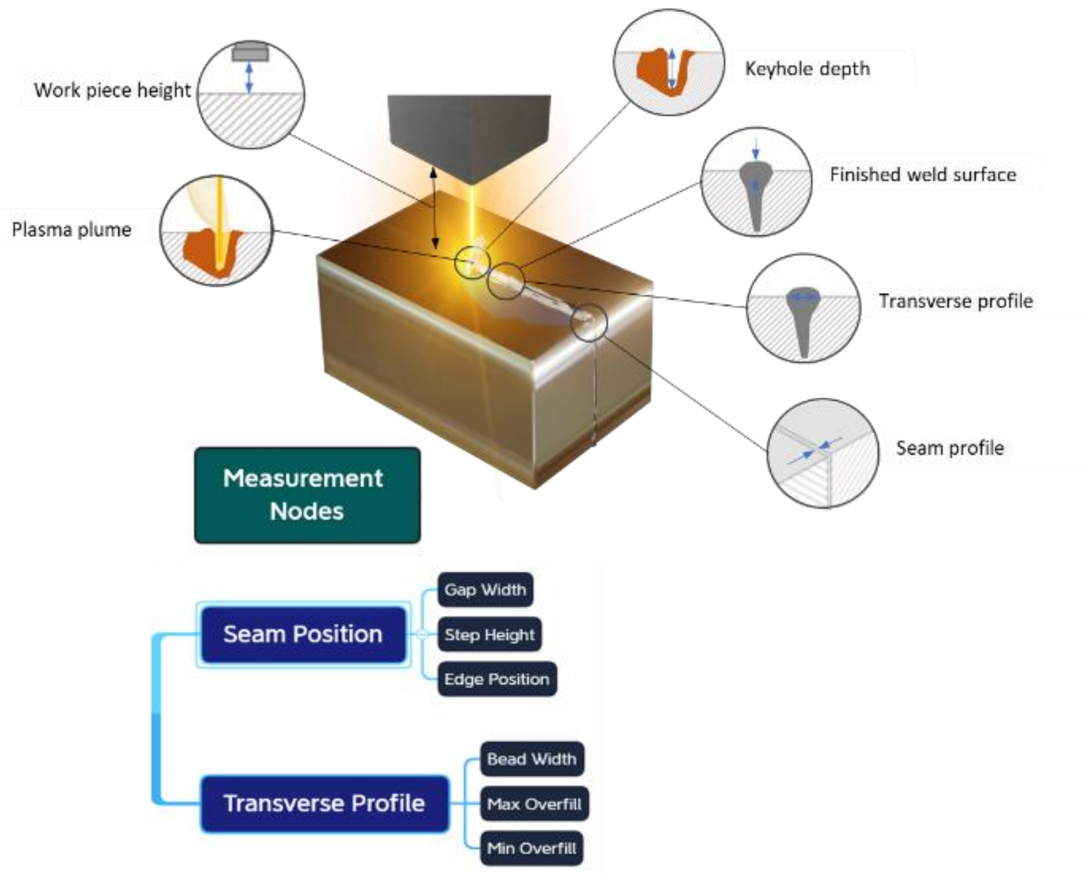

Figure 7. Defect detection in aluminum welding

To define the best configuration is one of the most important processes in the laser welding monitoring; this assures the correct data for monitoring, controlling, defining and predicting the welding quality results. Traditionally, coaxial and paraxial are the common sensing configurations, where the coaxial can get information directly above the welding zone and paraxial monitoring allows adjust the distance and angle of the device with reference to welding zone. Moreover, thermal and optical signals can be monitored at the same time with the use of coaxial and paraxial configurations by sensors and monitoring devices. Figure 8 illustrates the paraxial and coaxial monitoring devices configuration. In the following section, the most important method regarding the sensor monitoring of aluminum welding are discussed.

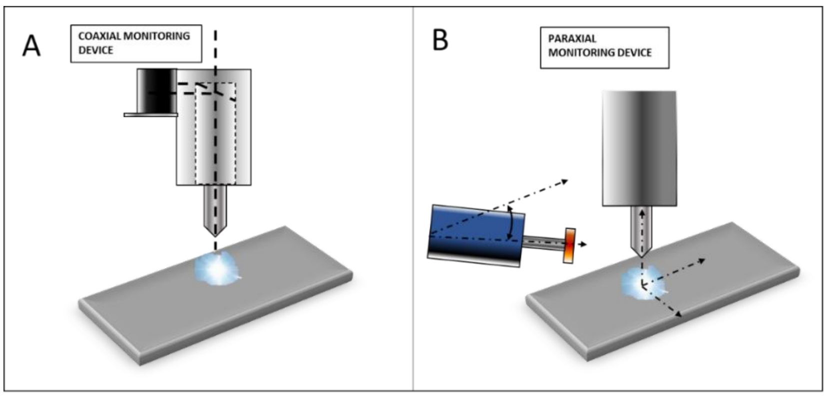

Figure 8. Illustration of monitoring configuration devices. A) Coaxial monitoring configuration. B) Paraxial monitoring configuration

1.8.2 Optical and Thermal signals

Due to the nature of laser welding process, thermal and optical signals have common application to be monitor. In fact, laser beam increases the temperature of the material plate above the melting temperature. Therefore, the laser welding process could be classified as a thermal fabrication process, in the keyhole where the energy of the laser beam is concentrated the thermal radiation signals are considerably and allow to capture of important information to characterize the process [55]. The molten pool composed of the melted metal and metallic vapor emits an enormous quantity of radiation too, thus those zones are interesting to monitoring. Using photodiodes, an optical parametric oscillator, and a plano-convex lens, it is feasible to determine the relationship between optical signals produced by the metal plume, material emission, and atoms emission and laser power and pulse duration. Some articles looked into the relationship between laser power and atom emissions in the plume for dissimilar aluminum laser welding [91]. High-speed cameras with filters and image sensors were utilized in certain investigations to collect images of the keyhole, molten pool, penetration hole, and metal plume, with great results and high accuracy in determining each of the welded zone's described features on real-time monitoring [92,93]. Convolutional neural networks and data from optical signals were also used to predict the quality of welding [93]. In order to improve artificial intelligence process analysis, photodiodes and spectrometers can be used to capture diverse optical spectrum ranges, such as visible light, infrared light, and ultraviolet light [91,94]. In order to capture radiation and temperature signals throughout the welding process, optical devices and particular temperature sensors could be used. To collect the thermal signal, sensors such as pyrometers and infrared cameras are typically utilized [95]. Pyrometer sensors are a low-cost, high-performance monitoring device that can be employed in extreme environments; however, they are typically limited by testing frequency [96]. Aluminum, on the other hand, is not like steel, where you can use a pyrometer to quantify the emissivity as a function of temperature with reasonable accuracy and then feed that information into a machine learning model. That would be fantastic to characterize the weld in addition with the high-speed camera and for sure give more accurate models. At NRC (national research council of Canada), we tested two FLIR cameras (InGas or InSb) in laser welding. The InSb was found the most effective since its wavelength was outside the range of the laser. However, itself just to use the images to accurately predict the temperature in the molten zone. Some studies use numerical simulation to predict the melt pool temperature by measuring the temperature outside the fusion zone. There are still issues, even at the solid-state with aluminum for temperature measurements. The Infrared camera reflects widely the temperature distribution of the welding zone, this benefit allows to collect surface temperature information [95]. Photodiode for temperature observation was used in some research to examine the temperature in Keyhole and plasma radiation to monitoring the welding process and obtain information to train a Support Vector Machine Classification Algorithm [94]. Figure 9 illustrates a usual setup for optical signal monitoring process, in this array the optical emission is collected by a collimator and is transmitted to be analyzed by the spectrometer. In continue, artificial intelligence use outcome data to determine next move for laser welding equipment. The correlation analysis of plasma optical spectra was used in some studies to determine the relationship between optical signals and weld quality in laser welding of aluminum alloys [71].

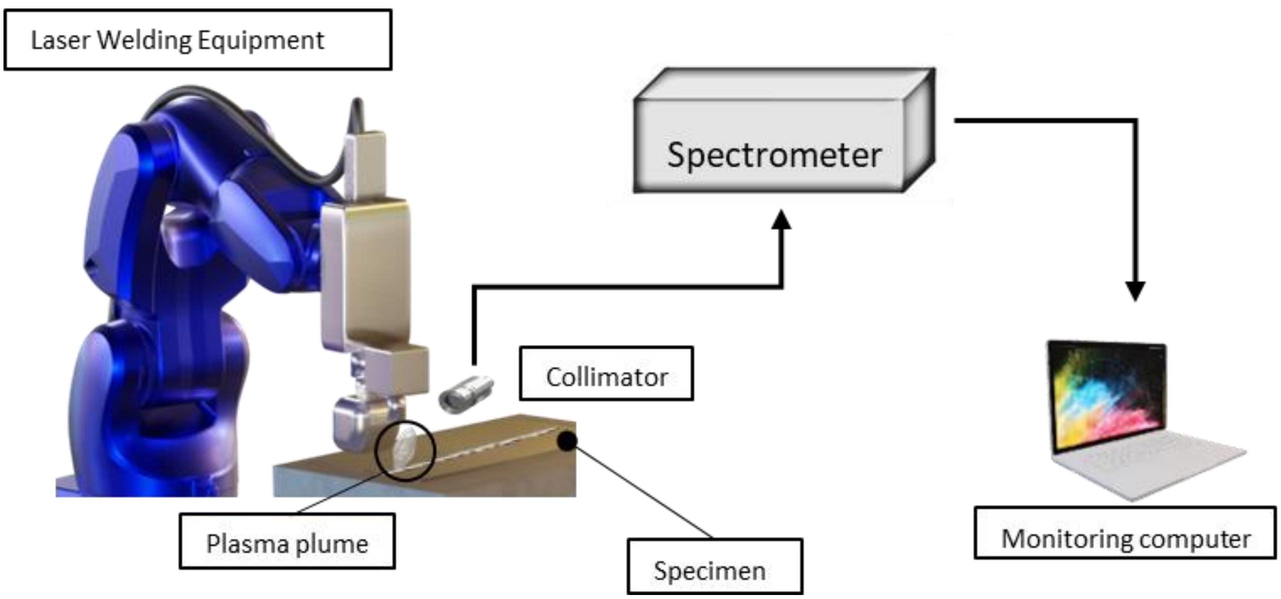

Figure 9. Monitoring system with spectrometer to get optical signals from laser welding

Table 4 mentions different types of sensors to obtain optical and thermal signal from laser welding process and describes the object where is possible capture the information to study and monitor the laser welding process of aluminum alloys.

Table 4. Welding inspection and monitoring sensor characteristics for both optical and thermal signals [77]

Sensor	Detection	Frequency	Capability to detect defects	Comments and limitations
Photodiode	Vapour plume, plasma Reflective laser	1–100	Incomplete Penetration Undercut	Low efficiency in identifying slight defect and Inefficient

	energy, Thermal radiation			to identify microdefects
Camera	Plasma plume and molten pool	0.5–5	Blowouts Lack of fusion Incomplete penetration Undercut	Requirement for additional component setup Low sampling speed and high price High computing demands
Spectrometer	Spectrum of plasma plume	0.1–1	Medium Blowouts Cracks Spatters Low Misalignment	Too sensitive to the noise of environment
Pyrometer	Temperature of molten pool or vapour plume	1-50	Incomplete Penetration Burn through	Limited capability of weld defects inspection
Charge sensor	Plasma charge current	1-100	Incomplete Penetration Humping	Limited application in solid-state-laser welding. However, the sensor to be placed close to the weld zone.

1.8.3 Acoustic signals

The acoustic emission refers to a sensor that translates process sounds into an electrical output that can be used to calculate a numerical variable. Condenser microphones with a capacitor that changes its capacitance depending on the sound being measured Measurement microphones are frequently employed [97]. Melting, vaporization, keyhole creation, and plasma emission could all benefit from acoustic monitoring. As a result, acoustic signals generated by laser welding provide information and data about material phase shifts, and have been used to assess welding quality [81]. A typical disadvantage of acoustical monitoring is that for non-contacting acoustical sensors the environmental noise could make hard to detect signals and in consequence, could be difficult to use it in online monitoring application. For this reason and with the objective to take advantage of these signals in the online monitoring process the current studies focus on how to improve the signal identification accuracy and to implement intelligent algorithms to correlate signals with welding parameters and quality [98]. Figure 10 shows the array of an aluminum laser welding with structure borne acoustic sensing monitoring, L. Schmidt et al. in [99] reported that is possible to monitor the process by a structure-borne acoustic emission system implementing microphones, getting information from the keyhole formation. Thanks to treat of the obtained signals using neural networks achieving a high prediction rate of over 95 % in speed identification for aluminum laser welding. In this case study, a variety of in-process signals can be recorded, processed, and used to assess welding quality with laser micro welding. It worth to mentioned that optics, acoustics, thermal, and imaging signals are among these signals. Observing a variation in the recorded signals can reveal a welding defect as well as its location and nature. Using real-time welding monitoring, quality control processes no longer must operate in an open loop, and accurate insights into the state of tools, equipment, and procedures can be obtained. At the end of the day, Big Data analysis can enhance and extract all the added information it contains. As a result of the use of machine learning and artificial intelligence techniques, as well as the accumulation of historical data, on-line process monitoring would soon identify specific welding defect signatures. An excellent tool for managing quality holistically across the ecosystem can be created by combining these data with data collected horizontally and vertically across the value chain and network. In fact, there are many references on acoustic defect detection of friction stir weld aluminum alloys and steel laser weld not on aluminum laser weld. To be more precise, laser welding still faces a challenge when it comes to in situ and real-time quality control. There are many dynamics involved with laser material interaction. In this contribution, researchers combined AE and optical sensing techniques to study the laser welding process of aluminum. X-ray and high-speed imaging were used in the experiments to overcome the difficulty of postmortem correlation between recorded signals and momentary events. As a result, optical sensors were found to work together with AE sensors to detect the different processes - surface melting, keyhole, solidification, etc. [100]. Signal analysis by visual inspection cannot detect events leading to defect formation. In general, the correlation between signals and postmortem quality analysis is not reliable because the events are dynamic and happen in quick succession, such as keyhole fluctuation, pore formation, and spattering. Using AE and optical sensors coupled with advances in signal processing and statistical analysis such as wavelet decomposition, various quality control methods will be possible for laser welding [101].

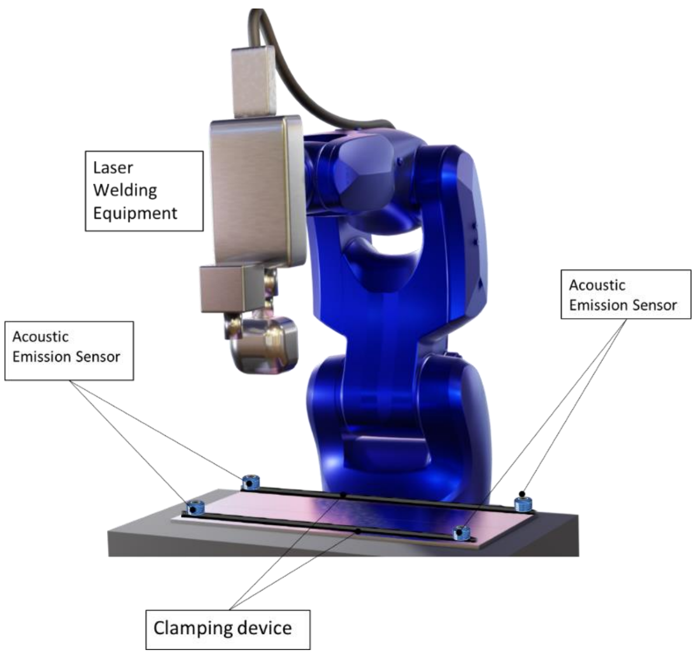

Figure 10. Monitoring system for acoustic signal, structure-borne acoustic signal sensing

1.9 AUTOMATIC COMPUTER AIDED INSPECTION (CAI) MONITORING

With the advancement of computer technology, CAI (Computer Aided Inspection) has become a necessary inspection method for manufacturing companies in a very short amount of time. 3D scanning can be used to create digital replicas of products by scanning them and storing them as point clouds. By reducing human intervention by a large margin, CAI opened up a world of new ways of inspecting, requiring less time and less money. The geometry model of an object is used together with structured light and machine vision cameras to inspect the object automatically. The location of points on the surface of the object is determined by analyzing the images captured by the camera. Laser scanners or other 3D scanning devices produce point-cloud data. The geometric model of the object is analyzed during a setup phase before object inspection. By comparing the manufactured part with the CAD model, the software provides a graphical comparison. Several points are eliminated to shorten data collection and analysis times and avoid errors caused by extraneous reflections. In subsequent inspections, points from areas of interest are spatially averaged to estimate the size of similar objects. An inspection device measures every surface of the object in a single pass by employing multiplexed sensors, each of which includes cameras and structured light sources. Outlines the planning logic that resulted in a recommended features inspection sequence, probe selection, and part orientation sequence. Features serve a key role in the system's modular construction [102–104]. Here, the CAI inspection is considered as a main consept of process monitoring throught all the process (Welding and forming). In this regard, following procedure are design as automatic inspection planning in real time (Figure 11).

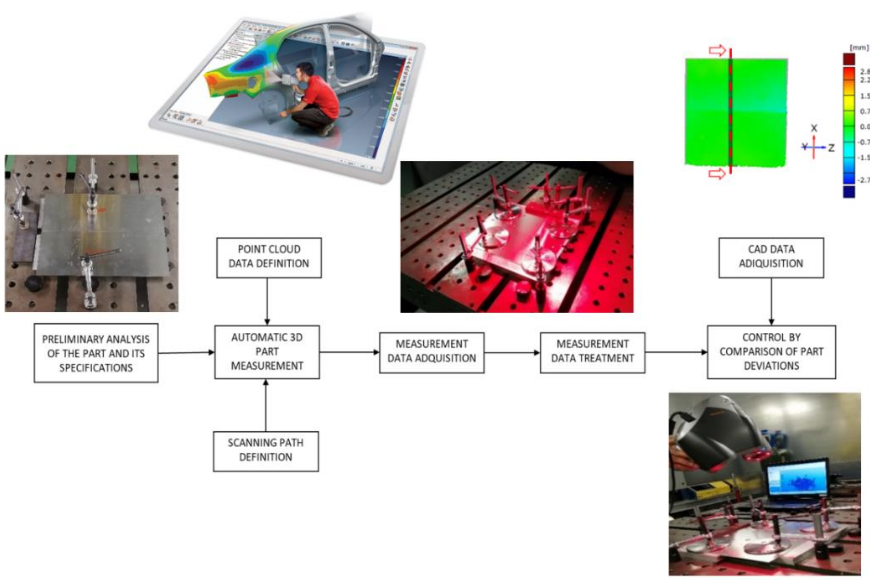

Figure 11. Inspection planning system model

1.10 SIGNAL PROCESSING OF LASER WELDING PROCESS

From laser welding is possible to get information that helps to understand, monitor, and control the status of the process. The most common signals obtained and studied for online monitoring are optical, thermal, and acoustical. Table 5 shows the type of the signals and the process monitoring stages specifying some cases of study and implemented instruments in each of them. In following sections, the types of signals are studied.

Table 5. Monitoring devices and signals associated to monitoring and stage process objective

Stage	**Monitoring objective**	**Monitoring signal**	**Monitoring equipment**	**Reference**
Pre-process	Seam tracking	Optical signal	CMOS camera 640 x 300 pixels.	[105]
	Gap Measuring		Camera-based Max. Rate 1500 Hz, Resolution 144 x 176 Pixels.	[94]
In-process (online)	Welding stability	Acoustic signal	Microphone of high definition and audible range of 20 Hz to 20 kHz.	[106]
	Defect's monitoring	Optical signal	High-speed camera system Memrecam fx RX6 (200 frames/s, Resolution 512 x 512 pixels	[107]
	Molten pool	Optical signal	A Photron SA4 high-speed camera.	[93]
	Keyhole Geometry	Optical signal	A Photron SA4 high-speed camera.	[93]
	Penetration hole	Optical signal	A Photron SA4 high-speed camera.	[93]

	Metal plume	Optical signal Thermal signal	Photodiode, Optical Parametric Oscillator, uncoated-planoconvex lens, Czerny-Turner style spectrometer	[108]
	Feedback Control	Thermal signal	Photodiode for Temperature Observation (wavelength 1100 - 1800 nm)	[109]
Post-process	Defect's monitoring	Optical signal	PbSn- Based Camera (resolution 32x 32 pixels, Frame rate 500Hz).	[94]
	Classification of Weld Geometry	Acoustic Emission	Microphone inspection, metallographic test.	[97]

1.11 INTELLIGENT MANUFACTURING MODEL FOR FORMING OF ALWB

Traditionally, forming of TWBs structure are divided into two main processes, welding (TIG, FSW, Laser, EBM etc.) and forming (deep drawing, incremental forming and bending). In this regard, all real-time monitoring and process mapping should be considered not only in laser welding but also for forming operation. Here, an intelligent system with flexible manufacturing concept based on lean manufacturing are proposed (Figure 12) As show in figure, this smart model is divided by four main steps. First, blank orientation, fixture condition and geometrical inspection of pre- process like seam tracing are check by laser 3D scanning. Followed by a fiber automated laser welding machine that is fed by the on-line monitoring process bases on optical and acoustic signals, it is used to manufacture a ALWBs, and welding process is monitor by a 3D scanner in process monitoring. Simultaneously, all the STL data will transfer to the point cloud via wireless. In this stage, all input parameters such as power, speed, amplitude, and wobbling patterns etc. are monitored for parameter condition surveil. On the other hand, critical objectives like distortion, residual stress, defect detection and are validated to make sure this production are pass all geometrical criteria. Secondly, handling robot put the TWBs which is made by the laser beam welding on the convers. Then, 3D scanning makes a new geometrical profile through the part and will check by GD&T analysis in the cloud. Such validated parts will go ahead into the forming step and online forming analysis is considered by force sensor to detect the maximum drawing depth. Forming parts will be checked by automatic inspection method to pass the forming criteria such as spring back and wrinkling. Meanwhile, the parts that do not satisfy the criteria will be considered as scrap and recycle. Finally, the successful parts tagged but the validate license for such other manufacturing operation like assembly not only this factory but also it is possible to use in other companies. Overall, this model is promising to use in some mega factories in order to improve the quality, productivity, production speed and decries the waste time, energy and manufacturing costs.

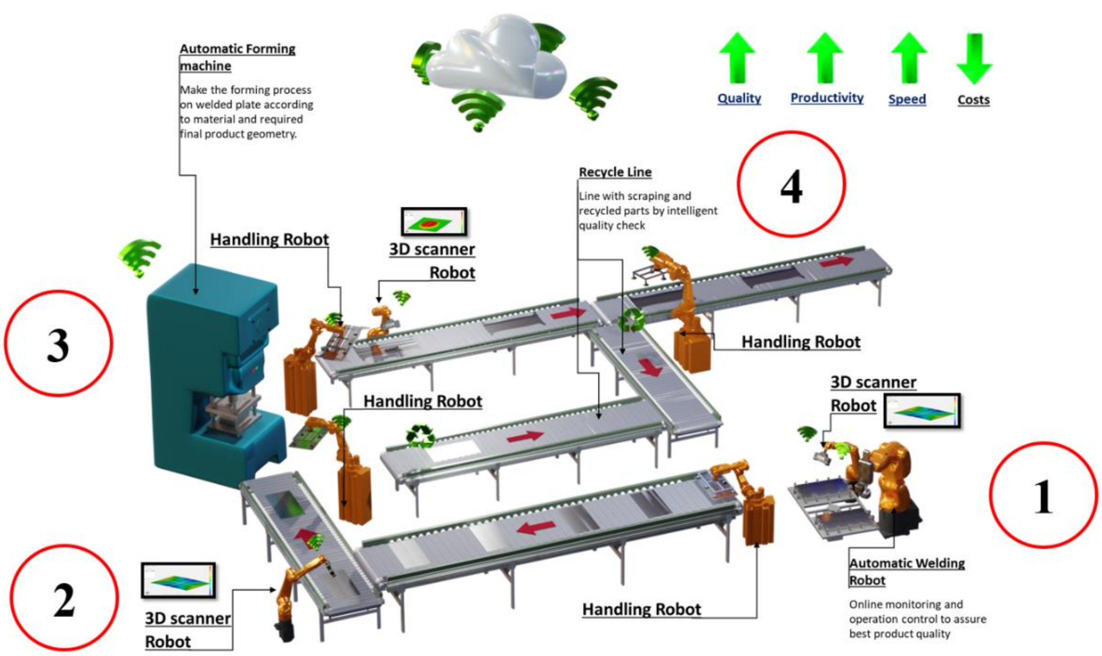

Figure 12. Intelligent system of TWBs production

1.12 CONCLUSION

The implementation of Aluminum Laser welding is increasing in industry, the material properties make monitor and control the process a challenge for the researchers and for the companies. This paper presented a review of the 4.0 technologies, smart inspection techniques, sensing technologies and algorithms that are, and can be applied to aluminum laser welding. To be more specific, laser material processing as a core of advanced manufacturing which is an umbrella of smart manufacturing is investigated and. In developing welding systems, different intelligent techniques can improve efficiency, quality, and reliability and also forming processes are considered. Aluminium is increasingly used in welding fabrication because of its size and complexity. As this grows, so must the industry's access to resources capable of providing guidance on how to weld aluminum. Showing the benefit to implement them for monitoring the process, and how their application can assure a better quality of welding. Also, in order to achieve a fully automated and intelligent TWBs factory a novel model is proposed. The next step for ALWBs is warm/hot stamping which is the topic of our project: qualification of laser welds in warm/hot stamping for formability and the effect of defect on quality. The other way is to use Friction Stir Welding for cold stampings which is used by TWB Company as well in production. FSW is expected to be used in higher strength Al welds compare to laser based on my knowledge. For future works we are going to apply this method on AA7075 hot stamping of FSW TWBs actually as we were the 1st worldwide to prove it in 2017 with Ford.

1.13 REFERENCES

[1] T. Pereira, L. Barreto, A. Amaral, Network and information security challenges within Industry 4.0 paradigm, Procedia Manuf. 13 (2017) 1253–1260.

[2] H. ElMaraghy, L. Monostori, G. Schuh, W. ElMaraghy, Evolution and future of manufacturing systems, CIRP Annals. 70 (2021) 635–658.

[3] A. Sharma, H. Pandey, Big Data and Analytics in Industry 4.0, Advances in Science, Technology and Innovation. (2020) 57–72.

[4] A. Aminzadeh, D. Rahmatabadi, M. Pahlavani, M. Moradi, J. Lawrence, Smart Laser Welding: A Strategic Roadmap Toward Sustainable Manufacturing in Industry 4.0, Sustainable Manufacturingin Industry 4.0: Pathways and Practices. (2023) 41–56.

[5] M. Javaid, A. Haleem, R.P. Singh, R. Suman, Substantial capabilities of robotics in enhancing industry 4.0 implementation, Cognitive Robotics. 1 (2021) 58–75.

[6] D. Buongiorno, M. Prunella, S. Grossi, S.M. Hussain, A. Rennola, N. Longo, G. Di Stefano, V. Bevilacqua, A. Brunetti, Inline Defective Laser Weld Identification by Processing Thermal Image Sequences with Machine and Deep Learning Techniques, Applied Sciences 2022, Vol. 12, Page 6455. 12 (2022) 6455.

[7] A. Aminzadeh, S.S. Karganroudi, M.S. Meiabadi, D.G. Mohan, K. Ba, A Survey of Process Monitoring Using Computer-Aided Inspection in Laser-Welded Blanks of Light Metals Based on the Digital Twins Concept, Quantum Beam Science 2022, Vol. 6, Page 19. 6 (2022) 19.

[8] Z. Ren, F. Fang, N. Yan, Y. Wu, State of the Art in Defect Detection Based on Machine Vision, International Journal of Precision Engineering and Manufacturing-Green Technology 2021 9:2. 9 (2021) 661–691.

[9] A. Aminzadeh, A. Parvizi, M. Moradi, Multi-objective topology optimization of deep drawing dissimilar tailor laser welded blanks; experimental and finite element investigation, Opt Laser Technol. 125 (2020) 106029.

[10] J. Stavridis, A. Papacharalampopoulos, P. Stavropoulos, Quality assessment in laser welding: a critical review, International Journal of Advanced Manufacturing Technology. 94 (2018) 1825–1847.

[11] D. Ma, P. Jiang, L. Shu, Z. Gong, Y. Wang, S. Geng, Online porosity prediction in laser welding of aluminum alloys based on a multi-fidelity deep learning framework, J Intell Manuf. (2033).

[12] B. Zhang, K.M. Hong, Y.C. Shin, Deep-learning-based porosity monitoring of laser welding process, Manuf Lett. 23 (2020) 62–66.

[13] K. Schwab, The fourth industrial revolution, Currency, 2017.

[14] S. Heinonen, J. Karjalainen, J. Ruotsalainen, Towards the third industrial revolution, Finland: Findland Future Research Centre FFRC EBook. 6 (2015) 2015.

[15] K. Schwab, The fourth industrial revolution, Currency, 2017.

[16] A. Aminzadeh, A. Parvizi, M. Moradi, Multi-objective topology optimization of deep drawing dissimilar tailor laser welded blanks; experimental and finite element investigation, Opt Laser Technol. 125 (2020).

[17] A. Aminzadeh, S.S. Karganroudi, N. Barka, A. El Ouafi, A real-time 3D scanning of aluminum 5052-H32 laser welded blanks; geometrical and welding characterization, Mater Lett. 296 (2021) 129883.

[18] A. Aminzadeh, N. Nasiri, N. Barka, A. Parvizi, K. Abrinia, M. Moradi, S. Sattarpanah Karganroudi, Statistical Analysis of Laser-Welded Blanks in Deep Drawing Process: Response Surface Modeling, J Mater Eng Perform. (2021) 1–17.

[19] A. Aminzadeh, S.S. Karganroudi, N. Barka, A novel approach of residual stress prediction in ST-14/ST-44 laser welded blanks; mechanical characterization and experimental validation, Mater Lett. 285 (2021) 129193.

[20] A. Aminzadeh, S.S. Karganroudi, N. Barka, A novel approach of residual stress prediction in ST-14/ST-44 laser welded blanks; Mechanical characterization and Experimental validation, Mater Lett. (2020) 129193.

[21] A. Rizzo, L. Nazari, N. Galliano, M.C. Calderaro, Development of a preventive maintenance software for an automation plant, (2021).

[22] W. Huang, Y. Qiao, X. Tang, Robust scene text detection with convolution neural network induced mser trees, in: European Conference on Computer Vision, 2014: pp. 497–511.

[23] A. Graves, S. Fernández, J. Schmidhuber, Multi-dimensional recurrent neural networks, in: International Conference on Artificial Neural Networks, 2007: pp. 549–558.

[24] A. Graves, Long short-term memory, in: Supervised Sequence Labelling with Recurrent Neural Networks, Springer, 2012: pp. 37–45.

[25] V. Nasir, M. Kooshkbaghi, J. Cool, Sensor fusion and random forest modeling for identifying frozen and green wood during lumber manufacturing, Manuf Lett. 26 (2020) 53–58.

[26] S.K. Kiangala, Z. Wang, An effective adaptive customization framework for small manufacturing plants using extreme gradient boosting-XGBoost and random forest ensemble learning algorithms in an Industry 4.0 environment, Machine Learning with Applications. 4 (2021) 100024.

[27] Q.P. He, J. Wang, Fault detection using the k-nearest neighbor rule for semiconductor manufacturing processes, IEEE Transactions on Semiconductor Manufacturing. 20 (2007) 345–354.

[28] W. Jaśkowski, O.R. Lykkebø, N.E. Toklu, F. Trifterer, Z. Buk, J. Koutnik, F. Gomez, Reinforcement Learning to Run… Fast, in: The NIPS'17 Competition: Building Intelligent Systems, Springer, 2018: pp. 155–167.

[29] D.T. Hogarty, J.C. Su, K. Phan, M. Attia, M. Hossny, S. Nahavandi, P. Lenane, F.J. Moloney, A. Yazdabadi, Artificial intelligence in dermatology—where we are and the way to the future: a review, Am J Clin Dermatol. 21 (2020) 41–47.

[30] I. SMLC, 21st century smart manufacturing, in: Workshop Summary Report, 2011.

[31] W.-H. Tsai, P.-Y. Chu, H.-L. Lee, Green activity-based costing production planning and scenario analysis for the aluminum-alloy wheel industry under industry 4.0, Sustainability. 11 (2019) 756.

[32] S.A. Babalola, N. Kumar, S. Dutta, N.C. Murmu, M. Chandra, A Critical Review on the Trends Toward Effective Online Monitoring of Defects in Friction Stir Welding of Aluminum Alloys, Recent Trends in Manufacturing and Materials Towards Industry 4.0. (2021) 851–868.

[33] S. Caruso, L. Filice, Sustainable manufacturing of ultra-fine aluminium alloy 6101 wires using controlled high levels of mechanical strain and finite element modeling, International Journal of Material Forming. 14 (2021) 1209–1219.

[34] M. Tannous, M. Miraglia, F. Inglese, L. Giorgini, F. Ricciardi, R. Pelliccia, M. Milazzo, C. Stefanini, Haptic-based touch detection for collaborative robots in welding applications, Robot Comput Integr Manuf. 64 (2020) 101952.

[35] D. Grube, A.A. Malik, A. Bilberg, SMEs can touch Industry 4.0 in the smart learning factory, Procedia Manuf. 31 (2019) 219–224.

[36] C. Gonzalez-Val, A. Pallas, V. Panadeiro, A. Rodriguez, A convolutional approach to quality monitoring for laser manufacturing, J Intell Manuf. 31 (2020) 789–795.

[37] P. Stavropoulos, A. Papacharalampopoulos, K. Sampatakakis, A CPS platform oriented for Quality Assessment in welding, in: MATEC Web of Conferences, 2020: p. 1030.

[38] P. Stavropoulos, A. Papacharalampopoulos, J. Stavridis, K. Sampatakakis, A three-stage quality diagnosis platform for laser-based manufacturing processes, The International Journal of Advanced Manufacturing Technology. 110 (2020) 2991–3003.

[39] W.E. Forum, Green New Deals | Strategic Intelligence | World Economic Forum, (2020).

[40] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, Intelligent laser welding through representation, prediction, and control learning: An architecture with deep neural networks and reinforcement learning, Mechatronics. 34 (2016) 1–11.

[41] D. Mishra, S.K. Pal, D. Chakravarty, Industry 4.0 in Welding, Welding Technology. (2021) 253–298.

[42] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, First steps towards an intelligent laser welding architecture using deep neural networks and reinforcement learning, Procedia Technology. 15 (2014) 474–483.

[43] B. Wang, S.J. Hu, L. Sun, T. Freiheit, Intelligent welding system technologies: State-of-the-art review and perspectives, J Manuf Syst. 56 (2020) 373–391.

[44] G. Dutta, R. Kumar, R. Sindhwani, R.K. Singh, Digital transformation priorities of India's discrete manufacturing SMEs--a conceptual study in perspective of Industry 4.0, Competitiveness Review: An International Business Journal. (2020).

[45] A. Aminzadeh, S. Sattarpanah Karganroudi, N. Barka, Experimental and numerical investigation of forming defects and stress analysis in laser-welded blanks during deep drawing process, The International Journal of Advanced Manufacturing Technology. (2021) 1–15.

[46] A. Aminzadeh, A. Parvizi, R. Safdarian, D. Rahmatabadi, Comparison between laser beam and gas tungsten arc tailored welded blanks via deep drawing, Proc Inst Mech Eng B J Eng Manuf. (2020).

[47] S. Echchakoui, N. Barka, INDUSTRY 4.0 and its Impact in PLASTICS INDUSTRY: A Literature Review, J Ind Inf Integr. (2020) 100172.

[48] E. Oztemel, S. Gursev, Literature review of Industry 4.0 and related technologies, J Intell Manuf. 31 (2020) 127–182.

[49] J. Butt, Exploring the interrelationship between additive manufacturing and Industry 4.0, Designs (Basel). 4 (2020) 13.

[50] S.S. Kamble, A. Gunasekaran, S.A. Gawankar, Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives, Process Safety and Environmental Protection. 117 (2018) 408–425.

[51] D. Mishra, R.B. Roy, S. Dutta, S.K. Pal, D. Chakravarty, A review on sensor based monitoring and control of friction stir welding process and a roadmap to Industry 4.0, J Manuf Process. 36 (2018) 373–397.

[52] R.Y. Zhong, X. Xu, E. Klotz, S.T. Newman, Intelligent manufacturing in the context of industry 4.0: a review, Engineering. 3 (2017) 616–630.

[53] S. Liang, M. Rajora, X. Liu, C. Yue, P. Zou, L. Wang, Intelligent manufacturing systems: a review, International Journal of Mechanical Engineering and Robotics Research. 7 (2018) 324–330.

[54] L.D. Evjemo, T. Gjerstad, E.I. Grøtli, G. Sziebig, Trends in Smart Manufacturing: Role of Humans and Industrial Robots in Smart Factories, Current Robotics Reports. 1 (2020) 35–41.

[55] S. Katayama, Introduction: Fundamentals of laser welding, Woodhead Publishing Limited, 2013.

[56] X. Wang, X. Zhou, Z. Xia, X. Gu, A survey of welding robot intelligent path optimization, J Manuf Process. (2020) 0–1.

[57] H. Wang, Applications of laser welding in the railway industry, Handbook of Laser Welding Technologies. (2013) 575–595.

[58] J. Klæstrup Kristensen, Applications of laser welding in the shipbuilding industry, Handbook of Laser Welding Technologies. (2013) 596–612.

[59] M. Graudenz, M. Baur, Applications of laser welding in the automotive industry, Handbook of Laser Welding Technologies. (2013) 555–574.

[60] L. Quintino, R. Miranda, U. Dilthey, D. Iordachescu, M. Banasik, S. Stano, Laser Welding of Structural Aluminium, (2010) 33–57.

[61] M. Matsui, T. Ono, T. Kamei, K. Mori, Generating conditions of argon laser-sustained plasma by disk, fiber and diode lasers, Vacuum. 167 (2019) 490–494.

[62] E. Punzel, F. Hugger, R. Dörringer, T.L. Dinkelbach, A. Bürger, Comparison of different system technologies for continuous-wave laser beam welding of copper, Procedia CIRP. 94 (2020) 587–591.

[63] E. Kennedy, G. Byrne, D.N. Collins, A review of the use of high-power diode lasers in surface hardening, J Mater Process Technol. 155–156 (2004) 1855–1860.

[64] S.L. Ream, Laser welding efficiency and cost: CO2, YAG, fiber, and disc, 1 (2018) 1.

[65] J.M. Sánchez Amaya, M.R. Amaya-Vázquez, F.J. Botana, Laser welding of light metal alloys: Aluminium and titanium alloys, 2013.

[66] M.D. Vijayakumar, V. Dhinakaran, T. Sathish, G. Muthu, P.M.B. ram, Experimental study of chemical composition of aluminium alloys, Mater Today Proc. (2020).

[67] N. Seto, S. Katayama, A. Matsunawa, Porosity formation mechanism and suppression procedure in laser welding of aluminium alloys, Welding International. 15 (2001) 191–202.

[68] B. Hu, I.M. Richardson, Mechanism and possible solution for transverse solidification cracking in laser welding of high strength aluminium alloys, Materials Science and Engineering: A. 429 (2006) 287–294.

[69] H. Zhao, D.R. White, T. DebRoy, Current issues and problems in laser welding of automotive aluminium alloys, International Materials Reviews. 44 (1999) 238–266.

[70] J. Xie, A. Kar, others, Laser welding of thin sheet steel with surface oxidation, WELDING JOURNAL-NEW YORK-. 78 (1999) 343--s.

[71] T. Sibillano, A. Ancona, V. Berardi, E. Schingaro, P. Parente, P.M. Lugarà, Correlation spectroscopy as a tool for detecting losses of ligand elements in laser welding of aluminium alloys, Opt Lasers Eng. 44 (2006) 1324–1335.

[72] O.O. Oladimeji, E. Taban, Trend and innovations in laser beam welding of wrought aluminum alloys, Welding in the World. 60 (2016) 415–457.

[73] D.Y. You, X.D. Gao, S. Katayama, Review of laser welding monitoring, Science and Technology of Welding and Joining. 19 (2014) 181–201.

[74] X. Cao, W. Wallace, J.-P. Immarigeon, C. Poon, Research and progress in laser welding of wrought aluminum alloys. II. Metallurgical microstructures, defects, and mechanical properties, Materials and Manufacturing Processes. 18 (2003) 23–49.

[75] X. Cao, W. Wallace, C. Poon, J.-P. Immarigeon, Research and progress in laser welding of wrought aluminum alloys. I. Laser welding processes, Materials and Manufacturing Processes. 18 (2003) 1–22.

[76] C. Fan, F. Lv, S. Chen, Visual sensing and penetration control in aluminum alloy pulsed GTA welding, International Journal of Advanced Manufacturing Technology. 42 (2009) 126–137.

[77] W. Cai, J.Z. Wang, P. Jiang, L.C. Cao, G.Y. Mi, Q. Zhou, Application of sensing techniques and artificial intelligence-based methods to laser welding real-time monitoring: A critical review of recent literature, J Manuf Syst. 57 (2020) 1–18.

[78] E.A. Gyasi, H. Handroos, P. Kah, Survey on artificial intelligence (AI) applied in welding: A future scenario of the influence of AI on technological, economic, educational and social changes, Procedia Manuf. 38 (2019) 702–714.

[79] C. Zhao, K. Fezzaa, R.W. Cunningham, H. Wen, F. De Carlo, L. Chen, A.D. Rollett, T. Sun, Real-time monitoring of laser powder bed fusion process using high-speed X-ray imaging and diffraction, Sci Rep. 7 (2017) 1–11.

[80] S. Shevchik, T. Le-Quang, B. Meylan, F.V. Farahani, M.P. Olbinado, A. Rack, G. Masinelli, C. Leinenbach, K. Wasmer, Author Correction: Supervised deep learning for real-time quality monitoring of laser welding with X-ray radiographic guidance, Sci Rep. 10 (2020) 1–2.

[81] L. Zhang, A.C. Basantes-Defaz, D. Ozevin, E. Indacochea, Real-time monitoring of welding process using air-coupled ultrasonics and acoustic emission, International Journal of Advanced Manufacturing Technology. 101 (2019) 1623–1634.

[82] J. Horvat, J. Prezelj, I. Polajnar, M. Čudina, Monitoring gas metal arc welding process by using audible sound signal, Strojniški Vestnik-Journal of Mechanical Engineering. 57 (2011) 267–278.

[83] P.G. Sanders, K.H. Leong, J.S. Keske, G. Kornecki, Real-time monitoring of laser beam welding using infrared weld emissions, J Laser Appl. 10 (1998) 205–211.

[84] A. Sun, E. Kannatey-Asibu Jr, M. Gartner, Sensor systems for real-time monitoring of laser weld quality, J Laser Appl. 11 (1999) 153–168.

[85] C. Stadter, M. Schmoeller, L. von Rhein, M.F. Zaeh, Real-time prediction of quality characteristics in laser beam welding using optical coherence tomography and machine learning, J Laser Appl. 32 (2020) 22046.

[86] C.Q. Gómez Muñoz, A. Arcos Jimenez, F.P. Garcia Marquez, M. Kogia, L. Cheng, A. Mohimi, M. Papaelias, Cracks and welds detection approach in solar receiver tubes employing electromagnetic acoustic transducers, Struct Health Monit. 17 (2018) 1046–1055.

[87] T. Sibillano, A. Ancona, V. Berardi, P.M. Lugarà, Real-time monitoring of laser welding by correlation analysis: The case of AA5083, Opt Lasers Eng. 45 (2007) 1005–1009.

[88] T. Beck, C. Bantel, M. Boley, J.P. Bergmann, OCT Capillary Depth Measurement in Copper Micro Welding Using Green Lasers, Applied Sciences. 11 (2021) 2655.

[89] J. Stavridis, A. Papacharalampopoulos, P. Stavropoulos, Quality assessment in laser welding: a critical review, International Journal of Advanced Manufacturing Technology. 94 (2018) 1825–1847.

[90] Y. Zhang, X. Gao, Analysis of characteristics of molten pool using cast shadow during high-power disk laser welding, International Journal of Advanced Manufacturing Technology. 70 (2014) 1979–1988.

[91] B.J. Simonds, B. Tran, P.A. Williams, In situ monitoring of Cu/Al laser welding using Laser Induced Fluorescence, Procedia CIRP. 94 (2020) 605–609.

[92] J. Chen, T. Wang, X. Gao, L. Wei, Real-time monitoring of high-power disk laser welding based on support vector machine, Comput Ind. 94 (2018) 75–81.

[93] Z. Zhang, B. Li, W. Zhang, R. Lu, S. Wada, Y. Zhang, Real-time penetration state monitoring using convolutional neural network for laser welding of tailor rolled blanks, J Manuf Syst. 54 (2020) 348–360.

[94] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, Intelligent laser welding through representation, prediction, and control learning: An architecture with deep neural networks and reinforcement learning, Mechatronics. 34 (2016) 1–11.

[95] W. Cai, J.Z. Wang, P. Jiang, L.C. Cao, G.Y. Mi, Q. Zhou, Application of sensing techniques and artificial intelligence-based methods to laser welding real-time monitoring: A critical review of recent literature, J Manuf Syst. 57 (2020) 1–18.

[96] M. Doubenskaia, Ph. Bertrand, H. Pinon, I.Smurov, On-line optical monitoring of Nd: YAG laser lap welding of Zn-coated steel sheets , IV International WLT-Conference on Lasers in Manufacturing. (2007) 543–547.

[97] T. Purtonen, A. Kalliosaari, A. Salminen, Monitoring and adaptive control of laser processes, Phys Procedia. 56 (2014) 1218–1231.

[98] J. Stavridis, A. Papacharalampopoulos, P. Stavropoulos, Quality assessment in laser welding: a critical review, International Journal of Advanced Manufacturing Technology. 94 (2018) 1825–1847.

[99] L. Schmidt, F. Römer, D. Böttger, F. Leinenbach, B. Straß, B. Wolter, K. Schricker, M. Seibold, J. Pierre Bergmann, G. Del Galdo, Acoustic process monitoring in laser beam welding, Procedia CIRP. 94 (2020) 763–768.

[100] T. Le-Quang, S.A. Shevchik, B. Meylan, F. Vakili-Farahani, M.P. Olbinado, A. Rack, K. Wasmer, Why is in situ quality control of laser keyhole welding a real challenge. Procedia CIRP. 74 (2018) 649–653.

[101] K. Wasmer, T. Le-Quang, B. Meylan, F. Vakili-Farahani, M.P. Olbinado, A. Rack, S.A. Shevchik, Laser processing quality monitoring by combining acoustic emission and machine learning: a high-speed X-ray imaging approach, Procedia CIRP. 74 (2018) 654–658.

[102] M. Mahmud, D. Joannic, M. Roy, A. Isheil, J.F. Fontaine, 3D part inspection path planning of a laser scanner with control on the uncertainty, CAD Computer Aided Design. 43 (2011) 345–355.

[103] M. Pejić, Design and optimisation of laser scanning for tunnels geometry inspection, Tunnelling and Underground Space Technology. 37 (2013) 199–206.

[104] J. Jones, P. McNutt, R. Tosi, C. Perry, D. Wimpenny, Remanufacture of turbine blades by laser cladding, machining and in-process scanning in a single machine, 23rd Annual International Solid Freeform Fabrication Symposium - An Additive Manufacturing Conference, SFF 2012. (2012) 821–827.

[105] M. Nilsen, F. Sikström, A.K. Christiansson, A. Ancona, In-process Monitoring and Control of Robotized Laser Beam Welding of Closed Square Butt Joints, Procedia Manuf. 25 (2018) 511–516.

[106] L. Zhang, A.C. Basantes-Defaz, D. Ozevin, E. Indacochea, Real-time monitoring of welding process using air-coupled ultrasonics and acoustic emission, International Journal of Advanced Manufacturing Technology. 101 (2019) 1623–1634.

[107] J. Chen, T. Wang, X. Gao, L. Wei, Real-time monitoring of high-power disk laser welding based on support vector machine, Comput Ind. 94 (2018) 75–81.

[108] B.J. Simonds, B. Tran, P.A. Williams, In situ monitoring of Cu/Al laser welding using Laser Induced Fluorescence, Procedia CIRP. 94 (2020) 605–609.

[109] E. Rodriguez, F. Medina, D. Espalin, C. Terrazas, D. Muse, C. Henry, E. MacDonald, R.B. Wicker, Integration of a thermal imaging feedback control system in electron beam melting, WM Keck Center for 3D Innovation, University of Texas at El Paso. (2012) 945–961.

CHAPITRE 2
ANALYSE BIBLIOMETRIQUE DE L'INTELLIGENCE ARTIFICIELLE ET DU SUIVI EN TEMPS REEL DE LA TECHNOLOGIE DU SOUDAGE A L'ERE DE L'INDUSTRIE 4.0

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Cet article a été soumis dans The International Journal of Engineering Applications of Artificial Intelligence le numéro de référence: Manuscript Number: EAAI-22-4959

2.1 RÉSUMÉ EN FRANÇAIS DU DEUXIÈME ARTICLE

Cette étude vise à effectuer une analyse bibliométrique des études portant sur la surveillance en temps réel de la technologie de soudage ; elle examine également les tendances et les connaissances connexes concernant la mise en œuvre des principes de fabrication intelligente. L'analyse est réalisée à l'aide des logiciels Bibliometrix R-tool et VOS viewer et couvre les études couvrant la période de 1986 à 2021. Dans le cadre de la caractérisation mécanique et de l'inspection en temps réel des paramètres du processus de

soudage, une variété de capteurs, tels que les capteurs de température (thermocouples, caméras thermiques), de vision (caméras haute définition, scanners 3D), acoustiques/ultrasoniques (pour la détection de défauts internes comme la porosité), et de déplacement et position (pour le contrôle de la précision du laser), sont mis en œuvre. Ces technologies permettent de surveiller et d'ajuster des paramètres critiques du soudage, incluant la température du bain de fusion, la vitesse de soudage, le positionnement du laser, ainsi que l'intégrité et les dimensions de la soudure, afin d'assurer l'optimalité de la fusion, la réduction des défauts, et l'amélioration générale de la qualité et de l'efficacité de la production de soudures. Les résultats indiquent ce qui suit : (1) "Soudage" est le mot-clé le plus couramment utilisé par les chercheurs dans le domaine ; (2) La recherche sur la surveillance en temps réel de la technologie du soudage peut être divisée en groupes distincts (Figure 30); (3) Les États-Unis, la Chine et l'Inde représentent les principales contributions à la recherche sur la surveillance en temps réel de la technologie du soudage ; (4) La croissance annuelle de la valeur indique que le soudage a été une technologie pionnière dans la recherche sur la surveillance des processus en temps réel au cours des dernières décennies.

2.2 CONTRIBUTIONS

Dans le deuxième article intitulé "A Bibliometric Analysis of Artificial Intelligence and Real-time monitoring of Welding Technology in the Era of Industry 4.0", les contributions scientifiques d'Ahmad Aminzadeh se manifestent à travers plusieurs dimensions clés, notamment la recherche, la méthodologie, et la surveillance en temps réel du soudage, comme suit :

Recherche approfondie : Ahmad Aminzadeh a conduit une analyse bibliométrique exhaustive pour cartographier l'état actuel de l'art de l'intelligence artificielle (IA) appliquée à la surveillance en temps réel de la technologie de soudage. Cette recherche comprenait la collecte et l'analyse de données issues de publications scientifiques, permettant de dégager des tendances, des lacunes et des opportunités dans le domaine.

Développement de la méthodologie : Il a élaboré une méthodologie systématique pour évaluer l'impact de l'IA sur le soudage dans le contexte de l'Industrie 4.0, en intégrant des techniques avancées pour l'extraction, l'analyse et la synthèse des données bibliométriques. Cette approche méthodologique a permis de quantifier la croissance de la recherche dans ce domaine et d'identifier les principaux acteurs et innovations.

Surveillance en temps réel : Ahmad Aminzadeh a proposé une nouvelle perspective sur l'application de l'IA pour le suivi en temps réel des paramètres critiques de soudage, tels que la température, la vitesse, et la qualité de la soudure. Il a souligné l'importance de développer des systèmes de surveillance intelligents capables de détecter les défauts en temps réel et d'ajuster automatiquement les paramètres de soudage pour améliorer la qualité.

Contribution à l'amélioration de l'article : Bien que le travail ait bénéficié de la collaboration et des conseils de Saïd Echchakoui, Noureddine Barka, Abderrazak E Ouafi1, et de l'examen technique par Abbas S. Milani, c'est Ahmad Aminzadeh qui a piloté la majorité des efforts de recherche et de rédaction, définissant le cadre de l'étude et assurant l'élaboration du contenu scientifique.

Ces contributions mettent en lumière l'engagement d'Ahmad Aminzadeh dans l'avancement des connaissances sur l'intégration de l'IA dans les processus de soudage, contribuant significativement à la littérature sur la surveillance en temps réel dans le soudage à l'ère de l'Industrie 4.0 et offrant des pistes pour des améliorations méthodologiques et des applications futures dans ce domaine.

2.3 TITRE DU DEUXIÈME ARTICLE

A Bibliometric Analysis of Artificial Intelligence and Real-time monitoring of Welding Technology in the Era of Industry 4.0

2.4 ABSTRACT

This study aims to perform a bibliometric analysis of studies examining the real-time monitoring of welding technology; it also investigates related trends and knowledge respecting the implementation of intelligent manufacturing principles. The analysis is conducted using the Bibliometrix R-tool and VOS viewer software and covers studies spanning the 1986 to 2021 period. The applicability of various sensors to define the mechanical characterization and real-time inspection of welding process parameters is discussed in detail. The results indicate the following: (1) "Weld" is the most commonly used keyword researchers in the field; (2) Real-time monitoring of welding technology research can be divided into distinct clusters; (3) The USA, China, and India account for the primary contributions to real-time monitoring of welding technology research; (4) Annual worth growth indicates that welding has been a pioneering technology in real-time process monitoring research over the past decades.

Keywords; Bibliometric analysis, Welding technology, Smart manufacturing, Industry 4.0, VOS viewer, R package, Web of science, Scopus

2.5 NOMENCLATURE

ZDM	zero-defect manufacturing
CPS	Cyber physical systems
FSW	Friction Stir Welding
WOS	Web of Science
CPS	Cyber-Physical Systems
RAMI 4.0	Reference Architectural Model Industry 4.0

GTAW	Gas Tungsten Arc Welding
GMAW	Gas Metal Arc Welding
DT	Digital Twin
HRI	Human-Robot Interaction

2.6 INTRODUCTION

In today's production context, high-quality product and zero-defect manufacturing (ZDM) have elevated the requirement for real-time monitoring of the manufacturing process [110]. Real-time monitoring is a method that allows industries to control the current state of production lines and to create a unified namespace for data collection [111]. Welding technology and intelligent systems play a key role in automation and allow to better understand the process parameters used in digital factories [43]. Intelligent systems, especially in manufacturing and production, also focus on interactions with human users in changing and dynamic physical and social environments. The last decade in particular has seen significant advances in computing technologies as they shift to increased miniaturization [112], processing power [113], learning algorithms [114] and the availability of big data [115]. A real-time understanding of the robot controller will be crucial for human-robot manufacturing systems in the future [116]. In fact, emerging sensor devices make a massive breakthrough in manufacturing systems and Human-Robot Interaction (HRI) is designed to respond to certain inputs (motion, touch heat, sound, light, etc.) by taking some predefined actions. Regarding welding technology, the use of industrial robots has replaced many welding operations using handheld tools [1-3]. However, such robots are preprogrammed machines with limited capacities, which means that skilled welders are still needed to achieve a reasonable final production quality. Figure 13 shows sensor revolution trends going all the way back to the 18^{th} century.

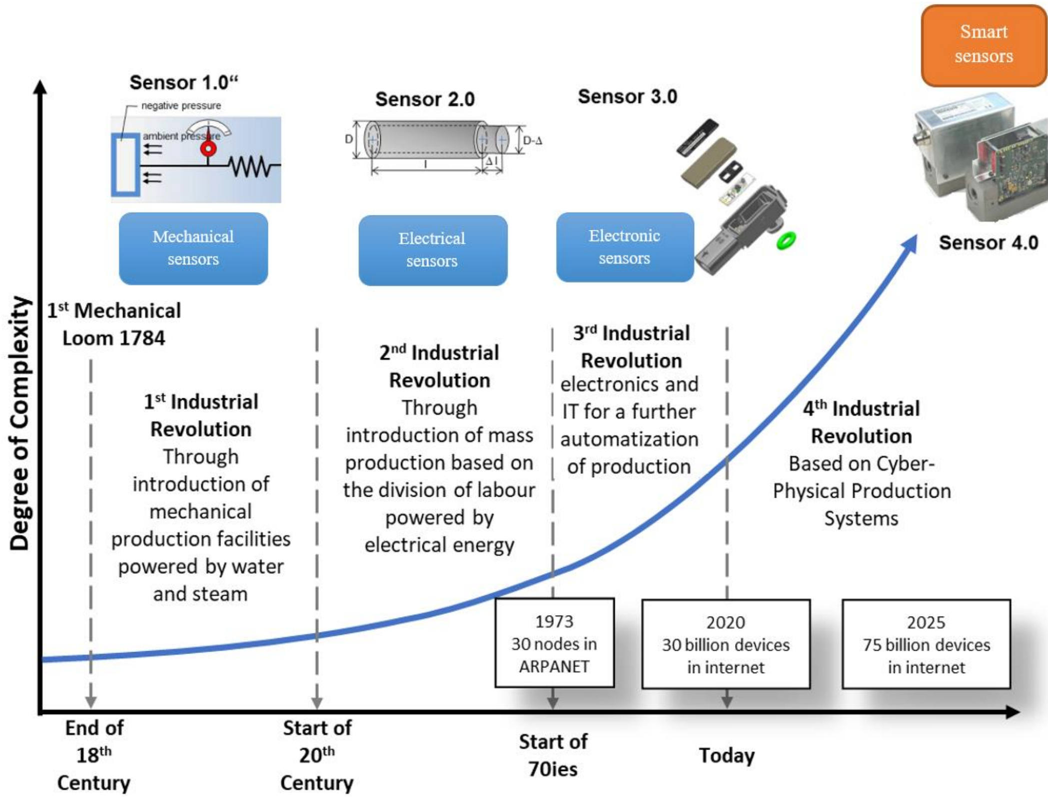


Figure 13. The evolution of sensors in production and manufacturing

It is clear that sensors play a key role in Industry 4.0 and smart manufacturing systems. Monitoring and controlling processes have been facilitated by the use of signals acquired through various sensors integrated into machines [4]. A product quality check often involves destructive tests, which can consume a lot of time. A monitoring system that uses signals enables commenting on quality aspects without having to conduct further tests. A close relationship between process signals and machine tool components makes them useful for equipment maintenance. It is important to monitor and control the signal's energy when there is a sudden failure or change in the system to minimize downtime [5]. It is thus crucial that all manufacturing processes be monitored and controlled. Sun et al. [84] reviewed different types of sensors used to monitor the laser weld quality in real time in order to ensure high product quality and production rates and low costs. In a similar study, Cai et al. [117]

studied a comprehensive critical review of recent literature on sensing techniques and artificial intelligence. Mishra et al. [118] developed a novel cloud-based remote and real-time monitoring and control scheme for friction stir welding (FSW) to avoid the occurrence of weld defects. Shevchik [119] et al. proposed a method for the real-time detection of process instabilities based on deep learning and Hard X-ray radiography which lead to defects. They found that the confidence of the quality classification ranged between 71% and 99%, with a temporal resolution down to 2 ms and a computation time per classification task as low as 2 ms. To tackle problems related to aluminum welding, Huang et al. [120] were detected and processed arc spectra in-situ using a spectrometer. By adjusting the welding current based on the results of the welding assembly, the Fuzzy-PID control system they used to achieve porosity control. Table 6 illustrates defect monitoring methods and signals.

Table 6. Defects monitoring methods and signals.

Monitoring technique	**Signal**	**Defects**	**Advantage and disadvantage**	**Reference**
Image processing technique	Thermal	Humping	Simultaneous penetration depth, bead width and torch position control are possible.	[121]
		Blowouts		
		Cracks		
		Porosity		
		Penetration		
	Vision	Penetration	This system has a large amount of information and is non-contact; it is difficult to track seams in 3-D, and its geometric constraints make seam-tracking difficult.	[122]
		Width		
		Undercut		
	Combined	Molten pool geometry		

		Undercut		[123]
		Crack porosity		
		Blowouts		
		Penetration		
Acoustic emission Technique	Acoustic	Penetration	There is no tactile information to monitor welding dynamics and quality characteristics.	[124]
Optical signal techniques	Photodiode sensor	Penetration		[125]
		Undercut		
	Spectrometer Sensor	Undercut		[126]
		Blowouts		
		Cracks		
	Pyrometer Sensor	Penetration		[127]
	Fused techniques	Molten pool geometry		[128]
		Crack porosity		
		undercut		
		Spatters		
	X-ray radiography	Porosity		[129]
		Cracks		
		Penetration		
		Slags		
Electro-magnetic sensors			Sensor deviations from the welding line were detected using a scanning motion despite the intense light and fumes of the arc	[130]

Modern production involves complex processes, including several unpredictable data, which is why industrial companies and customers must strive to better understand specific welding requirements and dynamic work environments [131]. The ability to collect and share information between units to improve decision-making is a vital part of this process, and it can be used both internally to improve operations and externally to evaluate lifecycles in industrial supply chains. Moreover, in industrial applications, welding is just one among many complicated processes, which also include forming [46], bending [132], cutting [133] and machining [134]. For instance, tailor welded blanks [16] as a novel production method in automobile application to make light and straight parts in vehicles. Therefore, real-time inspection of welding and using sensor 4.0 technology pave the way to improving welding processes, component performance, and subsequent service quality. Besides, innovations in the fields of computer science, control theory, robotics, and artificial intelligence are enabling the replacement of manual work with intelligent automation [135]. Among the many welding methods in industrial application, laser welding, spot welding, and friction stir welding those that are entirely automated. These concepts and their associated technologies have been explored in manufacturing research initiatives in contexts such as Industry 4.0 [136], lean manufacturing [137] and the Internet of Things (IoT) [138]. As a result, these tools are triggering as a driver, enablers, and platforms for upgrading welding systems into higher levels of intelligence. A real-time monitoring process plan is shown in Figure 14. Firstly, critical process parameters are defined, and then their targets are monitored during the welding process. Then, data acquisition from different segment sensors plays a key role as data transition occurs in online mode to detect the fluctuation during the process. There are many real-time monitoring levels, such as input parameters, welding conditions, side effect features like the temperature field and welding pool surface [139]. Thus, the monitoring techniques, procedure, data accuracy, and refine the results would be the next steps (Figure 14). Finally, the intelligent decision is taken by the cloud computing.

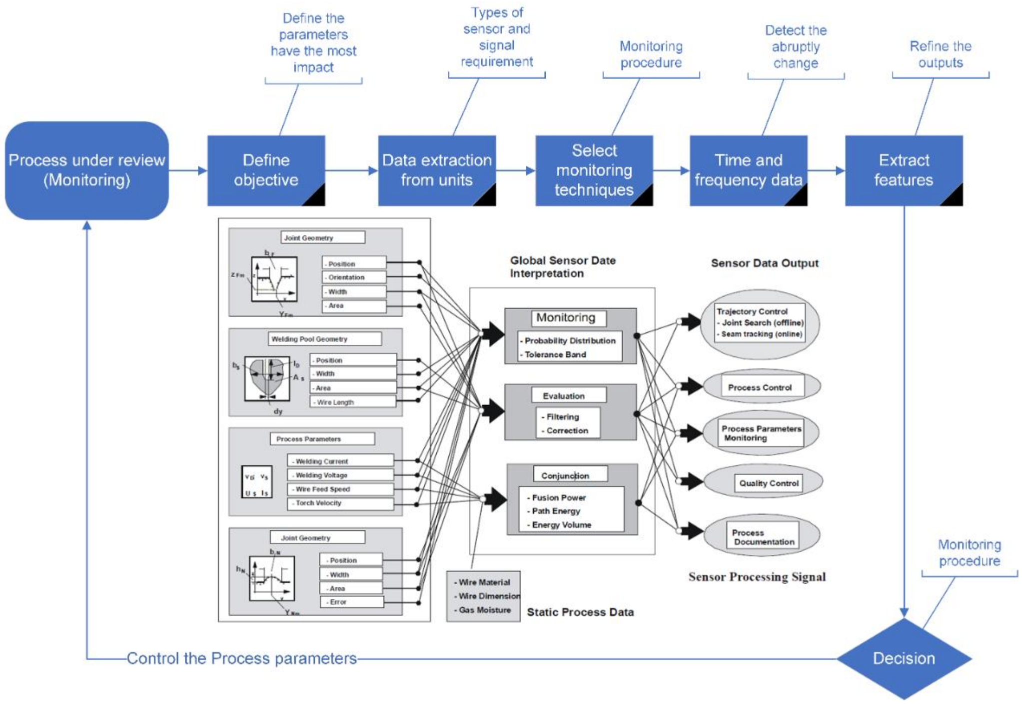


Figure 14. Monitoring and controlling diagram of welding

Based on the literature [140,141], in bibliometrics, papers, books, and other forms of communication are analyzed using mathematical and statistical methods. It has become clear that big data is on the rise in the age of big data, as we are seeing a massive explosion of data from mobile devices, social media, the Internet of Things, and other applications. Bibliometric approaches have been implemented to define scientific progress in many sciences and engineering disciplines, and constitute a common research instrument for the systematic analysis of publications [142–146]. For instance, Muhuri et al. studied a bibliometric analysis and an extensive survey on recent developments in the field of Industry 4.0 using the Web of Science (WOS) and Scopus and reported on how Industry 4.0 has developed over the last 5 years [147]. Although the Web of Science (WOS) and Scopus are the most important data collection in science, duplicate recorded could impact on the data accuracy and outcome. To address these critical points in the knowledge, a bibliometric analysis is conducted in the field of "real-time monitoring of welding technology" by searching through database using multiple, similar terms for real-time monitoring. Here, the Endnote software and the R package are applied to eliminate duplications publications from

WOS and Scopus. Also, implemented an evaluation of overall real time monitoring research and welding technology. Additionally, this evaluation looks at whether welding technology follows similar thematic trends and challenges as other industries and whether the research in one industry is underdeveloped in comparison to others. This investigation makes three main contributions. First, in the best of the authors knowledge, this research is the first investigating the evolution state of the real-time monitoring of welding technology by using the bibliometric analysis. The utilization of the latter is important because it is a quantitative and objective analysis, so it can eliminate the systematic review biases which can be induced by the researchers' subjective judgement. Second, this research explores the structure of knowledge by exploring the main authors, articles, journals, institutions, and countries that most influenced the real-time monitoring of welding technology. In addition, we explore the intellectual structure of real-time monitoring of welding technology by performing the co-citation analysis with regards to the authors and journals. Finally, we assess the conceptual structure of the real-time monitoring of welding technology literature exploring the thematic evolution of this concept and the co-occurrence network of the authors' keywords.

As technology and connectivity have advanced in manufacturing, industry ecosystems have evolved to include cyber-physical systems (CPS), the Internet of Things (IoT), big data, and artificial intelligence (AI). Cyber-physical systems are transforming centuries-old manual crafts into digitized processes governed by industrial informatics. By incorporating these characteristics into production methods, manufacturers are able to monitor, control, and optimize production efficiency and performance. Manufacturing companies are increasingly relying on smart manufacturing systems to meet their challenges as a result of Industry 4.0. The integration of a robot welding system with smart manufacturing, which entails all the manufacturing assets necessary, can result in the creation of a smart welding system. The operation and control systems of such a welding system can have improved uptimes and performances. Febriani et al. [148], used an experimental combination of Reference Architectural Model Industry 4.0 (RAMI 4.0) and smartization of welding systems. Mishra et al. [51] presented a roadmap for implementing the idea of Industry 4.0 in smart Friction stir welding (FSW) by different types of sensors such as force, torque, current, power, temperature, vibration, acoustic emission, and imaging. Furthermore, an innovation friction stir welding process (FSW) has developed via a cloud-based real-time monitoring and control scheme to prevent the formation of weld defects. According to the model, the machine is provided with feedback regarding the desired controlled parameters to improve the quality of the weld [118]. Tannous et al. used a collaborative system in a real industrial scenario, in which welding happens in real-time, a haptic-based touch detection strategy is described and tested [34]. Based on the results, the current model adds significant advances to enable the use of light and simple machine learning approaches in real-time applications. Benakis et al. [149] Based on ongoing research in robotic Gas Tungsten Arc Welding (GTAW) monitoring for defect detection and characterization, this article discusses the current state of welding process monitoring and the future trends in industrial implementation. Park et al. [150] to demonstrate how a robot welding system can be transformed to meet the challenges of smart manufacturing in a structured way, developed a Platform for Smart Manufacturing System based on the Reference Architectural Model Industry 4.0 (RAMI 4.0). Mann et al. [151] defined a basic framework and core elements of gas metal arc welding (GMAW) in terms of Industry 4.0 and they found that network connection is a main part of product quality. A specific Digital Twin model is introduced for real-time geometry assurance by Soderberg et al. and reported as an alternative to real-time individual adjustments, a Digital Twin model might also make batch-by-batch adjustments using data from batches of parts [152]. Welding robots can adapt to the challenges of "moving" seams and components by using sensors to provide the adaptive capability of touch and sight. Detect and measure process features and parameters are the most important application of sensors in automatic welding [153]. Besides, sensors are also implemented for weld inspection of properties, defects and control quality [154]. From robotic perspective, an ideal sensor should measure the welding points, should detect seam direction, and should be as small as possible. With the introduction of sensors, robotic automation has been able to assist in the welding of inconsistent joints by detecting the joint edge, tracking the joint seam, and measuring the joint width. As a matter of fact, there is no ideal sensor that will satisfy all requirements in practice. In spite of the benefits associated with robotic systems, it is important to take into consideration the associated problems, include the following:

- A consistent manufacturing sequence is required (e.g., tailor welded blanks) [16].
- When manufacturing or repairing low to medium volumes, programming can take a lot of time and effort [155].
- Variation in gap condition and Joint design with close tolerance (0.5 to 1 mm) [156].
- Calculation of return on investment (ROI) for initial cost and effect [157].
- Possible lacks of skilled welders [158].
- There are some areas, including pressure vessels, interior tanks, and ship bodies, where robotic welding is not possible due to a lack of suitable workspace [159].
- In some cases, the robot is unable to respond quickly to sensor information, leading to sluggish and sometimes unstable behavior [160].
- Investing in the first place is expensive [160].
- Processes take longer [161].
- The sensor equipment's physical dimensions [162].
- Process accuracy is not as accurate as desired [163].
- Welding automation has traditionally been difficult due to the "stacking up" of tolerances [164].

2.7 BIBLIOMETRIC METHODS

In 1922, E.Wyndham Hulme used the term statistical bibliography for two lectures at the University of Cambridge as Sandars Reader in Bibliography [165]. Specifically, peer review, funding, patents, and awards are quantitative indicators of research impact. This method could be applied across different types of areas, smart manufacturing, industry 4.0, cyber manufacturing, data science, real-time monitoring, internet of thing, economic, robotic, sustainability. Based on the literatures [166–168], there are three main clusters in bibliometric data collection. First, review technique is related to classical analysis (systematic and meta). According to Paste et al. [169], a systematically reviewed and meta-analyzed estimate showed that occupational exposure to welding fumes can cause trachea, bronchus, and lung cancer. Second, evaluative methods contain some other aspects such as impact measures, productivity measures and, hybrid measures (productivity and impact measures). Layus amn Kah [170] analysis a bibliometric study of welding scientific Publications by big data analysis. Moreover, VOS viewer and Microsoft Excel were used to analyze 12000 articles from the Scopus database relevant to arc welding, written between 2001 and 2012. Thirdly, utilizing relational techniques, we can identify networks between authors, publications, or journals. A combination of relational techniques and evaluative techniques is used in this study as bibliometric techniques [171].

2.8 DATA PROCESSING

Investigation on smart manufacturing publications is performed since 1989 via two chief Web bibliometric tools (WOS and Scopus). According to the literatures [172,173], selection procedure is adjusted based on systematic reviews and meta-analyses (PRISMA) flow diagram (Figure 15) and the main information of data processing are presented in Table 7. Based on PRISMA, following steps to identify a database for investigation:

- **Identification of studies.**

Following key words and criteria selection are presented as search digits in web bibliometric tools (WOS and Scopus):

- TITLE-ABS-KEY (("weld*" AND ("sens*" OR "signal" OR "acoustic sens*" OR "vision" OR "sound" OR "spectral" OR "ultrasonic sens*" OR "image" OR “multi sens*” OR “intelligent sens*” OR “signal processing” OR “collection” OR “acquisition” OR “Optical sens*” OR “Electro-magnetic sens*” OR “real-time monitoring”)))

Screening: in order to conduct screening two condition has been checked.

- English language context.

- publication types: books, book series, trade publications, and undefined.

Eligibility: the publication which has not assign with international standard serial number (ISSN) has been excluded from search tools.

Inclusion: The final database consisted of 11,937 publications on WI and 138 on PI.

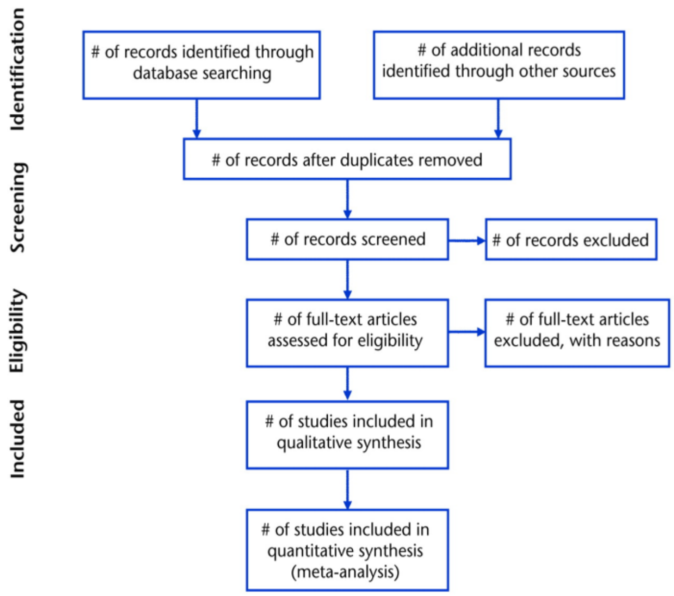


Figure 15. PRISMA Model [174]

Table 7. Main information extracted from WOS and Scopus.

Description	Results
Timespan	1989:2021
Sources (Journals, Books, etc.)	3835
Documents	11937
Average years from publication	9.75
Average citations per documents	10.38

Average citations per year per doc	1.079
References	173277
DOCUMENT TYPES	
article	7238
article; proceedings paper	557
proceedings paper	3999
review	143
DOCUMENT CONTENTS	
Keywords Plus (ID)	0
Author's Keywords (DE)	21993
AUTHORS	
Authors	24514
Author Appearances	45280
Authors of single-authored documents	603
Authors of multi-authored documents	23911
AUTHORS COLLABORATION	
Single-authored documents	683
Documents per Author	0.487
Authors per Document	2.05
Co-Authors per Documents	3.79
Collaboration Index	2.12

2.9 ANALYSIS PROCEDURE AND SOFTWARE

A number of software programs are used to analyze data, including Notepad ++, R language, and VOS viewer. Here, Notepad++ is used first for standardizing keywords and abstracts in articles. A procedure based on Aria and Cuccurullo [166] is then applied using the R language in particular the Bibliometrix package. In addition, a summary analysis is performed as well as a ranking of the number of cited references and author dominance. An important aspect of this project is the implementation of a VOSviewer that captures information on bibliographic network matrices, bibliographic co-citations, bibliographic collaborations, country scientific collaborations, co-citation networks, as well as keyword co-occurrences.

2.10 RESULTS AND DISCUSSION

In order to achieve a desirable investigation, first duplicates in the two databases have been removed. Then, articles and articles from conference proceedings are selected as central view of this study. The trend of research from 1989 to 2020 is illustrated in Figure 16. Generally, the initial studies were done in 1989 by 15 article but with progress in time this number has been strictly increasing almost 1000 publication in 2020. In fact, annual progress production shows strong influence of real-time monitoring over the past decade, and it makes an interesting topic not only for academic researcher but also for industrial application.

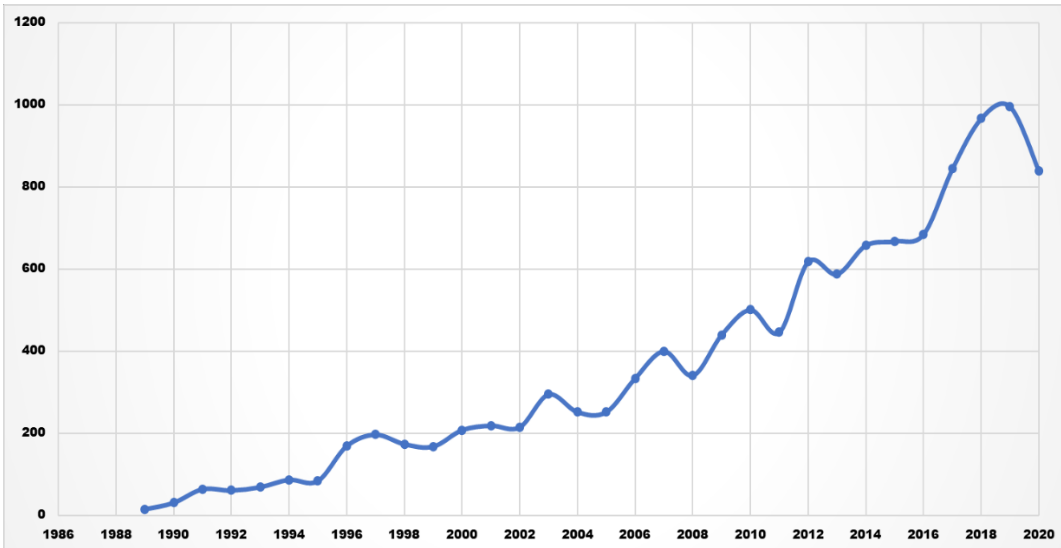


Figure 16. Annual publication of sensors in welding technology

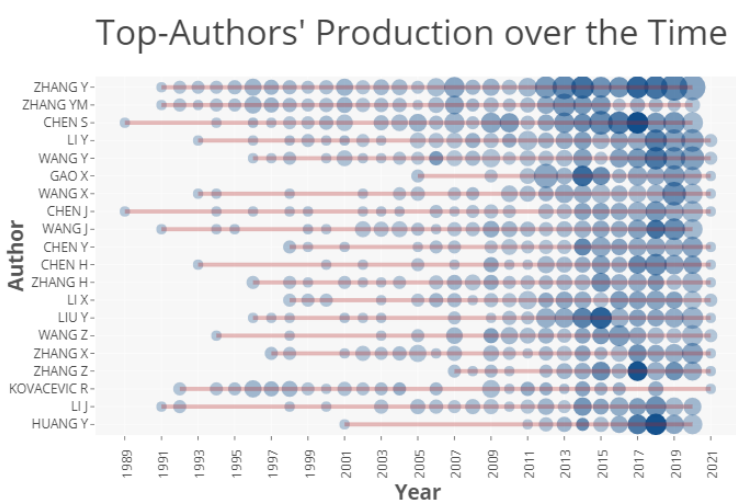
2.11 AUTHORS IMPACTS

Based on the number of publication and h-index the top 10 authors are presented in Table 8. First, number of publications have been checked then if two or more authors had the similar ranking h-index should be consider as second ranking criteria. According to the results, ZHANG Y was the most productive author by 140 articles (h-index =18) followed by ZHANG YM and CHEN S by 133 and 132 publications, respectively. Figure 17 displays that since 1989, two authors (CHEN S and CHEN J) constantly produced research on this field.

Table 8. Most productive authors in real time monitoring.

Author	h-index	TC	Number of publications	PY-start
ZHANG Y	18	965	140	2001
ZHANG YM	30	2248	133	1991
CHEN S	24	1627	132	1994
LI Y	17	1061	107	1993
WANG Y	14	939	103	1996
GAO X	15	827	92	2009

WANG X	10	472	84	2004
CHEN J	11	487	77	1994
WANG J	17	901	78	1999
CHEN Y	13	664	71	1998
CHEN H	17	783	71	2007
ZHANG H	15	585	69	1998
LI X	15	627	67	1998
LIU Y	14	616	69	1998
WANG Z	14	718	65	1998
ZHANG X	12	514	66	1997
ZHANG Z	18	774	65	2007
KOVACEVIC R	26	1651	64	1992
LI J	13	503	62	1992
HUANG Y	16	788	61	2012



Authors	**Articles**
ZHANG Y	142
ZHANG YM	133
CHEN S	132
LI Y	108
WANG Y	107
GAO X	92
WANG X	85
CHEN J	78
WANG J	78
CHEN Y	72
CHEN H	71
ZHANG H	70
LI X	69

Figure 17. Top authors production over time (1989-2021)

2.12 MOST RELEVANT SOURCES

The most relevant source for is the Materials Science and Engineering: R: Reports, with 305 papers, followed by Progress in Materials Science an International Review Journal (134 papers) and Metallurgical Transactions B (Process Metallurgy) (124 publications) (Table 9 and Figure 18).

Table 9. Most cited reference in international journals

Cited References	Citations
MISHRA RS, 2005, MAT SCI ENG R, V50, P1, DOI 10.1016/J.MSER.2005.07.001	305
NANDAN R, 2008, PROG MATER SCI, V53, P980, DOI 10.1016/J.PMATSCI.2008.05.001	134
GOLDAK J, 1984, METALL TRANS B, V15, P299, DOI 10.1007/BF02667333	124
KOU S, 2003, WELDING METALLURGY	93
OTSU N, 1979, IEEE T SYST MAN CYB, V9, P62, DOI 10.1109/TSMC.1979.4310076	88
THOMAS W, 1991, INTERNATIONAL PATENT APPLICATION, PATENT NO. [GB 9125978.8, 91259788]	79
THREADGILL PL, 2009, INT MATER REV, V54, P49, DOI 10.1179/174328009X411136	78
KOVACEVIC R, 1997, J MANUF SCI E-T ASME, V119, P161, DOI 10.1115/1.2831091	77
BAE KY, 2002, J MATER PROCESS TECH, V120, P458, DOI 10.1016/S0924-0136(01)01216-X	74
ZHANG W, 2012, WELD J, V91, P195S	74
NAGARAJAN S, 1992, IEEE T ROBOTIC AUTOM, V8, P86, DOI 10.1109/70.127242	69

MAHONEY MW, 1998, METALL MATER TRANS A, V29, P1955, DOI 10.1007/S11661-998-0021-5	68
WANG G, 2002, NDT\&E INT, V35, P519, DOI 10.1016/S0963-8695(02)00025-7	65
ZHANG ZY, 2000, IEEE T PATTERN ANAL, V22, P1330, DOI 10.1109/34.888718	64
LEITAO C, 2012, MATER DESIGN, V33, P69, DOI 10.1016/J.MATDES.2011.07.009	62
CHEN W, 1990, WELD J, V69, PS181	61
RENWICK RJ, 1983, WELD J, V62, PS29	60
XU YL, 2012, J MATER PROCESS TECH, V212, P1654, DOI 10.1016/J.JMATPROTEC.2012.03.007	60
ANCONA A, 2001, APPL OPTICS, V40, P6019, DOI 10.1364/AO.40.006019	59
PEEL M, 2003, ACTA MATER, V51, P4791, DOI 10.1016/S1359-6454(03)00319-7	59

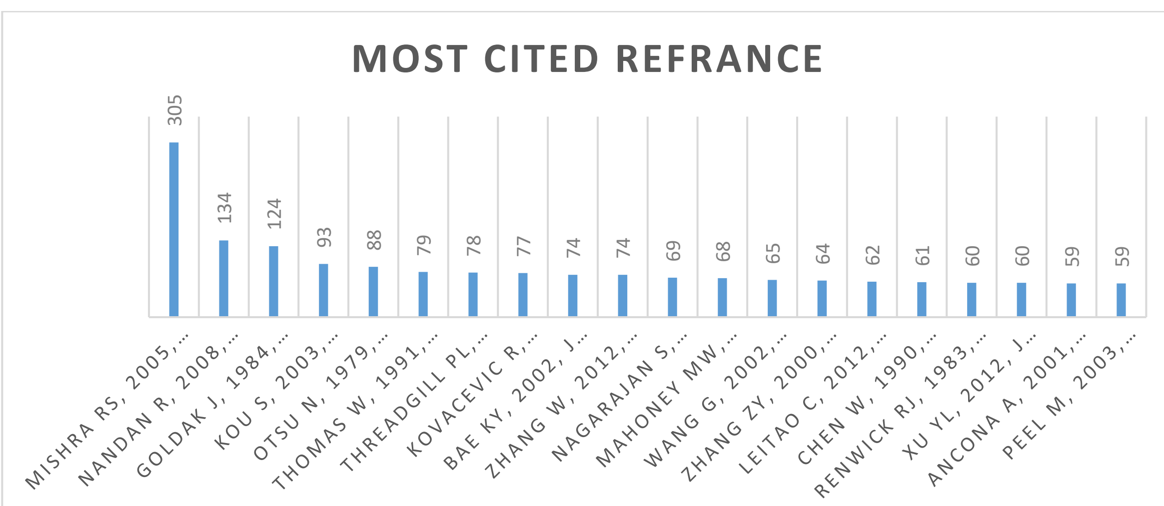


Figure 18. Most cited reference in international journals

2.13 MOST RELEVANT AFFILIATION

The most relevant affiliation was the *SHANGHAI JIAO TONG UNIV*, with 578 articles, followed by *HARBIN INST TECHNOL* (416 articles) and *UNIV KENTUCKY* (349 papers) (Table 10 and Figure 19).

Table 10. Most cited reference sorted by affiliation.

Affiliations	Articles
SHANGHAI JIAO TONG UNIV	578
HARBIN INST TECHNOL	416
UNIV KENTUCKY	349
OSAKA UNIV	327
TIANJIN UNIV	302
INDIRA GANDHI CTR ATOM RES	246
SHANDONG UNIV	229
INDIAN INST TECHNOL	198
TSINGHUA UNIV	197
GUANGDONG UNIV TECHNOL	195
HUAZHONG UNIV SCI AND TECHNOL	173
XI AN JIAO TONG UNIV	165
OHIO STATE UNIV	159
DALIAN UNIV TECHNOL	152
PENN STATE UNIV	137
UNIV MANCHESTER	136

UNIV MICHIGAN	127
KOREA ADV INST SCI AND TECHNOL	123
SOUTHWEST JIAOTONG UNIV	116
BEIJING UNIV TECHNOL	111

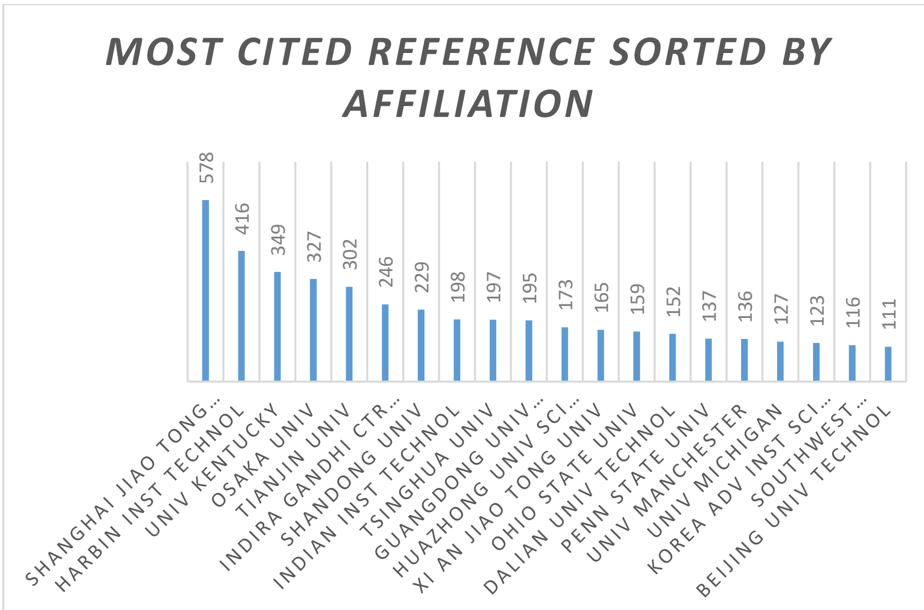


Figure 19. Most cited reference sorted by affiliation.

2.14 COUNTRIES PRODUCTION

The most productive countries were determined based on two indices: the country of affiliation of the author (Table 11 and Figure 20), the country that cited the most papers and the country that collaborated with the most papers. Chinese authors accounted for 8,695 out of the total 8,681, while Americans had 4,818, according to tables 11 and 12. According to the total number of citations by country, the USA has the most (29,240, followed by China with 23,820). Moreover, India, Germany, South Korea had third to five ranking in the author's country of affiliation (2087, 1980, 1687). Fig. 21 shows the five countries with the most scientific production. Again, China and the USA has the core highway in collaboration (Figure 22).

Table 11. The author's country of affiliation

Region	**Freq**
CHINA	8695
USA	4818
INDIA	2087
GERMANY	1980
SOUTH KOREA	1687
UK	1590
JAPAN	1571
FRANCE	977
ITALY	864
CANADA	774
BRAZIL	715
RUSSIA	558
SPAIN	538
IRAN	532
SWEDEN	374
TURKEY	350
AUSTRALIA	342
POLAND	334
PORTUGAL	328
NETHERLANDS	273

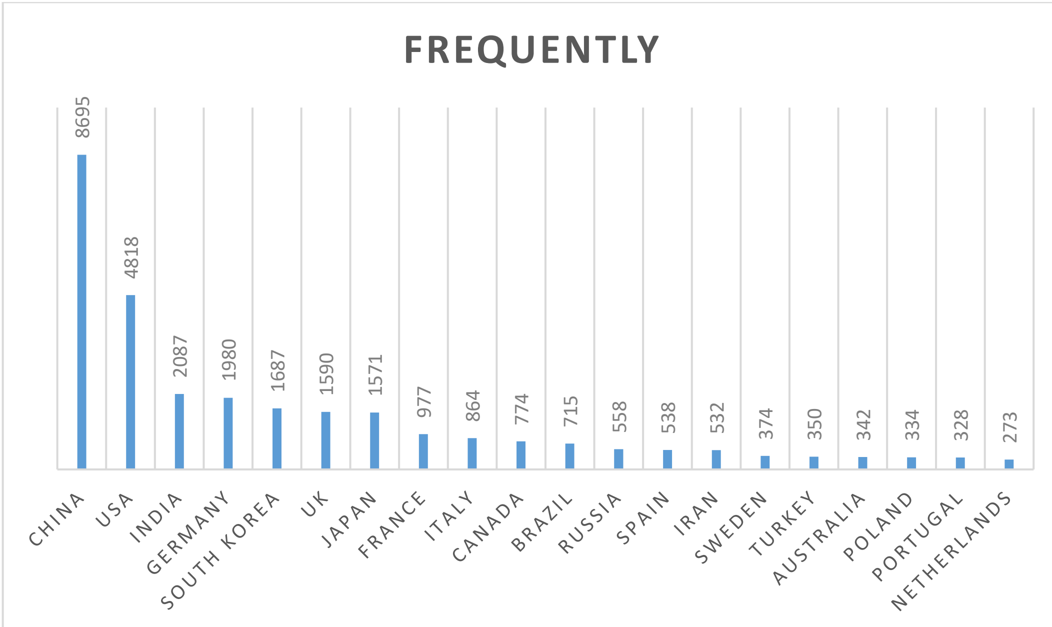


Figure 20. The author's country of affiliation

Table 12. Most cite countries.

Country	Total Citations
USA	29240
CHINA	23820
INDIA	8949
UNITED KINGDOM	8273
GERMANY	5882
JAPAN	5477
KOREA	4855
ITALY	4384
FRANCE	3821
CANADA	3576
IRAN	1759
SPAIN	1750
SWEDEN	1706
TURKEY	1681

BRAZIL	1652
AUSTRALIA	1585
PORTUGAL	1526
POLAND	1050
NETHERLANDS	1019
FINLAND	874

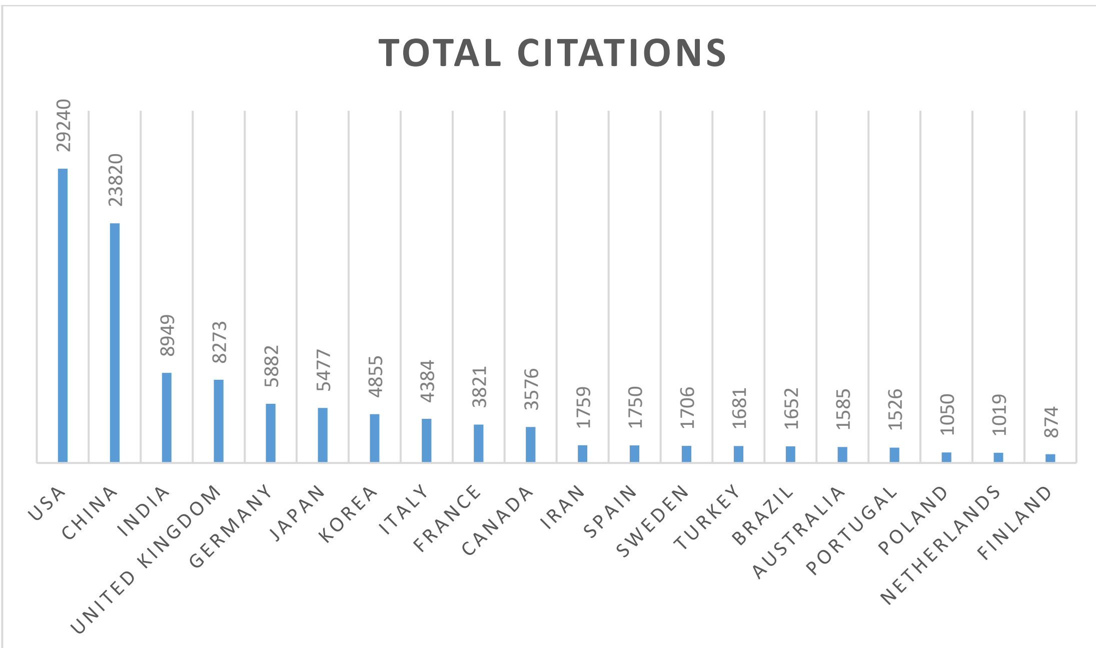


Figure 21. Most cited countries.

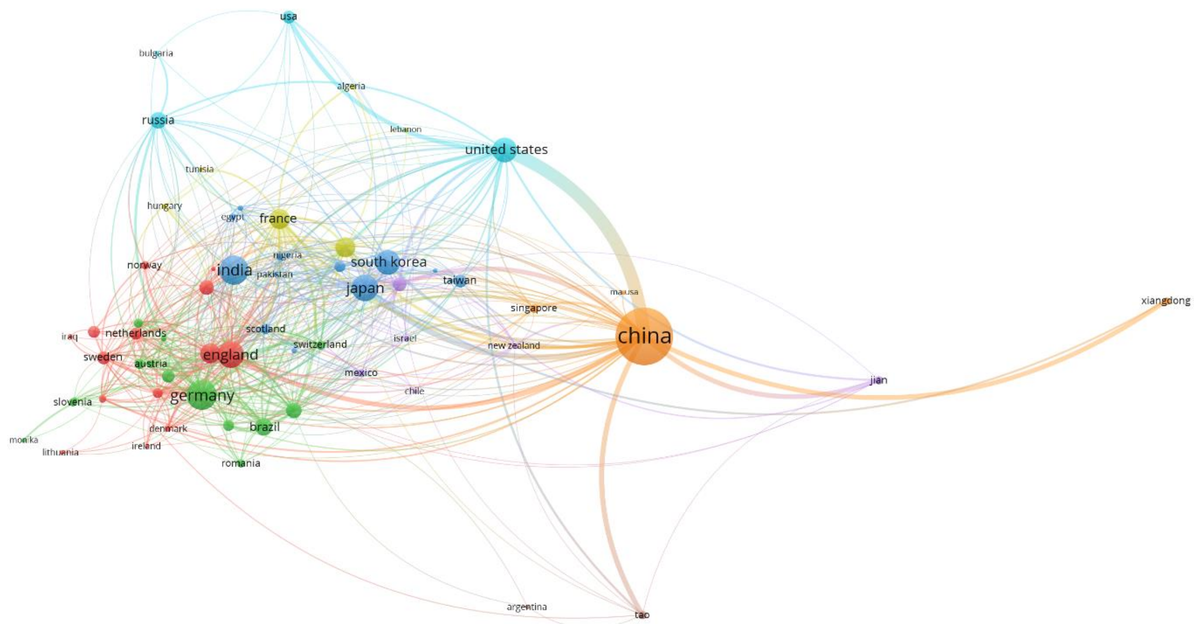


Figure 22. Countries collaboration

2.15 MOST CITED DOCUMENT

According to table 13 the greatest citation (793) has been recorded by TUTT LW which is published in Nature journal in 1992. Later, GARNETT EC and LI D are cited as the most influence document by 767 and 756, respectively. On the other hand, WELD J (6791), J MATER PROCESS TECH (5947), MAT SCI ENG A-STRUCT (5928) are the maximum cited sources (Table 16). However, INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY, JOURNAL OF MATERIALS PROCESSING TECHNOLOGY, SCIENCE AND TECHNOLOGY OF WELDING AND JOINING are the most Source impact (Table 13-15 and Figure 23).

Table 13. Most cited document

Paper	Total Citations
TUTT LW, 1992, NATURE	793
GARNETT EC, 2012, NAT MATER	767
LI D, 2009, ACCOUNTS CHEM RES	756
MACWAN DP, 2011, J MATER SCI	491
BARCELOUX DG, 1999, J TOXICOL -CLIN TOXICOL	390
RAI R, 2011, SCI TECHNOL WELD JOIN	374
BAGAVATHIAPPAN S, 2013, INFRARED PHYS TECHNOL	374
WITHERS PJ, 2007, REP PROG PHYS	366
ROY DP, 2010, REMOTE SENS ENVIRON	350
BRICKSTAD B, 1998, INT J PRESSURE VESSELS PIP	313
SINGH K, 2011, CRIT REV ENVIRON SCI TECHNOL	290
BUSSU G, 2003, INT J FATIGUE	287
HUANG JX, 2006, PURE APPL CHEM	280
ZHANG D, 2006, MATER SCI ENG B-SOLID STATE MATER ADV TECHNOL	274
ALLEYNE DN, 1992, NDT E INT	270
DONG P, 2001, INT J FATIGUE	268
WROBLICKY GJ, 1998, WATER RESOUR RES	265
LIU F, 1996, IEEE TRANS PATTERN ANAL MACH INTELL	259

MOCZO P, 2002, BULL SEISMOL SOC AMER	259
TONG T, 2007, IEEE TRANS COMPON PACKAGING TECHNOL	252

Table 14. Most cited sources

Sources	Articles
WELD J	6791
J MATER PROCESS TECH	5947
MAT SCI ENG A-STRUCT	5928
MATER DESIGN	4996
INT J ADV MANUF TECH	4090
SCI TECHNOL WELD JOI	3861
METALL MATER TRANS A	2316
INT J FATIGUE	2155
ACTA MATER	2069
NDT&E INT	1990
CORROS SCI	1877
SCRIPTA MATER	1852
J PHYS D APPL PHYS	1543
THESIS	1213
WELD WORLD	1199
J APPL PHYS	1162
J MATER SCI	1119
MEAS SCI TECHNOL	1117
J MANUF PROCESS	1063
MATER CHARACT	1020

Table 15. Source impact

Source	h_index	TC	NP	PY_start
INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	34	4639	354	1997
JOURNAL OF MATERIALS PROCESSING TECHNOLOGY	38	5820	256	1993
SCIENCE AND TECHNOLOGY OF WELDING AND JOINING	28	3645	213	1997
WELDING JOURNAL	30	3157	204	1989
MATERIALS & DESIGN	43	5257	158	2003
MATERIALS SCIENCE AND ENGINEERING A-STRUCTURAL MATERIALS PROPERTIES MICROSTRUCTURE AND PROCESSING	38	4780	150	1991
JOURNAL OF MANUFACTURING PROCESSES	18	1332	138	2013
WELDING IN THE WORLD	12	648	129	2009
INSIGHT	11	575	114	1994
JOURNAL OF LASER APPLICATIONS	16	799	91	1994
NDT \& E INTERNATIONAL	31	2527	88	1991
JOURNAL OF MATERIALS ENGINEERING AND PERFORMANCE	13	578	87	1993
METALLURGICAL AND MATERIALS TRANSACTIONS A-PHYSICAL METALLURGY AND MATERIALS SCIENCE	19	1268	80	1996
RUSSIAN JOURNAL OF NONDESTRUCTIVE TESTING	5	104	77	1992

INTERNATIONAL JOURNAL OF FATIGUE	25	2078	71	1991
OPTICS AND LASER TECHNOLOGY	19	1052	71	1999
SENSORS	13	605	71	2008
MEASUREMENT SCIENCE AND TECHNOLOGY	23	1275	70	1990
INTERNATIONAL JOURNAL OF PRESSURE VESSELS AND PIPING	15	1214	67	1989
METALS	7	157	65	2016

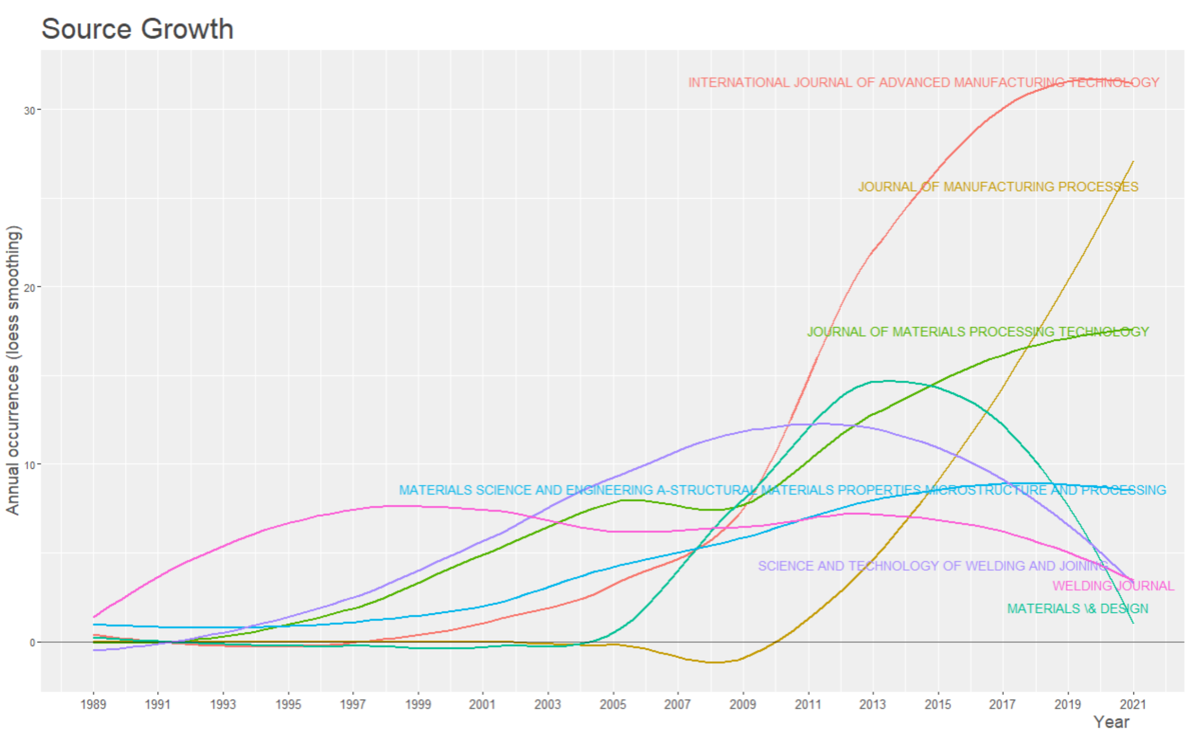


Figure 23. The trend of Journal source growth from 1989 to 2021

2.16 MOST FREQUENT WORDS

Keyword analysis in data science is a method of analyzing the keywords or search phrases that bring researchers through organic and paid search. As such, keyword analysis is the starting point and cornerstone of search marketing campaigns [175]. Thus, Keyword analysis has been an important research theme in bibliometrics. Here, we investigated both keyword frequency and keyword co-occurrences. Table 16 shows the most relevant keywords related to research. Two author keywords were relevant: “Weld” with 15% (1,123) and “Microstructure” with 7% (490). Actually, these words consist the material characterization in weld region is the most critical matter in welding technologies. Also, friction stir welding and laser welding is the most frequent word between welding techniques (Figure 24). Interestingly, based on the Figure 24, weld investigation was decreased from 2017 to 2020 but microstructure analysis increasing sharply without any fluctuation (Figure 25). Moreover, image processing is a common method regarding damage detection and real time monitoring of welding.

Table 16. Most frequent words

Words	**Occurrences**
Weld	1123
Microstructure	490
Friction_stir_weld	438
Laser_weld	414
Mechanical_property	276
Image_processing	250
Residual_stress	184
Stainless_steel	183
Fatigue	165
Weld_joint	163
Laser	150

Seam_tracking	148
Steel	142
Aluminum_alloy	140
Monitoring	134
Digital_image_correlation	124
Corrosion	118
Resistance_spot_weld	115
Modeling	104
Sensor	101
Weld_defect	101

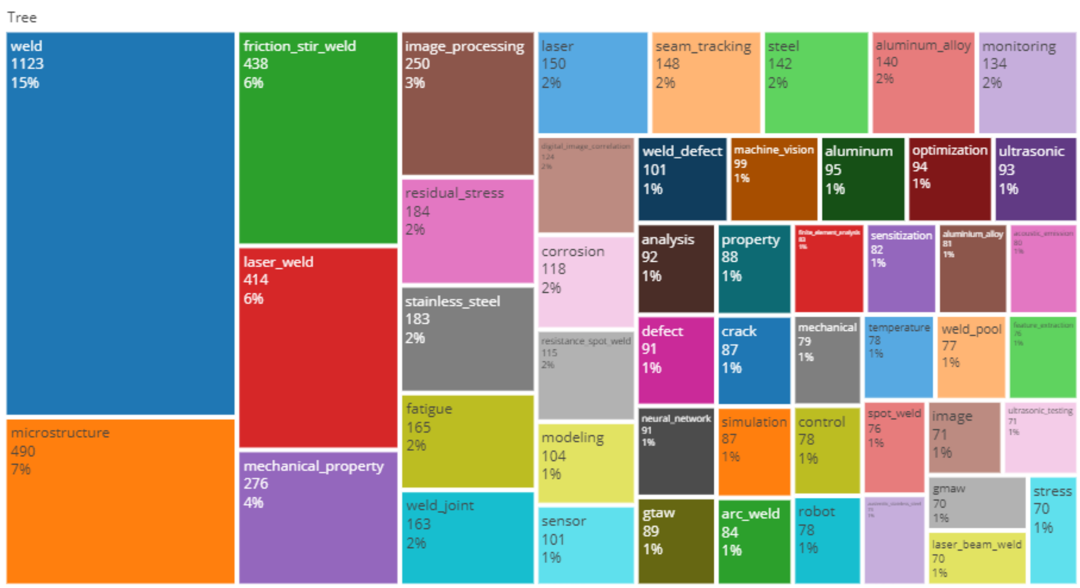


Figure 24. Key word percentage

Figure 25 depicts the annual growth in occurrences of specific terms related to welding within the scientific literature from 1990 to 2020. This visualization highlights significant trends; for example, the term "weld" exhibits robust exponential growth, indicating an increasing interest and ongoing research in the general field of welding. Terms such as "microstructure" and "friction_stir_weld" also show notable growth, suggesting a heightened focus on the study of welds' microstructural characteristics and the friction stir welding technique. Other keywords like "mechanical_properties", "laser_weld", and "image_processing_weld_joint" reveal a rising interest aligned with technological advances and the deepening of knowledge in these particular subdomains. Finally, terms such as "residual_stress" and "stainless_steel" are also represented, although their growth is more moderate, reflecting their sustained importance in welding studies. This bibliometric analysis provides valuable insights into the evolution of research interests and could serve as a guide for future work in the field of welding.

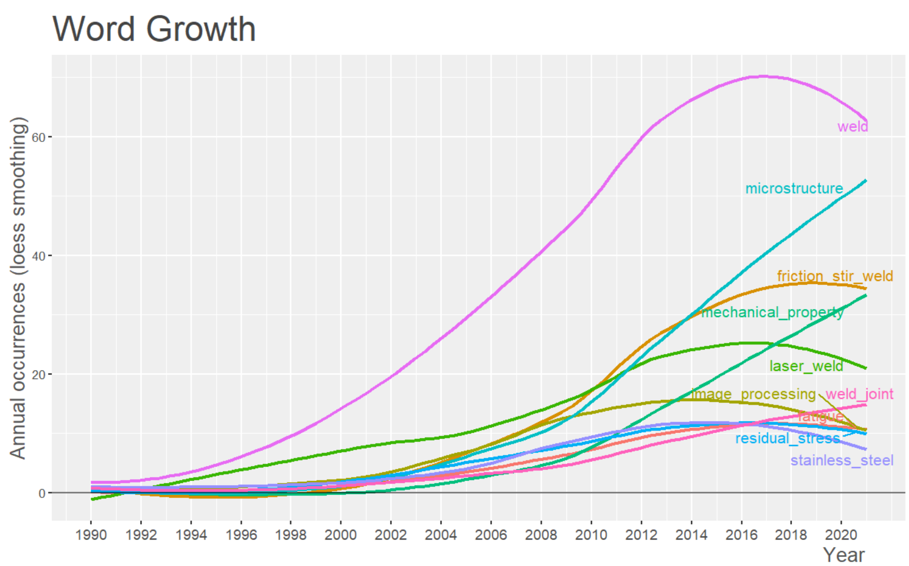


Figure 25. The word growth from 1990 to 2020

Figure 26 displays trending topics in welding-related scientific literature from 1996 to 2020, illustrating the logarithmic frequency of key terms over time. It captures the rise of subjects like "neural_network", "machine_learning", and "deep_learning", indicating a growing incorporation of artificial intelligence in the field of welding. Specific technical welding terms such as "laser_weld", "friction_stir_weld", and "weld_joint" also show an increased frequency, underscoring advancements and sustained interest in innovative welding methods. Additionally, focus on more specialized aspects like "additive_manufacturing" and "laser_powder_bed_fusion" unveils the expansion of research into new welding applications. Terms like "image_processing", "sensor", and "monitoring", on a steady incline, reflect a shift toward more sophisticated and automated quality control methods. This figure suggests that the welding sector is being shaped by significant technological advances and is moving towards smarter and more interconnected manufacturing practices.

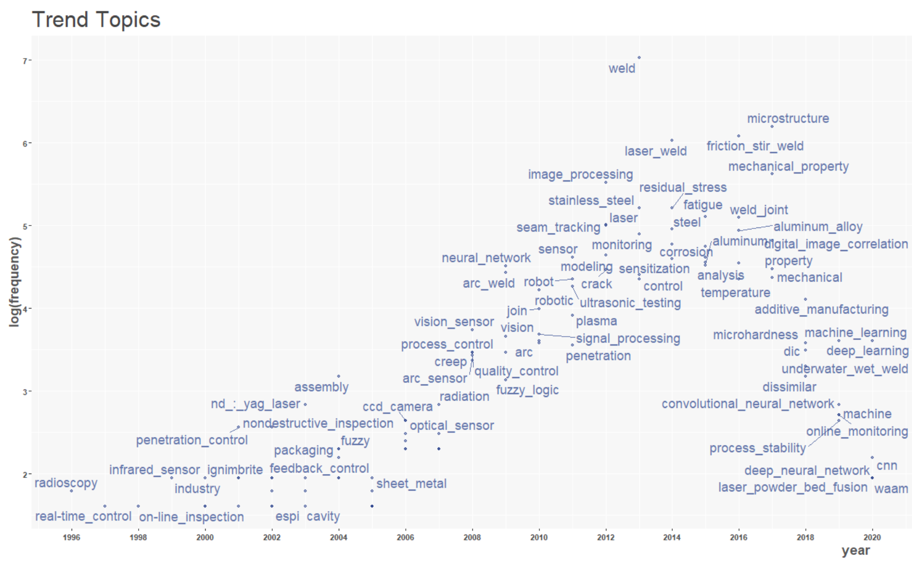


Figure 26. Trend Topics from 1996 to 2020

According to Figure 27, regarding welding technique friction stir welding is mostly analysis for steel and microstructure. Interestingly, residual stress has been investigated during 2010-2016 and there is a coloration relation between microstructure analysis and residual stress. Moreover, image processing method is considered in optimization methods. Furthermore, resistance spot welding and laser welding process are considered as automation and smart welding system.

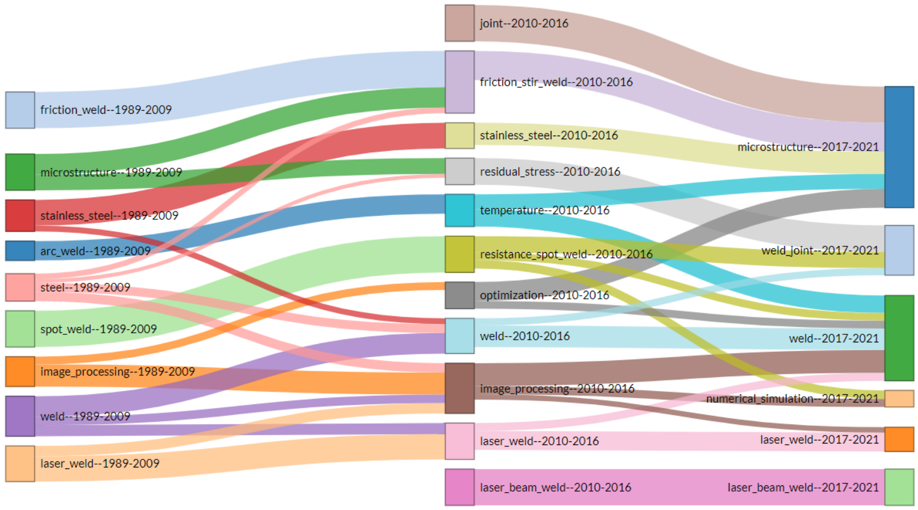


Figure 27. Key words connection

Conceptual Stricture map is drawn in Figure 28 which is aims at representing the conceptual structure of a framework using co-occurrence of words. The words can be replaced by authors' keywords, keywords plus, and terms extracted from titles or abstracts. As shown in Figure 29, there is three Clusters in this regard. First, technical concept and process-based analysis (red) and control-based concept (blue) have the most keywords, which means the attention of the researchers to the subject matter of the study. Again, development degree of topics shows image processing and machine vision analysis are the most interesting topics and stain less steel and corrosion have the greatest relevant degree.

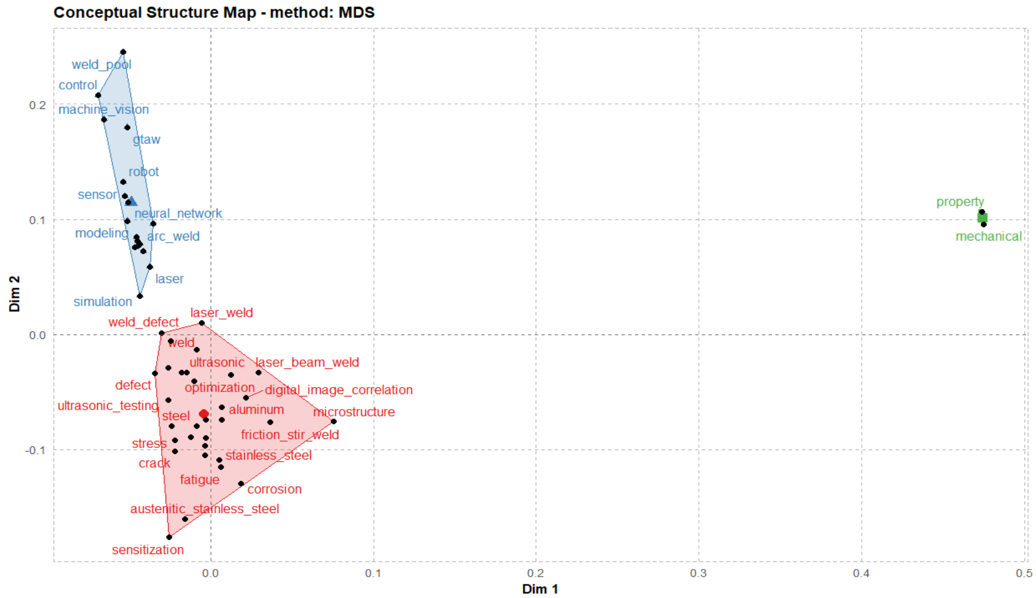


Figure 28. Conceptual Stricture map

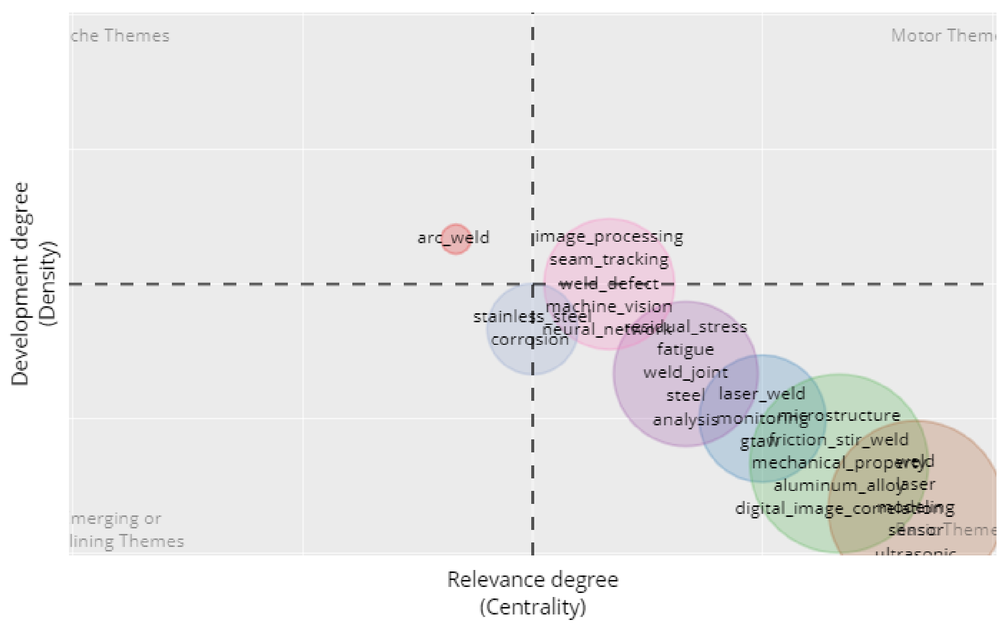


Figure 29. Development degree of topics

Figure 30 shows that author keywords can be separated into six clusters, each of which is identified by a different color. Figure 30 is a keyword occurrence map which visualizes the frequency and the relationship between various terms within the field of welding research. In these maps, the axes typically do not represent traditional X and Y values like in scatter plots but are rather a spatial representation of the co-occurrence or relatedness of terms in the literature; terms that often appear together in the literature are placed closer to each other. Each cluster contained nodes (circles) with the same color and included links or relationships (lines) between nodes. The first cluster (brown) included "Welding" as the dominant author keyword, plus other keywords, including "metal,". The two most important keywords in the second cluster (blue) were "welding defect," and "non-destructive-testing," This cluster also included many other keywords, such as "structural health monitoring, "ultrasonic," "radiography," and "defect detection," and "signal". The third cluster (green) included some important keywords, "friction stir welding" and "microstructure", and others such as "property," "fracture," "texture," "digital image correlation," and "information management." "laser welding," "neural network," "monitoring," "machine vision" "sensor" "seam tracking" "modeling" and "robotic" are examples of keywords in the fourth cluster (red). The fifth cluster (yellow) consisted of three main keywords: "stainless steel," "corrosion," "crack" and "sensitization." The sixth cluster (purple) contained "residual stress," "sensitivity analysis," "fatigue," and "numerical simulation." The seventh cluster (orange) included three keywords: "Taguchi," "Signal to noise ratio," and "Optimization."

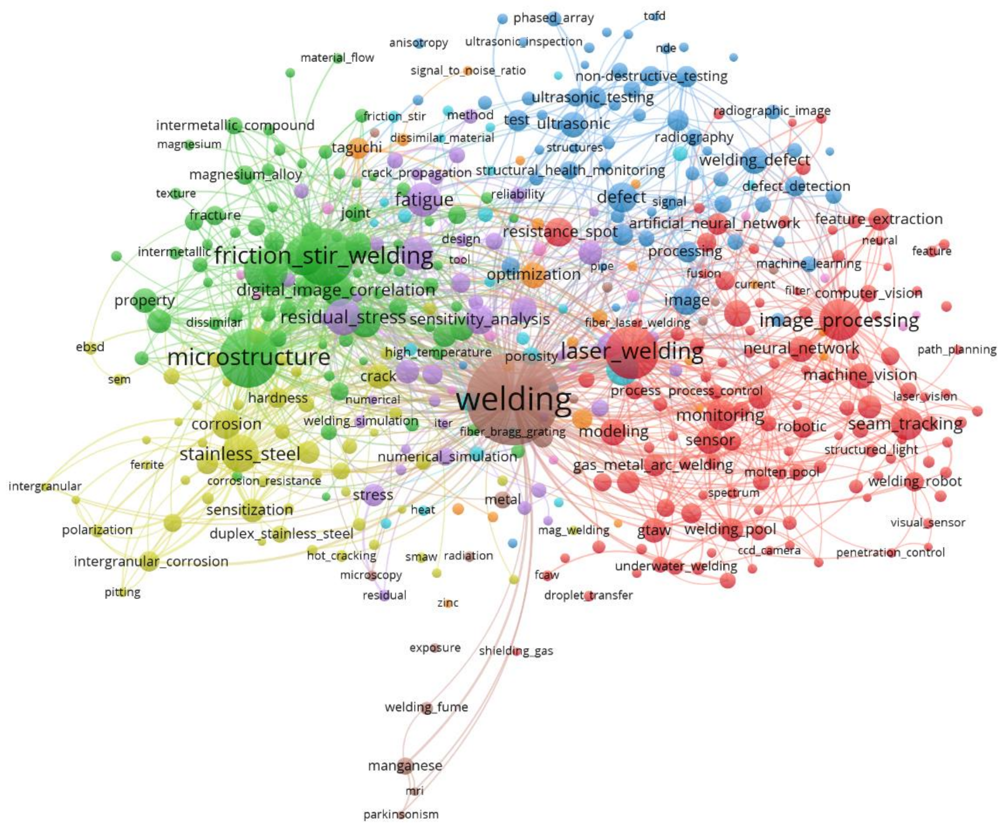


Figure 30. Keyword’s occurrences

VOS viewer software was used to perform three co-citations network analyses, each with a different unit of analysis: cited references, cited sources, and cited authors. Cited references can be either cited sources or cited authors. Figure 31 is an author co-citation network, a visual representation where the positioning of authors is based on how frequently their works are cited together in the scientific literature. In such networks:

- **Proximity:** Authors frequently cited together are positioned closer, suggesting they work in related fields or on similar topics.
- **Clusters:** Authors are often grouped into clusters representing subfields or specialties within a broader research field. Clusters can be identified by spatial proximity and often by color coding.

- **Connecting lines:** The lines connecting authors represent co-citations. Thicker or more numerous lines might indicate higher co-citation levels, signifying a closer relationship or closely related work.
- **Node size:** The size of the nodes (points representing authors) may indicate the total frequency of citations, with larger nodes representing authors who are cited more frequently.

The placement of elements is determined by a network layout algorithm designed to optimize readability, minimize line overlap, and highlight natural clustering structures from the co-citation data. For precise interpretation, one should refer to the legend or methodology section of the source document for details on the placement algorithm and the significance of different colors and sizes.

Based on Figure 31 and Figure 32, seven clusters were identified for WI research with respect to co-citation analysis based on cited sources. The green cluster included dense sources, such as Weld Journal, Journal of Manufacturing Science and Engineering, and Measurement Science and Technology. The second cluster (red) included four main sources: Materials Science and Engineering: R, Metallurgical and Materials Transactions B. The third cluster (yellow) contained three sources: Measurement Science and Technology, Journal of Materials Processing Technology, Science and Technology of Welding and Joining, and Applied Optics. Besides, the next cluster (purple) included four main sources: Weld journal, NDT & E International, Scientific Reports, and Expert Systems. The last cluster (blue) included Journal of Materials Processing Technology, Journal of Intelligent & Robotic Systems.

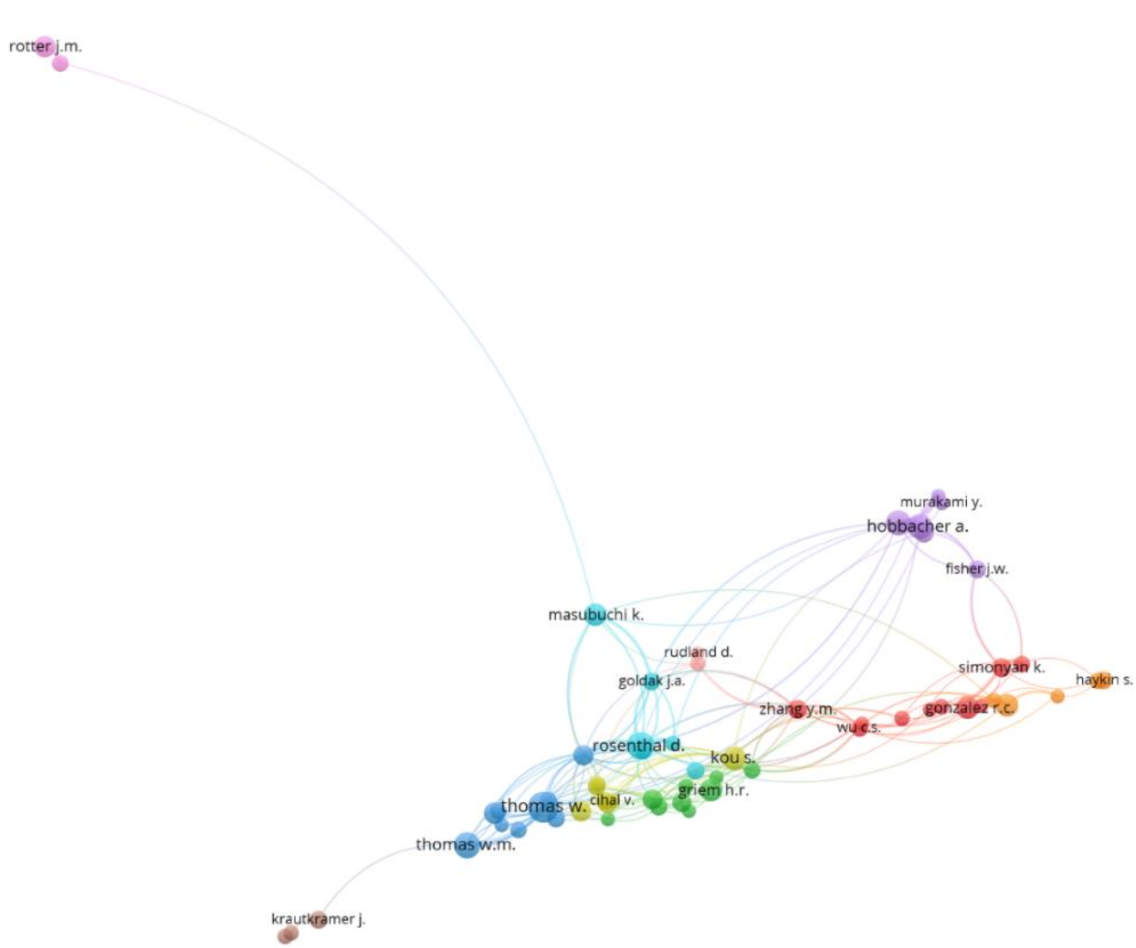


Figure 31. Authors co-citation

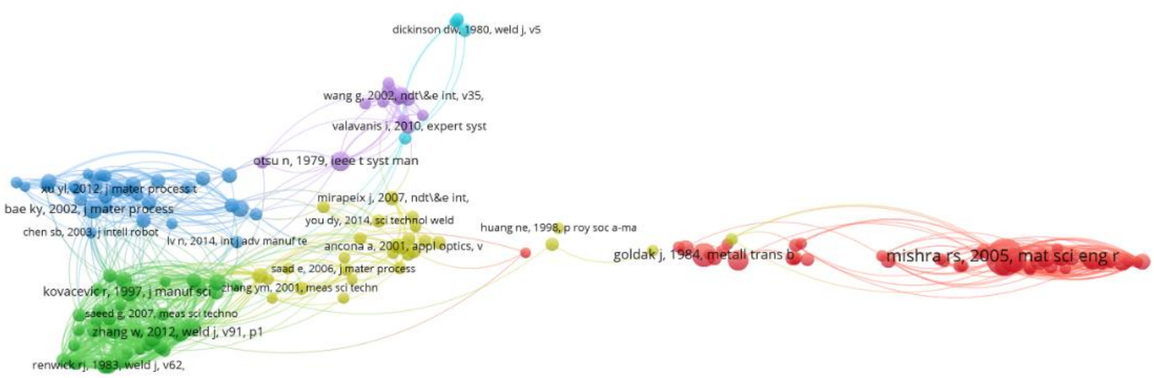


Figure 32. References co-citation

2.17 CONCLUDING REMARKS

The aim of this paper was to assess the conceptual and the intellectual structure of emerging industry 4.0 methods in welding research. To do that, we used bibliometric analysis, specifically we analysed 11,937 documents from two database WoS and Scopus between 1986 and 2021. This analysis showed different results as follows.

- First, despite some declining, the annual publication of sensors in welding technology is growing since 1986 with 17% as an average growth. This result illustrates that scholar's interest (e.g., Benakis et al. [46]; Febriani et al. [43]; Mishra et al. [44]) highly for incorporating the smart technology in the welding area.
- Second, our research showed that the most authors' affiliation was Shanghai Jiao Tong University (578 cited references). This result is consistent with our finding about the most countries production. Indeed, we found China as the most productive country (8 695 author's country of affiliation) followed by the USA with only 4 818 author's countries of affiliation. In addition, our study reveled that Zhang Y was the most productive author by 140 articles (number of publications = 140; h-index =18) followed respectively by Zhang YM (number of publications = 133; h-index =30) and Chen S (number of publications = 132; h-index =24). Finally, the co-citation analysis based on countries collaboration showed that the big cluster is represented by China. Consequently, we can argue that this country and their scholars influenced greatly on the progression of the real-time monitoring of welding technology.
- Third, the bibliometric analysis illustrates that the Weld Journal (TC = 6 791) is the most influenced source in the real-time monitoring of welding technology (see Table 9). It is followed respectively Journal of Materials Processing Technology (TC = 5 947), and Materials Science and Engineering: A (TC = 5 982). Nevertheless, regarding the productivity, the most productive source in terms of the number of papers is the International Journal of Advanced Manufacturing Technology (354 papers). It is followed correspondingly by the Journal of Materials Processing

Technology (256 papers), and the Science and Technology of Welding and Joining (213 papers).

The conceptual structure map performed with R software highlighted that there are some emerging themes in the real-time monitoring of welding technology as image processing, weld defect and machine vision. There are several basic and transversal themes such as laser weld, digital image, weld joint, neural network and sensor. In addition, residual stress has been investigated during 2010-2016 and there is a coloration relation between microstructure analysis and residual stress. These results were consistent with the keyword's occurrences performed in VOS viewer software. Indeed, the welding cluster, the most other big cluster were the welding defect (blue cluster), the friction stir welding as well as the microstructure (green clusters), and the laser welding as well as the image processing (red clusters). Finally, the literature authors co-citation highlighted many small clusters in the real-time monitoring of welding technology field. So, there are not dominant scholars' streams in this area. Consequently, we can argue that this field is not theoretically in a mature stage, but it in the growth stage. Indeed, this later also showed there are many small references cluster. Hence, we can also claim that no dominant references shape the research in the real-time monitoring of welding technology field.

2.18 LIMITATIONS AND FUTURE RESEARCH

This research had some limitations. First, the authors considered two databases which may probably limit the number of the papers analyzed. This limitation provides the opportunity as a future work for using other databases to amend this research. Second, the keywords used to retrieve papers from WoS and Scopus databases can be criticized as limited and not broader. Finally, other pertinent analysis as bibliography coupling and longitudinal period analysis may be performed.

2.19 REFERENCES

[110] A. Papacharalampopoulos, P. Stavropoulos, D. Petrides, Towards a digital twin for manufacturing processes: Applicability on laser welding, Procedia CIRP. 88 (2020) 110–115.

[111] P. Helo, A.H.M. Shamsuzzoha, Real-time supply chain—A blockchain architecture for project deliveries, Robot Comput Integr Manuf. 63 (2020) 101909.

[112] M.A. Rahman, K.S. Woon, M. Rahman, Miniaturization by precision micro cutting, Journal of Production Systems and Manufacturing Science. 1 (2020) 11.

[113] Z. Zhao, P. Lin, L. Shen, M. Zhang, G.Q. Huang, IoT edge computing-enabled collaborative tracking system for manufacturing resources in industrial park, Advanced Engineering Informatics. 43 (2020) 101044.

[114] E. Ruiz, D. Ferreño, M. Cuartas, A. López, V. Arroyo, F. Gutiérrez-Solana, Machine learning algorithms for the prediction of the strength of steel rods: an example of data-driven manufacturing in steelmaking, Int J Comput Integr Manuf. 33 (2020) 880–894.

[115] Y. Cui, S. Kara, K.C. Chan, Manufacturing big data ecosystem: A systematic literature review, Robot Comput Integr Manuf. 62 (2020) 101861.

[116] M.L. Nicora, R. Ambrosetti, G.J. Wiens, I. Fassi, Human--Robot Collaboration in Smart Manufacturing: Robot Reactive Behavior Intelligence, J Manuf Sci Eng. 143 (2021).

[117] W. Cai, J. Wang, P. Jiang, L. Cao, G. Mi, Q. Zhou, Application of sensing techniques and artificial intelligence-based methods to laser welding real-time monitoring: A critical review of recent literature, J Manuf Syst. 57 (2020) 1–18.

[118] D. Mishra, A. Gupta, P. Raj, A. Kumar, S. Anwer, S.K. Pal, D. Chakravarty, S. Pal, T. Chakravarty, A. Pal, others, Real time monitoring and control of friction stir welding process using multiple sensors, CIRP J Manuf Sci Technol. 30 (2020) 1–11.

[119] S. Shevchik, T. Le-Quang, B. Meylan, F.V. Farahani, M.P. Olbinado, A. Rack, G. Masinelli, C. Leinenbach, K. Wasmer, Supervised deep learning for real-time quality monitoring of laser welding with X-ray radiographic guidance, Sci Rep. 10 (2020) 1–12.

[120] Y. Huang, Y. Yuan, L. Yang, D. Wu, S. Chen, Real-time monitoring and control of porosity defects during arc welding of aluminum alloys, J Mater Process Technol. 286 (2020) 116832.

[121] S. Nagarajan, P. Banerjee, W. Chen, B.A. Chin, Control of the welding process using infrared sensors, IEEE Transactions on Robotics and Automation. 8 (1992) 86–93.

[122] K. Sung, H. Lee, Y.S. Choi, S. Rhee, Development of a multiline laser vision sensor for joint tracking in welding, Weld J. 88 (2009) 79–85.

[123] Y. Zhang, D. You, X. Gao, N. Zhang, P.P. Gao, Welding defects detection based on deep learning with multiple optical sensors during disk laser welding of thick plates, J Manuf Syst. 51 (2019) 87–94.

[124] H. Gu, W.W. Duley, A statistical approach to acoustic monitoring of laser welding, J Phys D Appl Phys. 29 (1996) 556.

[125] P. Norman, H. Engström, A.F.H. Kaplan, Theoretical analysis of photodiode monitoring of laser welding defects by imaging combined with modelling, J Phys D Appl Phys. 41 (2008) 195502.

[126] A.R. Konuk, R.G.K.M. Aarts, A.J. Huis, T. Sibillano, D. Rizzi, A. Ancona, others, Process control of stainless-steel laser welding using an optical spectroscopic sensor, Phys Procedia. 12 (2011) 744–751.

[127] X. Xiao, X. Liu, M. Cheng, L. Song, Towards monitoring laser welding process via a coaxial pyrometer, J Mater Process Technol. 277 (2020) 116409.

[128] A. Sun, E. Kannatey-Asibu Jr, M. Gartner, Monitoring of laser weld penetration using sensor fusion, J Laser Appl. 14 (2002) 114–121.

[129] E. Siryabe, E. Juliac, A. Barthe, C. Ferdinand, X-ray digital detector array radiology to infer sagging depths in welded assemblies, NDT \& E International. 111 (2020) 102238.

[130] Y. Wu, B. Gao, J. Zhao, Y. Wang, Z. Liu, J. Chen, Y. Ying, G.Y. Tian, Weld crack detection based on region electromagnetic sensing thermography, IEEE Sens J. 19 (2018) 751–762.

[131] J.M. Berge, Automating the welding process: successful implementation of automated welding systems, Industrial Press Inc., 1994.

[132] D. Vasilikis, S.A. Karamanos, S.H.J. van Es, A.M. Gresnigt, Ultimate bending capacity of spiral-welded steel tubes--Part II: Predictions, Thin-Walled Structures. 102 (2016) 305–319.

[133] R. Schäfer, P. Pasquale, The electromagnetic pulse technology (EMPT): forming, welding, crimping and cutting, Biuletyn Instytutu Spawalnictwa w Gliwicach. 58 (2014) 50–57.

[134] R. Ihara, Ji. Katsuyama, K. Onizawa, T. Hashimoto, Y. Mikami, M. Mochizuki, Prediction of residual stress distributions due to surface machining and welding and crack growth simulation under residual stress distribution, Nuclear Engineering and Design. 241 (2011) 1335–1344.

[135] P. Kah, M. Shrestha, E. Hiltunen, J. Martikainen, Robotic arc welding sensors and programming in industrial applications, International Journal of Mechanical and Materials Engineering. 10 (2015) 1–16.

[136] M. Rüßmann, M. Lorenz, P. Gerbert, M. Waldner, J. Justus, P. Engel, M. Harnisch, Industry 4.0: The future of productivity and growth in manufacturing industries, Boston Consulting Group. 9 (2015) 54–89.

[137] P. Garre, V.V.S.N. Bharadwaj, P.S. Shashank, M. Harish, M.S. Dheeraj, Applying lean in aerospace manufacturing, Mater Today Proc. 4 (2017) 8439–8446.

[138] C. Chen, N. Lv, S. Chen, Data-driven welding expert system structure based on internet of things, in: Transactions on Intelligent Welding Manufacturing, Springer, 2018: pp. 45–60.

[139] P. Kah, P. Layus, E. Hiltunen, J. Martikainen, Real-time weld process monitoring, in: Adv Mat Res, 2014: pp. 117–124.

[140] R.N. Broadus, Toward a definition of "bibliometrics," Scientometrics. 12 (1987) 373–379.

[141] W. Glänzel, U. Schoepflin, A bibliometric study of reference literature in the sciences and social sciences, Inf Process Manag. 35 (1999) 31–44.

[142] F. Chiarello, L. Trivelli, A. Bonaccorsi, G. Fantoni, Extracting and mapping industry 4.0 technologies using wikipedia, Comput Ind. 100 (2018) 244–257.

[143] L. Da Xu, L. Duan, Big data for cyber physical systems in industry 4.0: a survey, Enterp Inf Syst. 13 (2019) 148–169.

[144] M.Y. Santos, J.O. e Sá, C. Andrade, F.V. Lima, E. Costa, C. Costa, B. Martinho, J. Galvão, A big data system supporting bosch braga industry 4.0 strategy, Int J Inf Manage. 37 (2017) 750–760.

[145] N. Kalid, A.A. Zaidan, B.B. Zaidan, O.H. Salman, M. Hashim, H. Muzammil, Based real time remote health monitoring systems: A review on patients prioritization and related" big data" using body sensors information and communication technology, J Med Syst. 42 (2018) 30.

[146] I. Yaqoob, I.A.T. Hashem, A. Ahmed, S.M.A. Kazmi, C.S. Hong, Internet of things forensics: Recent advances, taxonomy, requirements, and open challenges, Future Generation Computer Systems. 92 (2019) 265–275.

[147] P.K. Muhuri, A.K. Shukla, A. Abraham, Industry 4.0: A bibliometric analysis and detailed overview, Eng Appl Artif Intell. 78 (2019) 218–235.

[148] R.A. Febriani, H.-S. Park, C.-M. Lee, An approach for designing a platform of smart welding station system, The International Journal of Advanced Manufacturing Technology. 106 (2020) 3437–3450.

[149] M. Benakis, C. Du, A. Patran, R. French, Welding process monitoring applications and industry 4.0, in: 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE), 2019: pp. 1755–1760.

[150] H.-S. Park, R.A. Febriani, Modelling a Platform for Smart Manufacturing System, Procedia Manuf. 38 (2019) 1660–1667.

[151] U. Reisgen, S. Mann, K. Middeldorf, R. Sharma, G. Buchholz, K. Willms, Connected, digitalized welding production—Industrie 4.0 in gas metal arc welding, Welding in the World. 63 (2019) 1121–1131.

[152] R. Söderberg, K. Wärmefjord, J.S. Carlson, L. Lindkvist, Toward a Digital Twin for real-time geometry assurance in individualized production, CIRP Annals. 66 (2017) 137–140.

[153] Y. Li, Y.F. Li, Q.L. Wang, D. Xu, M. Tan, Measurement and defect detection of the weld bead based on online vision inspection, IEEE Trans Instrum Meas. 59 (2009) 1841–1849.

[154] W. Huang, R. Kovacevic, A laser-based vision system for weld quality inspection, Sensors. 11 (2011) 506–521.

[155] V.D.R. Guide Jr, V. Jayaraman, J.D. Linton, Building contingency planning for closed-loop supply chains with product recovery, Journal of Operations Management. 21 (2003) 259–279.

[156] P. Wanjara, B. Monsarrat, S. Larose, Gap tolerance allowance and robotic operational window for friction stir butt welding of AA6061, J Mater Process Technol. 213 (2013) 631–640.

[157] U. Arslan, N. Akkus, Ismail Temiz, The Effects of Offline Simulation on Return on Investment for Robotic Investments, (n.d.).

[158] Y.-K. Liu, Y.-M. Zhang, Supervised learning of human welder behaviors for intelligent robotic welding, IEEE Transactions on Automation Science and Engineering. 14 (2015) 1532–1541.

[159] A. Shukla, H. Karki, Application of robotics in onshore oil and gas industry—A review Part I, Rob Auton Syst. 75 (2016) 490–507.

[160] R. Renner, S. Behnke, Instability detection and fall avoidance for a humanoid using attitude sensors and reflexes, in: 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2006: pp. 2967–2973.

[161] Y. Xu, H. Yu, J. Zhong, T. Lin, S. Chen, Real-time image capturing and processing of seam and pool during robotic welding process, Industrial Robot: An International Journal. (2012).

[162] B.Q. Leonardo, C.R. Steffens, S.C. da Silva Filho, J.L. Mór, V. Hüttner, E. do Amaral Leivas, V.S. Da Rosa, S.S. da Costa Botelho, Vision-based system for welding groove measurements for robotic welding applications, in: 2016 IEEE International Conference on Robotics and Automation (ICRA), 2016: pp. 5650–5655.

[163] K. Andersen, G.E. Cook, G. Karsai, K. Ramaswamy, Artificial neural networks applied to arc welding process modeling and control, IEEE Trans Ind Appl. 26 (1990) 824–830.

[164] G. Erd Hos, C. Kardos, Z. Kemény, A. Kovács, J. Váncza, Process planning and offline programming for robotic remote laser welding systems, Int J Comput Integr Manuf. 29 (2016) 1287–1306.

[165] A. Pritchard, others, Statistical bibliography or bibliometrics, Journal of Documentation. 25 (1969) 348–349.

[166] M. Aria, C. Cuccurullo, bibliometrix: An R-tool for comprehensive science mapping analysis, J Informetr. 11 (2017) 959–975.

[167] D. Mishra, A. Gunasekaran, T. Papadopoulos, S.J. Childe, Big Data and supply chain management: a review and bibliometric analysis, Ann Oper Res. 270 (2018) 313–336.

[168] F. Gómez-Garcia, J. Ruano, M. Aguilar-Luque, J. Gay-Mimbrera, B. Maestre-Lopez, J.L. Sanz-Cabanillas, P.J. Carmona-Fernández, M. González-Padilla, A. Vélez Garcia-Nieto, B. Isla-Tejera, Systematic reviews and meta-analyses on psoriasis: role of funding sources, conflict of interest and bibliometric indices as predictors of methodological quality, British Journal of Dermatology. 176 (2017) 1633–1644.

[169] F. Pega, N. Chartres, N. Guha, A. Modenese, R.L. Morgan, M.S. Martinez-Silveira, D. Loomis, The effect of occupational exposure to welding fumes on trachea, bronchus and lung cancer: A protocol for a systematic review and meta-analysis from the WHO/ILO Joint Estimates of the Work-related Burden of Disease and Injury, Environ Int. 145 (2020) 106089.

[170] P. Layus, P. Kah, Bibliometric study of welding scientific publications by big data analysis, International Journal of Mechanical Engineering and Applications. 3 (2015) 94–102.

[171] N. Mallig, A relational database for bibliometric analysis, J Informetr. 4 (2010) 564–580.

[172] A.F.G. Cicero, C. Kennedy, T. Knežević, M. Bove, C.M.G. Georges, A. e Šatrauskiene, P.P. Toth, F. Fogacci, Efficacy and Safety of Armolipid Plus®: An Updated PRISMA Compliant Systematic Review and Meta-Analysis of Randomized Controlled Clinical Trials, Nutrients. 13 (2021) 638.

[173] B.G. Santa Cruz, M.N. Bossa, J. Soelter, A.D. Husch, Public Covid-19 X-ray datasets and their impact on model bias-a systematic review of a significant problem, MedRxiv. (2021).

[174] A. Liberati, D.G. Altman, J. Tetzlaff, C. Mulrow, P.C. Gøtzsche, J.P.A. Ioannidis, M. Clarke, P.J. Devereaux, J. Kleijnen, D. Moher, The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration, Ann Intern Med. 151 (2009).

[175] I. Dodson, The art of digital marketing: the definitive guide to creating strategic, targeted, and measurable online campaigns, John Wiley & Sons, 2016.

CHAPITRE 3
NUMERISATION 3D EN TEMPS REEL DE FLANS SOUDÉS AU LASER EN ALUMINIUM 5052-H32 ; CARACTERISATION GEOMETRIQUE ET DE SOUDAGE

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Cet article a été publié dans Materials Letters, Volume 296, 1 August 2021, 129883

https://doi.org/10.1016/j.matlet.2021.129883

3.1 RÉSUMÉ EN FRANÇAIS DU TROISIÈME ARTICLE

Dans cette étude, la cartographie des déformations (déformation ou gauchissement) des flans soudés au laser en aluminium est étudiée au cours d'un processus de formage automatisé. La nouvelle approche d'inspection automatisée et en temps réel introduite dans cette étude contribue à une nette amélioration de la qualité du produit final en permettant une détection précise et instantanée des défauts, tels que la porosité, pendant le processus de soudage. Cette identification précoce des imperfections facilite des corrections immédiates, évitant la propagation de défauts et assurant une qualité supérieure du produit. Parallèlement, cette méthode réduit significativement les délais d'exécution en éliminant le besoin d'inspections post-production longues et laborieuses, permettant ainsi une progression plus rapide des pièces à travers la chaîne de production. Enfin, l'augmentation de la cadence de fabrication découle de la capacité de cette approche à intégrer et à analyser en continu les données du processus de soudage, optimisant les paramètres de soudage en temps réel pour

une efficacité accrue. En outre, la réduction des coûts du produit est réalisée grâce à la diminution des rebuts et des retouches nécessaires, rendant le processus de fabrication plus économique et efficient. En conséquence, les distorsions de la zone de la bride sont détectées dans la plage de ±3 mm, ce qui est considéré comme une grande déviation pour les assemblages en aluminium. L'admissibilité des distorsions inférieures à 3 mm dépendrait strictement des critères de performance et des normes de qualité définis pour le produit final. Pour des assemblages où la précision est critique, telles que les composants aérospatiaux ou ceux impliqués dans des systèmes de sécurité, toute distorsion, même minime, peut être jugée inacceptable. En revanche, pour des applications où les exigences sont moins rigoureuses, une tolérance plus grande pourrait être permise. Il est impératif d'évaluer cette tolérance dans le cadre des spécifications de conception et des limites fonctionnelles imposées par l'utilisation prévue de l'assemblage en aluminium. Les résultats du modèle proposé sont prometteurs pour se conformer à une évaluation de la sensibilité à la fissuration (CS) dans la structure de soudage en augmentant la distorsion nuisible, principalement en empêchant le traitement des pièces défectueuses dans la chaîne de valeur et en particulier dans les stations de goulot d'étranglement sont bien estimés. La sensibilité à la fissuration au sein des structures soudées est évaluée à l'aide d'analyses métallurgiques fines, qui permettent de détecter et de mesurer avec précision la progression des fissures au microscope. Le modèle avancé par la présente étude offre des perspectives optimistes pour répondre aux critères de ces évaluations, en identifiant proactivement les pièces présentant des distorsions préjudiciables susceptibles d'engendrer des fissures. Cela est particulièrement pertinent dans les segments critiques du processus de production, tels que les points de restriction où les goulots d'étranglement peuvent survenir. Ainsi, le modèle contribue à une gestion plus efficace du risque de fissuration, en évitant la progression de composants défectueux dans la chaîne de valeur. En somme, cette méthode d'inspection offre une solution complète pour améliorer la qualité, réduire les délais d'exécution et augmenter la cadence de fabrication, alignée avec les objectifs de productivité et d'efficacité de l'Industrie 4.0.

3.2 CONTRIBUTIONS

Les contributions scientifiques d'Ahmad Aminzadeh à l'article sur la numérisation 3D en temps réel des blanks soudés au laser en aluminium 5052-H32 peuvent être résumées de la manière suivante :

Recherche fondamentale : Ahmad Aminzadeh a conçu et exécuté des études expérimentales pour comprendre l'impact des paramètres de soudage sur les caractéristiques géométriques des blanks soudés.

Développement de la méthodologie : Il a développé la méthodologie pour la numérisation 3D en temps réel, incluant la sélection d'équipements adaptés et la définition des protocoles de capture des données tridimensionnelles.

Création d'analyse de données: Ahmad Aminzadeh a été à l'avant-garde de l'analyse des données collectées, utilisant des logiciels de traitement d'images pour modéliser la géométrie des soudures et identifier les défauts.

Contributions à la surveillance en temps réel: Il a intégré des outils de surveillance dans le processus de soudage, permettant la détection et la correction immédiates des problèmes de qualité.

Conception des supports visuels: Ahmad Aminzadeh a produit des graphiques et des tableaux pour visualiser les données et les résultats, facilitant ainsi la compréhension et la communication des découvertes.

Collaboration et révision: Tout en collaborant avec Sasan Sattarpanah Karganroudi, Noureddine Barka, et Abderrazak El Ouafi, Ahmad Aminzadeh a joué un rôle de premier plan dans la direction de la recherche et la rédaction de l'article.

Les contributions d'Ahmad Aminzadeh, qui s'étendent de la conception initiale de la recherche à la production de la documentation finale, démontrent un engagement profond et une expertise dans le domaine du soudage assisté par numérisation 3D et caractérisation en temps réel.

3.3 TITRE DU TROISIÈME ARTICLE

A real-time 3D scanning of aluminum 5052-H32 laser welded blanks; geometrical and welding characterization

3.4 ABSTRACT

In this study, distortion mapping (deformation or warping) of aluminum Laser Welded Blanks (LWBs) is investigated during an automated forming process. Here, a novel approach of automated and real-time inspection is presented which enhances final product quality, reduces lead time, and increases manufacturing cadence while reducing product cost. As a result, flange zone distortions are detected in the range of ±3 mm which considers as a large deviation for aluminum assemblies. Promising the proposed model results to comply with an evaluation of Cracking Susceptibility (CS) in the welding structure by increasing the harmful distortion, mainly by preventing the processing of defective parts in the value chain and especially in bottleneck stations are well estimated.

3.5 NOMENCLATURE

CS	Cracking Susceptibility
VCFSW	Vertical compensation friction stir welding
YLS	Yterbium Fiber Lasers
3LS	3D Laser Scanning Inspection
CL	Cloud Mapping

DOE	Design of Experiences
DIC	Digital Image Correlation
SEM	Scanning Electron Microscope
LMP	Laser Material Processing
AA	Aluminum Alloys
TWBs	Tailor Welded Blanks
LWBs	Laser welded Blanks
CAD	Computer Aided Design
ANOVA	Analysis of Variance
DMAIC	Design Measure Analyze Improve Control
CAM	Computer Aided Manufacturing
CAI	Computer Aided Inspection
QA	Quality Assurance
P	Power
V	Welding Speed
A	Amplitude

3.6 INTRODUCTION

Recently, laser welding is considered a very promising process to manufacture and assemble a wide range of metal structures [176], marine and automotive industries [16,177], and railway industries [178]. On the other hand, welding distortion is one of the major factors affecting geometrical and dimensional defects in LWB structures. More recently, Abu–Okail et. al manufactured a TWBs structure using a vertical compensation friction stir welding (VCFSW) method [179]. Although image processing is a very useful inspection tool, the difficulties in contrast manipulation involve considerable errors that outstand point cloud mapping as a powerful alternative. To this end, computer-aided inspection (CAI) methods based on point cloud metrology of industrial parts are developed for aluminum sheet-metal parts [180,181]. The deflection of panels reduces buckling and load-carrying capacity of sheet-metal welded structures where distortion and residual stress are formed as unavoidable consequences [20,182]. Akyel et al. performed strain distribution using digital image correlation (DIC) method in order to mapping the reduction of distortion in dissimilar material combinations via laser beam welding [183]. the literature review confirms that no research works have thoroughly proposed an automated real-time inspection of aluminum LWBs by point cloud mapping. In the current study, distortion of LWBs aluminum alloy (5052-H32) is analyzed using 3D laser scanning to exploit distortion contribution plots to analyze spring back and wrinkling in forming processes. This real-time inspection technique automatically rejects parts that have a negative effect on the conformity of parts and labor capacity of the machine and value chain in automobile industries. By doing so, not only manufacturing wastes (defects, overproduction, waiting, non-utilization, handling, inventory, motion, excess processing, and set up time) are reduced but also the preparatory and subsidiary times are shortened and the correction of the tool adjustment, set up and assembly time in the operating position on the machine is controlled.

3.7 EXPERIMENTAL SET-UP AND COMPUTER-AIDED INSPECTION ANALYSIS

Regarding the experimental investigation, two half of Al 5052-H32 with 1.2 mm thickness is cut in rectangle dimension (150 mm × 125 mm). Then, pre-preparation is done to clean contaminates and oxides alongside the joint zone. Besides, the mechanical properties and chemical composition of Al 5052-H32 are listed in table 17. A robotized laser welding (FANUC M-710ic), using IPG Photonics YLS-3000 (Ytterbium Fiber Lasers) with a wavelength of 1070 nm and focal diameter of 0.45 mm is used and then subjected to forming process. Finally, the geometrical information of fixture alignment, welded workpiece, and forming process via a 3D seam extraction algorithm is performed based on point cloud segmentation. The schematic method and concept of this study are presented in Figure 33 based on six sigma-DMAIC (Define, Measure, Analyze, Improve, Control). The measurement flowchart represents those sheets are fixed by a special welding jig and fixture then computer-aided inspection (CAI) using 3D scanning is applied to validate the alignments and improve measurement precision. Additionally, other fundamental setups such as laser power, welding speed, and amplitude are adjusted on 1800 (W), 30 (mm/s) and 1.125 (mm), respectively. Then, LWB is subjected to a forming process with constant setup parameters such as speed (1.5 mm/sec), blank holder force (20 pounds), and dry lubrication condition. A load cell is also used to monitor forming force during the process. In order to achieve reliable distortion measurement results, the blanks are formed at a critical rupture position. Finally, distortion and strain analysis are investigated based on CAI using point cloud reconstruction in GOM™ software.

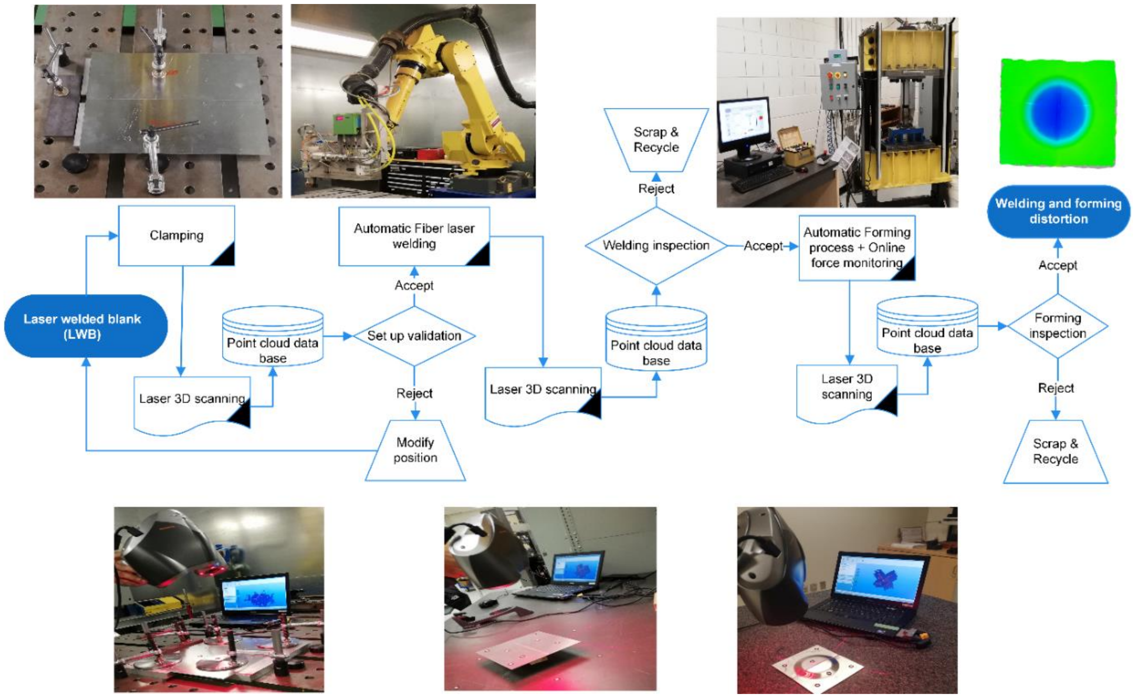


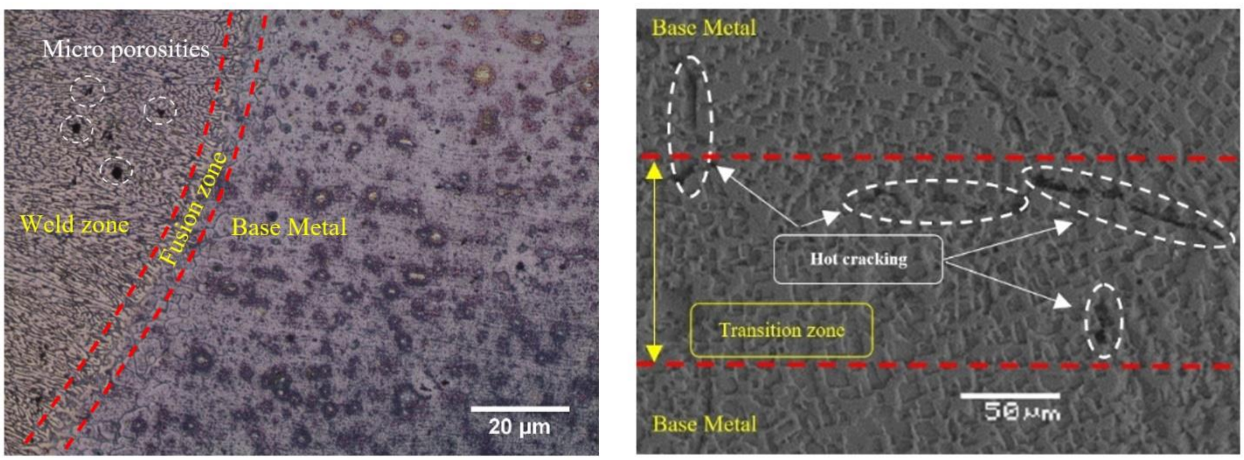
Figure 33. Schematic method presentation and concept of distortion measurement based on CAI.

Table 17. Chemical composition (% wt) and Mechanical properties of AA 5052-H32 [184]

Chemical composition	**Cr**	**Cu**	**Fe**	**Mg**	**Mn**	**Si**	**Zn**	**Al**
% wt	0.15 - 0.35	0.1	0.4	2.2 - 2.8	0.1	0.25	0.1	Balance
Mechanical properties	Ultimate strength (MPa)	Proof strength (MPa)	Elongation (%)	Brinell hardness	Poisson's ratio	Modulus of Elasticity (GPa)		
Value	230	195	12	60	0.33	70.3		

3.8 RESULTS AND DISCUSSION

Regarding the evaluation of Cracking Susceptibility (CS) in the welding structure, scanning electron microscope (SEM) image (Figure 34-a) examination shows hot cracking channels. On the other hand, an optical microscope (Figure 34-b) detected small micro porosities at the weld seam region, even though not large enough to be critical. Due to the presence of Mg in aluminum alloys, its sensitive to solidification cracking during the welding process [185]. Also, due to the high conductivity and well reflection surface, the molten metal reflects much of the energy of the light beam whereby keyhole instability has affected the quality of the weld zone. Interestingly, due to the increasing of the work hardening micro-hardness is improved by the development of the intensification material properties [186].



(a) (b)

Figure 34. Microstructural analysis of AL-LWBs a) optical microscope b) SEM image.

Here, a real-time CAI method based on points cloud of 3D laser scanner is applied as a novel approach to define global distortion in LWBs. These point clouds can also extrapolate and develop a reconstruction model [187]. From a welding perspective, thermal conductivity in aluminum alloys and cooling rate cycle in laser processes are the most important reasons for catastrophic failure due to residual stress produced through welded parts. According to Figure 35-a and b, distortions in welding appear in the range of 1 mm. Due to the plate geometry, distortions take place mostly vertically and transversely along the profile. The largest distortions can be observed on welding seam areas at the start point of welding, which is reasonable due to the great temperature difference between the plate and the welding zone. In addition, suitable welding power with good penetration shows a strong correlation with the level of joint quality and the magnitude of distortions through the path line. Regarding aluminum productions in automotive industries, almost 1 mm distortion is considered as out of acceptable tolerances in lean manufacturing [188]. However, these out tolerances have occurred in a small zone at welding start which will be trimmed out following to forming step. There is also a correlation between distortion and weld line movement in LWB which is a major problem in assembly units. Thus, the results suggest that welding distortions may be alleviated with strategic design of structures or optimized process parameters. In LWBs, due to generating different stress distribution, cooling rate, and material properties in three different zone (Base metal 1, weld zone and Base metal 2), spring back and wrinkling are challenging. In addition, these two phenomena are trigging not only for rupture but also weld line movement in deep drawing process. Generally, a material with a greater elastic modulus will react less spring back than a material with a lower elastic modulus [189]. Here, a straight welding path line is projected to define maximum distortion through LWBs part based on point cloud which is extracted from high-resolution 3D scanning. As depicted in profile distortion of LWB (Figure 35-c), spring back is occurred in the flange zone ($R\times \theta = 28.74$ mm $\times \theta$) [190]. According to the distortion contour (Figure 35-d), in the flange zone distortions changes from -3 mm to +2.95 mm which considers a large deviation for aluminum alloy. Here, using an automated real-time CAI reject out of tolerance parts improves tooling processes and reduce significantly manufacturing costs. Besides, due to arbitrary distortions (almost 1 mm) from the edge of plate to 30 mm through plate generate a wrinkling phenomenon. In fact, wrinkling is usually determined by peculiar and non-uniform wavy shapes throughout the sheet which waves quantities depends on material properties and process factors such as geometrical features, forming forces, blank holder force, die cavity depth and radius, punch speed, and lubrication condition. Recently, theoretical models and numerical analysis are proposed to define and predict wrinkling phenomena [191]. However, these models are complex and time-consuming which are less accurate and without any online quality check. In this novel automation inspection approach, wrinkling and spring back are selected as manufacturing criteria in order to find the optimum objective. Furthermore, our proposed approach is a trigging into smart and connected manufacturing in sheet metal products and it is the first step towards intelligent production in manufacturing sectors.

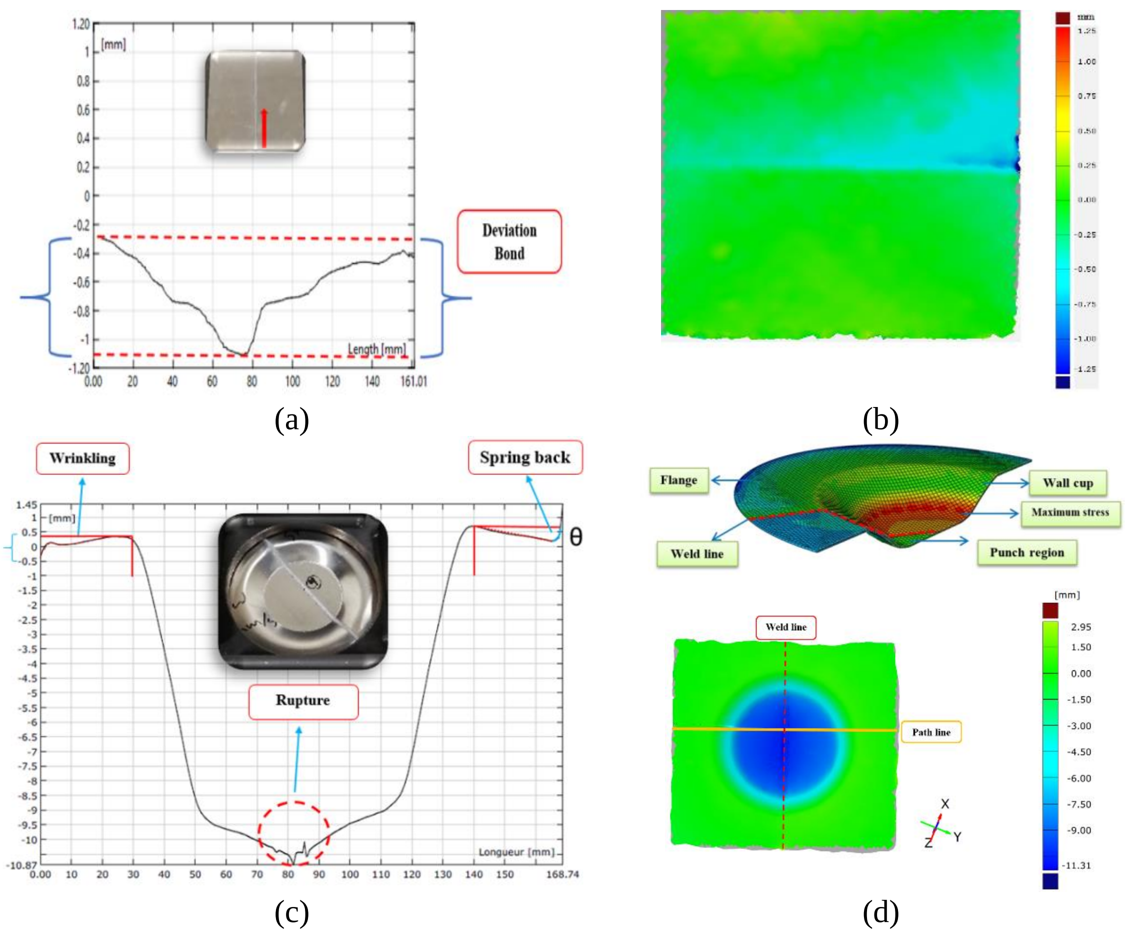


Figure 35. LWBs distortion: a,b) after laser welding c,d) after forming process.

3.9 CONCLUSIONS

An automated real-time CAI method and distortion analyses of aluminum LWBs using a 3D laser scanner are presented in this paper along with experimental validation. The process is followed by an automatic forming and loud monitoring to define the optimum production in a controlled condition. Analyzing distortions after forming process, the proposed method identified defects on flange area in the range of ±3 mm, which enables rejecting parts out of tolerances before succeeding to the next step in the value chain. In that case, the formability of LWBs depends on hot cracking and porosities in the HAZ and microstructure of the weld region. Although results are promising, future research can perform tests on LWBs and make a cloud computing model based on intelligent decision techniques using artificial intelligence to pave the way towards digital factories in the industry 4.0 era.

3.10 REFERENCES

[176] R. Indhu, M. Tak, L. Vijayaraghavan, S. Soundarapandian, Microstructural evolution and its effect on joint strength during laser welding of dual phase steel to aluminium alloy, J Manuf Process. 58 (2020) 236–248.

[177] A. Gumenyuk, New developments in high power laser and hybrid welding of thick plates for application in modern ship building, (2020).

[178] E. Gündougdu Is, P. Topuz, E. Akman, M. Yilmaz, Effect of laser welding speed on pore formation in AA 6061 T6 alloy, Materials Testing. 62 (2020) 979–984.

[179] M. Abu--Okail, M.H. Ata, A. Abuoqail, G.M.F. Essa, T.S. Mahmoud, I. Hassab Allah, Production of tailor-welded blanks by vertical compensation friction stir welding technique, Materials Science and Technology. 34 (2018) 2030–2041.

[180] S.S. Karganroudi, J. C. Cuillière, V. Francois, S.A. Tahan, Automatic fixtureless inspection of non-rigid parts based on filtering registration points, The International Journal of Advanced Manufacturing Technology. 87 (2016) 687–712.

[181] S.S. Karganroudi, J. C. Cuillière, V. François, S. A. Tahan, “What-if” scenarios towards virtual assembly-state mounting for non-rigid parts inspection using

permissible loads, The International Journal of Advanced Manufacturing Technology. 97 (2018) 353–373.

[182] M.A. Zaeem, M.R. Nami, M.H. Kadivar, Prediction of welding buckling distortion in a thin wall aluminum T joint, Comput Mater Sci. 38 (2007) 588–594.

[183] F. Akyel, S. Olschok, U. Reisgen, Dissimilar material combination in laser beam welding: reduction of distortion and residual stress, in: High-Power Laser Materials Processing: Applications, Diagnostics, and Systems IX, 2020: p. 112730B.

[184] G.E. Totten, D.S. MacKenzie, Handbook of Aluminum: Volume 2: Alloy Production and Materials Manufacturing, CRC press, 2003.

[185] T. Soysal, A criterion to find crack-resistant aluminium alloys to avoid solidification cracking, Science and Technology of Welding and Joining. 26 (2021) 99–105.

[186] R. Mirahmadi Babaheydari, S.O. Mirabootalebi, G.H. Akbari Fakhrabadi, Effect of Alloying Elements on Hardness and Electrical Conductivity of CU Nanocomposites Prepared by Mechanical Alloying, Iranian Journal of Materials Science and Engineering. 18 (2021) 1–11.

[187] P. Jenke, M. Wand, M. Bokeloh, A. Schilling, W. Straßer, Bayesian point cloud reconstruction, in: Computer Graphics Forum, 2006: pp. 379–388.

[188] S. Greinacher, L. Overbeck, A. Kuhnle, C. Krahe, G. Lanza, Multi-objective optimization of lean and resource efficient manufacturing systems, Production Engineering. (2020) 1–12.

[189] Y. Choi, J. Lee, S.S. Panicker, H.-K. Jin, S.K. Panda, M.-G. Lee, Mechanical properties, springback, and formability of W-temper and peak aged 7075 aluminum alloy sheets: Experiments and modeling, Int J Mech Sci. 170 (2020) 105344.

[190] R.H. Wagoner, H. Lim, M.-G. Lee, Advanced issues in springback, Int J Plast. 45 (2013) 3–20.

[191] M. Taylor, B. Davidovitch, Z. Qiu, K. Bertoldi, A comparative analysis of numerical approaches to the mechanics of elastic sheets, J Mech Phys Solids. 79 (2015) 92–107.

CHAPITRE 4

ANALYSE EXPERIMENTALE DU SOUDAGE LASER A FIBRES SUPERPOSEES POUR LES ALLIAGES D'ALUMINIUM : RECONNAISSANCE DE LA POROSITE ET INSPECTION DE LA QUALITE

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Cet article a été publié dans The International Journal of Optic and Laser in Engineering le numéro de reference; https://doi.org/10.1016/j.optlaseng.2023.107890

4.1 RÉSUMÉ EN FRANÇAIS DU QUATRIÈME ARTICLE

Ces dernières années, le soudage au laser est devenu de plus en plus populaire dans l'industrie manufacturière en raison de ses avantages, notamment une zone affectée par la chaleur étroite, de faibles niveaux de distorsion, la possibilité de traitement à distance et des vitesses de soudage élevées par rapport aux techniques conventionnelles de soudage à l'arc électrique. Dans l'industrie automobile, le besoin de soudage de joints superposés, en particulier pour l'assemblage des châssis, est devenu de plus en plus important. La détection et le contrôle de la porosité interne dans le soudage au laser des alliages d'aluminium ont fait l'objet d'une attention particulière. Pour aider les utilisateurs de laser à optimiser le processus de soudage, cet article présente une méthodologie expérimentale suivie d'une analyse phénoménologique de la qualité des joints soudés par recouvrement. L'étude se concentre sur le soudage au laser de deux configurations différentes d'alliages d'aluminium (AA 6061-T6 de 1,6 mm d'épaisseur et AA 6061-T6 de 2 mm d'épaisseur) en utilisant trois stratégies de soudage (système de soudage laser à distance ScanLab, tête laser Trumpf D70 et tête oscillante Precitec YW52) afin d'évaluer les variantes à laser unique et multiple pour

l'ajustement des paramètres du processus. En outre, l'article traite de l'utilisation de la technologie des rayons X comme méthode de contrôle hors ligne pour la reconnaissance de la porosité, et analyse la caractérisation du faisceau laser et la forme du profil du faisceau pour calculer la distribution du faisceau. Une analyse statistique de toutes les méthodes est ensuite réalisée, ainsi qu'une analyse de régression. Ces résultats fournissent des indications précieuses sur l'intégration de la technologie de soudage au laser dans les secteurs de l'automobile et du transport de surface. L'analyse des résultats indique que lorsque la taille du spot diminue, la taille réelle du spot change plus brusquement avec l'augmentation de la position Z, alors qu'avec une taille de spot plus importante, la taille du faisceau reste stable jusqu'à (+/-) 20-30 mm dans la position Z en raison de la grande lentille. La porosité est principalement due à une taille de spot trop petite (en l'absence d'oscillation ; ≤0,4 mm) ou à une vitesse de déplacement trop faible (≤4,0-4,5 m/min). En revanche, si la taille du point est trop importante, une fissuration à chaud peut se produire lors du soudage laser autogène.

4.2 CONTRIBUTIONS

Dans le quatrième article intitulé "Experimental Analysis of Overlap Fiber Laser Welding for Aluminum Alloys: Porosity Recognition and Quality Inspection", les contributions spécifiques et détaillées d'Ahmad Aminzadeh comprennent :

Conception et réalisation des expériences : Ahmad Aminzadeh a joué un rôle crucial dans la conception des expériences, y compris la sélection des alliages d'aluminium pour le soudage au laser à fibre et la définition des paramètres de soudage. Il a également réalisé les expériences, en surveillant attentivement les processus pour garantir la collecte de données précises.

Développement de la méthodologie de surveillance en temps réel : Il a développé une méthodologie innovante pour la surveillance en temps réel de la porosité dans les soudures au laser, intégrant des techniques avancées d'imagerie et d'analyse de données pour identifier et quantifier les défauts.

Analyse des données et reconnaissance de la porosité : Ahmad Aminzadeh a utilisé des méthodes d'apprentissage automatique pour analyser les données collectées pendant le soudage, ce qui a permis d'identifier efficacement la présence de porosité dans les soudures et d'évaluer la qualité du soudage.

Création de supports visuels : Il a été responsable de la génération de tous les tableaux, figures et graphiques qui illustrent les résultats de l'étude, permettant une compréhension claire et accessible des découvertes.

Rédaction et révision de l'article : Ahmad Aminzadeh a pris l'initiative de la rédaction de l'article, en expliquant clairement la méthodologie, les résultats et les conclusions de l'étude. Il a également activement participé au processus de révision, intégrant les retours des coauteurs et des experts pour améliorer la qualité du manuscrit.

Collaboration : Bien que la contribution de Noureddine Barka, Abderrazak El Ouafi, Fatemeh Mirakhorli et François Nadeau ait enrichi l'étude par des conseils et une expertise technique, c'est Ahmad Aminzadeh qui a dirigé les efforts de recherche, démontrant une expertise profonde dans l'analyse expérimentale du soudage laser des alliages d'aluminium et l'utilisation de l'intelligence artificielle pour l'inspection de la qualité.

Ces contributions mettent en avant l'expertise d'Ahmad Aminzadeh dans la conduite d'analyses expérimentales complexes et son innovation dans l'application de l'apprentissage automatique pour améliorer la surveillance et la qualité du soudage laser des alliages d'aluminium.

4.3 TITRE DU QUATRIÈME ARTICLE

A comprehensive study on Porosity recognition of overlap aluminum laser welding; Experimental and Statistical Investigation

4.4 ABSTRACT

In recent years, laser welding has become increasingly popular in the manufacturing industry due to its advantages, including a narrow heat affected zone, low levels of distortion, the possibility of remote processing, and high welding speeds compared to conventional electric arc welding techniques. In the automotive industry, the need for overlapped joint welding, particularly for chassis assembly, has become increasingly relevant. The internal porosity detection and control in laser welding of aluminum alloys has gained significant attention. To support laser users in optimizing the welding process, this paper presents an experimental methodology followed by a phenomenological analysis of the quality of overlapped welded joints. The study focuses on the laser welding of two different aluminum alloy configurations (1.6-mm-thick AA 6061-T6 and 2-mm-thick AA 6061-T6) using three welding strategies (ScanLab remote laser welding system, Trumpf D70 laser head, and Precitec YW52 wobbling head) to evaluate single and multiple laser variants for process parameter tuning. Additionally, the paper discusses the use of X-ray technology as an offline monitoring method for porosity recognition and analyzes laser beam characterization and beam profile shape to calculate beam distribution. Then, statistical analysis of all methods is conducted, and regression analysis is performed. These findings provide valuable insights into the integration of laser welding technology in the automotive and surface transportation industries. The analysis of results indicates that as the spot size decreases, the real spot size changes more abruptly with increasing Z position, whereas with a larger spot size, the beam size remains stable up to +/- 20-30 mm in Z position due to the large lens. Porosity is mainly caused by either a too small spot size (in the absence of wobbling; ≤0.4mm) or low travel speed (≤4.0-4.5m/min). On the other hand, if the spot size is too large, hot cracking can occur in autogenous laser welding.

4.5 NOMENCLATURE

DOE	Design of Experiences
LMP	Laser Material Processing
AA	Aluminum Alloys
ROC	Receiver Operating Characteristic
FPR	False Positive Rate
PMF	Programmable Motorized Focusing
SLJ	Laser-Welded Single Lap Joints
NDT	Non-destructive methods
CMOS	Complementary metal oxide semiconductor
ISO	International Organization for Standardization
ANOVA	Analysis of Variance
DMAIC	Design Measure Analyze Improve Control
CAM	Computer Aided Manufacturing
CAI	Computer Aided Inspection
QA	Quality Assurance
P	Power
V	Welding Speed

A	Amplitude
CNN	Convolutional Neural Network
R^2	R squared, coefficient of determination

4.6 INTRODUCTION

In the modern landscape of manufacturing, there exists a growing imperative to ensure the production of high-quality products without any defects, while also minimizing lead times and enhancing production rates. Particularly in the realm of assembly manufacturing, laser processes have attained a pivotal role in producing mechanical components that find application across a wide array of industries, including the automotive sector [192], aerospace industry [193], home appliance manufacturing [194], and even the food industry [195]. Moreover, the employment of metal manufacturing, specifically in the context of aluminum alloys, is considered indispensable across multiple industrial sectors due to the inherent characteristics of the fabricated components, such as mechanical strength, rigidity, and long-term durability. Laser welding emerges as a favorable technique for material joining, attributed to its elevated energy density and minimized heat-affected zone. Nonetheless, the presence of defects, including porosity, cracking, lack of fusion, and incomplete penetration, can compromise the integrity of the welded assemblies. To mitigate these challenges and maintain uniform quality, the implementation of real-time, process-level quality monitoring is imperative. The adoption of such a monitoring framework obviates the necessity for empirical parameter design and expensive post-process evaluations, thereby facilitating the streamlined optimization of process variables and the consequent reduction in associated expenditures. Moradi et al, examined the stability of weld surface quality in laser-arc hybrid welding of 4 mm thick steel, with high arc voltage and short laser-arc distances leading to destabilization. The design of experiment method's efficacy for these applications was also evaluated, with high-speed imaging aiding in understanding the observed trends [196]. Moreover, S500MC steel, used widely in the automotive and agricultural sectors, was welded using both laser beam welding (LBW) and gas tungsten arc welding (GTAW) to compare their mechanical and metallurgical properties. While LBW produced a finer microstructure with a narrower fusion zone due to lower heat input, GTAW joints displayed superior mechanical properties compared to LBW joints [197]. The study uses Response Surface Methodology (RSM) to optimize bead geometry in CO_2 laser butt-welding of Ti 6Al 4V, an alloy with applications in industries like aerospace and medical. By examining the relationship between welding parameters and process responses, the study identifies optimal welding conditions to enhance productivity and reduce costs, with validation showing model errors under 12.5% [198]. Recently, Laser oscillating welding of 5A06 aluminum alloy using an S-curve power distribution refines the grain structure, narrows the columnar region, and enhances mechanical properties, with a tensile strength increase of 35.3%. This method offers a novel approach for optimizing the performance of welded joints, yielding a tensile strength nearly equivalent to the base metal and demonstrating higher ductility [199]. Moreover, a porous high entropy alloy (HEA) coating on steel improved the wettability and spreadability during dissimilar laser joining of Al to steel, leading to enhanced joint strength and ductility. This novel method changes the fracture mode from brittle to ductile, offering a solution for strengthening challenging dissimilar combinations [200]. Also, using a Pd interlayer in NiTi-Ti6Al4V laser joints significantly reduced the formation of embrittling Ti2Ni intermetallic compounds, leading to joints with superior mechanical properties and superelastic behavior. The Pd-added joint's tensile strength and rupture strain more than doubled, reaching 520 MPa and 5.6%, respectively, demonstrating the potential for greater design flexibility in aerospace and biomedical applications [201]. The work of Dwivedi et al. [202] conducted a comprehensive review of the parameters involved in deep drawing and identified avenues for future research in this field. The results of the study demonstrated the successful production of aluminum alloy cups through this process. Previous studies have evaluated the influence of key process parameters on the objective function through experimental investigations [203–207]. In light of the increasing demand for enhanced product quality and elevated production rates, there has been a growing interest in monitoring automated welding operations. The lack of monitoring in this process can result in undetected malfunctions, leading to significant financial consequences. The mechanism of defect formation during the melting process in welding has been the subject of interest among both researchers in the manufacturing sector and those in the fields of materials science and physics. An in-depth understanding of this mechanism is essential to achieving high-quality results in laser welding. Moreover, aluminum possesses unique properties that make welding it more challenging compared to other metals. Laser Material Processing is a vital aspect of the Green New Deals and is considered a significant area of research in the field of manufacturing [208]. The utilization of laser welding technology has become ubiquitous in modern industrial production lines, providing high precision and fast welding capabilities [209]. However, the complexity of the laser welding process makes it challenging to perform quality control and defect analysis. To address these control issues, cognitive laser welding systems have been proposed and developed, which have demonstrated improved performance in defined workpieces after setup [210,211]. With the advancement of technology, automated welding systems have replaced many hand-welding operations, and welding methods are now trending towards personalized production methods utilizing next-generation welding systems [212]. Collection and sharing of welding information through big data is crucial for improving operations and evaluating the life-cycle of industrial supply chains [213]. The production of Laser Welded Blanks, by joining sheets of varying thicknesses, strengths, and coatings, offers the benefits of flexible designs, cost reduction, weight reduction, and increased strength [207,214]. The application of laser welding offers a myriad of advantages, encompassing heightened productivity, substantial welding penetration, and elevated welding speeds, resulting in superior welding outcomes compared to conventional welding techniques [215]. This stems from the potential for automation through the integration of artificial intelligence, data science, and machine learning techniques into the welding process.

Effective real-time monitoring technologies play a pivotal role in enhancing welding efficiency and ensuring product quality. Consequently, laser welding has found extensive utility across diverse industries, including automotive, aerospace, shipbuilding, railway, and electronics [56–59]. Fiber lasers, a well-established technology, have gained prominence in high-volume welding applications within both established and emerging markets. The growing adoption of fiber lasers is underpinned by factors such as increased production yields, enhanced design flexibility, and greater energy efficiency. The transition to intelligent manufacturing processes necessitates the acquisition of high-quality real-time data. To enable decentralized decision-making, laser welding processes increasingly rely on technologies that serve as the 'eyes and ears' of the manufacturing operation. Fiber laser technology is renowned for its reliability, offering improved quality and automation capabilities when compared to other types of laser systems (Table 18)

Table 18. A comparative analysis of characteristics among prominent high-power Industrial Lasers

Characterization	**Fiber Laser**	**Nd:YAG**	**CO_2**	**Disc**	**Reference**
Wavelength	1.07 µm	1.06 µm	10.6 µm	1.03 µm	[215]
Output Powers	to 100 kW	to 7 kW	to 15 kW	to 16 kW	[215]
BPP (4/5kW)	< 2.5	25	6	8	[216,217]
Diode Life times	100,000 h	10,000 h	N.A.	10,000 h	[218]
Cooling	Air/Water	Deionized	Water	Water	[218]
Floor Space (4/5kW)	< 1 m^2	6 m^2	3 m^2	> 4 m^2	[216]
Operating Cost/hour	$21.31	$38.33	$24.27	$35.43	[219]
Maintenance	Not Required	Often	Required	Often	[218]

The demand for lightweight structures in the automotive industry has led to increased use of aluminum alloys (AA) [220]. AA offers desirable properties such as low density, corrosion resistance, specific strength, and recyclability [221]. Laser welding is a preferred joining technique for AA, despite challenges posed by its physical properties [222, 223]. AA alloys can be categorized as non-heat-treatable (1xxx, 3xxx, 4xxx, and 5xxx) and heat-treatable (2xxx, 6xxx, and 7xxx) [224]. Laser welding confers several advantages, including the generation of narrow fusion zones, enabling deep penetration into materials, facilitating high production rates, and granting access to intricate geometries [225-228]. Research has explored factors affecting weld penetration, including Mg evaporation, laser absorption, and process parameters [45-49] [233]. Quality issues like porosity and cracking require monitoring and parameter adjustments for quality assurance [234,237]. Additionally, the integration of Industry 4.0 technologies and intelligent welding systems (IWS) has become increasingly relevant in the context of metal welding, offering automation, real-time monitoring, and data-driven decision-making to enhance welding processes. Table 19 summarizes key aspects of previous reviews on Intelligent Welding Systems (IWS) along with their objectives and references. These reviews delve into the realm of Industry 4.0 technologies and their applications, shedding light on their influence on manufacturing processes. The topics covered include research trends, real-time monitoring, data analytics, and the synergy between Industry 4.0 and additive manufacturing. These comprehensive reviews offer valuable insights into the potential benefits and advancements brought about by intelligent welding systems in various industrial sectors, particularly in the context of Industry 4.0.

Table 19. previous reviews on intelligent welding systems (IWS).

Application/scope	**Objective**	**Reference**
Industry 4.0 technologies offer automation, efficiency, improved product quality, customization, and new business models for the plastics industry.	Research trends and knowledge in Industry 4.0 using bibliometric analysis.	[238]
The advancement of welding systems, real-time monitoring and control, and the integration of data analytics and AI in intelligent welding systems.	covers critical aspects such as sensing and signal processing, feature extraction and selection,	[212]

	modeling, decision-making, and learning.	
Explores Industry 4.0 advancements and their impact on manufacturing and production processes.	Introduce six design principles of Industry 4.0.	[48]
AM and Industry 4.0 synergize for advancements in product design, production, and supply chain.	This paper analyzes the relationship between Industry 4.0 and Additive Manufacturing (AM), exploring their direct and indirect elements.	[239]
Industry 4.0 technologies have the potential to foster a sustainable and eco-friendly manufacturing sector.	Overview of current Industry 4.0 research themes and topics.	[240]

The literature review highlights a significant research gap in the comprehensive exploration of porosity recognition in overlap aluminum laser welding, particularly through a combined experimental and statistical approach. To bridge this gap, our study was designed to scrutinize the sensitivity of crack indices and porosity recognition, employing various laser welding heads, namely the Remote Scanner, TRUMF Pulse, and Precitec models. Additionally, we conducted an in-depth analysis of laser beam characterization and beam profile shape to quantify beam distribution. Our overarching objective was to reduce manufacturing waste, minimize setup times, and optimize tool adjustments, thereby enhancing overall efficiency. The study leveraged offline monitoring techniques, notably X-ray analysis, across three distinct strategies. Given the multifaceted nature of laser welding, which can be influenced by numerous inputs, noise factors, and disturbances, we adopted an experimental methodology complemented by a phenomenological discussion on the quality of overlapped welded joints. Our investigations involved the joining of two different aluminum alloy configurations, specifically 1.6 mm-thick AA 6061-T6 and 2 mm AA 6061-T6. We explored three welding strategies to evaluate multiple laser variants and mitigate the sensitivity to hot cracking. The outcomes of our research underscore the feasibility of employing X-ray technology for porosity recognition as an offline monitoring tool. These findings hold substantial significance for the integration of laser welding technology within the automotive and surface transportation sectors. Furthermore, we emphasize the effectiveness of Design of Experiments (DOE) as a robust data collection and analysis tool, particularly in assessing the factors governing parameter values or interactions. DOE's capacity to manipulate multiple inputs concurrently is pivotal in identifying critical interactions that might otherwise be overlooked in single-factor experimentation. For future investigations, we suggest considering the incorporation of high-speed cameras as an online process monitoring technique. This would enable real-time inspection and the automatic rejection of parts that could compromise product conformity, labor capacity, and the overall value chain within the automotive industry.

4.7 MATERIALS AND METHODS

Laser welding provides a range of advantages, including enhanced productivity, versatility, and efficiency, across diverse industrial applications. Nevertheless, due to the intricate nature of this process, rigorous quality monitoring becomes imperative. Such monitoring is conventionally employed at three key stages: prior to, during, and following the welding process. Its primary purpose is to ameliorate the influence of variables impacting the mechanical attributes of the welded joint while simultaneously mitigating the potential for fatigue-related failures [55]. Aluminum, as one of the lightest engineering metals, boasts a superior strength-to-weight ratio compared to steel [56]. However, laser welding of aluminum is susceptible to seven major types of weld defects, including porosity [57], cracking [58], inclusions [59], lack of penetration or fusion [60], weld oxidation [61], and loss of alloying elements [62]. Our investigation has identified several key process parameters that play a role in the laser welding process, including laser power, power density, welding speed, type and flow of shielding gas, beam shape on the workpiece, and the position of the focal beam plane [24, 63, 64]. Of these variables, some have a greater impact on the laser welding process and are also easier to control and predict. Previous studies [65, 66] have investigated the effects of speed and power and have demonstrated significant impacts, with control over these parameters more readily achievable through the use of artificial intelligence. The Ishikawa diagram is a visual tool used in laser welding to analyze the relationship between process parameters and the quality of welded joints (Figure 36). Parameters like laser power, power density, welding speed, shielding gas type and flow, beam shape, and focal beam position are considered. In addition to the mentioned parameters, there are other critical factors that significantly impact the quality and outcome of laser welding processes. These factors include Continuous Wave (CW) versus Pulsed Wave (PW) laser modes, as well as the fundamental influence of the laser beam profile. The choice between CW and PW laser modes is essential as it affects the energy delivery to the workpiece. The diagram helps identify significant variables and their interactions, providing an overview of potential causes for defects in laser welding of aluminum. CW mode provides a continuous and steady energy input, while PW mode delivers pulses of energy. Each mode has its advantages and limitations based on the specific application and material being welded. The energy distribution and heat input from these modes influence the heat-affected zone, penetration depth, and overall weld characteristics.

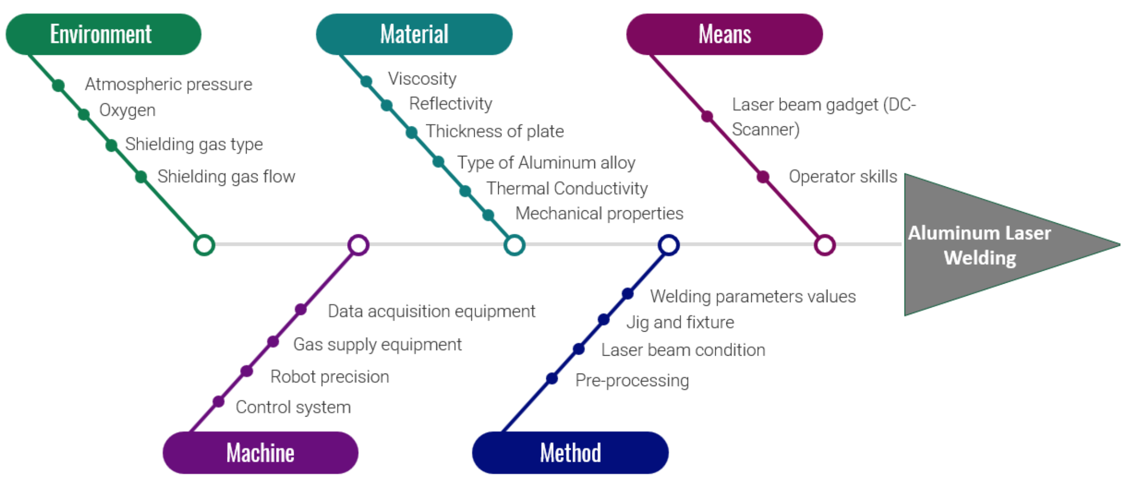


Figure 36. Classification of laser process parameters.

In this study, two different thicknesses of aluminum alloys, specifically 1.6 mm thick AA6061-T6 and 2 mm thick AA6061-T6, were employed as the overlap joint configuration.

The choice of aluminum alloy 6061, also known as "Alloy 61S," was made due to its widely recognized mechanical properties, weldability, and widespread usage in extrusion, with the exception of 6063, which is the most popular alloy used for this purpose. It is important to note that aluminum alloy 6061 is a precipitation-hardened aluminum alloy composed of magnesium and silicon as its primary alloying elements, and is widely utilized for general-purpose applications. The chemical composition of the welded sheets, as well as the relevant mechanical properties, are documented in Table 20.

Table 20**.** Chemical composition (% wt) and Mechanical properties of AA 6061-T6 [184]

Chemical composition	**Al**	**Cr**	**Cu**	**Fe**	**Mg**	**Mn**	**Other, total**	**Si**	**Ti**	**Zn**
% wt	0.15 - 0.35	0.1	0.4	2.2 - 2.8	0.1	0.25	0.1	0.4 - 0.8	Max 0.15	Max 0.25
Mechanical properties	Ultimate strength (MPa)	Proof strength (MPa)	Elongation (%)	Brinell hardness	Poisson's ratio	Modulus of Elasticity (GPa)	Density	Melting Point	Thermal Expansion	Thermal Conductivity
Value	230	195	12	60	0.33	70.3	2.70 g/cm³	650 °C	23.4 x10^-6 /K	166 W/m.K

The goal of the study was to identify the porosities and determine the appropriate conditions. The samples were made from AA6061-T6 aluminum alloy in an overlap welding configuration, with two different thicknesses (1.6 mm and 2 mm). The AA6061 aluminum alloy is known for its good mechanical properties, weldability, and popularity for general-purpose use. Here, the laser welding process was carried out using three different laser heads (Figure 37):

1. **ScanLab remote:** The remote welding head is equipped with advanced scanning technology, which enables high-speed and accurate movement of the laser beam.
2. **Trumpf D70:** The intelligent monitoring system continuously monitors important operating values and provides fault diagnosis, ensuring optimal performance and minimizing downtime.
3. **Precitec YW52:** The main purpose is to focus and direct the laser beam onto the workpiece during the welding process. This helps to achieve efficient and controlled melting and solidification of the material, resulting in strong and reliable weld joints.

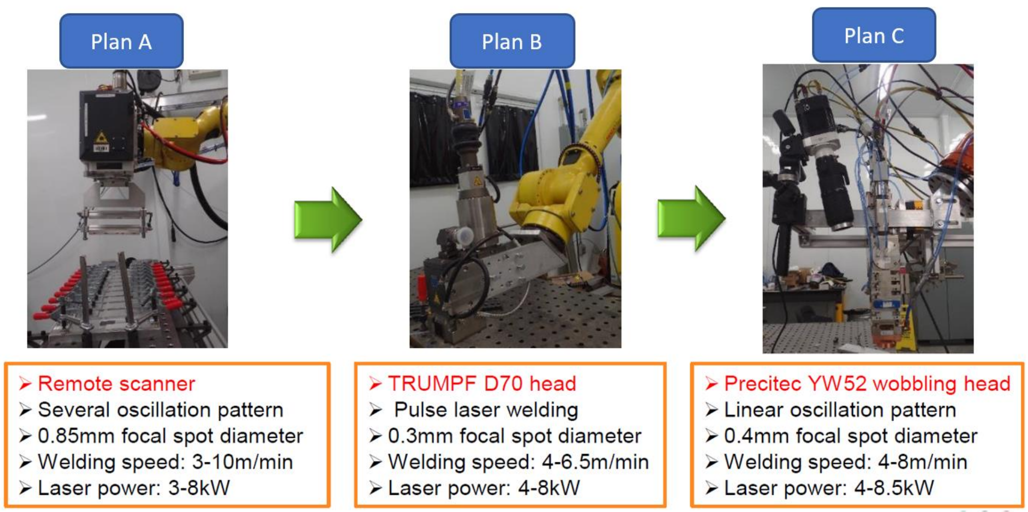
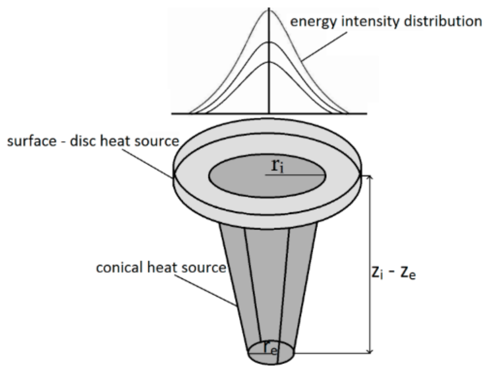


Figure 37. Three different plans of laser welding

4.8 BEAM CHARACTERIZATION

The energy of the laser beam can be adjusted according to the material being welded to ensure optimal results. Different materials absorb the energy differently, and it is crucial to determine the absorption capacity of the metal to set the laser parameters accordingly. Steel, for example, has a higher absorption capacity compared to aluminum or silver, thus requiring a lower power setting. According to literature, a mixture of conical volumetric and surface heat sources with gradually increasing energy intensity (Gaussian model) is considered the significant model for laser beam [229]. The conical volumetric heat distribution is described by a Gaussian distribution model and can be described by the equation where Q_0, r_i-r_e, and z_i-z_e represent the maximum volumetric heat flux density, upper and lower conical radius dimension, and conical heat source depth, respectively (Figure 38).



$$Q(x,y,z) = Q_0 + \exp\left(-\frac{x^2+y^2}{ro^2(z)}\right) \qquad (1)$$

$$ro(z) = re + \frac{ri - re}{zi - ze}(z - ze) \qquad (2)$$

Figure 38. Gaussian model Heat-source in laser-welding simulation.

In this study, the thermal conductivity of the material being welded is taken into account in order to properly model the heat transfer during the laser welding process. The Fourier's law of heat transfer is considered as one of the key factors, which states that the rate of heat transfer is proportional to the temperature gradient. This can be represented mathematically as:

$$Q/A = -k\,\nabla T \qquad (3)$$

Where Q is the heat flow rate, A is the surface area, k is the thermal conductivity, and ∇T is the temperature gradient. Additionally, the Petro-Galerkin convection effect is also taken into account, which considers the heat transfer due to the flow of fluid surrounding the material. This effect can be represented as:

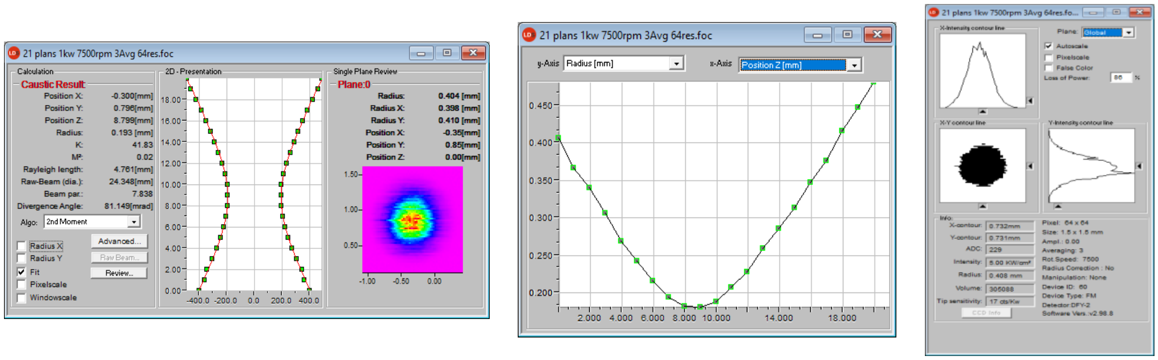
$$Q/A = h\,(T - T\_\infty) \qquad (4)$$

Where Q is the heat flow rate, A is the surface area, h is the heat transfer coefficient, T is the temperature of the material, and T_∞ is the temperature of the surrounding fluid. The consideration of both of these factors, the Fourier's law and Petro-Galerkin convection effect, allows for a more accurate modeling of the heat transfer during the laser welding process and helps to ensure the quality and consistency of the final weld:

$$\rho c(T)\frac{\partial T}{\partial t} = \frac{\partial}{\partial x}\left(k(T)\frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y}\left(k(T)\frac{\partial T}{\partial y}\right) + \frac{\partial}{\partial z}\left(k(T)\frac{\partial T}{\partial z}\right) + qv \tag{5}$$

$$\frac{\partial T}{\partial t} + \mathrm{v}.\nabla\mathrm{T} = \nabla.(\mathrm{k}\nabla\mathrm{T}) + \mathrm{Q} \tag{6}$$

Laser beam characterization is an important aspect of laser welding as it helps to understand the behavior of the laser beam and how it affects the quality of the weld. The beam profile, intensity distribution, spot size, focus position, and other parameters are analyzed to determine the best configuration for a particular welding application. A full characterization of a laser beam involves determining its complex amplitude profile in one plane perpendicular to the beam, which can be calculated using beam propagation software (Figure 39). The relationship between laser beam characterization and mechanical properties is a complex one, as the mechanical properties of a laser-welded joint depend on many factors, including the type and thickness of the material being welded, the laser power, the laser beam profile, the speed of the laser, and the cooling rate of the weld. The beam profile, in particular, has a strong influence on the resulting mechanical properties. For example, a Gaussian laser beam profile will produce a narrower, more focused weld than a uniform laser beam profile. This can lead to stronger welds, as the heat is concentrated in a smaller area. On the other hand, a wider beam profile can result in a shallower, wider weld, which may be weaker.



(a) (b) (c)

Figure 39. Beam characteristic using PRIMES system. A) Caustic Result, B) Position Z and C) Intensity

4.9 DESIGN OF EXPERIMENT (DOEs) AND STATISTICAL ANALYSIS

Design of Experiments (DOEs) is conducted to analyze the impact of various factors on the response variable and determine optimal conditions. In laser welding, the response variable includes mechanical properties like porosity, crack index, and ductility. Independent variables are typically process parameters such as laser power, welding speed, and cooling rate. Regression analysis is employed to establish the relationship between the response and independent variables, identifying influential factors and optimal conditions. The regression line is calculated by minimizing the squared distances between data points and the line. This enables predictions for different process conditions [230]. In this study, we're focusing on classification analyses to categorize our data into distinct groups. Following this, we will be embarking on a prediction analysis to forecast potential trends and outcomes. DOEs systematically test input variable combinations to determine optimal conditions for laser welding (Table 21). Statistical analysis results can then create predictive models to optimize welding and enhance mechanical properties. The combined approach of DOEs, regression analysis, and statistical analysis provides a robust method for understanding laser weld properties and optimizing industrial applications. Simple linear regression examines the relationship between a dependent variable and independent variable, while multiple linear regression extends this analysis to multiple predictors. The objective is to find the best-fit line or plane that minimizes squared residuals. Hypothesis testing determines predictor variable significance, and measures like R-squared and residual plots evaluate model goodness of fit. In simple linear regression, the relationship between variables is represented as:

$$Y = \beta 0 + \beta 1X + \varepsilon \tag{7}$$

Here, Y is the response variable, X is the predictor, β0 and β1 are the regression coefficients, and ε is the error term. The regression coefficients indicate the change in Y corresponding to a unit change in X, and ε represents the difference between the observed and predicted values of Y. The objective is to find the regression line that minimizes the sum of squared residuals, which are the differences between observed and predicted values. Multiple linear regression extends this analysis to include multiple predictor variables:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta pXp + \varepsilon \tag{8}$$

In this equation, Y is the response variable, X1, X2, ..., Xp are the predictor variables, β0, β1, β2, ..., βp are the regression coefficients, and ε is the error term. The coefficients β1, β2, ..., βp represent the change in Y corresponding to a unit change in each predictor variable. The goal is to find the regression plane that minimizes the sum of squared residuals. This study focuses on investigating the crack sensitivity in laser welding by analyzing the effects of various laser welding configurations: ScanLab remote laser welding system, Trumpf D70 laser head, and Precitec YW52 wobbling head. The crack sensitivity is assessed using X-ray inception examination, which helps identify any cracks that may have formed in the welded samples. Regression analysis is then performed to establish the relationship between the crack sensitivity (dependent variable) and the different laser welding configurations (independent variables). By analyzing the data obtained from X-ray inception examination, the study aims to identify the optimal laser welding configuration that minimizes crack sensitivity. This information is crucial for determining the welding parameters and conditions that ensure the highest quality and reliability of the welded joints. In this study, statistical modeling techniques were employed to analyze the crack sensitivity in the three different laser welding configurations. The experimental investigation provided the basis for the statistical model, and Minitab software was utilized for the analysis process, allowing for a comprehensive and robust analysis of the crack sensitivity in laser welding.

Table 21. Input Variable of the laser welding process

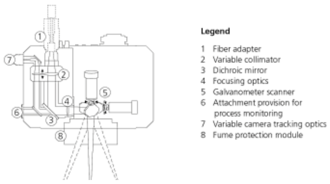
Variable	Unit	Level min	Level max
Laser Power	kW	3.5	10
Travel Speed	m/min	3	10
Focal Distance	mm	-4	12
Oscillation amplitude	mm	0.2	1
Oscillation Frequency	Hz	50	500
Oscillation shape	-	Infinite, Circle, Sin	

4.10 RESULTS AND DISCUSSION

4.10.1 Plan A: Remote scanner for laser welding overlap joint

Plan A involves developing a remote scanner for laser welding overlap joints and expanding its application to fillet seams. This method was successfully tested and qualified for industrial use; it has been implemented in BMW Mini door production [241]. This system allows welding of fillet seams, improving efficiency and offering advantages like smaller flanges and zero gap welding of galvanized material. The integration of scan heads on industrial robots enhances beam utilization and manufacturing efficiency. The scan head features a zoom axis, precise seam tracking, and meets industrial requirements. It accommodates up to 8 kW lasers and offers process monitoring options (Table 22). The central control unit, the Scan Control Unit, manages the entire laser welding system.

Table 22. ScanLab remote laser welding system technical configuration [242]



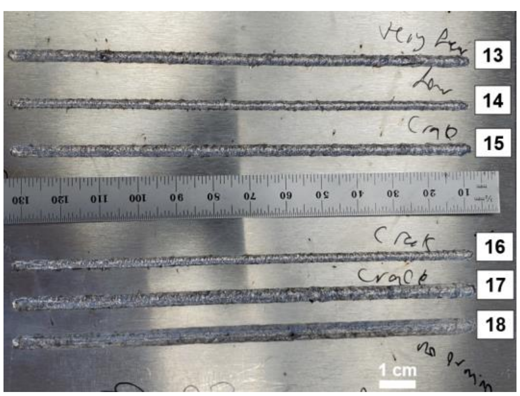
Optical Configuration	**IntelliWELD II PR (with prefocus optic)**	
Focal length, focusing optics	470 mm	660 mm
Focal length, collimator	135 mm	110 mm
Limiting NA (half angle)	0.11	0.13
Image ratio Focus diameter	1:3.5 350 µm	1:4.3 430 µm
Fiber diameter	≥ 50 µm	≥ 50 µm
Operating distance to protective window	301 mm	494 mm
Image field size (z=0, elliptical)	ca. (300 x 330) mm	ca. (450 x 480) mm
Image field size (z=0, rectangular)	ca. (270 x 270) mm	ca. (450 x 470) mm
Focus range in z direction	ca. ± 50 mm	ca. ± 100 mm
Wavelength	1030 nm - 1105 nm	
Maximum laser power (with specified cooling)	8 kW	
Fiber adapter	QBH, Q5/LLK-B, QD/LLK-D	

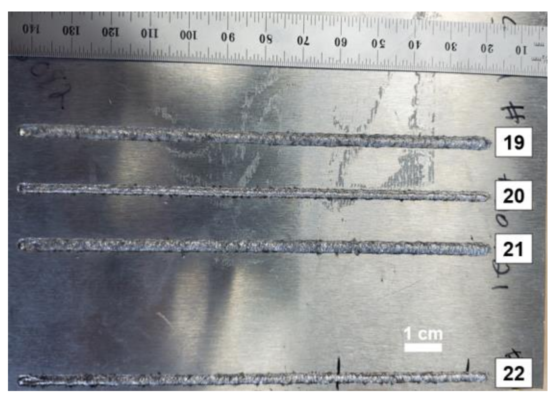
The chart below presents the initial set of parameters (Table 23). It is noteworthy that no protective gas was utilized during the welding process. X-ray imaging reveals the presence of weld cracks; however, a more comprehensive evaluation of the cracks can be achieved through top surface and cross-section metallography of selected specimens to calculate the crack susceptibility index (Figure 40, 41). The red arrows in Weld 17 illustrate an instance of the micro-crack locations as identified through X-ray imaging. It can be hypothesized that welds with higher penetration depth exhibit greater crack sensitivity. Regarding the_pass/fail criteria used in the experiment were P (pass) and F (fail). The pass/fail criteria were determined based on the presence of defects in the welded joints. The criteria changed depending on the combination of laser power, travel speed, focal distance, oscillation shape, oscillation frequency, and oscillation amplitude. Specifically, the criteria changed from pass to fail when the laser power was increased from 6 kW to 8 kW, when the travel speed was increased from 5 m/min to 7.5 m/min, when the focal distance was changed from 4 mm to -4 mm, when the oscillation shape was changed from infinite to circle or sine, and when the oscillation frequency was increased from 200 Hz to 500 Hz. The criteria did not change significantly with the pulse mode or oscillation amplitude.

Table 23. Experimental planification for remote scanner-laser welds-overlap joint

Identification	Laser power (kW)	Travel speed (m/min)	Focal distance (mm)	Pulse	Oscillation shape	Oscillation frequency (Hz)	Oscillation amplitude (mm)	Criteria (Pass/Fail)
#13	6	5	4	NA	Infinite	200	0.2	P
#14	6	7.5	4	NA	Infinite	200	0.2	P
#15	8	7.5	4	NA	Infinite	200	0.2	F
#16	8	10	4	NA	Infinite	200	0.2	F
#17	10	7.5	4	NA	Infinite	200	0.2	F
#18	3	5	4	NA	Infinite	200	0.2	P
#19	6	5	4	NA	Infinite	200	0.5	P
#20	6	7.5	4	NA	Infinite	200	0.5	P
#21	8	7.5	4	NA	Infinite	200	0.5	F
#22	8	10	4	NA	Infinite	200	0.5	F
#25	6	5	4	NA	Infinite	500	0.5	P
#26	6	7.5	4	NA	Infinite	500	0.5	P
#27	8	7.5	4	NA	Infinite	500	0.5	F
#28	8	10	4	NA	Infinite	500	0.5	F
#29	10	7.5	4	NA	Infinite	500	0.5	F
#30	10	10	4	NA	Infinite	500	0.5	F
#31	6	5	-4	NA	Infinite	50	1	P
#32	6	7.5	-4	NA	Infinite	50	1	P
#33	8	7.5	-4	NA	Infinite	50	1	F
#34	8	10	-4	NA	Infinite	50	1	P
#35	10	7.5	-4	NA	Infinite	50	1	F
#36	10	10	-4	NA	Infinite	50	1	F
#37	6	5	4	V	Infinite	200	0.5	F
#38	6	7.5	4	V	Infinite	200	0.5	P
#39	8	7.5	4	V	Infinite	200	0.5	F
#40	8	10	4	V	Infinite	200	0.5	P
#41	10	7.5	4	V	Infinite	200	0.5	F

#42	4	3	4	V	Infinite	200	0.5	F
#43	6	5	4	NA	Infinite	100	0.5	F
#44	6	7.5	4	NA	Infinite	100	0.5	P
#45	8	7.5	4	NA	Infinite	100	0.5	F
#46	8	10	4	NA	Infinite	100	0.5	F
#47	10	7.5	4	NA	Infinite	100	0.5	F
#48	5	3	4	NA	Infinite	100	0.5	F
#49	6	5	4	NA	circle	200	0.5	P
#50	6	7.5	4	NA	circle	200	0.5	P
#51	8	7.5	4	NA	circle	200	0.5	F
#52	8	10	4	NA	circle	200	0.5	P
#53	10	7.5	4	NA	circle	200	0.5	F
#54	5	3	4	NA	circle	200	0.5	P
#61	6	5	4	NA	sin	125	0.2	P
#62	6	7.5	4	NA	sin	125	0.2	P
#63	8	7.5	4	NA	sin	125	0.2	F
#64	8	10	4	NA	sin	125	0.2	P
#65	10	7.5	4	NA	sin	125	0.2	F
#66	10	10	4	NA	sin	125	0.2	F





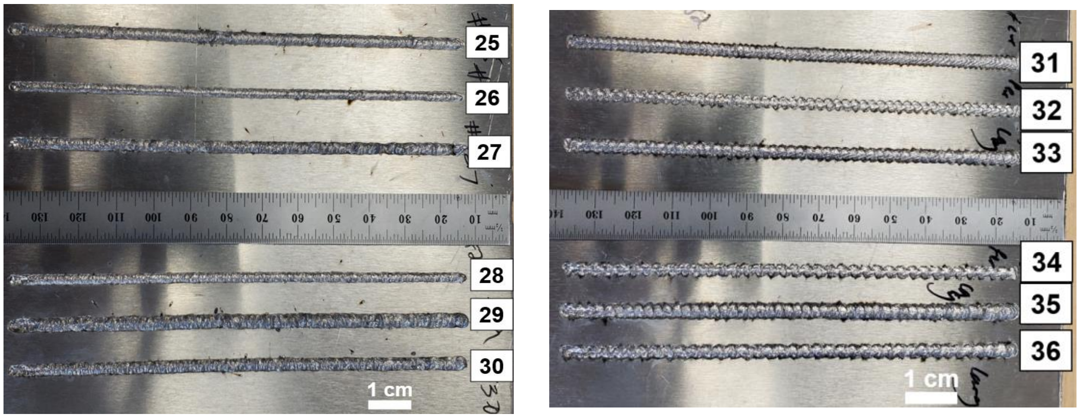


Figure 40. Experiments study of remote scanner-laser welds-overlap joint

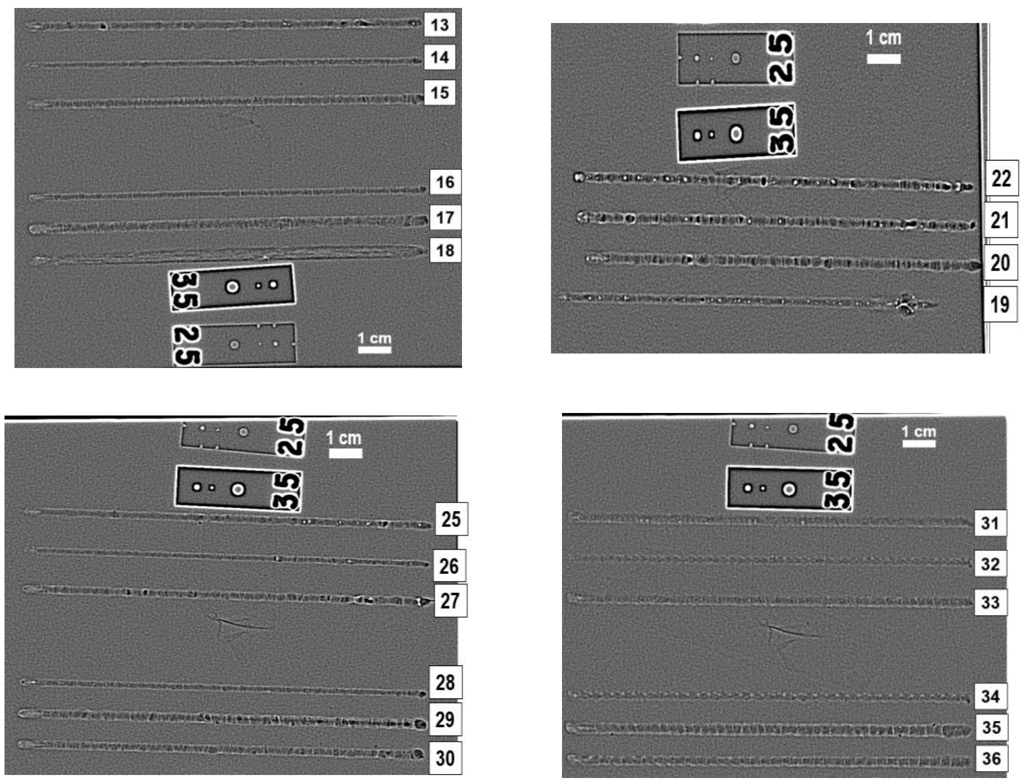


Figure 41. X-Ray analysis of remote scanner-laser welds-overlap joint

The experimental data for laser welding of aluminum alloy shows various combinations of laser power, travel speed, focal distance, pulse, oscillation shape, oscillation frequency, oscillation amplitude, and criteria. A comprehensive analysis of the process and pass/fail criteria is as follows:

- *Process analysis:*

Laser power: The laser power used in the experiment ranged from 3 kW to 10 kW. The results show that higher laser power generally led to better welding performance. Specifically, when the laser power was increased from 6 kW to 8 kW, the criteria changed from pass to fail for some of the experiments, indicating that the optimal power may vary depending on the other parameters.

Travel speed: The travel speed used in the experiment ranged from 3 m/min to 10 m/min. The results show that the optimal travel speed depends on the other parameters. Generally, higher travel speed resulted in better welding performance, except for some experiments where the criteria changed from pass to fail when the travel speed was increased from 5 m/min to 7.5 m/min. Porosity formation is significantly impacted by welding speed due to the thermal dynamics involved in the laser welding process. A higher welding speed can result in insufficient heat input, leading to rapid solidification of the molten pool. This rapid solidification may trap gas bubbles, preventing them from escaping, and ultimately resulting in porosity. Conversely, lower welding speeds allow for more heat input and slower solidification, which can help gases escape, reducing porosity.

Focal distance: The focal distance used in the experiment was 4 mm and -4 mm. The results show that the focal distance had a significant effect on the welding performance, and the optimal focal distance varied depending on the other parameters. Specifically, when the focal distance was changed from 4 mm to -4 mm, the criteria changed from pass to fail for some of the experiments, indicating that the optimal focal distance may vary depending on the other parameters. The defocus distance, or the distance between the laser focus point and the workpiece surface, affects the size and shape of the laser beam. When the defocus distance is too small (under focused), the beam can become tightly focused, leading to a narrow and deep weld, which may increase the likelihood of trapping gas within the weld pool. Conversely, when the defocus distance is too large (overfocused), the beam may become too wide, resulting in inadequate penetration and potential porosity due to incomplete fusion. The optimal defocus distance strikes a balance between these extremes, allowing for adequate penetration and minimizing the risk of gas entrapment.

Pulse: Some experiments used pulsed laser welding, while others used continuous laser welding. The results show that the pulse mode did not have a significant effect on the welding performance.

Oscillation shape: Some experiments used oscillation shapes, while others did not. The results show that the oscillation shape had a significant effect on the welding performance. Specifically, when the oscillation shape was changed from infinite to circle or sine, the criteria changed from pass to fail for some of the experiments, indicating that the optimal oscillation shape may vary depending on the other parameters.

Oscillation frequency: The oscillation frequency used in the experiment ranged from 50 Hz to 500 Hz. The results show that the optimal oscillation frequency depends on the other parameters. Generally, higher oscillation frequency resulted in better welding performance, except for some experiments where the criteria changed from pass to fail when the oscillation frequency was increased from 200 Hz to 500 Hz.

Oscillation amplitude: The oscillation amplitude used in the experiment ranged from 0.2 mm to 1.0 mm. The results show that the optimal oscillation amplitude depends on the other parameters. Generally, higher oscillation amplitude resulted in better welding performance, except for some experiments where the criteria changed from pass to fail when the oscillation amplitude was increased from 0.2 mm to 0.5 mm.

4.10.2 Statistical analysis for plan A (ScanLab remote laser welding system):

Regression analysis is a statistical method used to examine the relationship between a dependent variable and one or more independent variables. In this study, regression analysis was conducted to predict a binary response variable ("pass" or "fail") in the context of crack sensitivity analysis in laser welding. The results of the analysis indicated an 80% accuracy for predicting the "pass" category and an 84.6% accuracy for predicting the "fail" category.

The overall accuracy of the model was determined to be 82.6%. The misclassification table provided insights into the model's classification accuracy, including sensitivity, specificity, and the occurrence of type I and type II errors. The choice of the optimal number of nodes in the model was based on achieving a balance between model complexity and accuracy, and it was determined to be 2. The model showed accurate classification by using a threshold of 0.50 to determine the predicted probability level. It is important to note that the threshold value can be adjusted depending on the specific analysis requirements and objectives, which may impact the model's accuracy and should be carefully considered. Regression analysis is a valuable tool in crack sensitivity analysis for laser welding as it helps understand the relationships between parameters and the likelihood of crack formation under different conditions. However, it is crucial to consider the assumptions, limitations, and interpret the results cautiously in light of the data and research question. Table 24 presents the statistical analysis results for the remote scanner-laser welds-overlap joint, employing binary response analysis through regression. The binary response variable consisted of 20 "pass" and 26 "fail" occurrences. The model achieved high prediction accuracies, with 80% for "pass," 84.6% for "fail," and an overall accuracy of 82.6%. The confusion matrix and misclassification table provided insights into the model's classification accuracy, considering sensitivity, specificity, type I and type II errors. Notably, the model misclassified a few cases in both training and test datasets, indicating the need for further refinement. The analysis also identified important predictors and determined the optimal number of nodes to balance model complexity and accuracy. Furthermore, as illustrated in Figure 42, which provides insights into the interpretation and relative significance of process parameters, it becomes evident that the optimal point in the trade-off between relative cost and the number of nodes corresponds to 0.3538. Notably, laser power and travel speed emerge as the most influential factors in the laser welding process.

Table 24. Statistical for remote scanner-laser welds-overlap joint

Numerical Value		Confusion Matrix					
		Predicted Class (Training)			Predicted Class (Test)		
Actual Class	**Count**	**P**	**F**	**% Correct**	**P**	**F**	**% Correct**
P (Event)	20	16	4	80.0	16	4	80.0
F	26	4	22	84.6	4	22	84.6
All	46	20	26	82.6	20	26	82.6

Statistics	Training (%)	Test (%)
True positive rate (sensitivity or power)	80.0	80.0
False positive rate (type I error)	15.4	15.4
False negative rate (type II error)	20.0	20.0
True negative rate (specificity)	84.6	84.6

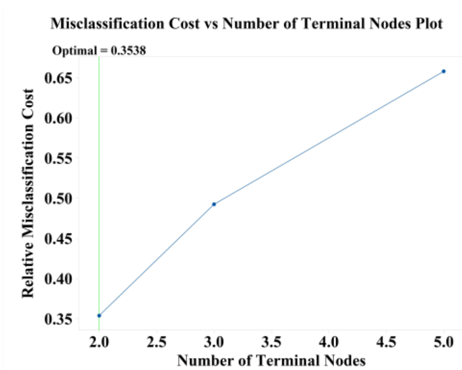
	Misclassification	
Input Misclassification Cost	**Predicted Class**	
Actual Class	P	F
P		1.00
F	1.00	

		Training			Test		
Actual Class	**Count**	**Misclassed**	**% Error**	**Cost**	**Misclassed**	**% Error**	**Cost**
P (Event)	20	4	20.0	0.2000	4	20.0	0.2000
F	26	4	15.4	0.1538	4	15.4	0.1538
All	46	8	17.4	0.1769	8	17.4	0.1769

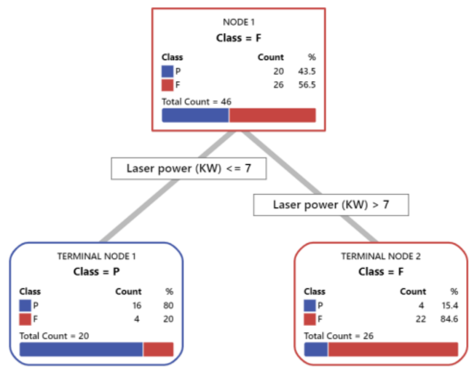
Binary Response Information			
Variable	**Class**	**Count**	**%**
Criteria	P (Event)	20	43.48
	F	26	56.52
	All	46	100.00

Model Summary				
Model metric	**Value**	**Statistics**	**Training**	**Test**
Total predictors	7	Average -loglikelihood	0.4602	0.4934
Important predictors	4	Area under ROC curve	0.8231	0.7183

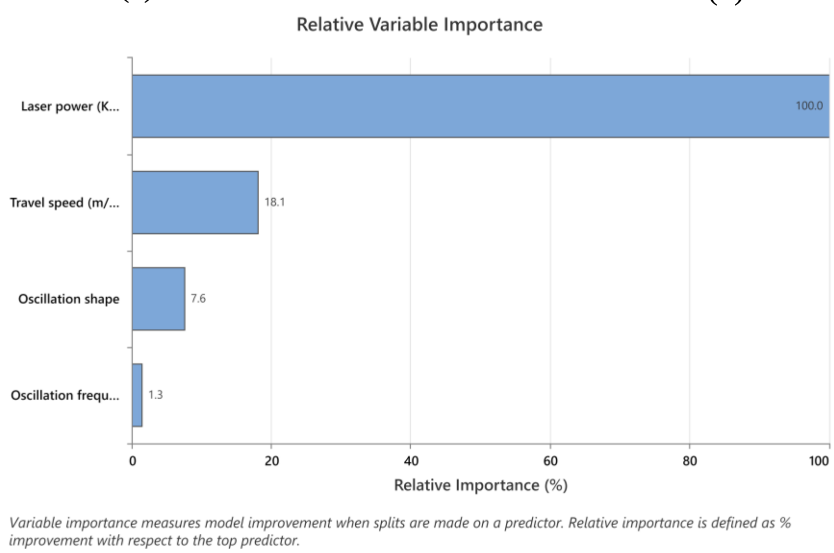
Number of terminal nodes	2	95% CI	(0.07515, 1)	(0.5483, 0.8882)
Minimum terminal node size	20	Lift	1.8400	1.1500
		Misclassification cost	0.3538	0.3538



(a)



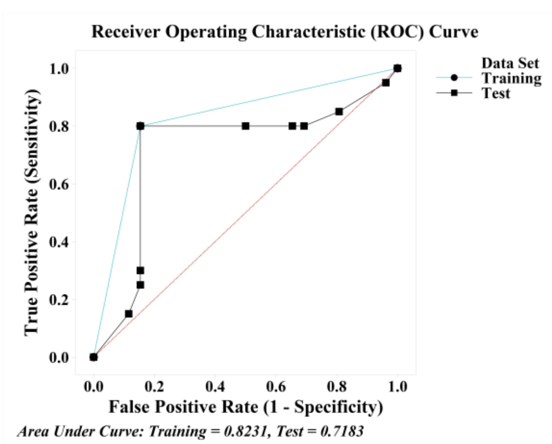
(b)



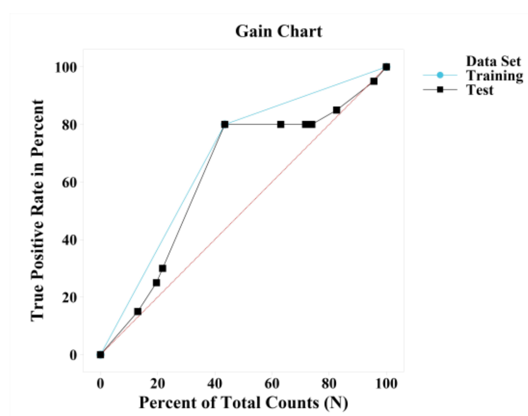
(c)

Figure 42. Interpretation and relative importance of process parameters

Additionally, Figure 43 displays a correlation relationship between the test and training set. The Lift chart plots the true positive rate as a function of the cumulative percentage of the data. The Lift chart provides a measure of the degree to which the model improves the accuracy of predictions over random chance. A value of 1 indicates that the model is not improving predictions over random chance, while a value greater than 1 indicates that the model is improving the accuracy of predictions over random chance. In this example, the Lift chart shows a clear improvement over random chance, with the curve rising steeply at the beginning and then leveling off (Fig 43b). The performance of the classification model can be evaluated by using the Gain and Lift charts. Specifically, the Receiver Operating Characteristic (ROC) curve plots the True Positive Rate (TPR), also referred to as sensitivity, on the y-axis and the False Positive Rate (FPR), also referred to as type 1 error, on the x-axis. The area under the ROC curve ranges from 0.5 to 1, where 1 indicates perfect class separation and 0.5 indicates a random assignment. A higher area under the ROC curve indicates a better classifier. The area under the ROC curve for the test data is approximately 83% and 72% for the training data, indicating reasonable classification performance. Using a validation method, Minitab creates two ROC curves, one for the training data and the other for the validation data. The validation results determine if the model can predict the response values accurately for new observations or summarize the relationships between the response and predictor variables accurately. Training results are usually more optimistic and are only used as a reference. A k-fold area under the ROC curve that is substantially lower than the area under the ROC curve may indicate over-fitting, which occurs when the model includes unnecessary terms that are specifically tailored to the training data, making it less useful for predictions on the population. It is also important to consider the misclassification rate of the model, which is the proportion of observations that are incorrectly classified. The misclassification rate can be used to assess the overall accuracy of the binary classification model and can be used to compare different models. In addition, the misclassification rate can be used to determine the optimal threshold value for classifying observations, as the misclassification rate is dependent on the threshold value. A threshold value that results in a low misclassification rate is desirable. The Gain chart plots the total positive rate as a percentage versus the percentage of total counts. The chart can demonstrate the efficiency of resources by showing the proportion of events within a certain proportion of data. For example, the gain chart may indicate that 80% of events are in 40% of the data, meaning that by focusing on 40% of the data, 80% of true positives can be achieved. In this case, the gain chart shows a sharp increase above the reference line, then flattens. Approximately 40% of the data accounts for approximately 80% of the true positives (Figure 43a). It is important to note that the ROC curve and the Gain chart are commonly used evaluation metrics for binary classification models, but they are not the only metrics. Other evaluation metrics include precision, recall, F1-score, and the Matthews correlation coefficient. Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. Recall, also known as sensitivity or true positive rate, is the ratio of correctly predicted positive observations to the total actual positive observations. The F1-score is the harmonic mean of precision and recall and provides a balance between the two. The Matthews correlation coefficient is a measure of the quality of binary classifications, taking into account true and false positives and negatives. In many applications, the performance of a binary classification model can be numerically evaluated using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve. The area under the ROC curve ranges from 0.5 to 1, with a value of 1 indicating perfect separation of the classes and a value of 0.5 indicating no better than random assignment. By comparing these metrics, the performance of the model can be evaluated, and improvements can be made to optimize the model. It is important to consider the business context and the desired outcome when selecting which evaluation metrics to use. For example, if the cost of false positive predictions is high, precision might be a more important metric. On the other hand, if false negative predictions are more costly, recall might be a more important metric. In addition, it is also important to keep in mind that no single evaluation metric can fully capture the performance of a binary classification model. It is recommended to use multiple evaluation metrics to provide a comprehensive view of the model's performance. Furthermore, it is also important to validate the model's performance on new, unseen data to ensure its generalizability. This can be done through methods such as cross-validation or using a holdout validation set. The performance of the model on the validation data should be similar to its performance on the training data, indicating that the model has not over-fit to the training data and can generalize to new observations. In conclusion, the results of the statistical analysis in the context of crack sensitivity analysis in laser welding provide valuable insights into the relationship between the parameters and the response. The use of regression analysis and binary classification models can help to optimize the conditions for welding to minimize crack formation. The use of metrics such as R-squared and the area under the ROC curve, as well as the Gain and Lift charts, can provide a comprehensive assessment of the performance of the models. The results of the statistical analysis indicate reasonable classification performance, but it is important to consider the misclassification rate and the degree to which the model improves the accuracy of predictions over random chance when interpreting the results. In the Lift chart, the cumulative lift is calculated by dividing the cumulative true positive rate by the expected cumulative true positive rate, which is the same as the reference line in the Gain chart. The lift chart provides an assessment of the ability of the predictive model to accurately identify positive events. The cumulative lift is an important metric in business applications as it represents the degree to which the predictive model outperforms random chance in identifying positive events. A lift of 1 means that the model performs no better than random chance, while a lift greater than 1 means that the model is performing better than random. In this example, the lift chart shows that the predictive model is performing better than random, with the lift gradually decreasing as more of the data is considered. This indicates that the model may be losing its predictive power as the number of data points increases. In such a scenario, the model may need to be modified or re-calibrated to ensure that it continues to provide accurate predictions.



(a)



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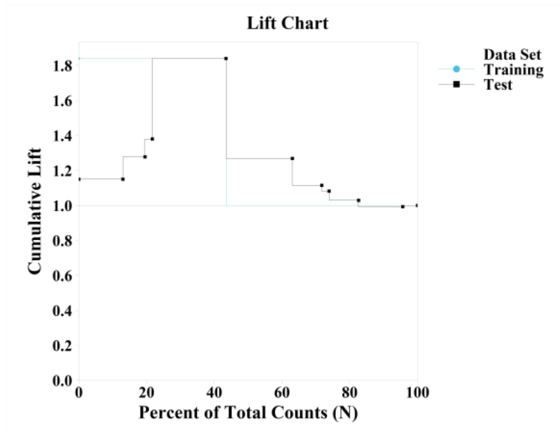


(c)

Figure 43. Correlation relation between test and training set. a) ROC curve, b) Gain chart and c) Lift chart

4.10.3 Plan B: TRUMF pulse laser welding of aluminum in overlap joint configuration

The Trumpf D70 laser head comprises four key components: Focal position, Intelligent monitoring, Remote Services, and Flexible use. The focal position allows for easy adjustment of the laser's focal position using programmable motorized focusing (PMF). Intelligent monitoring ensures continuous monitoring of vital operating values and fault diagnosis, while Remote Services offer remote assistance for minimizing downtime. The D70 laser head is compatible with various TRUMPF solid-state lasers and features a broadband coating. In laser welding, Multifocus plays a crucial role by splitting the laser beam into multiple partial beams, creating a stable and customized keyhole formation. This prevents collapse during welding and enables media-tight welds. The Multifocus arrangement enhances process control, reduces porosity and spatter, and allows for productive welding speeds. By combining Multifocus with BrightLine Weld, process efficiency and weld quality improve, enabling consistent welding depths. Media-tight welds can be achieved in aluminum alloys ranging from 0.8mm to 2.5mm thickness.

Table 25. Trumpf D70 laser head technical configuration [243]

Laser Parameters	Avalable range
Wavelength	-
Power	Up to 8000 W (cw)
Numerical Aperture	typ. 0.11 / max. 0.12
Laser light cable type	LLK-D, LLK-B, LLK-A
Collimation	150 / 200 mm
Focal length	100 / 150 / 200 / 300 / 400 / 600 mm
Dimensions (w x h x d)	189 mm x 524 mm x 78 mm
Weight	6 kg

Crack tendency calculation is a critical step in the evaluation of the quality of a welded joint. The measurement of crack tendency can be performed through various techniques such as X-ray imaging, top surface metallography, and cross-section metallography (Figure 44, 45). The results obtained from these techniques can be used to quantify the crack tendency of the welded joint. In the absence of shielding gas, the crack tendency of the welded joint may increase due to exposure to the ambient environment. This highlights the importance of using shielding gas to minimize the risk of cracks in the welded joint. The use of metallography techniques to calculate crack tendency is a common practice in the welding industry and provides valuable information for the assessment of the quality of the welded joint. The results obtained from these techniques can be used to make informed decisions on the design and optimization of the welding process to improve the quality of the welded joint. In Table 8, the experimental plan for TRUMPF pulse laser welding of aluminum is presented, consisting of various parameters and corresponding outcomes categorized as "Pass" or "Fail." This experimental design aims to investigate the influence of laser power (kW), travel speed (m/min), and focal distance (mm) on the success or failure of the welding process. First, it's crucial to note that the welding criteria are based on whether the welded joint meets the required quality standards, where "Pass" signifies a successful weld that adheres to the desired quality parameters, while "Fail" indicates a weld that does not meet these standards, potentially due to defects such as porosity or cracking. The experimental setup involves nine different combinations of laser power, travel speed, and focal distance. These combinations vary across a range of values, reflecting the typical operating conditions encountered in practical laser welding applications. Upon analyzing the outcomes in Table 8, several key observations and trends emerge:

- **Laser Power (kW):** The laser power varies from 3.5 kW to 7.4 kW. The results show that when the laser power is within the range of approximately 4 kW to 7.4 kW (including values such as 5.13 kW, 5.7 kW, and 6.27 kW), the welding process tends to be successful (marked as "Pass"). This suggests that higher laser power levels are generally favorable for achieving quality welds.

- **Travel Speed (m/min):** Travel speed varies between 2.5 m/min and 6.5 m/min. Notably, most of the experiments with travel speeds ranging from 4 m/min to 6.5 m/min (including 4.5 m/min, 5 m/min, and 5.5 m/min) result in "Pass" outcomes. This indicates that moderate to high travel speeds are associated with successful welding.

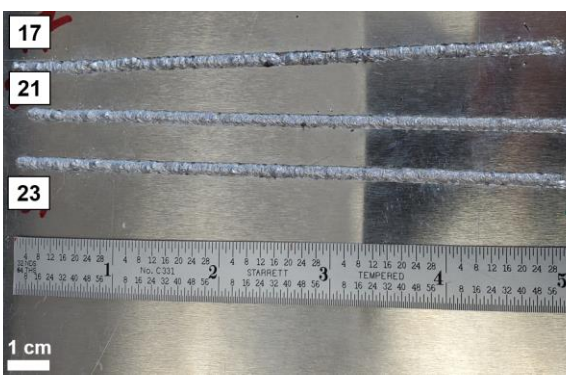
- **Focal Distance (mm):** The focal distance is kept constant at 6 mm for all experiments in Table 8, suggesting that this specific parameter is not being investigated for variation in this particular experimental plan.

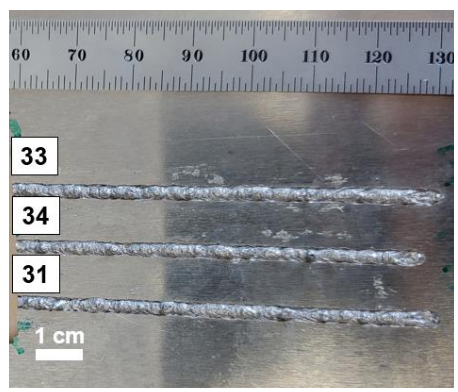
- **Overall Trends:** From the provided data, it is evident that welding parameters within certain ranges of laser power and travel speed lead to successful welds, while deviations from these ranges tend to result in welding failures.

In summary, the experimental plan in Table 26 provides valuable insights into the influence of laser power and travel speed on the success of TRUMPF pulse laser welding of aluminum. These insights can be further analyzed to determine optimal parameter settings that yield consistently high-quality welds, which is essential for ensuring the reliability and durability of laser-welded components in various industrial applications.

Table 26. Experimental planification for TRUMPF pulse laser welding of aluminum

ID	Laser power (kW)	Travel speed (m/min)	Focal distance (mm)	Criteria (Pass/Fail)
17	5.13	4.5	6	F
19	3.5	2.5	6	F
21	4	3.5	6	F
22	7.4	6.5	6	P
23	4.55	4	6	F
24	5.7	5	6	F
25	6.27	5.5	6	P
33	5.4	4.5	6	P
34	4.95	5	6	P
31	4.95	4.5	6	P





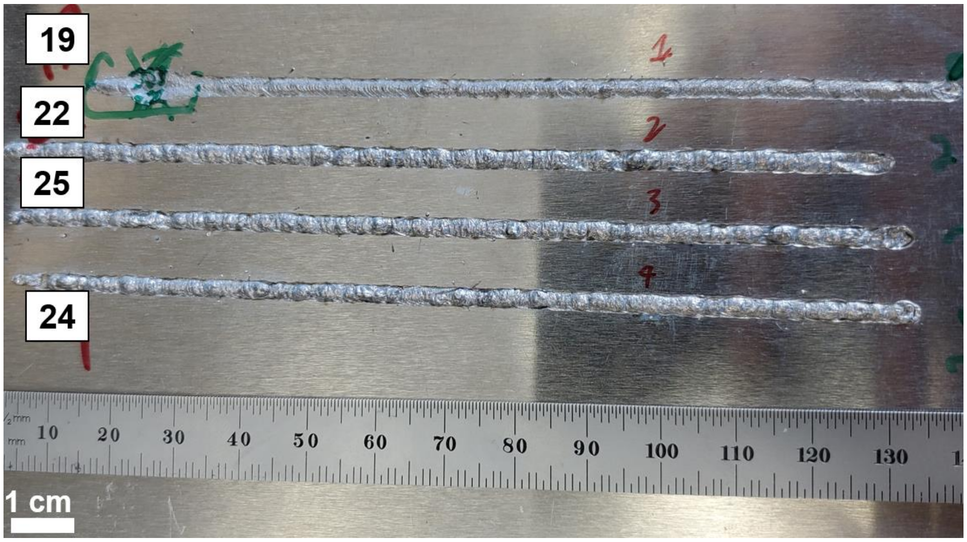


Figure 44. Experiments study of TRUMPF pulse laser welding of aluminum

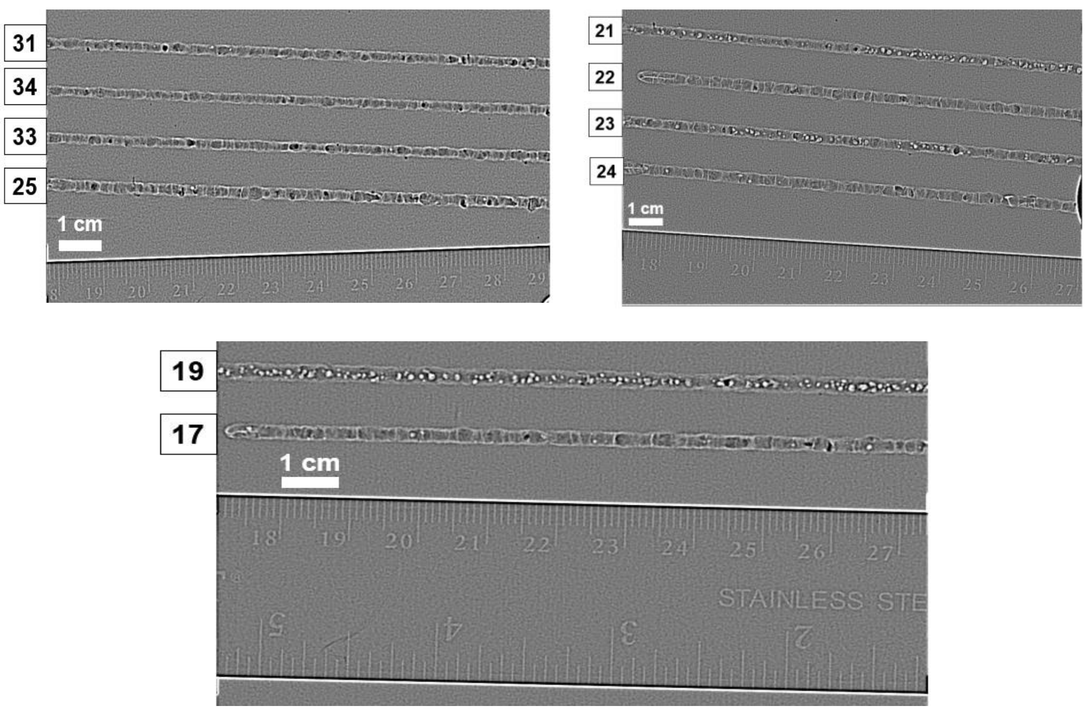
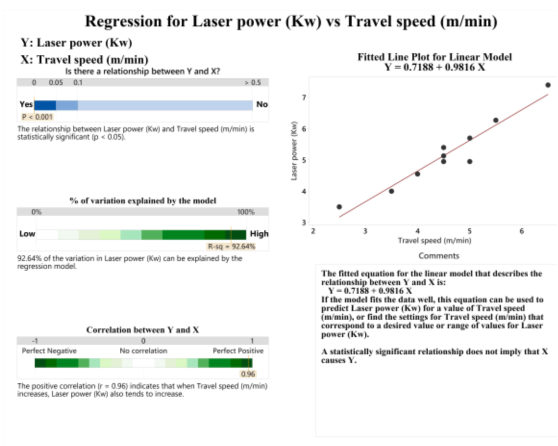


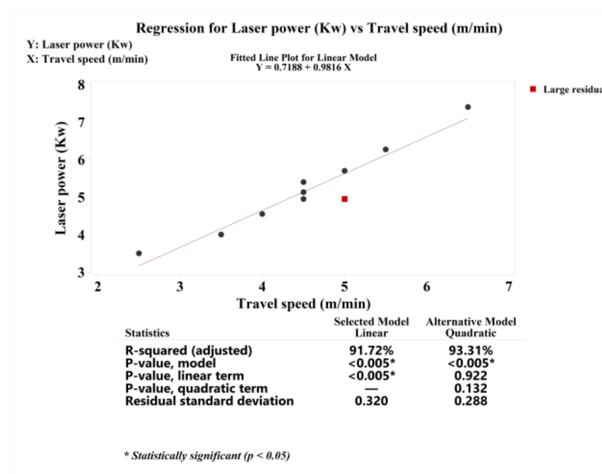
Figure 45. X-ray study of TRUMPF pulse laser welding of aluminum

4.10.4 Statistical analysis TRUMF pulse laser welding of aluminum in overlap joint configuration

The statistical analysis for TRUMF pulse laser welding is summarized in Figure 46. Regression analysis is utilized to establish the relationship between predictor variables and the response variable, enabling predictions for new observations. The analysis employs linear regression using ordinary least squares estimation to minimize residuals. The p-value associated with each predictor variable tests the significance of its effect on the response variable. A low p-value indicates a meaningful relationship between the predictor and response variables. Simple linear regression focuses on the linear relationship between one predictor and one response variable, improving prediction accuracy. The regression model provides an equation that quantifies the relationship and facilitates prediction.



(a)



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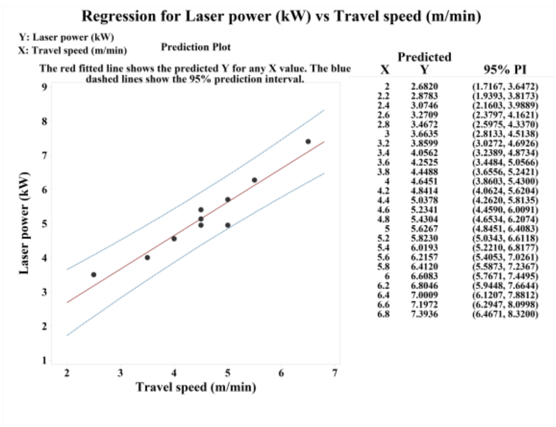

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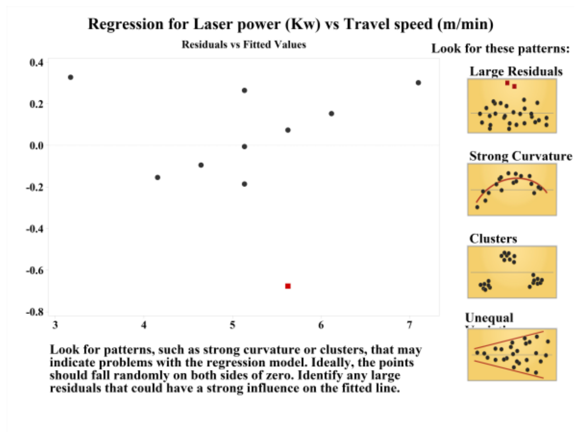


(d)

Figure 46. Statistical analysis TRUMF pulse laser welding of aluminum in overlap joint configuration

4.10.5 Plan C: Porosity reduction using Precitec wobbling head:

The YW52 Welding Head is a compact system designed to be utilized in conjunction with diode and solid-state laser machines. Its modular design allows for customization to meet the unique requirements of various applications. The basic version offers cost-effectiveness, while the full process monitoring capabilities make it well-suited for fully automated production processes. Precitec has integrated the Scan Tracker technology into the YW52 laser welding head, providing a solution for controlling weld position and seam width (Table 27). The Weld Master system, also integrated into the solution, offers real-time process control and quality monitoring, making it a versatile and comprehensive solution for complex welding challenges under varying conditions. The Weld Master system measures the lateral position of the joint and the width of the gap, using the integrated scanner mirror of the Scan Tracker to precisely control the focal position. The system also features a mechanically controlled collimation lens to compensate for any changes in the standoff distance, and a freely programmable laser power that is synchronized with the pendulum motion. The seam width can be adjusted through an analog interface, without the need for additional control. The Weld Master system has been successfully implemented in various automotive engineering applications, including laser welding and quality control of gear units, aluminum connections in the drive train, and aluminum fillet welds in body construction. In order to properly characterize a laser beam, it is important to use specialized equipment, such as a PRIMES system. This system can provide detailed information about the laser beam profile, including the beam diameter, intensity distribution, and frequency spectrum. This information can then be used to optimize the laser welding process and to ensure that the final product meets the desired mechanical properties. The laser beam can be characterized in various ways, including beam profiling, optical power measurement, and spectroscopy. Beam profiling is a method used to determine the intensity distribution of the laser beam, which can be used to understand how the beam behaves when it is focused and how it affects the material being welded. There are different methods of beam profiling, including knife-edge, knife-edge with aperture, knife-edge with beam profiler, and knife-edge with pinhole. Optical power measurement is used to determine the power of the laser beam. There are different types of power meters, such as photodiodes and thermal detectors. For permanent monitoring, optical power monitors can be used. Moreover, spectroscopy is a method of analyzing the composition and properties of materials using light. This can be useful in laser welding to determine the optical properties of the material being welded, such as its absorption and transmission characteristics. In general, laser beam characterization is used to optimize the laser welding process and to ensure that the final product meets the desired mechanical properties. By understanding the relationship between laser beam characterization and the resulting mechanical properties, engineers and technicians can make adjustments to the laser welding process in order to achieve the desired results. This can involve changes to the laser power, beam profile, speed, and cooling rate, as well as changes to the material being welded and the welding technique used. In the example mentioned in the previous response, a Precitec wobbling head 10-kW solid-state disk laser with a wavelength of 1030 nm was used for laser welding. The beam diameter at the focal point was determined to be 0.39 mm using the PRIMES system. The PRIMES analysis also showed that the smaller the spot size, the more abruptly the real spot size changes with an increase in the Z position. The use of a scanner helps to stabilize the beam size up to +/- 20-30 mm in the Z position because the lens is very large. In future studies, the relation between beam characterization and weldability will be further analyzed.

Table 27. Technical specification of YW52 Welding Head [244]

Laser Parameters	Available range
Max laser power	20kW
Collimation	100 mm (NA ≤ 0.25), 125 mm (NA ≤ 0.18), 150 mm (NA ≤ 0.15),185 mm (NA ≤ 0.13), 200 mm (NA ≤ 0.12)
Focal lenghts	150 to 680 mm
Dimensions	74 x 74 mm (edges dimension)
Weight	3 -6 kg 3 to 6 kg, depending on construction

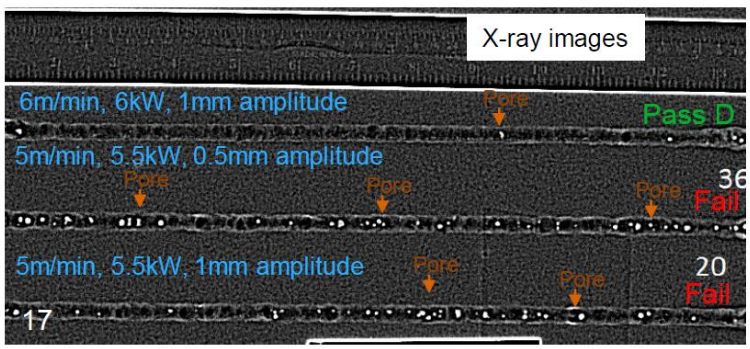
In this study, an ABB 6-axis robot (IRB 4400 M 2004), a fiber laser device (YW52-PRECITEC Welding Head), a worktable capable of providing different magnetic fields by changing the current, and an Argon shielding gas equipment (with a flow rate of 25 L/min) were used to assemble the welding system. The compact YW52 Welding Head is suitable for use with both diode and solid-state laser machines and offers modular design, enabling customers to customize the package to meet their specific requirements. The basic version is cost-effective, while the complete system, with its full process monitoring features, is ideal for fully automated production processes. The welding system features a linear oscillation pattern with a nominal spot size of 0.4mm, fiber size of 200μm, and lens size of 300μm. To ensure consistent material surface quality, the workpieces were polished with sandpaper and cleaned with absolute ethyl alcohol. The parameters were selected to produce an overall porosity range of 1-6%. The nominal spot size was 0.4mm, and no shielding gas was used. To assess weld cracks, X-ray images and metallography of the top surface and cross-sectional metallography of the samples were analyzed. The formation of porosity was eliminated when the welding speed was higher than 5.5m/min. Table 11 presents an experimental plan for YW52-PRECITEC welding head overlap joint. The table contains several welding parameters such as laser power, travel speed, focal distance, oscillation amplitude, oscillation frequency, maximum pore diameter, porosity amount, ISO 13919-2 criteria, and crack index.

The laser power used in this experiment ranges from 4 kW to 8.25 kW. Higher laser power is expected to increase the heat input and penetration depth of the weld. Weld #44 has the highest laser power of 8.25 kW, while weld #62 has the lowest power of 4 kW. Travel speed is another critical parameter that determines the quality of the weld. It is the rate at which the laser beam moves along the joint during welding. The travel speed used in this experiment ranges from 4.5 m/min to 8 m/min. Weld #62 has the lowest travel speed of 4.5 m/min, while weld #51 has the highest speed of 8 m/min. Focal distance is the distance between the laser source and the workpiece surface. It affects the spot size and the energy density of the laser beam at the workpiece surface. The focal distance used in this experiment is fixed at 12 mm for all welds. Oscillation amplitude and frequency are additional parameters used to enhance the welding quality. Oscillation amplitude refers to the maximum distance of the welding head's lateral movement during welding. The amplitude used in this experiment ranges from 0.2 mm to 1 mm. Oscillation frequency refers to the number of times per second that the welding head oscillates during welding. The frequency used in this experiment ranges from 200 Hz to 500 Hz. Maximum pore diameter and porosity amount are critical factors that affect the weld's quality. Welds with high porosity amounts may lead to reduced strength, which could cause the weld to fail under load. The ISO 13919-2 criteria provide a measure of the weld's quality, and the crack index indicates the tendency of the weld to form cracks (Figure 47). Weld #43 has the lowest porosity amount of 0.17%, while weld #62 has the highest porosity amount of 16.16%. In summary, the data provided in Table 28 provides an experimental plan for YW52-PRECITEC welding head overlap joint. The experimental plan considers critical parameters such as laser power, travel speed, focal distance, oscillation amplitude, oscillation frequency, maximum pore diameter, porosity amount, ISO 13919-2 criteria, and crack index to achieve the desired welding quality. The results obtained from the experimentation showed that the porosity formation was significantly impacted by the welding speed and defocus distance. At welding speeds higher than 5.5m/min, the formation of porosity was eliminated, and majority of the welds at speeds higher than 6m/min passed class B and C of ISO13919. In fact, ISO 13919-1:2016 is an international standard that provides guidelines for arc welding of metallic materials. It establishes general requirements for quality, such as the formation of acceptable welds, the use of proper welding techniques and equipment, and the selection of appropriate filler materials. It also includes specific requirements for welds made by the manual, semi-automatic and automatic processes. Class B and C of ISO13919 refer to the quality level of the weld, where Class B welds are suitable for critical applications requiring high quality, and Class C welds are suitable for general applications where lower quality is acceptable. Additionally, a positive defocus distance of +12 showed less tendency to form porosity. The results also showed that the welding power had a significant impact on the quality of the welds, with majority of the welds at a power higher than 6kW passing class B and C of ISO13919. Moreover, the heat input was adjusted in such a way as to obtain optimum penetration depth, and it did not show any significant correlation with the porosity fraction. These findings highlight the importance of carefully controlling the welding parameters in order to produce high-quality welds with minimal porosity formation.

Table 28. Experimental planification YW52-PRECITEC welding head overlap joint.

Weld #	**Laser power (kW)**	**Travel speed (m/min)**	**Focal distance (mm)**	**Oscillation amplitude (mm)**	**Oscilation Frequency (Hz)**	**ϕmaximum pore (mm)**	**Porosity amount (%)**	**ISO 13919-2**	**Crack index**
17	5.5	5	12	1	500	1.22	4.40%	Fail all	0.03
20	5.5	5	12	0.5	500	1.34	5.65%	Fail all	0.11
36	6	6	12	1	400	0.98	0.21%	pass D	0
41	6.75	6.5	12	1	400	0	0.00%	pass B	0.06
43	7	7	12	1	400	0.58	0.17%	pass B	0.04
44	8.25	8	12	1	400	0	0.00%	pass B	0.12
48	6	6.5	12	0.5	400	0.51	0.22%	pass B	0.01
49	6	6.5	12	0.2	400	0.8	0.61%	pass C	0.05
50	6.5	7	12	0.2	400	0.66	0.50%	pass C	0.06

51	7.5	8	12	0.2	400	0	0.00%	pass B	0.16
21	5.5	5	12	0.5	200	1.29	3.67%	Fail all	0.01
22	5.5	5	12	0.8	200	0.85	1.88%	pass D	0.01
62	4	4.5	6	1	500	1.64	16.16%	Fail all	0
59	5	6	6	1	400	1.34	2.63%	Fail all	0.01
52	5.5	6	6	1	400	1.1	0.62%	pass C	0.05



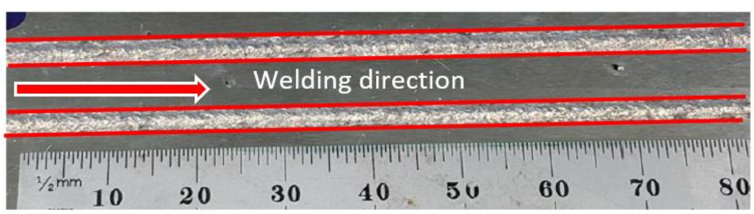


Figure 47. X-ray analysis for Weld top surface- no shielding gas

4.10.6 Microstructure Analysis

To further expand on the findings, it is important to note that the microstructural analysis and micro-hardness tests helped in identifying the influence of the stitch weld shape, depth penetration, and weld geometry on the mechanical properties of the welded joints. Additionally, the chemical composition analysis provided valuable insight into the microstructure and chemical phases present in the welded region, further supporting the observations from the microstructural analysis and hardness tests. As seen in Figure 48 (a-d), increasing the input parameters such as power, speed, and amplitude led to an increase in the depth of penetration, from 2.2mm to 2.8mm. This increase in depth of penetration could potentially result in a higher sensitivity to crack formation, which should be considered in future experiments. It is noteworthy that the frequency for all the tests was adjusted to 400Hz, which could have played a role in the results obtained. Despite no cracks being observed under optical microscopy, suspicions of cracks were revealed through x-ray images, indicating the need for further investigation in this regard.

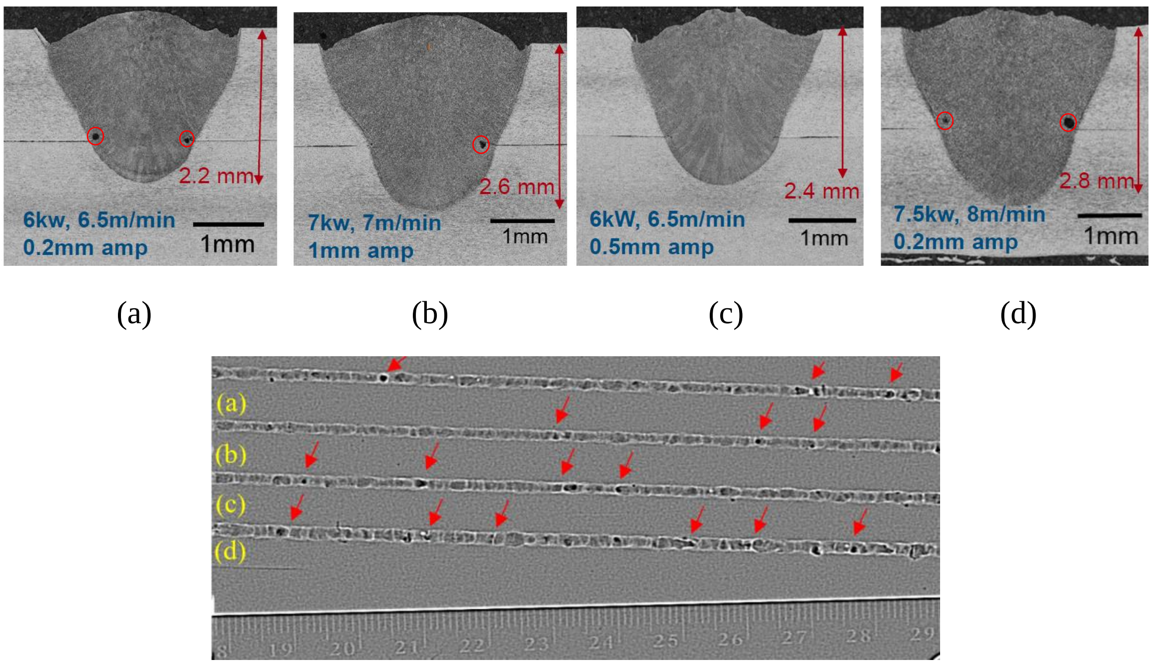
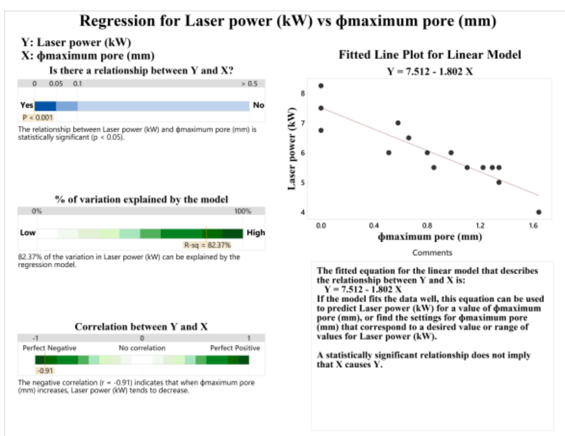


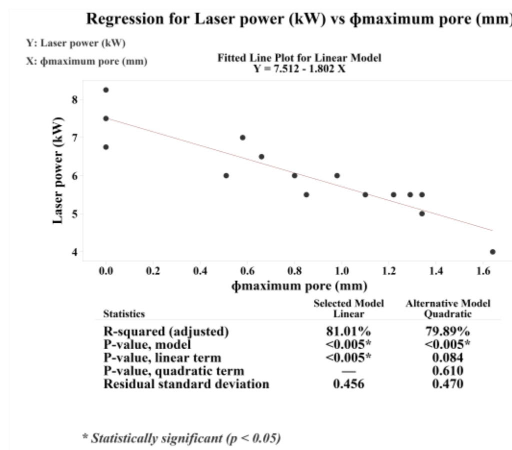
Figure 48. Microstructure analysis

4.10.7 Statistical analysis Plan C. Crack index and porosity amount

The following equations provide a regression equation and its interpretation for the porosity amount. These equations present a rough approximation of the relationship between the independent and dependent variables, which can be represented graphically. Figure 49 and Figure 50 present the regression between Laser Power and Maximum Pore (mm), and Travel Speed (m/min) and Maximum Pore (mm), respectively. These graphs provide visual representation of the relationship between the independent and dependent variables, offering insights into the impact of these parameters on porosity formation in laser welding. According to Figure 49, In our comprehensive examination of laser welding dynamics, regression analysis shed light on a crucial relationship: as laser power increases, there's a consistent decrease in the maximum pore size, as quantified by the equation Y=7.512−1.802x. This inverse correlation not only underscores the significance of laser power in the welding process but also offers a tangible metric for its impact. An adjusted R-squared value of 81.01% further solidifies the robustness of this relationship, suggesting that a large portion of the variability in pore size can be attributed to changes in laser power. This insight holds profound implications for the welding industry, implying that careful calibration of laser power can lead to enhanced weld quality by mitigating porosity—a recurrent challenge in the field.



(a)



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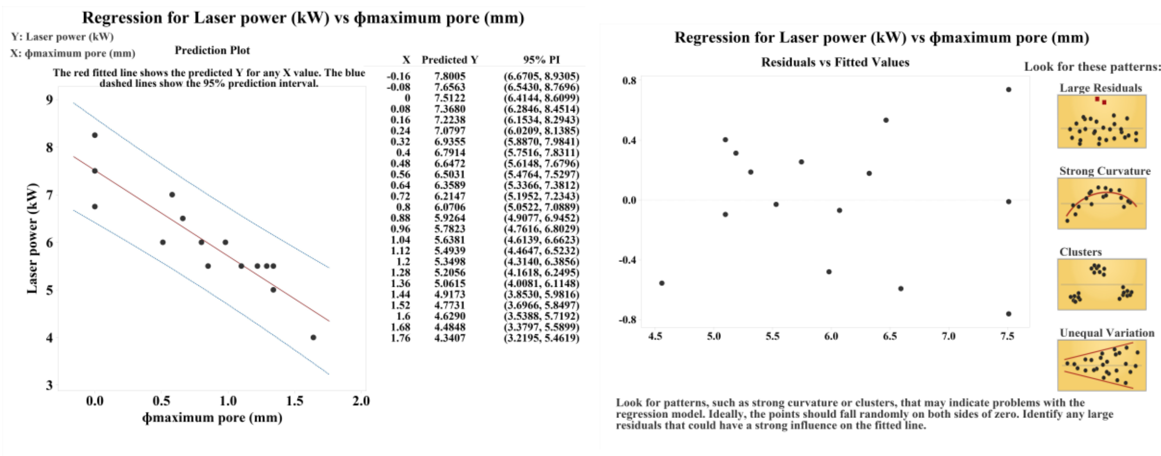


(c) (d)

Figure 49. Regression for Laser power vs maximum pore (mm)

According to Figure 50, In the realm of laser welding, our analysis spotlighted a pivotal relationship between travel speed and the maximum pore size. The derived regression equation Y=7.588−1.773X indicates a pronounced inverse correlation, suggesting that as the travel speed increases, there's a consistent decrement in the maximum pore size. This insight is further bolstered by an adjusted R-squared value of 71.10%, reflecting that travel speed can account for a significant portion of the variability observed in pore size. Such findings emphasize the critical role of travel speed in the welding process, with faster speeds potentially yielding superior weld quality through diminished porosity. This discovery offers a valuable avenue for industry professionals to refine their welding techniques and achieve enhanced outcomes.

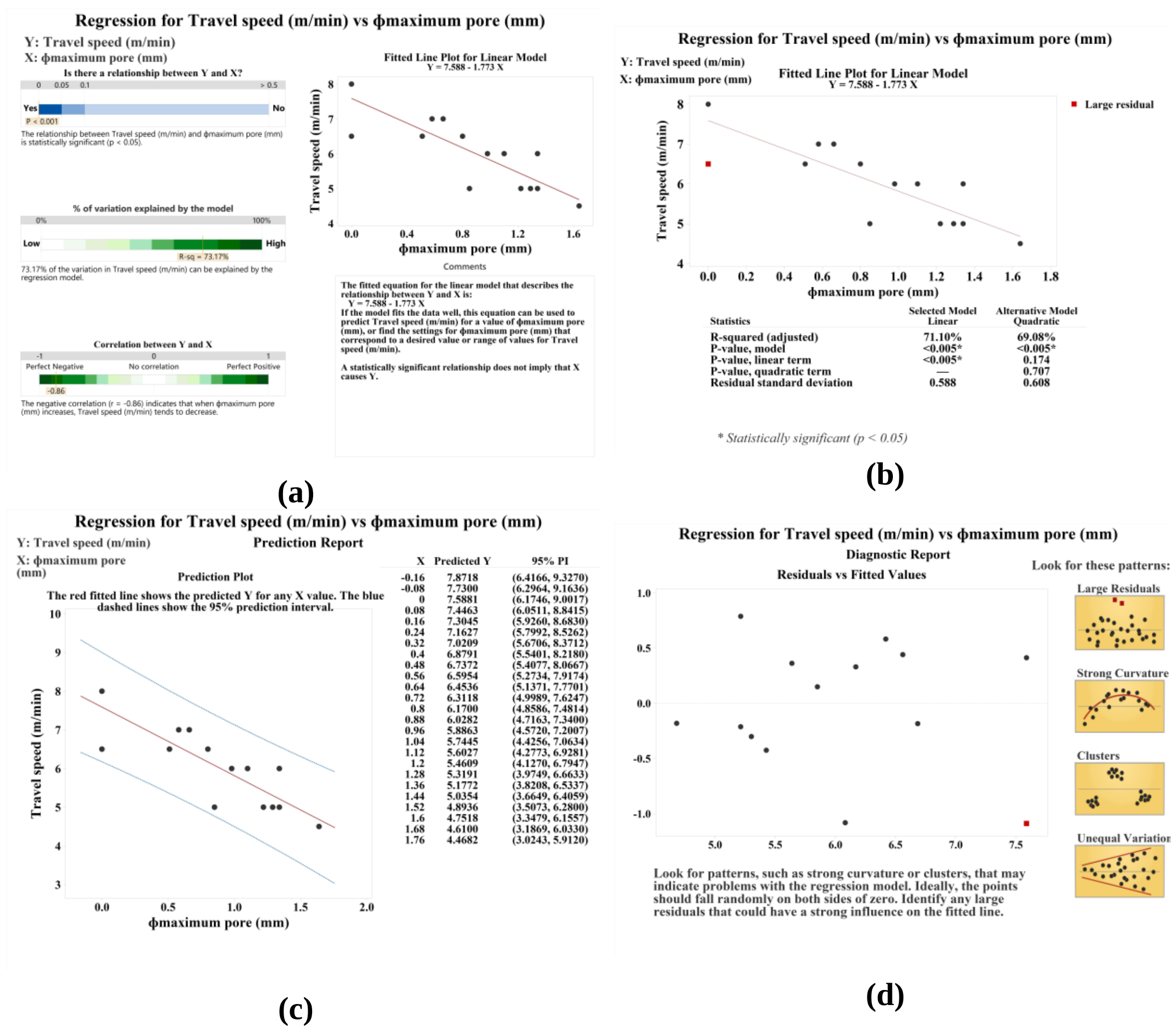


Figure 50. Regression for travel speed vs. maximum pore (mm)

In the comprehensive visualization using a Bubble Plot, the relationship between laser power (4-7 kW) and travel speed (4.5-7 m/min) was distinctly mapped (Figure 51). Each bubble's position on the plot elucidates the interplay between laser power and travel speed, while its size could represent an additional parameter, such as the frequency of specific combinations or perhaps the resulting weld quality. Such a plot can reveal patterns or clusters, indicating optimal combinations of laser power and travel speed that yield desired outcomes. By studying the distribution and size of the bubbles, we can gain insights into the synergistic effects of laser power and travel speed, potentially unveiling zones of efficiency or regions of concern in the welding process.

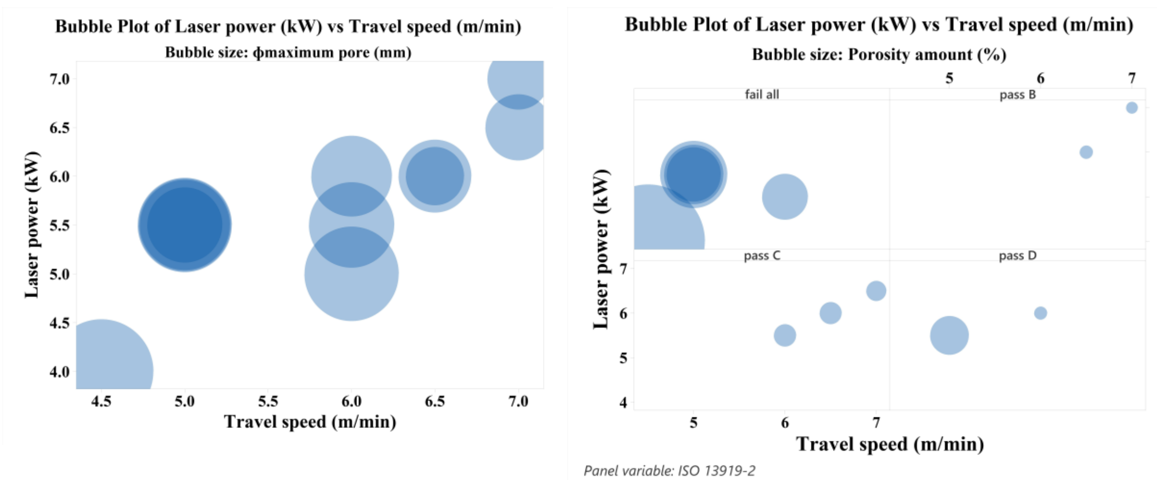


Figure 51. Bubble plot of laser power (Kw) vs Travel speed (m/min)

4.11 CONTOUR PLOT

In statistical analysis, contour lines can be used to represent the relationship between two variables and the frequency of occurrence of a third variable. For example, in a three-dimensional plot of welding process parameters (such as laser power, travel speed, and penetration depth), contour lines can indicate the constant levels of porosity or crack index for a given set of parameters. In this way, contour lines can provide insight into the optimal process parameter combinations for reducing porosity or preventing cracks in the welded joint. In laser welding, contour lines can be used to visualize and interpret the effect of process parameters on the weld quality and identify the optimal parameter combinations for specific applications. A contour line, in mathematics and cartography, refers to a curve that connects points of equal value for a given function of two variables. It is essentially a cross-section of the three-dimensional representation of the function that lies parallel to the (x,y) plane. In topographical maps, contour lines join points of equal elevation above a reference level, such as mean sea level, and illustrate valleys, hills, and the slope of terrain. The contour interval, which is the difference in elevation between successive contour lines, provides information on the steepness of slopes. The gradient of the function is always perpendicular to the contour lines, and closer lines indicate steeper variations. The concept of a level set is a generalization of contour lines for functions with multiple variables. Contour lines can be traced on a visible three-dimensional model or interpolated from estimated surface elevations, with the method of interpolation affecting the reliability of the isolines and their representation of slope, peaks, and pits. The arrangement of contour lines allows for the inference of the relative gradient of a parameter and its estimation at specific locations. According to Figure 52, the contour plot provides an insightful visualization of the intricate relationship between the Crack Index, Maximum Pore size, and the associated process parameters (Laser Power, Travel Speed, Focal distance, and Oscillation frequency) in the context of laser welding processes. On the x-axis, the Crack Index serves as an indicator of the weld's structural integrity, while the y-axis represents the Maximum Pore size, a key determinant of weld quality. The contours on the plot capture varying Laser Power levels, offering a third dimension of data.

- **Interplay laser power (figure 52a):**

A preliminary observation would be to understand how the Crack Index and Maximum Pore size interact. Regions, where contours are closely spaced, might indicate rapid changes in Laser Power as either Crack Index or Pore Size changes. Conversely, widely spaced contours suggest that Laser Power changes more gradually across those regions. The contour lines, each representing a specific Laser Power level, can be studied to determine optimal settings. For example, if there's a particular range of Laser Power that's ideal for welding (neither too low nor too high), the associated contour can be traced to understand the combinations of Crack Index and Pore Size that yield that power. It's essential to identify any "hotspots" or "cold spots" on the plot—regions where Laser Power is consistently high or low, respectively. These zones can provide insights into particularly challenging or favorable combinations of Crack Index and Pore Size. Understanding this plot has direct practical implications. For instance, if a specific region indicates a high Crack Index and large Pore Size but requires low Laser Power, it might suggest a need to adjust the welding process or technique to mitigate these unfavorable outcomes. While the contour plot provides a wealth of information, further analyses, perhaps using advanced statistical or machine learning techniques, could delve deeper into predicting Laser Power based on the other two parameters, or even exploring causal relationships. In conclusion, the contour plot serves as a comprehensive visual tool, capturing the complex interdependencies between the Crack Index, Maximum Pore size, and Laser Power. Through careful analysis, it offers valuable insights that can guide optimization strategies in the laser welding process.

- **Interplay travel speed (figure 52b):**

The contour plot vividly illustrates the interplay between the crack index, maximum pore size, and travel speed in the context of laser welding. With the crack index represented on the x-axis and the maximum pore size on the y-axis, the contours capture various levels of travel speed. The relationship between the crack index and maximum pore size can be directly observed from the distribution of data points. If data points cluster in specific regions of the plot, it indicates a strong association between certain crack index values and pore sizes. The contours represent constant travel speeds. By tracing these contours, one can infer how travel speed varies with changes in both crack index and pore size. Closely spaced contours suggest rapid changes in travel speed across small changes in crack index or pore size. Widely spaced contours indicate regions where travel speed remains relatively constant despite variations in the crack index or pore size. Look for regions where the contours are particularly dense or sparse. Dense regions might indicate sensitive areas where slight changes in crack index or pore size lead to significant shifts in required travel speed. Sparse areas could suggest stability in the process parameters. Given the critical nature of crack index and pore size in determining weld quality, understanding their relationship with travel speed is invaluable. If certain combinations of crack index and pore size consistently result in optimal travel speeds (as indicated by specific contour levels), these combinations can be targeted in welding processes for enhanced outcomes. The contour plot serves as a roadmap for laser welding practitioners. By navigating the interdependencies between crack index, pore size, and travel speed, welders and engineers can fine-tune their processes. For example, if aiming for a specific travel speed is crucial for a particular application, this plot can guide the necessary adjustments in crack index and pore size to achieve that speed.

- **Interplay focal distance (figure 52c):**

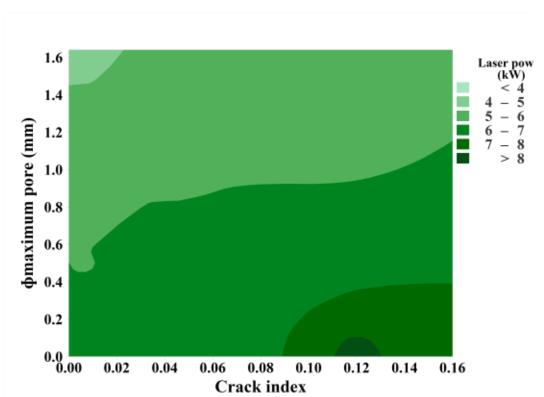
The contour plot visualizes the intricate relationship between the Crack Index, Maximum Pore Size, and Focal Distance in the context of laser welding processes. The x-axis represents the Crack Index, while the y-axis corresponds to the Maximum Pore Size in millimeters. A glance at the plot reveals how these two parameters interact and influence the focal distance. The contours represent constant values of the Focal Distance in millimeters. This is the distance at which the laser beam is focused, and it plays a crucial role in determining the quality and characteristics of the weld. By examining the contour lines, one can observe regions where the Focal Distance remains relatively constant, indicating specific combinations of Crack Index and Maximum Pore Size that lead to stable focusing conditions. Conversely, areas where contour lines are closely spaced might indicate rapid changes in the Focal Distance for slight variations in the other two parameters, highlighting sensitive zones in the process. For practitioners, understanding these interactions is invaluable. For instance, if there's a target Focal Distance that's known to yield optimal welding results, this contour plot can guide the selection of Crack Index and Maximum Pore Size to achieve that specific focal point. Conversely, if certain Crack Index or Pore Size values are observed during a welding process, this plot can predict the resulting Focal Distance, allowing for adjustments in real-time. If there are areas on the contour plot where the Focal Distance varies drastically over a small range of Crack Index or Maximum Pore Size, it might indicate regions of instability in the welding process. Such insights can guide further investigations or optimizations to enhance the overall weld quality. In summary, this contour plot offers a rich visualization of the complex interplay between three pivotal parameters in laser welding. By understanding the depicted relationships, professionals can make more informed decisions, leading to improved weld characteristics and outcomes.

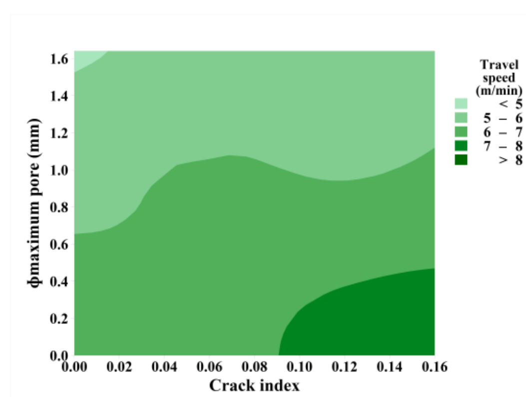
- **Interplay oscillation amplitude (figure 52d):**

The contour plot offers an insightful visual exploration into the relationship between the crack index, maximum pore size, and oscillation amplitude in the context of laser welding. The x-axis, representing the crack index, and the y-axis, depicting the maximum pore size, intersect to illustrate regions of varying oscillation amplitudes, as delineated by the contour lines. The positioning and density of the contour lines might indicate how changes in the crack index affect the maximum pore size, and vice versa. For instance, closely spaced contour lines suggest regions where oscillation amplitude varies rapidly, pointing to sensitive areas in the process parameters. The contour values represent different oscillation amplitudes. Regions with higher amplitude values might suggest combinations of crack index and pore size that result in more pronounced oscillations during welding. Conversely, lower amplitude values could signify stable regions with minimal oscillations. Areas with densely packed contours can signal rapid changes in oscillation amplitude and might be zones of concern or require closer attention. On the other hand, areas with widely spaced contours may represent regions of stability, where variations in crack index or pore size have minimal impact on oscillation amplitude. Understanding these relationships is pivotal for optimizing the welding process. For instance, if a particular combination of crack index and pore size results in high oscillation amplitude, it may necessitate adjustments in the welding parameters or technique to maintain product quality and integrity. In conclusion, this contour plot serves as a valuable tool for understanding the intricate relationships between the crack index, maximum pore size, and oscillation amplitude in laser welding. By identifying patterns and regions of interest, welding professionals can make informed decisions to optimize the process and achieve desired outcomes. The presented contour plot provides a nuanced visualization of the relationship between the Crack Index, Maximum Pore Size, and Oscillation Frequency in the context of a specific process. On the horizontal axis, we have the Crack Index, while the vertical axis represents the Maximum Pore Size (in mm). The contours, depicted with varying intensities or colors, represent different oscillation frequencies (in Hz).

- **Interplay oscillation frequency (figure 52e):**

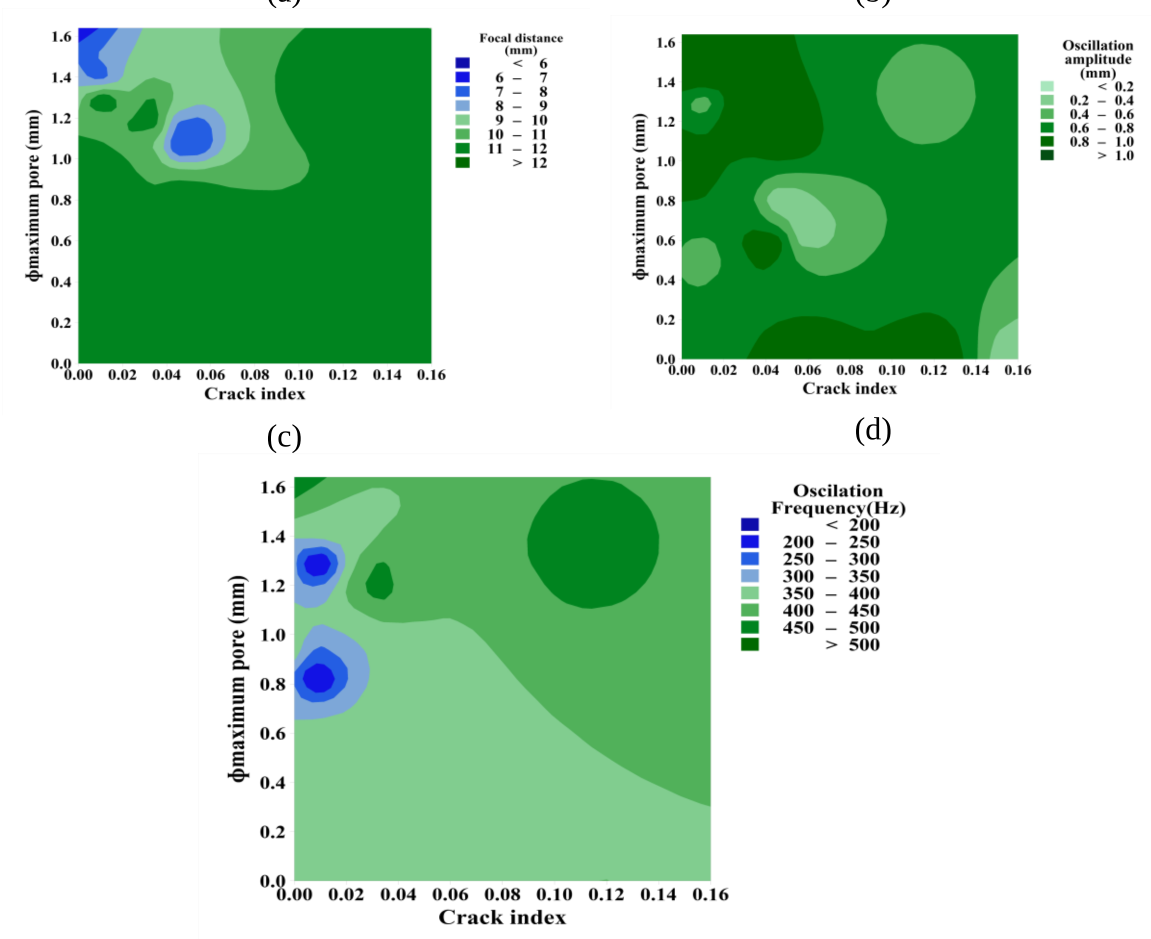
The positioning of the contour lines can give insights into how oscillation frequency varies with changes in both the Crack Index and Pore Size. For instance, closely spaced contours in a specific region would indicate rapid changes in oscillation frequency for small changes in either the Crack Index or Pore Size. Dense contour regions might signify areas where specific combinations of Crack Index and Pore Size lead to higher or lower oscillation frequencies. Such regions could be of particular interest, as they might represent optimal or sub-optimal operating conditions. The gradient of the oscillation frequency can be inferred from the orientation of the contours. If the contours are more vertical, it suggests that the oscillation frequency is more sensitive to changes in the Crack Index. Conversely, horizontal contours would indicate sensitivity to changes in Pore Size. Understanding the relationship between these three parameters is crucial. For instance, if there's an area where the oscillation frequency remains stable (flat contour lines) across a range of Crack Index and Pore Size values, this might be an ideal operating zone. Conversely, regions with steep gradients might require careful control of process parameters to avoid rapid changes in oscillation frequency. While the contour plot provides a snapshot of the current understanding, further experiments or simulations might help refine the contours, especially in regions with high variability or where data might be sparse. In summary, the contour plot offers a holistic view of the interdependencies between the Crack Index, Maximum Pore Size, and Oscillation Frequency. Such insights are invaluable for process optimization, quality control, and understanding underlying physical phenomena.





(a) (b)

(c) (d)



(e)

Figure 52. Contour plot for process parameters

4.12 CONCLUSION

In conclusion, our research delved into how laser welding parameters namely power, speed, and defocus distance influence the porosity fraction and crack sensitivity in welded joints. Here are the key findings:

- This research examined the influence of laser welding parameters (power, speed, defocus distance) on porosity fraction and crack sensitivity in welded joints. The highest porosity was noted at a speed of 5m/min, and the lowest at a defocus distance of +12.

- Regression analysis revealed a positive correlation between laser power and porosity fraction; however, travel speed had no significant effect. The weld geometry, stitch weld shape, and penetration depth significantly influenced the mechanical properties of the joints.
- Porosity in laser welding can result from a small spot size or low travel speed. A large spot size can lead to hot cracking in autogenous laser welding, but wobbling can reduce porosity by enlarging the weld pool.
- In overlap joints, the interface width should be 1.6 times the top sheet's thickness. The load case in single-lap shear specimens is a mix of flexion/tension and depends on overlap length and sheet thickness. Finite element analysis followed by lap-shear tensile testing can help determine optimal conditions.
- The study had limitations like a small sample size and a narrow range of tested variables. Future research could benefit from a broader experiment scope, alternative welding techniques, and further analysis on the impact of interface width and overlap length on mechanical properties.

4.13 REFERENCE

[192] M. Tisza, Development of lightweight steels for automotive applications, in: Engineering Steels and High Entropy-Alloys, Intech Open, 2020.

[193] J. Szyndler, L. Madej, Metal forming methods dedicated for aerospace industry, Computer Methods in Materials Science. 15 (2015) 294–310.

[194] T. Trzepieciński, Recent Developments and Trends in Sheet Metal Forming, Metals (Basel). 10 (2020) 779.

[195] V. Prakash, D.R. Kumar, Performance evaluation of bio-lubricants in strip drawing and deep drawing of an aluminium alloy, Advances in Materials and Processing Technologies. (2020) 1–14.

[196] M. Moradi, M. Ghoreishi, J. Frostevarg, A.F.H. Kaplan, An investigation on stability of laser hybrid arc welding, Opt Lasers Eng. 51 (2013) 481–487.

[197] S. Meiabadi, F. Nematzadeh, K. Kornokar, H. Mostaan, M. ShamsBorhan, R. Khandan, V. Demers, J. Lawrence, M. Moradi, Contrasting the mechanical and metallurgical properties of laser welded and gas tungsten arc welded S500MC steel, Welding in the World. 67 (2023) 2215–2224.

[198] A. Khorram, M. Ghoreishi, M. Reza, S. Yazdi, M. Moradi, Optimization of Bead Geometry in CO_2 Laser Welding of Ti 6Al 4V Using Response Surface Methodology, Engineering. 2011 (2011) 708–712.

[199] Z. Tan, B. Pang, J.P. Oliveira, L. Chen, X. Bu, Z. Wang, B. Cong, Z. Zeng, Effect of S-curve laser power for power distribution control on laser oscillating welding of 5A06 aluminum alloy, Opt Laser Technol. 149 (2022) 107909.

[200] M. Zheng, J. Yang, J. Xu, J. Jiang, H. Zhang, J.P. Oliveira, X. Lv, J. Xue, Z. Li, Interfacial microstructure and strengthening mechanism of dissimilar laser al/steel joint via a porous high entropy alloy coating, Journal of Materials Research and Technology. 23 (2023) 3997–4011.

[201] F.B. Teshome, B. Peng, J.P. Oliveira, J. Shen, S. Ao, H. Li, L. Chen, C. Tan, X. Song, N. Zhou, Z. Zeng, Role of Pd interlayer on NiTi to Ti6Al4V laser welded joints: Microstructural evolution and strengthening mechanisms, Mater Des. 228 (2023) 111845.

[202] R. Dwivedi, G. Agnihotri, Study of deep drawing process parameters, Mater Today Proc. 4 (2017) 820–826.

[203] J. Tenner, K. Andreas, A. Radius, M. Merklein, Numerical and experimental investigation of dry deep drawing of aluminum alloys with conventional and coated tool surfaces, Procedia Eng. 207 (2017) 2245–2250.

[204] W.-C. Xiao, B.-Y. Wang, Y. Kang, W.-P. Ma, X.-F. Tang, Deep drawing of aluminum alloy 7075 using hot stamping, Rare Metals. 36 (2017) 485–493.

[205] M. Habibi, R. Hashemi, M.F. Tafti, A. Assempour, Experimental investigation of mechanical properties, formability and forming limit diagrams for tailor-welded blanks produced by friction stir welding, J Manuf Process. 31 (2018) 310–323.

[206] A. Aminzadeh, A. Parvizi, M. Moradi, Multi-objective topology optimization of deep drawing dissimilar tailor laser welded blanks; experimental and finite element investigation, Opt Laser Technol. 125 (2020).

[207] A. Aminzadeh, A. Parvizi, R. Safdarian, D. Rahmatabadi, Comparison between laser beam and gas tungsten arc tailored welded blanks via deep drawing, Proc Inst Mech Eng B J Eng Manuf. (2020).

[208] W.E. Forum, Green New Deals | Strategic Intelligence | World Economic Forum, (2020).

[209] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, Intelligent laser welding through representation, prediction, and control learning: An architecture with deep neural networks and reinforcement learning, Mechatronics. 34 (2016) 1–11.

[210] D. Mishra, S.K. Pal, D. Chakravarty, Industry 4.0 in Welding, Welding Technology. (2021) 253–298.

[211] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, First steps towards an intelligent laser welding architecture using deep neural networks and reinforcement learning, Procedia Technology. 15 (2014) 474–483.

[212] B. Wang, S.J. Hu, L. Sun, T. Freiheit, Intelligent welding system technologies: State-of-the-art review and perspectives, J Manuf Syst. 56 (2020) 373–391.

[213] G. Dutta, R. Kumar, R. Sindhwani, R.K. Singh, Digital transformation priorities of India’s discrete manufacturing SMEs--a conceptual study in perspective of Industry 4.0, Competitiveness Review: An International Business Journal. (2020).

[214] A. Aminzadeh, S. Sattarpanah Karganroudi, N. Barka, Experimental and numerical investigation of forming defects and stress analysis in laser-welded blanks during deep drawing process, The International Journal of Advanced Manufacturing Technology. (2021) 1–15.

[215] S. Katayama, Introduction: Fundamentals of laser welding, Woodhead Publishing Limited, 2013.

[216] M. Matsui, T. Ono, T. Kamei, K. Mori, Generating conditions of argon laser-sustained plasma by disk, fiber and diode lasers, Vacuum. 167 (2019) 490–494.

[217] E. Punzel, F. Hugger, R. Dörringer, T.L. Dinkelbach, A. Bürger, Comparison of different system technologies for continuous-wave laser beam welding of copper, Procedia CIRP. 94 (2020) 587–591.

[218] E. Kennedy, G. Byrne, D.N. Collins, A review of the use of high power diode lasers in surface hardening, J Mater Process Technol. 155–156 (2004) 1855–1860.

[219] S.L. Ream, Laser welding efficiency and cost: CO2, YAG, fiber, and disc, 1 (2018) 1.

[220] M. Merklein, M. Geiger, New materials and production technologies for innovative lightweight constructions, J Mater Process Technol. 125 (2002) 532–536.

[221] A. Graf, Aluminum alloys for lightweight automotive structures, in: Materials, Design and Manufacturing for Lightweight Vehicles, Elsevier, 2021: pp. 97–123.

[222] F. Findik, Recent developments in explosive welding, Mater Des. 32 (2011) 1081–1093.

[223] J.M. Sánchez Amaya, M.R. Amaya-Vázquez, F.J. Botana, Laser welding of light metal alloys: Aluminium and titanium alloys, 2013.

[224] M.D. Vijayakumar, V. Dhinakaran, T. Sathish, G. Muthu, P.M.B. ram, Experimental study of chemical composition of aluminium alloys, Mater Today Proc. (2020).

[225] G.Çam, G.Ipekouglu, Recent developments in joining of aluminum alloys, The International Journal of Advanced Manufacturing Technology. 91 (2017) 1851–1866.

[226] S. Kainuma, T. Mori, A study on fatigue crack initiation point of load-carrying fillet welded cruciform joints, Int J Fatigue. 30 (2008) 1669–1677.

[227] D. Ren, L. Liu, Y. Li, Investigation on overlap joining of AZ61 magnesium alloy: laser welding, adhesive bonding, and laser weld bonding, The International Journal of Advanced Manufacturing Technology. 61 (2012) 195–204.

[228] S. Janasekaran, M.F. Jamaludin, M.R. Muhamad, F. Yusof, M.H. Abdul Shukor, Autogenous double-sided T-joint welding on aluminum alloys using low power fiber laser, The International Journal of Advanced Manufacturing Technology. 90 (2017) 3497–3505.

[229] A. Aminzadeh, A. Parvizi, M. Moradi, Multi-objective topology optimization of deep drawing dissimilar tailor laser welded blanks; experimental and finite element investigation, Opt Laser Technol. 125 (2020) 106029.

[230] A. Aminzadeh, N. Nasiri, N. Barka, A. Parvizi, K. Abrinia, M. Moradi, S. Sattarpanah Karganroudi, Statistical Analysis of Laser-Welded Blanks in Deep Drawing Process: Response Surface Modeling, J Mater Eng Perform. (2021) 1–17.

[231] A. Aminzadeh, S.S. Karganroudi, N. Barka, A novel approach of residual stress prediction in ST-14/ST-44 laser welded blanks; Mechanical characterization and Experimental validation, Mater Lett. (2020) 129193.

[232] A. Aminzadeh, S.S. Karganroudi, N. Barka, A. El Ouafi, A real-time 3D scanning of aluminum 5052-H32 laser welded blanks; geometrical and welding characterization, Mater Lett. 296 (2021) 129883.

[233] Z.M. Beiranvand, F.M. Ghaini, H.N. Moosavy, M. Sheikhi, M.J. Torkamany, M. Moradi, The relation between magnesium evaporation and laser absorption and weld penetration in pulsed laser welding of aluminum alloys: Experimental and numerical investigations, Opt Laser Technol. 128 (2020) 106170.

[234] M. Idriss, F. Mirakhorli, A. Desrochers, A. Maslouhi, Overlap laser welding of 5052-H36 aluminum alloy: experimental investigation of process parameters and

mechanical designs, The International Journal of Advanced Manufacturing Technology. 119 (2022) 7653–7667.

[235] R.P. Verma, M.K. Lila, A short review on aluminium alloys and welding in structural applications, Mater Today Proc. 46 (2021) 10687–10691.

[236] J. Rapp, C. Glumann, F. Dausinger, H. Hügel, Laser welding of aluminium lightweight materials: problems, solutions, readiness for application, Opt Quantum Electron. 27 (1995) 1203–1211.

[237] B. Zhang, K.-M. Hong, Y.C. Shin, Deep-learning-based porosity monitoring of laser welding process, Manuf Lett. 23 (2020) 62–66.

[238] S. Echchakoui, N. Barka, INDUSTRY 4.0 and its Impact in PLASTICS INDUSTRY: A Literature Review, J Ind Inf Integr. (2020) 100172.

[239] J. Butt, Exploring the interrelationship between additive manufacturing and Industry 4.0, Designs (Basel). 4 (2020) 13.

[240] S.S. Kamble, A. Gunasekaran, S.A. Gawankar, Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives, Process Safety and Environmental Protection. 117 (2018) 408–425.

[241] J.Y. Choi, J.H. Jeon, J.H. Lyu, J. Park, G.Y. Kim, S.Y. Chey, Y.-J. Quan, B. Bhandari, B.G. Prusty, S.-H. Ahn, Current Applications and Development of Composite Manufacturing Processes for Future Mobility, International Journal of Precision Engineering and Manufacturing-Green Technology. (2022) 1–23.

[242] Operation Options, Scanlab, (n.d.).

https://www.scanlab.de/en/products/software-calibration/laserdesk/features/operation-options (accessed September 14, 2023).

[243] Processing optics TRUMPF, (n.d.). https://www.trumpf.com/en_CA/products/lasers/processing-optics/ (accessed September 14, 2023).

[244] Focusing optics YW30/YW52 Laser welding | PRECITEC, (n.d.). https://www.precitec.com/laser-welding/products/processing-heads/yw30/(accessed September 14, 2023).

CHAPITRE 5

SURVEILLANCE EN TEMPS REEL DE LA POROSITÉ DU SOUDAGE LASER DE L'ALUMINIUM À L'AIDE DE L'APPRENTISSAGE AUTOMATIQUE BASE SUR LES CARACTÉRISTIQUES DE LA MORPHOLOGIE 3D DU TROU DE SERRURE

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5.1 RÉSUMÉ EN FRANÇAIS DU CINQUIÈME ARTICLE

Dans le cadre de l'avancement des techniques de soudage au laser, particulièrement pour les alliages d'aluminium dans l'industrie automobile, cette étude introduit une approche novatrice pour la surveillance en temps réel de la porosité à l'aide de l'apprentissage automatique. En examinant la morphologie 3D du trou de clé de soudure, la recherche vise à identifier et à atténuer la porosité, un défaut courant qui compromet l'intégrité mécanique des soudures. Utilisant un modèle de Random Forest (RF), entraîné sur un vaste ensemble de données d'images de trous de clé avec des niveaux de porosité associés, l'étude fournit un cadre prédictif pour évaluer la qualité de la soudure en temps réel. La méthodologie implique la capture de données du bain de soudure en cours de processus par imagerie coaxiale à haute vitesse, facilitant un mécanisme d'ajustement innovant en temps réel pour optimiser les paramètres de soudage et réduire la porosité. Malgré une précision significative dans la détection de

la porosité, l'étude reconnaît les complexités de prédiction des pores micro et sous la surface. Les résultats soulignent l'efficacité du modèle RF dans la surveillance en temps réel de la porosité et mettent en lumière la relation nuancée entre les dynamiques de trou de clé et la formation de porosité, contribuant des perspectives précieuses au développement continu des technologies de soudage intelligentes. Cette recherche marque un pas en avant dans l'intégration de l'apprentissage automatique avec le contrôle des processus de soudage, promettant des améliorations dans la qualité et l'efficacité des opérations de soudage au laser dans le cadre de l'Industrie 4.0.

5.2 CONTRIBUTIONS

Dans l'article "Real-time porosity monitoring of aluminum laser welding using machine learning based on keyhole 3D morphology characteristics", les contributions scientifiques spécifiques et notables d'Ahmad Aminzadeh englobent:

Innovation dans la surveillance de la porosité : Ahmad Aminzadeh a conceptualisé et développé une méthodologie novatrice pour le suivi de la porosité en temps réel dans le soudage laser de l'aluminium, se basant sur l'analyse des caractéristiques morphologiques 3D du trou de serrure. Cette approche représente une avancée significative en permettant une détection précise et immédiate de la porosité pendant le processus de soudage.

Intégration de l'apprentissage automatique : Il a conçu et mis en œuvre un système basé sur l'apprentissage automatique, en utilisant spécifiquement l'algorithme de la forêt aléatoire (Random Forest), pour analyser les données visuelles et géométriques collectées et prédire la présence de porosité. Cela démontre une application pratique et efficace de l'IA dans l'amélioration de la qualité du soudage.

Création de supports visuels et analyse des données : Ahmad Aminzadeh a été responsable de la collecte, du traitement et de l'analyse des données, ainsi que de la création des tableaux, figures et graphiques qui illustrent clairement les résultats et les découvertes de l'étude, rendant l'information accessible et compréhensible.

Méthodologie expérimentale rigoureuse : Il a établi une méthodologie expérimentale solide, y compris la sélection des matériaux, la configuration des expériences de soudage laser, et la collecte des données de manière structurée pour garantir la fiabilité et la validité des résultats.

Collaboration et leadership : Bien qu'il ait bénéficié des conseils et de l'expertise technique de Noureddine Barka, Abderrazak El Ouafi et de l'équipe du CNRC (Fatemeh Mirakhorli, François Nadeau, Siyu Tu et Marc-Olivier Gagné), c'est Ahmad Aminzadeh qui a dirigé la recherche, prouvant ses compétences en gestion de projet et en leadership scientifique.

Les efforts d'Ahmad Aminzadeh dans la conduite de cette recherche ont abouti à une contribution significative dans le domaine du soudage laser, en particulier dans l'optimisation de la qualité du soudage à travers la technologie de surveillance innovante basée sur l'apprentissage automatique, démontrant ainsi son expertise et son impact dans le domaine.

5.3 TITRE DU CINQUIÈME ARTICLE

Real-time porosity monitoring of aluminum laser welding using machine learning based on keyhole 3D morphology characteristics

5.4 ABSTRACT

In the context of advancing laser welding techniques, particularly for aluminum alloys in the automotive industry, this study introduces a novel approach to real-time porosity monitoring using machine learning. By examining the 3D morphology of the welding keyhole, the research aims to identify and mitigate porosity, a prevalent defect that undermines the mechanical integrity of welds. Utilizing a Random Forest (RF) model, trained

on an extensive dataset of keyhole images with associated porosity levels, the study provides a predictive framework for assessing weld quality in real-time. The methodology involves capturing in-process weld-pool data through high-speed coaxial imaging, facilitating an innovative real-time adjustment mechanism to optimize welding parameters and reduce porosity. Despite achieving significant accuracy in porosity detection, the study acknowledges the complexities of predicting micro and deep subsurface pores. The findings underscore the efficacy of the RF model in real-time porosity monitoring and highlight the nuanced relationship between keyhole dynamics and porosity formation, contributing valuable insights to the ongoing development of intelligent welding technologies. This research marks a step forward in integrating machine learning with welding process control, promising enhancements in the quality and efficiency of laser welding operations within the framework of Industry 4.0.

5.5 NOMENCLATURE

ISO	International Organization for Standardization
SVM	Support Vector Machine/ Machine à vecteurs de support
PCA	Principal Component Analysis
TWBs	Tailor Welded Blanks
LWBs	Laser welded Blanks
CAD	Computer Aided Design
ANOVA	Analysis of Variance
DMAIC	Design Measure Analyze Improve Control

CAM	Computer Aided Manufacturing
CAI	Computer Aided Inspection
QA	Quality Assurance
P	Power
V	Welding Speed
A	Amplitude
CNN	Convolutional Neural Network
R^2	R squared, coefficient of determination
ML	Machine Learning
Random Forest	RF
CPU	Central processing unit
GPU	Graphics Processing Units
Inline coherent imaging	(ICI)
Region Of Interests	ROI
Mean Squared Error	MSE
Out Of Bag	OOB
MDA	Mean Decrease Accuracy

5.6 INTRODUCTION

The contemporary manufacturing scenario is witnessing an escalating demand for the fabrication of superior-quality mechanical components characterized by minimal defects and abbreviated lead times, while concurrently amplifying the manufacturing tempo. The adoption of deformation-centric manufacturing methodologies, notably laser-driven processes, has emerged as indispensably crucial in catering to these requisites. Laser-induced processes, encompassing laser welding, laser cutting, and laser drilling, have acquired extensive endorsement across a plethora of industrial domains, prominently within the automotive sector, courtesy of their inherent advantages including elevated precision, swiftness, and adaptability. These attributes render laser processes as an exemplary choice for the production of high-caliber mechanical components. Moreover, the versatility of laser processes is further exemplified by their capacity to cater to a diverse spectrum of materials, including metals, plastics, ceramics, and composites, thereby broadening their applicability across various applications. Within the automotive industry, laser welding and cutting techniques are ubiquitously employed owing to their high precision, speed, and flexibility, which are instrumental in fabricating high-quality mechanical components. The engagement with metal manufacturing, particularly concerning aluminum alloys, is imperative for attaining the desired levels of strength, stiffness, and enduring durability [245–249]. Numerous investigations have delved into the exploration of process parameters and their consequent impact on product quality with the aim to optimize metal manufacturing for enhanced efficiency and quality. These advancements are pivotal in steering towards the realization of zero-defect manufacturing, thereby significantly reducing lead times across various industrial sectors. Through a meticulous analysis and optimization of process parameters, these studies not only foster a profound understanding of the intricacies underlying metal manufacturing processes but also pave the way for substantial improvements in operational efficiency and product quality. The reverberations of these advancements extend beyond merely achieving manufacturing excellence and play a crucial role in bolstering the competitive edge of industries in a rapidly evolving global manufacturing landscape [16,46,250–252]. Over recent decades, an escalating demand for lightweight structures has been observed, engendering an amplified utilization of aluminum alloys (AA) within the automotive sector. The exceptional attributes of AA, encompassing low density, commendable corrosion resistance, high specific strength, appealing aesthetic, and inherent recyclability, have significantly propelled their burgeoning demand. Concomitant with the widespread deployment of AA, scholarly endeavors have been embarked upon to devise diversified joining techniques for this material. However, the domain of aluminum laser welding presents a formidable challenge, primarily attributed to the suboptimal welding reliability of aluminum alloys when juxtaposed with other industrial metals such as steel. This predicament predominantly emanates from their distinct physical properties, notably the high thermal conductivity, elevated reflectivity, and low viscosity. These inherent properties of aluminum alloys necessitate meticulous process control and advanced technological interventions to surmount the challenges poised in laser welding applications, thereby ensuring the structural integrity and long-term performance of the resultant welded joints [65]. Aluminum alloys are bifurcated into two predominant categories: Non heat-treatable and heat treatable. The initial tensile strength of non-heat-treatable alloys is principally dictated by the hardening effect imbued by alloying elements such as silicon, iron, manganese, and magnesium. These non-heat-treatable alloys are predominantly encountered in the 1xxx, 3xxx, 4xxx, and 5xxx series. Conversely, the heat-treatable alloys are chiefly located within the 2xxx, 6xxx, and 7xxx alloy series. Among these, the 7xxx series alloys are characterized by the inclusion of zinc, constituting between 4 and 8%, and magnesium, constituting between 1 and 3%. This categorization not only elucidates the inherent structural distinctions but also underscores the varying mechanical properties and potential applications of these aluminum alloys within the industrial landscape. The meticulous understanding and exploitation of these alloy series, in accordance with their distinct mechanical and thermal properties, are instrumental in leveraging aluminum alloys for diverse applications, especially in scenarios demanding superior strength-to-weight ratios and corrosion resistance [66]. The increasing adoption of aluminum alloys, however, also beckons a concomitant need for advanced manufacturing and joining techniques to ensure the durability and reliability of the assembled structures. This, in turn, instigates a fertile ground for academic and industrial research aimed at addressing the challenges and harnessing the opportunities presented by the widespread utilization of aluminum alloys in automotive applications [253]. The burgeoning demand for lightweight structures within the automotive domain has catalyzed the adoption of Aluminum Alloys (AA) due to their notable attributes such as low density and high specific strength [254] This trend has ignited a slew of research initiatives aimed at devising various joining techniques for AA [255]. Despite the promise, aluminum laser welding exhibits challenges primarily attributed to the distinctive physical properties of AA like high thermal conductivity and reflectivity when compared to other industrial metals like steel [65] The categorization of aluminum alloys into non-heat treatable and heat treatable, each with their unique series and alloying elements, adds a layer of complexity in handling AA [66]. The trajectory of employing laser welding techniques for amalgamating AA has been upward owing to its unique advantages such as high-power density leading to a narrow fusion zone and heat-affected zone [253] [256], and high weld accessibility for complex geometries [254]. Diverse studies, including those by Janasekaran et al. [256] and Beiranvand et al. [257], have explored the optimization of process parameters and the impact of alloy composition on weld quality, proposing real-time monitoring methodologies to refine the welding process. Various studies have explored the optimization of process parameters and the impact of alloy composition on weld quality, proposing real-time monitoring methodologies to enhance the welding process [258] Aminzadeh et al. [46–49] delved into examining the ramifications of key process parameters on aluminum laser welding, offering a real-time monitoring approach to mitigate defects like undercut, porosity, and cracking. Research endeavours have extensively probed into understanding defect formation, particularly porosity, which detrimentally impacts joint quality. Techniques like high-speed imaging and X-ray transmission have been employed to elucidate the dynamics of keyhole and molten pool during welding, shedding light on porosity formation mechanisms [260] Real-time monitoring during welding processes, segmented into pre-processing scanning, in-process monitoring, and post-process diagnosis [261] has been emphasized as a pivotal stride towards defect mitigation and quality assurance. The different stages of welding monitoring, depicted in Figure 53 [117], encompass a pre-processing scanning stage chiefly aimed at addressing the seam tracking challenge, where the joint gap between workpieces is meticulously scanned to ascertain the alignment of the laser beam spot with the gap's center, thereby facilitating the formation of reliable joints. Transitioning to the in-process monitoring stage, the focus shifts to the real-time observation of welding characteristics including the keyhole, molten pool, plasma, and spatters, among others, employing a variety of equipment. This stage enables the prediction and adjustment of the welded joint's quality by analyzing the dynamic alterations in these characteristics, leveraging advanced AI-based methodologies for enhanced accuracy and real-time modifications.

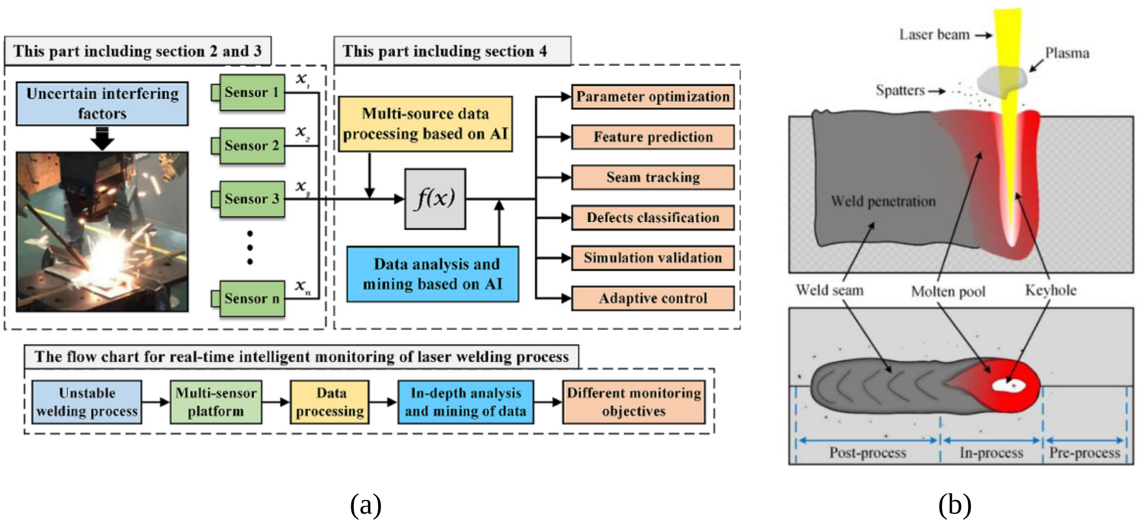


Figure 53. Flowchart for real-time monitoring of laser welding [117]

Recent studies by Xu et al. have illuminated those significant fluctuations in keyhole formation during laser welding are a critical factor contributing to the emergence of bubbles and pores [262]. However, a holistic online porosity monitoring framework for laser welding processes remains elusive in existing literature. A novel endeavor to address this lacuna manifested in the proposal of a deep-learning-based in-process porosity monitoring scheme. This scheme employs a Convolutional Neural Network (CNN) model with an automatic feature-learning capability to extract salient features from high-dimensional weld-pool image data, captured using a high-speed camera [263]. The laser welding technique, renowned for its high energy density and narrow heat affected zone, has ascended as a favorable alternative to traditional material joining processes [264]. Yet, the integrity of welded components could be undermined by defects induced during the laser-induced material melting-solidification sequence, such as porosity, cracking, lack of fusion, and incomplete penetration. These adversities necessitate a trial-and-error approach for process parameter design and invoke the deployment of expensive post-process metrology for quality inspection, highlighting the imperative for real-time process-level quality monitoring schemes in laser welding processes. The lack of online process surveillance could obscure malfunctions, accruing significant costs in the process. The distinctive attributes of aluminum, alongside real-time monitoring challenges such as the deployment of diverse monitoring tools, expansive IT infrastructures, reporting dilemmas, and network and connectivity inadequacies, represent the pragmatic challenges frequently confronted by modern industries. The incorporation of industrial lasers in welding applications has been extensively acknowledged for offering substantial advantages, embodying a confluence of speed, precision, robustness, and accessibility that fosters time and cost efficiencies in serial production, alongside facilitating more efficacious product designs. The literature review underscores a discernible void in research concerning the development of an automated real-time monitoring system for overlap aluminum laser welding that melds image processing and machine learning techniques for the analysis of keyhole features. This study endeavors to bridge this gap by proposing a classification-based in-process porosity monitoring scheme for aluminum laser welding. The envisaged monitoring system leverages X-ray analysis and high-speed camera technology to prognosticate the probability of porosity as an objective function for classification. This real-time inspection methodology is capable of autonomously rendering decisions on the pass or fail estimation of welded components, thus mitigating the adverse impact on the conformity of parts and the labor capacity of the machine and value chain in the automobile industry. The image processing strategy encompasses the automatic detection of regions of interest (ROI) by a high-speed camera (720 frames) and ImageJ software, which are harnessed as inputs to delineate features such as keyhole area and geometrical characterization. A Convolutional Neural Network (CNN) model with automatic feature-learning capacity is then deployed to extract features from the high-dimensional weld-pool image data. Additionally, X-ray technology is utilized to validate and inspect the porosity recognition and size of defects. A Random Forest (RF) classification model is trained to detect the occurrence of porosity in keyhole laser welding of 6061 Aluminum alloy, achieving a classification accuracy of nearly 80%. This attests that the RF-based monitoring scheme can accurately forecast the occurrence of porosity. Finally, an intelligent machine learning-based model is propounded which integrates computer-integrated manufacturing (CIM) and artificial intelligence (AI) for data-enabled adaptability throughout the production cycle, from product design to process scheduling, control, optimization, and product quality assurance. This manufacturing paradigm embraces techniques such as smart scheduling and predictive maintenance which are indispensable for real-time monitoring. Figure 54 illustrates the proposed monitoring chart.

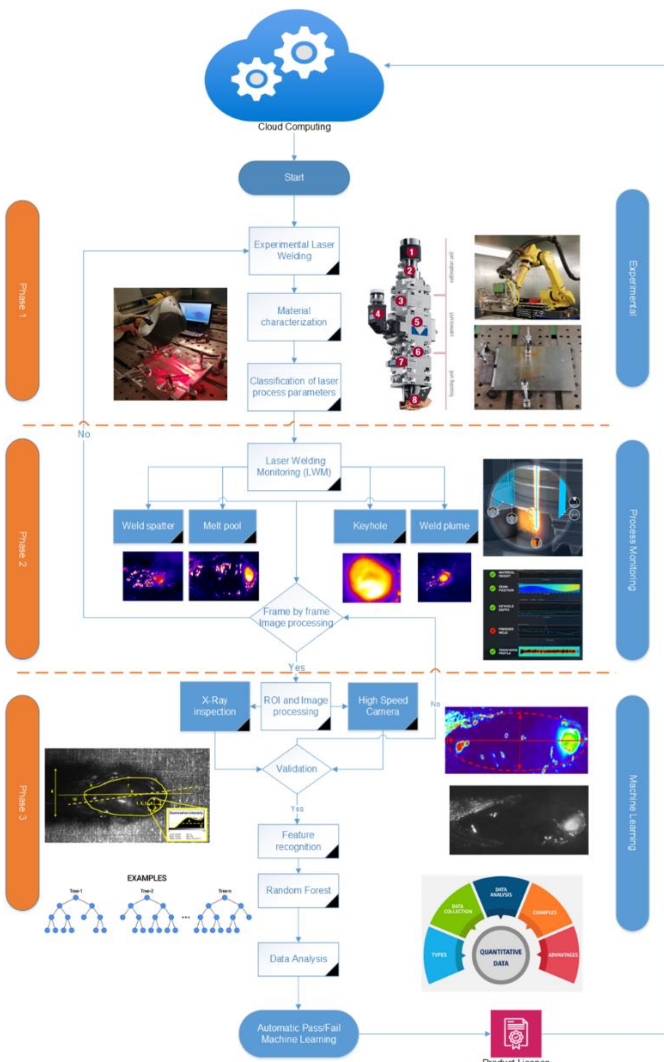


Figure 54. Propose Monitoring chart

5.7 MATERIALS AND METHODS

5.7.1 Experimental procedure

Laser Welding (LW) technology has emerged as a preferred methodology for permanent connections in industrial applications, attributed to its superior productivity, versatility, and minimized distortion among other advantages, as compared to traditional welding methods [265]. However, the process is complex with the quality of the joint being influenced by various factors including microstructural defects and changes in laser beam properties. Ensuring joint quality is critical for industrial utilization, necessitating comprehensive quality monitoring throughout the welding process [266]. Aluminum, although lightweight and having a higher strength-to-weight ratio compared to steel, presents challenges in laser welding. It is prone to several weld defects such as porosity, cracking, and inclusions, which are influenced by various process parameters [67]. Based on recent research [55,72,73], has graphically outlined these parameters in Ishikawa's diagram (Figure 55), highlighting some as more impactful and controllable through artificial intelligence [74,75]. The detection and analysis of porosity, a common defect in aluminum welding, require a deep understanding of its root causes, which could range from improper material cleaning to high heat input during welding. Image recognition techniques, employing high-speed cameras and X-ray imaging systems, have proven to be effective tools for real-time monitoring of the welding process, facilitating the analysis of keyhole and molten pool dynamics leading to porosity formation. Additionally, real-time monitoring of process variables such as laser power and welding speed allows for in-process adjustments to minimize porosity risk. In summary, effective porosity detection and analysis in aluminum welding are crucial for maintaining quality control in industrial manufacturing. Employing a combination of image recognition and real-time monitoring techniques can significantly aid in identifying the root causes of porosity, enabling timely adjustments to the welding process, thus mitigating defect risks and enhancing the overall quality of the welded joint.

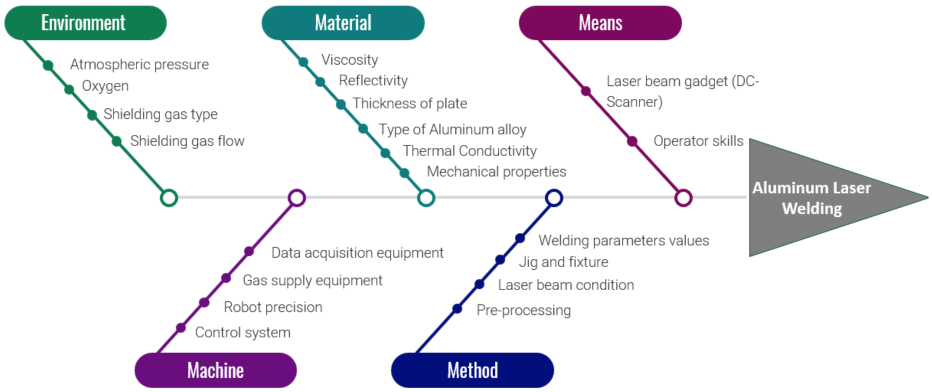


Figure 55. Classification of laser process parameters.

In the conducted study, Aluminum alloys of AA6061-T6 in an overlap configuration were utilized, with thicknesses ranging from 1.6mm to 2mm. The choice of aluminum alloy 6061 was predicated on its attributes as a precipitation-hardened alloy with magnesium and silicon as its primary alloying constituents. This alloy, renowned for its versatile application owing to its superior welding attributes, corrosion resistance, and an optimal strength-to-weight ratio, finds extensive use across various domains. Table 29 elucidates the dimensions, chemical composition, and mechanical properties of the welded sheets. Aluminum alloys pose a welding challenge attributable to their high thermal conductivity and surface vapor barrier formation, which could culminate in defects like porosity and inadequate penetration. Hence, the meticulous selection of process parameters and monitoring methodologies is imperative to ascertain the quality of welded joints in industrial settings. The monitoring endeavor in aluminum welding within the manufacturing realm is particularly daunting due to the high-velocity nature of the process coupled with the exigency for real-time data procurement and analysis. Additionally, the diminutive size of the weld pool and aluminum's high thermal conductivity obstruct the capture of high-resolution imagery of the welding sequence. The challenges aforementioned have spurred the advancement of sophisticated monitoring techniques encompassing X-ray imaging, high-speed cameras, and ultrasonic sensors, all aiming to garner detailed insights into the welding process. Despite their capabilities, these techniques in isolation fall short of furnishing a comprehensive understanding of the welding process, thereby escalating the demand for advanced data analytic and machine learning techniques to decipher useful information from the raw data. The burgeoning interest in recent years towards the evolution of image recognition techniques for real-time porosity monitoring in aluminum welding is noteworthy. A significant hurdle in this domain is the precise detection and categorization of minute and nuanced defects like porosity in high-resolution images of the weld pool. This necessitates leveraging advanced image processing techniques, for instance, convolutional neural networks (CNNs), for feature extraction from images and their subsequent classification. Proposed approaches for real-time porosity monitoring include utilizing high-speed cameras for real-time weld pool imagery, which are then subjected to image recognition algorithms for defect detection and classification. Concurrently, X-ray imaging can unveil detailed insights into the weld's internal structure, assisting in defect identification. While promising in laboratory settings, these techniques encounter several industrial challenges, notably the requirement for robust image processing algorithms capable of managing high-resolution, high-speed imagery, alongside efficient data storage and communication infrastructure for real-time analysis. The quest for real-time porosity monitoring techniques in aluminum welding is intricate, necessitating the amalgamation of advanced image processing, machine learning algorithms with high-speed cameras, and X-ray imaging systems. Continued research and development endeavors in this direction hold the promise of transitioning these techniques from laboratory to industrial settings, potentially enhancing the quality and uniformity of aluminum welded components.

Table 29. Chemical composition (% wt) and Mechanical properties of AA 6061-T6 [184]

Chemical composition	**Al**	**Cr**	**Cu**	**Fe**	**Mg**	**Mn**	**Other, total**	**Si**	**Ti**	**Zn**
% wt	0.15 - 0.35	0.1	0.4	2.2 - 2.8	0.1	0.25	0.1	0.4 - 0.8	Max 0.15	Max 0.25
Mechanical	Ultimate stren	Proof stren	Elongation (%)	Brinell	Poisson's ratio	Modulus of	Density	Melting	Thermal	Thermal

proper ties	gth (MPa)	gth (MPa)		hard ness		Elasticity (GPa)		Point	Expansion	Conductivity
Value	230	195	12	60	0.33	70.3	2.70 g/cm³	650 °C	23.4 x10^-6 /K	166 W/m.K

The experimental endeavor in aluminum laser welding encapsulated a series of pivotal steps encompassing material preparation, welding setup, and data acquisition and analysis. Initially, material preparation was undertaken, entailing a meticulous cleaning of the workpieces with acetone followed by polishing with sandpaper to ensure a uniform surface quality. Subsequently, the welding setup was established, featuring a Trumpf TruDisk 10kW laser, a YW52 Precitec wobbling head, and a SCANLAB's intelliWELD 30 FC galvanometer scanner (Table 30). The laser beam, channeled through a 200-µm fiber, had its spot size adjusted to 0.4mm. Throughout the welding process, a meticulous examination of various process parameters was conducted to attain high-quality welds; these parameters included laser power, travel speed, oscillation amplitude, and oscillation frequency. Additionally employed were a welding jig and fixture capable of supplying variable magnetic fields by modulating the current, alongside an argon shielding gas apparatus set at a flow rate of 25 L/min. Data collection was facilitated through high-speed cameras, with subsequent analysis performed using image processing software to scrutinize the dynamics of the keyhole and molten pool—primary determinants of porosity formation. Conclusively, a comparative analysis of the results was conducted employing various metallurgical and microstructural analysis techniques to validate the efficacy of the proposed method. For the execution of the experimental study, a Trumpf TruDisk 10kW solid-state disk laser, operating at a wavelength of 1030 nm, was harnessed for the preparation of laser-welded single lap joints (SLJ). The laser beam, once passed through a 200-µm fiber, was focused on the workpiece utilizing a SCANLAB's intelliWELD 30 FC galvanometer scanner, yielding a nominal spot size of 0.4mm. This scanner facilitated remote laser welding at a work distance of 460 mm (±70) while enabling remote adjustment of welding parameters. Employed also was a welding jig and fixture for supplying a variable magnetic field, alongside an argon shielding gas apparatus ensuring a stable welding environment. The comprehensive version of YW52 Precitec wobbling head was integrated, offering process monitoring features, thereby rendering the system ideal for fully automated production processes (Table 31). The YW52 welding head, a high-precision, advanced laser welding head extensively utilized in industrial laser welding applications, is endowed with a compact design, high precision, and high-speed attributes. Its technical specifications encompass a high-precision, high-resolution scanner for precise laser beam control, a high-speed control system enabling real-time process monitoring and control, alongside advanced optical sensors and imaging systems for meticulous process measurement and analysis. The welding head also boasts safety features safeguarding both the operator and equipment during the welding process. With its broad adjustment options for laser beam parameters—spot size, focus position, and beam shape, alongside the fine-tunable process parameters like laser power, travel speed, oscillation amplitude, and oscillation frequency, the YW52 welding head manifests as a versatile, reliable tool well-adapted to a wide spectrum of industrial welding applications. This welding head, coupled with the meticulous material preparation and the rigorously designed experimental setup, aimed at achieving the pinnacle of precision and accuracy in the resultant data, forming the backbone of the study.

Table 30. Laser Welding Process Parameters of YW52 Welding Head

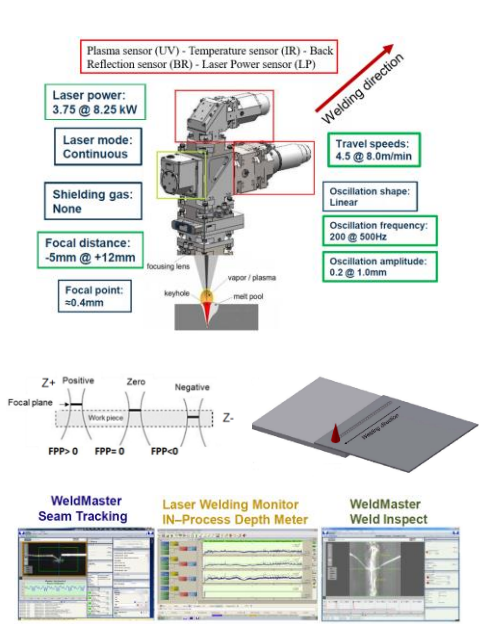
ID	Laser power (kW)	Travel speed (m/min)	Oscillation amplitude (mm)	Oscillation frequency (Hz)
#1	5.5	5.0	0.5	200

Table 31. Technical specifications of YW52 Welding Head. Available parameters

Parameters	Value
Max. laser power	4-8.5kW
Welding speed	4-8m/min

Focal lengths collimation	80 mm (NA ≤ 0.25), 100 mm (NA ≤ 0.25), 125 mm (NA ≤ 0.18), 150 mm (NA ≤ 0.15), 185 mm (NA ≤ 0.13), 200 mm (NA ≤ 0.12)
Focal lengths focusing	150 to 680 mm
Weight	3 to 6 kg, depending on construction
Dimensions (standard module)	74 x 74 mm (edges dimension)

In the current investigation, a well-instrumented laser welding system served as the research testbed. The core of the system was a 1000 W fiber laser head, diligently mounted on a robot as illustrated in Figure 56. The task of data capture from the camera during the experimental phase was accomplished using IC Capture software, engineered by the camera's manufacturer, The Imaging Source. Confronting the challenge posed by the high contrast of weld-pool images surpassing the camera's dynamic range, a strategic insertion of a narrow band pass filter, with a center wavelength of 532 nm, was employed to mitigate the effects of weld-pool irradiations. Moreover, a 200-mW green laser was engaged to illuminate the vicinity of the weld pool. A systematic sequence of overlap laser welding experiments was conducted, employing AA6061 Aluminum alloy plates, each with a thickness of 1 mm. The interface gap between the juxtaposed plates was meticulously maintained at zero, a configuration known to induce maximum porosity, thus facilitating the construction of a data-driven porosity monitoring model by virtue of accruing more data samples replete with porosity. The welding parameters were set at a speed of 50 m/min and a laser power of 5.5 KW, a combination discerned to engender optimum surface appearance quality, as corroborated by literature review and equipment validation. At the selected welding speed, the spatial resolution of the camera images approximated 59 lm/frame. To augment the precision of data acquisition and analysis, a repertoire of image processing techniques was applied to the collated images. This encompassed image enhancement, thresholding, and feature extraction. The image enhancement procedures aimed at ameliorating the visibility of the weld pool and its periphery, while the thresholding techniques were employed to segment the images into distinct regions of interest. Subsequently, feature extraction techniques were deployed to delineate relevant features from the segmented images, such as the size, shape, and intensity of the weld pool and its adjacent area. For the validation of the proposed monitoring system's effectiveness, a spectrum of metallurgical and microstructural analysis techniques was applied to the welded samples. This array included optical microscopy, scanning electron microscopy (SEM), and X-ray analysis as delineated in prior research [267]. These techniques furnished intricate information regarding the microstructure and composition of the welded samples, which was then correlated with the features extracted from the images. Moreover, a machine learning-centric model was developed to prognosticate the manifestation of porosity in the welded samples based on the extracted features. The model was trained employing a substantial dataset of images amassed during the welding experiments and was validated using a distinct set of images. The results manifested that the proposed monitoring system could accurately predict the incidence of porosity in the welded samples with a high degree of accuracy, thereby showcasing the potential efficacy of the integrated approach in monitoring and ensuring welding quality. This investigation accentuates the viability of employing image processing and machine learning algorithms for the real-time monitoring of porosity during aluminum laser welding processes. The devised monitoring system, demonstrating significant accuracy in predicting porosity occurrences in welded samples, holds promise for integration within industrial welding operations to augment both quality and efficiency. Beyond the instrumental laser welding system, this study delves into the impact of laser spot size on porosity formation in aluminum alloy welding, employing a single mode (100mm focal) and dual spot laser welding technique. The single mode technique utilizes a singular focused beam with a smaller spot size, while the dual spot approach engages two overlapping beams with larger spot sizes, facilitating a comparative analysis on the influence of spot size on porosity formation and the efficacy of the proposed monitoring methodology. Furthermore, the variation in spot sizes enables an examination of heat input's effect on the microstructure and mechanical attributes of the welded joints. The findings from these experiments are anticipated to yield crucial insights towards optimizing laser welding parameters for aluminum alloy and advancing real-time monitoring strategies for porosity detection. By amalgamating image processing, machine learning, and diverse laser welding techniques, this study aims to contribute a nuanced understanding that could significantly inform the optimization of welding parameters and real-time monitoring schemes, thereby addressing a pivotal industrial need in the realm of aluminum laser welding.

<table>
<tr><th>Monitoring set-up</th><th>Variants</th><th>Experiments</th><th>Spot status</th></tr>
<tr><td rowspan="2">
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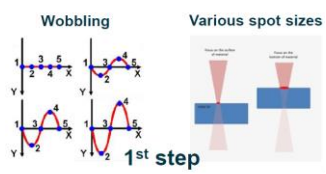
<td>
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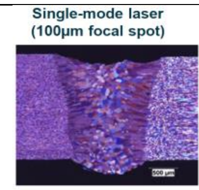
<td>
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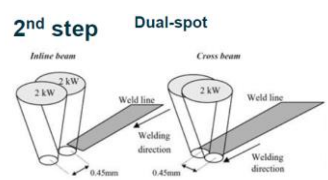
<tr><td>
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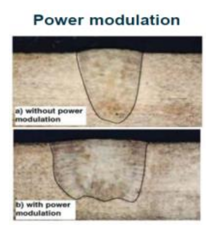
<td>
</td>
<td>Dual spot</td></tr>
</table>

Figure 56. Monitoring of the laser welding process with the Laser Welding Monitor LWM

5.8 REAL-TIME MONITORING

In the narrative of in-process inspections, the usage of single mode or dual spot techniques in laser welding embodies a meticulous approach towards monitoring weld quality. The single mode technique, characterized by a singular focal point, and the dual spot technique, characterized by two focal points, enable a systematic monitoring of weld pool dimensions and metal temperature. These techniques, when coupled with high-speed cameras and advanced image processing software, provide a comprehensive analysis of the keyhole and molten pool dynamics, which are pivotal in the genesis of porosity. Further, the post-process inspections, conducted post the welding process, encompass a myriad of metallurgical and microstructural analysis techniques. These techniques, ranging from visual inspection to ultrasonic and radiographic testing [268]. As a validation matrix for assessing the performance of the proposed methodologies while unearthing potential areas for enhancement. The triad of pre-process, in-process, and post-process inspections emerges as a linchpin in maintaining weld quality and mitigating the risk of defects which could potentially impair the performance of the final product. Pivoting to online monitoring, the domain of laser welding has seen a burgeoning interest in real-time monitoring systems, bifurcated into non-destructive testing (NDT) and process monitoring paradigms. While NDT techniques like x-ray computed tomography furnish invaluable insights into the finished welds, their cost and time-intensive nature often relegates them to lesser feasibility in mainstream industrial applications. On the contrary, process monitoring emphasizes real-time assessment of process variables, thereby facilitating immediate adjustments to the welding process through an array of sensors such as thermocouples, optical pyrometers, and high-speed cameras. These sensors are adept at gauging parameters like weld pool temperature, laser beam power, and geometry of the weld pool, thereby enabling the identification of potential defects and real-time rectification. The amalgamation of high-speed imaging and image processing techniques, especially when intertwined with machine learning algorithms, heralds a promising avenue for defect identification and prediction in welding processes like porosity, cracking, and lack of fusion. The synergy of these real-time monitoring systems with robotic frameworks allows for a fully automated, closed-loop control of the welding process, manifesting in enhanced process quality and cost-effectiveness. This narrative underscores a seminal shift towards real-time defect detection and process adjustments, with the fusion of high-speed imaging, image processing, and machine learning algorithms serving as a catalyst for elevating the efficiency, reliability, and cost-effectiveness of laser welding operations. The ongoing advancements in sensor technology, embodying laser triangulation and camera-based seam following, underscore the burgeoning emphasis on real-time monitoring, which is instrumental in amplifying both the quality and efficiency of aluminum laser welding processes. In this study, a novel classification-based in-process porosity monitoring scheme was envisioned for aluminum laser welding. The image processing strategy was meticulously designed to autonomously detect regions of interest (ROIs) employing a high-speed camera operating at 10,000 frames per second, alongside ImageJ software. These ROIs served as inputs to delineate features like the keyhole area and geometrical characterization. An automatic feature-learning model was devised to extract nuanced features from the high-dimensional weld-pool image data collected via the high-speed camera. Concurrently, X-ray technology was harnessed to validate and inspect porosity recognition and defect sizing, thereby furnishing a multi-modal evaluation framework. Additionally, the synergy between the high-speed camera and image processing software facilitated real-time monitoring of the welding process, heralding the potential for immediate detection and rectification of any emerging issues. The implementation of a classification-based algorithm for porosity monitoring showcased a more precise and efficient method of defect identification compared to conventional manual inspection methods. The findings underscore the significant potential to ameliorate the quality and efficiency of aluminum laser welding by leveraging advanced in-process sensing techniques. However, further research is imperative to refine and optimize these methodologies, ensuring their seamless integration and successful deployment in industrial settings, which is instrumental for realizing enhanced weld quality and operational cost savings.

5.9 RESULTS AND DISCUSSION

5.9.1 Image-based monitoring of keyhole characterization

A monitoring system for keyhole characterization in laser welding typically includes sensors and imaging techniques to measure the characteristics of the keyhole. The three main features that are typically characterized are weld width, keyhole recognition, and keyhole depth. Weld width is typically measured using a laser triangulation sensor, which uses a laser beam to project a line onto the surface of the weld and a camera to capture the image of the line. The width of the weld can then be calculated by analyzing the image. Keyhole recognition is typically achieved using a high-speed camera that captures images of the keyhole during the welding process. These images can be analyzed to determine the shape and size of the keyhole, which can provide important information about the quality of the weld. Keyhole depth can be determined by measuring the amount of energy absorbed by the keyhole using a pyrometer or by using a laser sensor. This information can be used to adjust the welding parameters to achieve the desired depth and shape of the keyhole. In summary, a monitoring system for keyhole characterization in laser welding typically includes sensors and imaging techniques to measure the characteristics of the keyhole, such as weld width, keyhole recognition, and keyhole depth, which can provide important information about the quality of the weld. In addition to the sensors and imaging techniques mentioned earlier, other monitoring systems for keyhole characterization in laser welding may include:

- **Spectroscopy**: This technique uses a spectrometer to analyze the light emitted by the keyhole during welding. This can provide information about the temperature, composition, and state of the material being welded.
- **Thermography**: This technique uses a thermal camera to capture images of the temperature distribution in the keyhole and the surrounding area during welding. This can provide information about the thermal history of the weld and the heat affected zone.
- **In-situ monitoring**: This technique involves measuring the process variables, such as the laser power, beam diameter, and beam focus, in real-time during welding. This can provide information about the energy input to the keyhole and how it changes over time.
- **Finite element modeling**: This technique uses computer simulations to model the thermal and mechanical behavior of the keyhole during welding. This can provide information about the keyhole shape and size, as well as the stresses and strains that occur in the material.

Overall, a monitoring system for keyhole characterization in laser welding can use a combination of these techniques to provide a detailed understanding of the keyhole and the welding process. This information can be used to optimize the welding parameters and improve the quality of the weld. In this study, an experimental approach utilizing high-speed imaging and X-ray analysis was employed to investigate the dynamics of the molten pool and keyhole in laser welding. The high-speed images were captured using a Phantom High-Speed camera operating at 1000 frames per second and analyzed using ImageJ software, including macro codes for automatic detection of the keyhole. The coaxial camera integrated with the laser head was upgraded to a DMK 33UX174 monochrome high-speed camera, which was capable of recording 640 x 480-pixel images at 720 frames per second, with 8-bit resolution and a data storage capacity of 211 MB. The field of view of the camera covered an area of approximately 638×479 pixels, which encompassed the region of the weld pool and its surrounding area. Additionally, X-ray analysis based on ISO 13919-2 was utilized to classify and quantify the probability of porosity and crack index in the weld zone. The combination of these techniques allowed for a comprehensive assessment of the welding process and the identification of potential defects (Figure 57). In this study, an image processing strategy was employed to detect regions of interest (ROI) in high-speed camera images of laser welding. The ROI were automatically identified using ImageJ software and were characterized based on features such as keyhole area and geometric properties. Automatic feature-learning algorithms were used to extract meaningful information from the high-dimensional weld-pool image data captured by the high-speed camera. The architecture of the high-speed camera used in this study is illustrated in Figure 54. ImageJ, a widely-used public domain Java image processing program, was used to process the high-speed camera images. It is capable of reading a wide range of image formats commonly used in heat-generated imaging, such as those used in laser welding. In addition to image processing functions, ImageJ also offers tools for data analysis, visualization, and measurement. After collecting data from 720 frames, the welding defects were classified into two categories: those with porosity and those without. The porosity recognition and size of defects were also validated using X-ray technology.

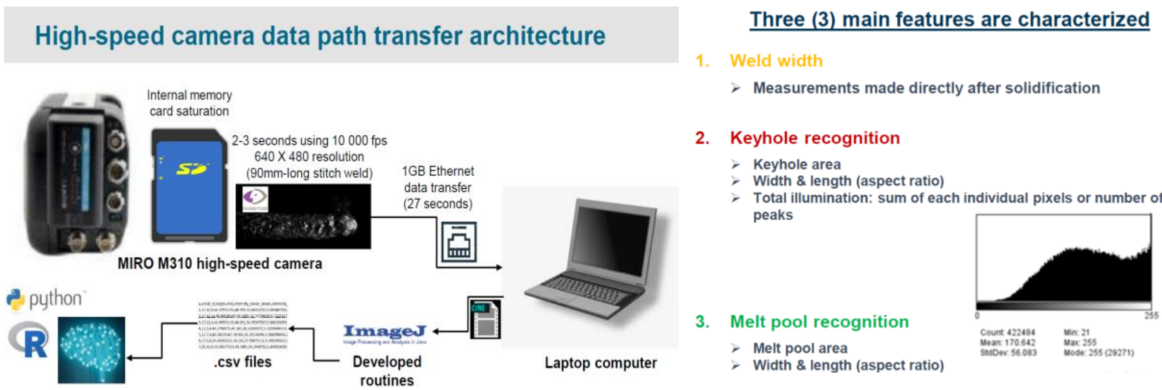


Figure 57. Image-based monitoring of keyhole characterization

In the field of laser welding, high-speed cameras are commonly used to capture detailed images of the welding process in real-time. These cameras are capable of capturing thousands of frames per second, providing a detailed understanding of the dynamics of the weld pool, keyhole, and other important process variables. To ensure that the high-speed camera data is captured and transferred in a timely and efficient manner, a data path transfer architecture must be implemented. One common approach for high-speed camera data path transfer is to use a dedicated data acquisition system, which is connected to the camera via a high-speed data link such as Camera Link or GigE Vision. The data acquisition system is responsible for capturing the high-speed camera data and transferring it to a host computer for further analysis. This approach is particularly useful in environments where the camera data must be captured and transferred in real-time, such as in closed-loop control systems. Another approach is to use a camera-embedded data path transfer architecture, which utilizes the onboard memory of the camera to buffer the captured data. This approach is useful in applications where the camera data does not need to be transferred in real-time, and can be transferred to a host computer at a later time. In some cases, both of the above approaches can be combined to provide an optimal solution for high-speed camera data path transfer. For example, a high-speed camera can be connected to a data acquisition system in real-time, while also utilizing its onboard memory to buffer the captured data for later transfer. Overall, the high-speed camera data path transfer architecture should be chosen based on the specific requirements of the application, such as the need for real-time data transfer, data storage and analysis requirements, and the available infrastructure. Real-time monitoring of weld spatter, weld plume, weld melt pool, weld width, and keyhole using high-speed cameras and image processing is an important aspect of laser welding. High-speed cameras can capture images at high frame rates, allowing for detailed analysis of the welding process. Image processing techniques can then be used to extract relevant information from the captured images, such as the size and shape of the melt pool, the width of the weld, and the presence of keyholes. This information can be used to optimize the welding process, reduce defects, and improve the overall quality of the weld. The data collected can also be used to identify patterns and trends that can be used to predict and prevent future problems. The high-speed camera data path transfer architecture used in laser welding typically includes the camera, data acquisition system, and data storage and analysis system. The data is transferred from the camera to the data acquisition system in real-time, where it is then stored and analyzed using image processing techniques. High speed cameras, typically operating at frame rates of several thousand frames per second, can capture detailed images of the laser welding process in real time. These images can then be analyzed using image processing techniques to extract information about various aspects of the welding process, such as the shape and size of the weld melt pool, the width of the weld, and the presence of weld spatter or keyholes. One common technique for real-time monitoring of the welding process using high speed cameras is laser triangulation. This method uses a laser line projected onto the weld area and a camera positioned at a known angle to capture images of the line as it is distorted by the shape of the weld melt pool. The position of the laser line in the camera's field of view can then be used to calculate the shape and size of the weld pool. Another technique commonly used in high-speed camera-based weld monitoring is stereo imaging. This method uses two cameras positioned at different angles to capture images of the weld area. The two images are then processed to extract information about the shape and size of the weld melt pool, as well as the position of the weld joint. In addition to these techniques, image processing algorithms can be used to analyze the high-speed camera images to extract information about other aspects of the welding process, such as the presence and size of weld spatter, the shape and size of the weld plume, and the width of the weld. Overall, high speed camera-based monitoring and analysis of laser welding can provide a wealth of information about the welding process, allowing for real-time adjustments to be made to improve weld quality and reduce defects. Keyhole recognition in laser welding involves the use of image processing techniques to analyze images of the keyhole and extract geometric information about its shape and position. This information can be used to adjust the laser parameters and ensure that the keyhole is properly aligned and has the desired shape. One of the key geometric features used in keyhole recognition is the keyhole's aspect ratio, which is the ratio of its width to its depth. A high aspect ratio indicates that the keyhole is wide and shallow, while a low aspect ratio indicates that the keyhole is narrow and deep. Other geometric features that can be used include the keyhole's circularity, which is a measure of how circular its shape is, and the keyhole's symmetry, which is a measure of how symmetrical its shape is. Image processing algorithms that are commonly used for keyhole recognition include edge detection, thresholding, and morphological operations. These techniques can be used to extract the keyhole's shape and position from the images. Once the keyhole is detected and its geometric features are extracted, this information can be used to adjust the laser parameters in real-time to maintain the desired keyhole shape, position and other parameters. This study aimed to improve the transform used for detecting the diameter of each pore with high efficiency and spatial resolution. The resolution achieved was as fine as 4.12 μm. The porosity characteristics such as pore number, pore diameter, porosity volume and porosity ratio were calculated for each laser welded weld. In accordance with the physics of laser welding phenomena and literature, three main features were considered in laser welding: weld width, keyhole recognition and melt pool recognition. In this study, keyhole recognition was given the most attention. The acquisition speed was set at 10,000 frames per second, and the analysis size was reduced to 2,000 frames per second. Additionally, various geometrical features such as keyhole circumference, keyhole major (a or b; longer), keyhole aspect ratio (a/b), illumination intensity sum, illumination intensity mean, weld width, melt pool area, melt pool perimeter, melt pool major, and melt pool deviation from centerline were considered for feature recognition. One method to correspond the features from high-speed camera images to X-ray porosity position and size is through the use of image registration techniques. This involves aligning the high-speed camera images with the X-ray images by identifying and matching corresponding features in both images, such as the edges of the weld or the position of the keyhole. Once the images are registered, the porosity position and size can be determined by comparing the features in the high-speed camera images to the X-ray images. Another approach is to use machine learning algorithms to train a model to automatically detect and classify porosity in the high-speed camera images and then use the model to predict the corresponding porosity position and size in the X-ray images (Figure 58).

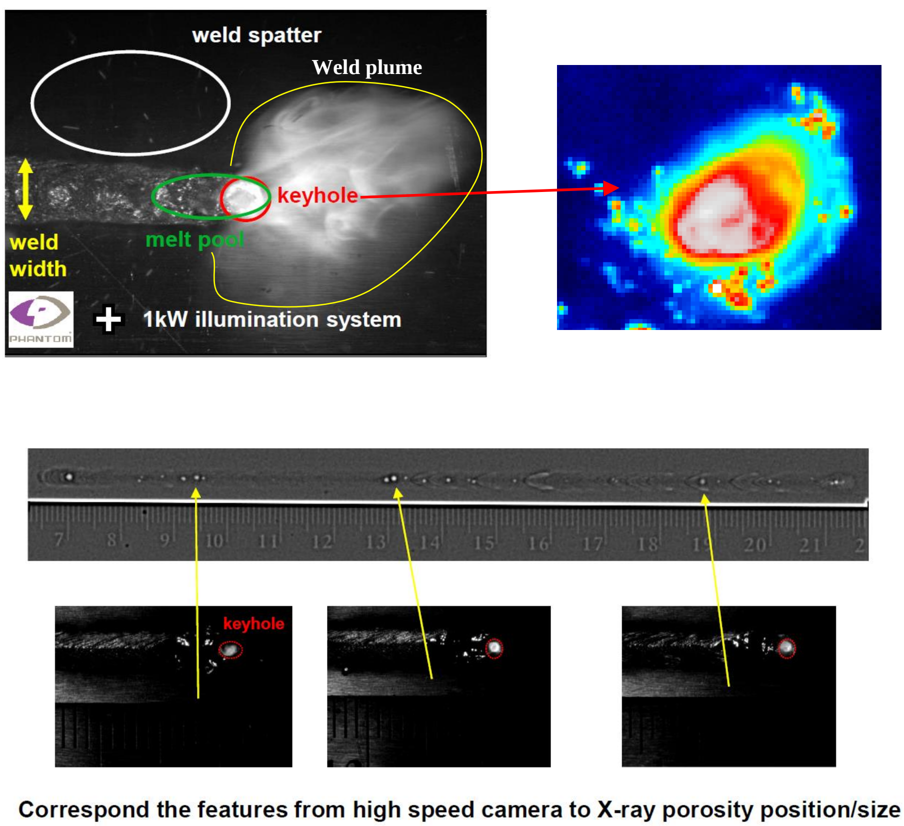
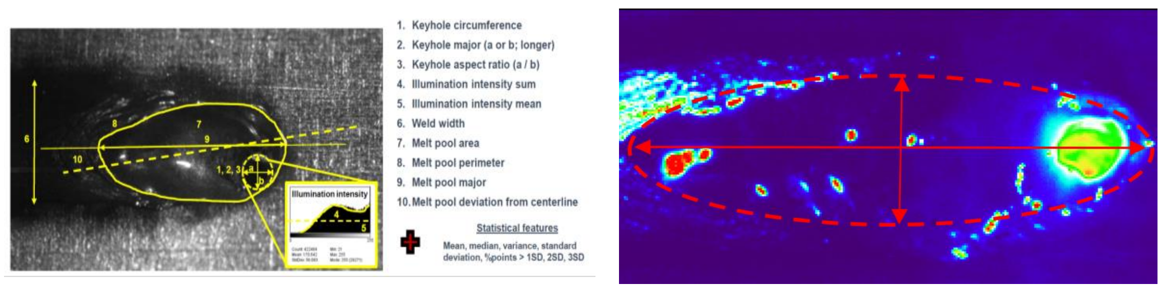


Figure 58. Correspond the features from high-speed camera to X-ray

In image processing applications, feature extraction is a crucial step in the dimensionality reduction process. It involves selecting and combining variables from the raw data into features that effectively reduce the amount of data while still accurately and originally describing the data set. This technique is useful when dealing with large data sets and the need to reduce the number of resources without losing important information. Feature extraction also helps to eliminate redundant data from the data set. In the field of engineering, feature extraction is a crucial step in the analysis and interpretation of data, particularly in the context of image processing. The use of ImageJ, a powerful and widely used image processing software, can greatly aid in this process. ImageJ can be used to extract various features from images, including shape, edges, and motion, which can be used to analyze and understand the data. Additionally, ImageJ can also be used to perform various image processing tasks, such as background subtraction, area and pixel value statistics, and density histograms, which can be used to extract additional information from the images. One specific application of ImageJ in engineering is in the analysis of laser welding images. The high-speed camera is used to capture images of the weld pool, and ImageJ can be used to extract features from these images, such as the size and shape of the weld pool, the presence of any defects, and the overall quality of the weld. This information can then be used to optimize the welding process and improve the overall quality of the welds. Another application of ImageJ in engineering is in the analysis of X-ray images. X-ray images can be used to detect defects in a material, such as porosity or cracks, but the process of extracting this information can be difficult. ImageJ can be used to extract features from the X-ray images, such as the size and position of defects, and this information can be used to make more accurate predictions about the integrity of the material. Its wide range of features and easy-to-use interface make it an ideal choice for researchers and engineers looking to extract meaningful information from their data. One popular tool for feature extraction in image processing is ImageJ, a public domain Java image processing program. It can read and display a wide range of image formats, including TIFF, GIF, JPEG, BMP, DICOM, FITS, and "raw". It also includes a number of useful tools for image processing such as background subtraction, area and pixel value calculations, density histograms, and standard image processing functions such as contrast enhancement, sharpening, smoothing, and edge detection [269]. Additionally, ImageJ has a plug-in called Bio-Formats, which allows for the reading of many instrument-specific file formats and includes controls for loading and displaying multi-dimensional data [270]. In addition to its image processing capabilities, ImageJ can also be used for thermal analysis in laser welding. By analyzing the distribution of heat on the surface of the melt pool and weld seam, engineers can gain insight into subsurface features such as fusion in a lap joint. This information can then be used to optimize the welding process and improve the quality of the finished weld. In conclusion, ImageJ is a powerful tool for engineering feature extraction, and its application in various fields like laser welding, X-ray imaging and many other can greatly aid in the analysis and understanding of data (Figure 59).



(a) (b)

Figure 59. Feature recognition using image processing a) High-speed camera b) ImageJ using thermal filter

In this study, keyhole image processing was performed using high-speed cameras and image processing software, specifically ImageJ. The keyhole was successfully detected and all relevant feature engineering information was extracted from 270 frames. However, some frames were lost during the image extraction process due to the abrupt changes in keyhole position and pixels. Images are typically stored digitally as arrays of pixels, with each pixel representing the smallest element of an image. The most commonly used color space is the RGB color space, where every color is defined by three values: red, green, and blue. These values are typically represented as 8-bit unsigned integers, with a range of 0-255, also known as the color depth. To improve the number of frames detected, various types of filters were implemented in ImageJ. Filters are mathematical functions that take the image as input and return a new image as output. They can be applied on a pixel-level, a global-level, or a channel-level. In addition to using filters, a human annotation method was also employed to achieve the maximum number of frame detections. The image processing results were compared with X-ray analysis to validate the detection of porosity and size of defects in the weld zone. In addition to the techniques mentioned above, ImageJ also allows for the use of advanced image processing algorithms such as edge detection, feature extraction, and pattern recognition. These algorithms can be used to extract specific features from an image, such as edges, shapes, or patterns, that can be used for further analysis or for control purposes in an automated system. One example of this is in the field of thermal analysis, where ImageJ can be used to extract temperature data from thermal images. This data can then be used to calculate heat flux, thermal conductivity, and other thermal properties. Additionally, ImageJ can also be used to perform image registration, which is the process of aligning multiple images of the same scene taken at different times or from different viewpoints. This can be particularly useful in the field of welding, where multiple images of the weld pool need to be aligned in order to accurately measure the size and shape of the weld. Overall, ImageJ is a versatile and powerful tool that can be used for a wide range of image processing tasks in the field of engineering and materials science. Its ability to read and process a wide range of image formats, combined with its advanced image processing algorithms, make it an essential tool for scientists and engineers working in these fields. One of the main technical challenges faced when dealing with lost frames in image processing is the lack of consistency in the data. If a certain frame is missing, it can disrupt the continuity of the image sequence and make it difficult to accurately analyze the data. Additionally, lost frames can also lead to errors in the extraction of features, as the missing data may not be able to be replaced or interpolated easily. This can negatively impact the accuracy and reliability of the image analysis results. Another challenge is the difficulty in detecting lost frames, as they may not be immediately obvious in the data. Developing algorithms to automatically detect missing frames can be a complex task, as it requires the analysis of multiple frames in order to identify patterns or inconsistencies. Furthermore, the image processing methods used for keyhole detection may not be robust enough to handle lost frames and may require further development or modification. Moreover, one of the main technical challenges in image processing for lost frames is related to the dynamic nature of the welding process. The keyhole position and size can change rapidly and unpredictably, making it difficult to capture clear images. This can lead to lost frames, as the camera may not be able to capture the keyhole in the correct position. Additionally, the intense light and high temperatures generated by the welding process can also cause problems for the camera and image processing software. High-speed cameras, which are commonly used in welding applications, may not be able to handle the high frame rates and high-resolution images required for accurate detection of the keyhole. Furthermore, the image processing algorithms used to detect the keyhole may not be able to handle the high levels of noise and distortion present in the images. This can lead to false positives or negatives in the detection of the keyhole, resulting in lost frames and inaccurate measurements. Finally, another technical challenge is the human annotation method. Human error can also cause lost frames, as it is difficult to ensure that the annotator is accurately detecting the keyhole in every frame (Figure 60).

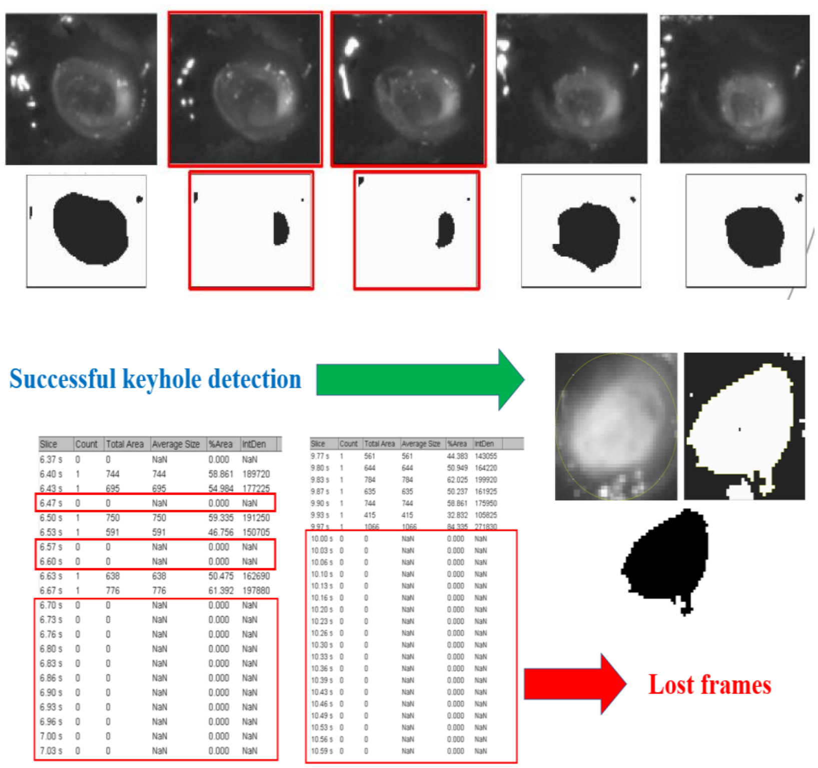


Figure 60. Keyhole detection

5.10 VIDEO ANNOTATION

Additionally, video annotation also includes tasks such as identifying objects or events within the video, tracking their motion, and labeling the actions that are taking place. This can be used to train models for tasks such as object tracking, activity recognition, and scene understanding [271]. The process of video annotation is typically time-consuming and requires a high level of attention to detail, as mistakes in annotation can lead to poor performance in the final machine learning model. To mitigate this, it is important to have a clear annotation protocol in place and to use multiple annotators to ensure consistency and accuracy in the final dataset. Furthermore, it is crucial to have a quality control process in place to check the annotation results and make necessary adjustments. Image annotation work typically includes the following tasks:

- Preparing the image dataset
- Specifying object classes that annotators will use to label images.
- Assigning labels to images
- Marking objects within each image by drawing bounding boxes
- Selecting object class labels for each box
- Exporting the annotations in a format that can be used as a training dataset.
- Post processing of the data to check if labeling is accurate.
- In case of inconsistent labeling, the system should enable a second or third labeling round with voting between annotators.

In this study, the use of human annotation in video processing has been deemed essential in order to achieve accurate and reliable results. Human annotators have been utilized to train a machine learning model to understand the nuances and complexities of the video data, and to make accurate predictions in real-world scenarios. The process of video annotation involves manually labeling features on every video frame, which is then used to train a machine learning model for video detection. To facilitate the annotation process, various software and tools have been employed, such as Vatic, Labelbox, and RectLabel. These tools are designed to streamline the annotation process and make it more efficient by automating certain tasks, providing annotation guidelines, and facilitating collaboration among annotators. In this study, human annotation has been used to precisely define the keyhole and to characterize the most important features of the welding zone. Specifically, 720 frames were annotated for training the machine for pass, while 720 images were annotated for fail through the 6 mm welding (Figure 61). Ultimately, 1440 photos were labeled with a high level of precision. The use of these annotated images has allowed for the creation of a training dataset that can be used to train the machine learning model for video detection, enabling the model to accurately recognize keyhole dynamics and other important features in the welding process. Human annotation for laser welding can provide valuable information for training machine learning models to detect and classify various features of the welding process, such as keyhole shape, size, and position. However, there are several technical challenges that must be considered when using human annotation for this purpose. One of the main challenges is ensuring the accuracy and consistency of the annotations. This can be achieved by using multiple annotators to label the same image, and using majority voting to select the label that is most likely to be correct. Additionally, it is important to provide clear guidelines and instructions to the annotators, and to provide ongoing training and feedback to ensure that they are able to accurately identify and label relevant features in the images. Another challenge is dealing with the high volume of data that is generated during the welding process. High-speed cameras are often used to capture images of the welding process at a very high frame rate, which can result in large amounts of data that must be processed and annotated. This can be addressed by using automated image processing techniques to pre-process the data, and by using tools such as ImageJ to assist with the annotation process. Finally, it is important to consider the format and structure of the annotated data, in order to ensure that it can be easily integrated into machine learning models for training and testing. This may involve exporting the annotations in a standard format, such as COCO or PASCAL VOC, and using software libraries such as TensorFlow or PyTorch to work with the data. Overall, while human annotation can provide valuable information for training machine learning models for laser welding, it also requires careful planning and management in order to ensure accuracy and consistency, as well as to handle the large volume of data generated during the process.

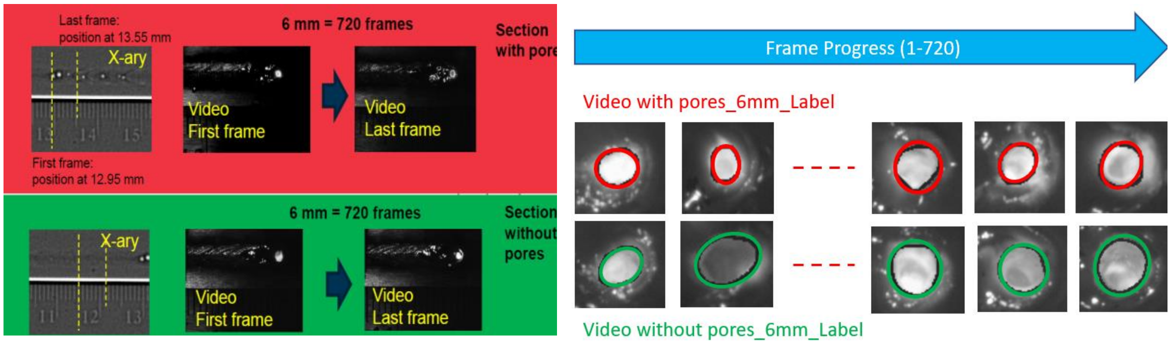


Figure 61. Video Annotation

5.11 FRAME BY FRAME ANALYSIS

In the field of video technology, the concept of video is often described as a sequence of frames that are mapped against time. The frame-by-frame analysis of a video is centered on the individual frames that make up the video. When a video is broken down into its most basic elements, it can be seen as a collection of static images that are chronologically arranged to create the illusion of motion. The human eye perceives these rapidly changing images as a continuous dynamic motion. The number of frames per second (fps) in a video plays a crucial role in determining the video's clarity and quality. The standard number of frames per second for most videos is 24 fps, which means that in every second, there is a fixed transition of 24 frames. However, an increasing number of frames per second in a video can result in a higher quality video. For example, a video with 60 fps captures 60 different moments or activities within a single second, as opposed to 24 fps which captures 24 different moments within a single second. It's also worth noting that the number of frames per second is not the only factor that determines the video's quality. Other factors such as resolution, bitrate, and compression also play a role in determining the video's quality. The use of advanced video compression techniques like H.264 and H.265, for example, can help to achieve a higher quality video at a lower bitrate [272]. Overall, the frames per second in a video is just one aspect of the video technology, however, it is an important one and is often used as a benchmark for video quality. As technology advances and frame rates increase, it is likely that we will see a continued improvement in video quality (Figure 62).

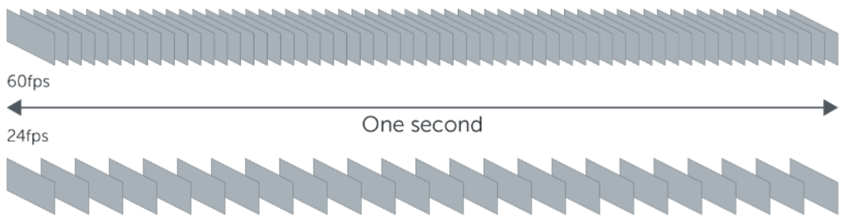
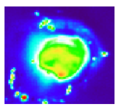
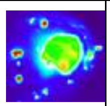
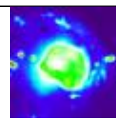
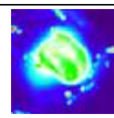
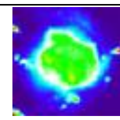
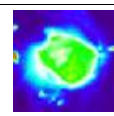
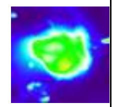
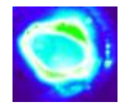
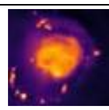
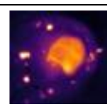
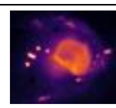
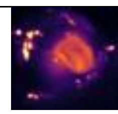
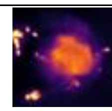
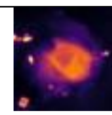
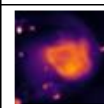
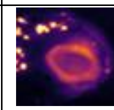


Figure 62. Frame by frame section of a video [273,274]

In order to fully understand and analyze video data, it is important to consider both the temporal and spatial aspects of the data. Temporal information refers to the sequence of frames in the video, and how they change over time. Spatial information refers to the objects and features present in each individual frame. By utilizing both temporal and spatial information, we can gain a deeper understanding of the scene and the actions taking place within it. One important technique in video analysis is optical flow estimation. Optical flow is the process of measuring the movement of pixels between consecutive frames in a video. By analyzing the optical flow, we can gain insight into the motion of objects in the scene, and track their movement over time. This is particularly useful for tasks such as object tracking and action classification. In this study, we aim to investigate the use of video analysis techniques in the field of porosity detection in laser welding. Computer vision algorithms are commonly used to analyze static images; however, video analysis requires a deeper understanding of sequences of images, 6D inputs, and time-related scenes. As such, it presents a new challenge and a next step in the field of computer vision. In order to accomplish this task, we have chosen to focus on a 6mm section of weld for porosity detection using a Pass/Fail analysis method. The analysis is based on X-ray imaging and a dataset of 720 frames of an overlap welded structure, designated as No. #416, with a range of 12.95 mm to 13.55 mm, was selected for the failure response (Fail = 0). This dataset is used as train data for prediction analysis in Python. Additionally, another set of 720 frames of the same weld number No. #416, with a range of 10.3 mm to 10.9 mm, is chosen as the test dataset (Pass = 1) for prediction analysis. The results of this study will contribute to the understanding of the capabilities and limitations of video analysis in porosity detection in laser welding and provide insight into potential applications in other related fields (Figure 63).

Train : #416- 12.95 mm-13.55 mm (6 mm sections)

With porosity: Fail = 0

Frames	1	2	3	4	5	6	7	…	720
Thermal Filter									
Infrared Filter									

Test: #416- 10.3 mm -10.9 mm

Without porosity: Pass = 1

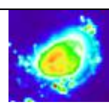
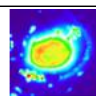
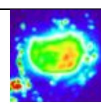
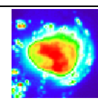
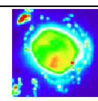
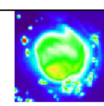
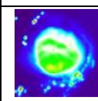
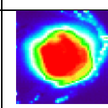
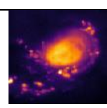
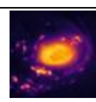
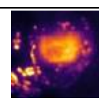
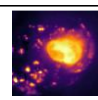
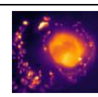
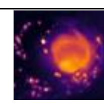
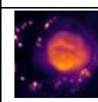
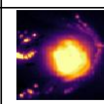
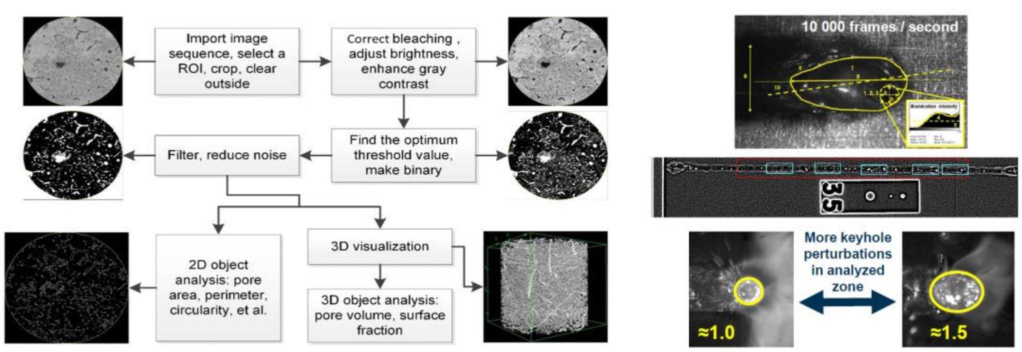
Frames	1	2	3	4	5	6	7	…	720
Thermal Filter								…	
Infrared Filter								…	

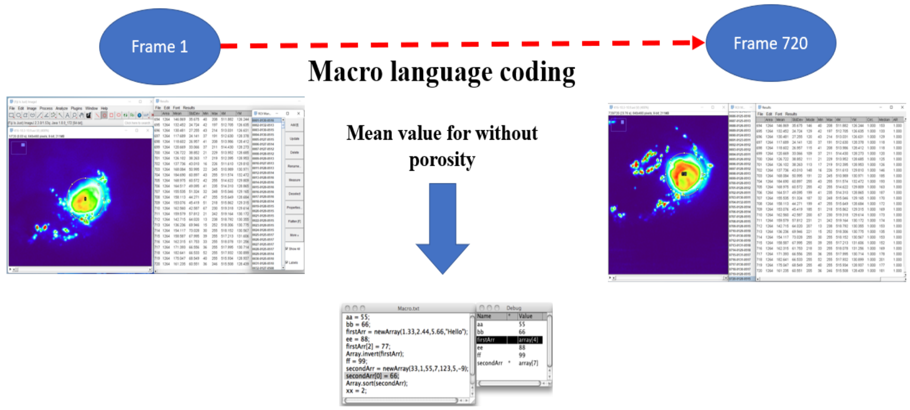
Figure 63. Frame by frame analysis of laser welding

In the field of image processing, the concept of Region of Interest (ROI) is widely used to analyze specific areas of an image. ROI is a selected portion of an image that is of particular interest for further analysis. The ROI Manager in ImageJ is a tool designed to help users save, manage and manipulate ROIs in an efficient manner. It allows users to create, edit, and analyze ROIs, as well as perform set operations such as union, intersection, and subtraction. In the context of laser welding, the ROI Manager can be used to analyze the keyhole and other important features within the weld zone (Table 32). The keyhole is a crucial aspect of the laser welding process, and its shape and size can affect the quality of the weld. By using the ROI Manager, users can easily select and analyze specific regions within the keyhole, such as the size and shape of the keyhole, the temperature of the weld, and the presence of any defects. This data can then be used to improve the quality of the weld and optimize the laser welding process. Additionally, the ROI Manager can also be used to analyze other features of the weld zone, such as the heat-affected zone, the size and shape of the weld pool, and the penetration depth. Overall, the ROI manager in ImageJ is a powerful tool that can be used to improve the efficiency and accuracy of the laser welding process. It allows users to easily select and analyze specific regions of interest within the weld zone, providing valuable insights into the keyhole and other important features of the weld. Moreover, the concept of Region of Interest (ROI) plays a crucial role in the analysis of digital images. In the context of this study, the use of ROI was employed in the analysis of laser welding, specifically in the detection of porosity. The process involved the extraction of frames from a video, with the range of frames being from 1 to 720. The selections, or ROIs, were created using the tools provided in the ImageJ toolbar. It is worth noting that while ImageJ allows for the simultaneous display of multiple ROIs through the use of overlays and the ROI Manager, only one selection can be active at a time. Additionally, the extracted ROIs can be further analyzed and measured for further insights and analysis (Figure 64 and 65).

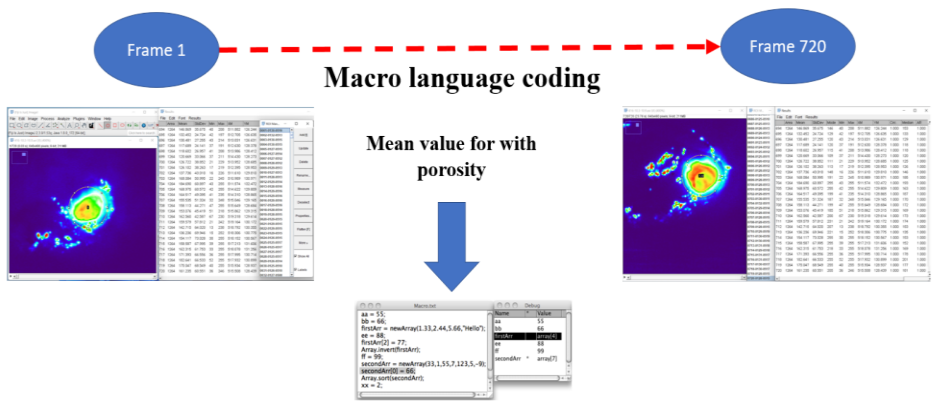


(a) **(b)**

Figure 64. Flowchart of image processing using ImageJ software. a) Flowchart [275] b) Enhance contrast function



(a)



(b)

Figure 65. Data extraction from region of interest (ROI). a) without porosity and b) with porosity

In the present study, an exhaustive analysis was undertaken to delve into the intricacies of laser welding, focusing on the dynamics of laser-induced plume and keyhole, alongside investigating the mechanisms underlying porosity formation and the strategies for its suppression. A spectrum of optical and X-ray methodologies were deployed to garner high temporal resolution observations of the welding process. The materials scrutinized encompassed Al-alloys, stainless steels, among others. Hard X-ray radiography was harnessed as a pivotal method to observe sub-surface events crucial for weld quality. A prominent challenge in laser welding of Al-alloys is the manifestation of hydrogen-induced porosity, characterized by diminutive blow holes. The molten pool's average temperature in laser welding significantly surpasses that of arc welding, culminating in elevated soluble hydrogen levels and the genesis of numerous pores. The sole efficacious measure to mitigate porosity entails the elimination of hydrogen sources during the welding venture. Another variety of porosity observed arises from the intense metal evaporation in the keyhole, leading to the instability of both the keyhole and weld pool. This porosity variant is characterized by its large size, which can be diminished through judicious pulse shaping in spot welding, optimal pulse modulation adoption, and a proper angle of beam incidence. Adhering to ISO standards, porosity exceeding 1mm was identified as a true pore region. Attributes of porosity, such as the porosity status (true: pore, false: no pore) and size, were extracted from each porosity region and coupled with the weld-pool images at corresponding longitudinal positions, forming a coherent input-output data pair. This data pair holds the potential to serve as the foundation for training a supervised deep learning model, thereby paving the path toward a more nuanced understanding and control over porosity in laser welding processes, which is crucial for advancing the field and ensuring superior weld quality.

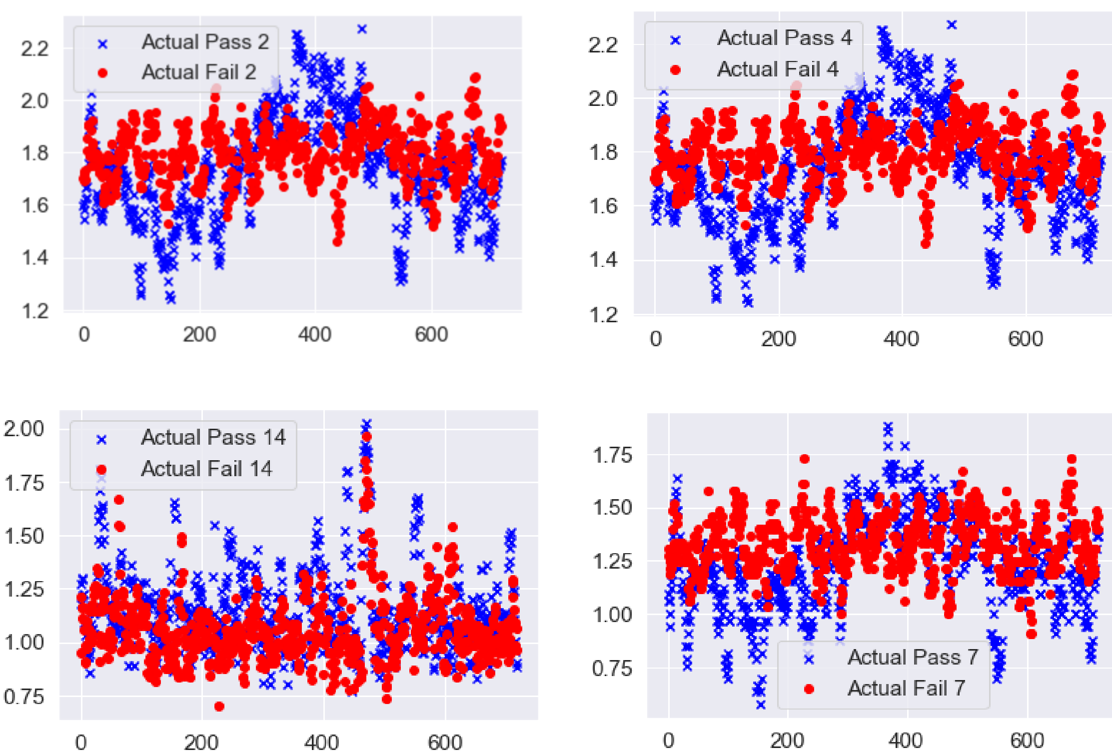
Table 32. Feature definition for keyhole recognition [276]

Features	**Definition**
Area	Selection area in square pixels. The area is expressed in calibrated units, such as square millimeters, if the image was spatially calibrated using the Analyze>Set Scale function.
Centroid	The centroid of a given selection is defined as the point situated at the mean position of all pixels encompassed within the image or selection. It can be ascertained by computing the arithmetic mean of the X and Y coordinates, which can subsequently be located in the Results table, denoted under the headings "X" and "Y".
Center of Mass	The center of mass, weighted by brightness, of all the pixels within the image or selected region is computed by taking into account both the intensity and the location of each pixel. The coordinates of this brightness-weighted center of mass are denoted in the Results table under the headings "XM" for the X-coordinate and "YM" for the Y-coordinate. These

	coordinates embody the first-order spatial moments of the image or selected region.
Perimeter	The term "perimeter of the selection" denotes the cumulative length of the exterior boundary.
Bounding Rectangle	The bounding box encapsulating the selection is delineated as the minimal rectangle encompassing the entirety of the selection. The rectangle's upper left vertex is denoted by the coordinates "BX" and "BY", while the dimensions of the rectangle, specifically its width and height, are represented under their respective headings.
Fit Ellipse	The chosen segment is delineated employing an elliptical framework, yielding resultant parameters encompassing the lengths of the major and minor axes, the angular deviation between the major axis and a line running parallel to the x-axis, alongside an option to exhibit the coordinates of the ellipse's centroid (X and Y) provided the Centroid option is activated. It merits emphasis that the precise computation of the lengths of the major and minor axes within ImageJ necessitates a Pixel Aspect Ratio of 1.0 as stipulated in the Set Scale dialog.
Shape	The computation and representation of shape descriptors are executed to further analyze the geometric attributes of the entities in question. The descriptors delineated include Circularity, Aspect Ratio, Roundness and Solidity. These descriptors are computed and exhibited, with the provision to activate the "Fit Ellipse" option within the Analyze>Set Measurements menu to procure information regarding the major and minor axes. It is imperative to acknowledge that exceedingly diminutive particles may yield invalid values, necessitating cautious interpretation of the resultant data.
Feret's Diameter -	The Feret diameter, represented by the maximum caliper, denotes the longest distance between any two points along the perimeter of the selected boundary. The angle subtended between the Feret diameter and a line parallel to the x-axis is defined as the Feret Angle, with a range of 0 to 180 degrees.

	Additionally, the minimum caliper diameter is referred to as the MinFeret. The initial coordinates of the Feret diameter are displayed as FeretX, FeretX and FeretY. For visualizing the Feret diameter corresponding to the current selection, the Draw Feret Diameter macro can be employed.

Regarding the data visualization, actual pass data refers to the data that represents instances where a particular process, product or system has passed a quality test or met certain criteria for success. In the context of machine learning, it is often used as the ground truth or target variable for training and evaluating predictive models. Actual pass data is typically used alongside actual fail data to build a predictive model that can accurately classify new instances as pass or fail based on the features or variables that are measured (Figure 66).



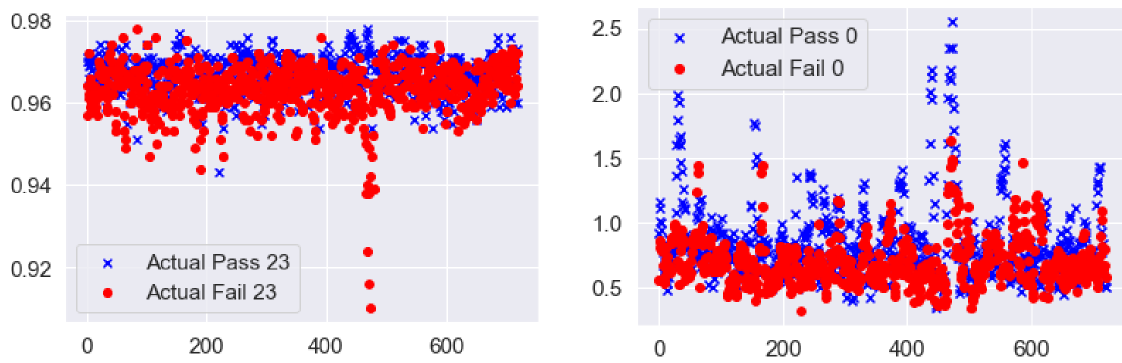


Figure 66. Comparison between actual pass and actual fail

5.12 MACHINE LEARNING IMPLEMENTATION

5.12.1 Random Forest (RF) classification

Random Forest stands as a notable ensemble learning technique employed for classification, regression, and various other analytical tasks. It operates by orchestrating numerous decision trees during the training phase, subsequently yielding the class that represents the mode of the classes (in classification) or the mean prediction (in regression) engendered by the individual trees. The essence of Random Forests resides in amalgamating multiple decision trees to curb overfitting and augment the model's accuracy. This objective is realized by training each tree on a randomly selected subset of the data and considering a random subset of the features at every split. Such a strategy decouples the trees, rendering the ensemble more resilient to overfitting. Furthermore, Random Forest employs a metric of feature importance to discern the most informative features for data splits. Evidently, Random Forest emerges as a supervised machine learning algorithm, ubiquitously applied in both classification and regression challenges. It harnesses decision trees, constructed on disparate samples, and adopts a majority voting mechanism for classification, while resorting to averaging for regression tasks. The genesis of the algorithm for random decision forests can be traced back to 1995, pioneered by Tin Kam Ho, marking a significant milestone in the evolution of ensemble learning methodologies. Through the prism of this algorithm, the synergy of decision trees, when orchestrated in a Random Forest ensemble, holds the promise of delivering superior predictive insights while averting the pitfalls of overfitting, hence exemplifying a robust machine learning approach for a myriad of analytical undertakings [277] utilizing the random subspace method, which is a method to implement the "stochastic discrimination" approach to classification as proposed by Eugene Kleinberg [278]. An extension of the algorithm was cultivated by Leo Breiman and Adele Cutler [279], who registered "Random Forests" as a trademark in 2006. Random forest algorithms have showcased robust predictive capabilities for both small sample sizes and high-dimensional data, gaining popularity across industries and businesses. In the realm of laser welding, Random Forest can be employed to predict the occurrence of porosity, a prevalent issue in laser welding of Al-alloys. Hydrogen-induced porosity is typified by small blowholes, engendered by the high average temperature of the molten pool, which escalates the solubility of hydrogen, leading to the formation of a plethora of pores. To mitigate porosity, it's imperative to eliminate the source of hydrogen during welding. Another variant of porosity in laser welding is induced by the intense metal evaporation in the keyhole, which exacerbates the instability of the keyhole and weld pool. This type of porosity can be ameliorated through judicious pulse shaping in spot welding and the adoption of optimal pulse modulation. In this investigation, Random Forest classification was employed to prognosticate the occurrence of porosity in keyhole laser welding of overlap aluminum laser welding. A dataset comprising 720 ROIs labeled as "Pass" and 720 ROIs labeled as "Fail" was harnessed to train the RF classification model. The model attained a classification accuracy of nearly 80%, substantiating that the RF-based monitoring scheme is proficient in accurately predicting porosity occurrence. Additionally, an intelligent ML-based model integrating computer-integrated manufacturing (CIM) and artificial intelligence (AI) for data-driven adaptability throughout the production cycle was proposed. Figure 67 delineates a comprehensive diagram of various machine learning algorithms.

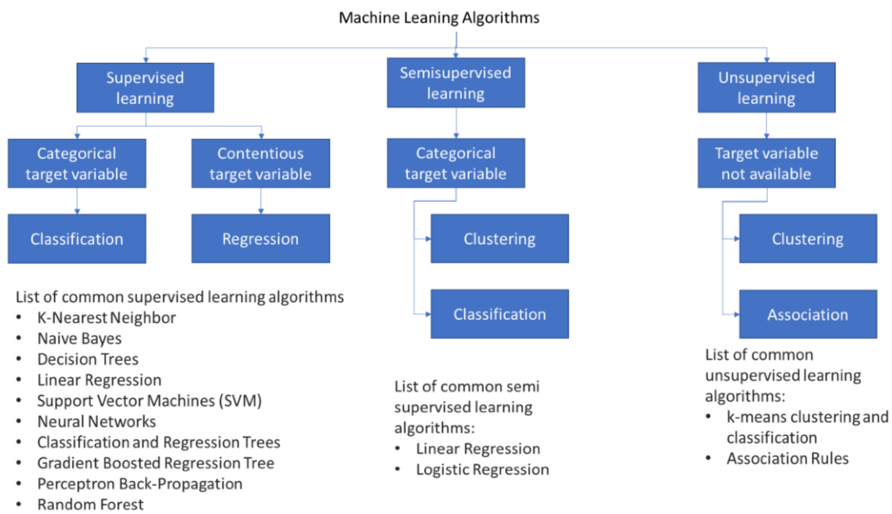


Figure 67. A comprehensive diagram of various machine learning algorithms [280]

In deploying a Random Forest model, there are three principal hyperparameters that necessitate configuration: the node size, the number of trees, and the count of features sampled at each split. These parameters can be fine-tuned to enhance the model's performance. Additionally, a segment of the training data, designated as the out-of-bag (oob) sample, is allocated for cross-validation purposes. The Random Forest algorithm introduces an element of randomness via feature bagging, which augments the diversity in the dataset and diminishes correlation amongst decision trees (Figure 68). The ultimate prediction is ascertained differently contingent on the nature of the problem: for regression undertakings, the predictions from individual decision trees are averaged, while for classification tasks, a majority vote is garnered among the categorical variables. The oob sample is subsequently employed for final cross-validation. The procedural steps encompassed in the Random Forest algorithm are delineated as follows:

- Selection of a random data subset from the training set.
- Construction of a decision tree on the selected data subset.
- Iteration of steps 1 and 2 for a predefined number of trees (n_estimators).
- Utilization of the majority vote or the mean of the predictions from each decision tree as the final prediction.

- Employment of the oob sample for cross-validation.
- Hyperparameter adjustments as requisite to optimize the model's performance.

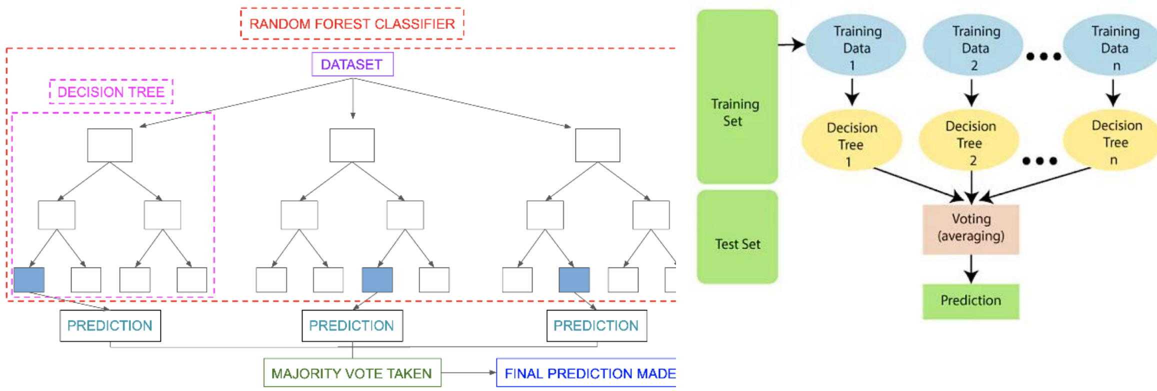


Figure 68. Diagram of Random Forest Classifier [281]

The merits of the Random Forest algorithm are manifold, encompassing a diminished propensity for overfitting, a pronounced flexibility, and a facile determination of feature importance. A salient advantage of the Random Forest algorithm lies in its capability to mitigate the risk of overfitting, a prevalent issue in decision tree models. This is realized through the averaging of predictions from uncorrelated decision trees, engendering a reduction in overall variance and prediction error, thereby rendering the Random Forest algorithm a robust predictor for both small sample sizes and high dimensional data. Another notable benefit of the Random Forest algorithm is its inherent flexibility. The algorithm adeptly handles both continuous variables in regression scenarios and categorical variables in classification tasks. Moreover, the feature bagging technique employed within the algorithm renders it an efficacious tool for imputing missing values, maintaining accuracy even in the presence of missing data portions. Furthermore, the Random Forest algorithm facilitates straightforward determination of feature importance by evaluating each variable's contribution to the model. Various methods, such as Gini importance, Mean Decrease in Impurity (MDI), and Permutation Importance (or Mean Decrease Accuracy (MDA)), can be employed to ascertain feature importance. These measures afford insights into the variables pivotal for the model, aiding in the elucidation of underlying data patterns. The mathematical exploration of Random Forests predominantly centers on comprehending the properties of the ensemble in totality and its application in prediction endeavors. Some quintessential concepts in the mathematical analysis of Random Forests include:

- **Bias-variance trade-off:** Random Forests curtail overfitting by averaging across myriad distinct decision trees. Each tree is trained on a disparate data subset, resulting in an ensemble with lower variance as compared to a singular decision tree. Nonetheless, the ensemble exhibits higher bias than a single decision tree, necessitating a consideration of the trade-off between bias and variance when employing Random Forests.
- **Feature importance:** Random Forests can be utilized to estimate the importance of each feature in the data, typically by measuring the decrease in impurity (e.g., Gini impurity or entropy) when a feature is employed to split the data. Features precipitating larger decreases in impurity are deemed more significant.
- **Out-of-bag error estimation:** Given that each tree is trained on a distinct data subset, the error of the ensemble can be estimated by averaging the predictions of the trees on samples not used in training each tree. This is termed the out-of-bag error estimate, serving as a proficient approximation of the model's true error.
- **Generalization error:** The generalization error of Random Forests can be upper bounded utilizing Rademacher complexity or PAC-Bayesian bounds. Additionally, the Bernstein inequality can bound the generalization error when the base learner is a decision tree, and the sample size is substantial.

It warrants mention that the mathematical analysis of Random Forests is a vibrant research domain, with numerous other concepts and techniques employed to comprehend and optimize the performance of these models. The mathematical formulation of Random Forests amalgamates decision tree learning and statistical learning techniques. At a macroscopic level, the fundamental steps in training a Random Forest encompass:

1. Generating a random data subset (with replacement) to create a bootstrap sample.
2. Selecting a random feature subset for each split in the decision tree.

3. Training a decision tree on the bootstrap sample, utilizing the random feature subset for each split.
4. Iterating through steps 1-3 for a specified number of trees (n_estimators).
5. For classification, the mode of the predictions from individual trees is taken for each sample, while for regression, the mean of the predictions from individual trees is taken for each sample.

In terms of mathematical notation, let T be the number of decision trees in the random forest, N be the number of samples in the training set, M be the number of features, $fi(x)$ be the prediction of the i-th tree for a sample x, and y the true label for x.

The prediction for a given sample is typically computed as:

- For classification: $f(x) = mode(f1(x), f2(x), \ldots, fT(x))$
- For regression: $f(x) = mean(f1(x), f2(x), \ldots, fT(x))$

The overarching objective of training a Random Forest is to curtail the expected prediction error, typically assessed through metrics such as Mean Squared Error (MSE) for regression tasks or classification error rate for classification tasks. The generalization error in Random Forests is often evaluated via the Out-of-Bag (OOB) error, constituting an error rate estimate of the Random Forest model derived from the mean error rate of predictions rendered by individual trees on out-of-bag samples. Additionally, mathematical optimization methodologies like gradient descent can be harnessed to ascertain optimal values of the Random Forest parameters, encompassing the number of trees, the depth of each tree, and the number of features considered at each split. In any Random Forest model, multiple indicators reflecting feature importance can be computed. One such indicator predicated on the OOB error is termed Mean Decrease Accuracy (MDA), which essentially disrupts the eigenvalues of the out-of-bag sample data randomly and subsequently re-evaluates the OOB error for each engendered tree. In this study, the Random Forest Classification algorithm was applied to a dataset of pass and fail samples using the python library, with the parameters n_estimators =100, criterion = 'gini', max_features= 5, and random_state = 0. The ensuing confusion matrix and feature importance were delineated based on the predictions of pass and fail. A pronounced challenge posed by the Random Forest algorithm resides in its time-intensive nature. Given its capability to manage large datasets, the data computation for each distinct decision tree can be sluggish. Moreover, larger datasets necessitate more resource allocation for storage. Additionally, the prediction from a singular decision tree is generally more interpretable compared to a forest of decision trees, rendering the Random Forest algorithm more intricate. A cardinal advantage of the Random Forest algorithm is its reduced susceptibility to overfitting. Decision trees inherently risk overfitting as they endeavor to snugly fit all samples within the training data. However, employing a substantial number of decision trees in a Random Forest ensures the classifier won't overfit the model, as the averaging of uncorrelated trees diminishes the overall variance and prediction error. The Random Forest algorithm also epitomizes flexibility as it adeptly handles both regression and classification tasks with commendable accuracy, thereby enjoying popularity among data scientists. Moreover, the algorithm facilitates effortless evaluation of variable importance or contribution to the model. Permutation feature importance is a technique employed to gauge a feature's importance in the Random Forest algorithm by computing the augmentation in the model's prediction error subsequent to permuting the feature's values. Introduced by Breiman (2001) [282] this method enables the discernment of a feature's importance or lack thereof, based on its impact on the model's error. The permutation feature importance algorithm proposed by Fisher, Rudin, and Dominici [283] was also leveraged in this study to further scrutinize the feature importance and its correlation to the model's prediction error.

5.12.2 Permutation Feature Importance

The notion of Geometrical Feature Importance entails the evaluation of the criticality of a specific geometric feature in delineating the outcome of a classification or regression problem. Within the ambit of laser welding, the geometry of the keyhole is a pivotal feature influencing weld quality and porosity formation. The Random Forest algorithm emerges as a potent tool for gauging feature importance in laser welding scenarios. It operates by training a multitude of decision trees on diverse data subsets and subsequently amalgamating the predictions of these trees to furnish a final prediction. Through scrutinizing the relative importance of disparate features in determining the prediction outcome, Random Forest aids in pinpointing which geometric attributes of the keyhole are most crucial to weld quality. Practically, Geometrical Feature Importance can be ascertained employing a spectrum of techniques, including Permutation Feature Importance, Gini Importance, and Mean Decrease in Impurity (MDI). These methodologies function by assessing the alteration in the model's prediction error post the permutation or exclusion of a specific feature. For instance, Permutation Feature Importance quantifies the augmentation in the model's prediction error following the permutation of a feature's values, thereby disrupting the correlation between the feature and the actual outcome. A feature is deemed "important" if shuffling its values escalates the model error, indicative of the model's reliance on that feature for prediction. Conversely, a feature is branded "unimportant" if its value shuffling leaves the model error unaltered, signifying the model's disregard for that feature in prediction. Broadly, Geometrical Feature Importance is a salient concept for comprehending the dynamics of laser welding and for crafting efficacious methodologies for monitoring and controlling the welding process. By identifying the key features of the keyhole, it becomes feasible to devise models and algorithms capable of predicting and thwarting porosity formation and other defects, thereby enhancing weld quality and augmenting efficiency in the welding process. The Permutation Feature Importance algorithm, a modality for discerning feature importance in machine learning models, hinges on the premise that a feature's importance is inversely related to the model's performance post-permutation of that feature's values. Proposed by Fisher, Rudin, and Dominici [283], the algorithm unfolds as follows:

1. Inaugurate by training a machine learning model on a dataset encompassing all features.
2. For each feature, execute a random permutation of its values in the test set, retaining the training set intact.
3. Compute the model's performance on the permuted test set.
4. Determine the deviation between the original performance and the performance on the permuted test set, as this disparity measures the feature's importance.

5. Iterate steps 2-4 multiple times to obtain a more robust estimate of feature importance.

This algorithm holds a distinct advantage over other feature selection methods due to its model-agnostic nature, computational efficiency, and applicability to large datasets. Moreover, it provides a straightforward and intuitive pathway to discern which features significantly impact a model. However, certain limitations are inherent, such as sensitivity to the choice of performance metric for model evaluation, and potential inadequacy in dealing with highly correlated features. Despite these limitations, the Permutation Feature Importance algorithm remains a valuable asset for understanding the importance of features in a machine learning model. The mathematical formula for computing permutation feature importance: Let X be the matrix of features and y be the vector of labels. Let f be a machine learning model trained on (X, y) and let P be a permutation matrix.

1. Train the model f on (X, y).
2. For each feature i, randomly permute the values of the feature in the test set to obtain X_P, where X_P = XP(:, P(i)).
3. Compute the model's performance on the permuted test set, denoted as the score_perm.
4. Calculate the difference between the original score and the score_perm for feature i: diff_i = score - score_perm
5. Repeat steps 2-4 M times to get a set of M differences diff_1, diff_2, ..., diff_M for each feature.
6. Compute the average difference for each feature i:

PI_i = (1/M) * sum_{j=1}^{M} diff_{i,j}   (9)

The PI_i value for feature i represents the permutation feature importance of that feature. A larger PI_i value indicates that the feature is more important in the model. In the context of laser welding, geometrical feature importance refers to the measurement of the relative importance of different geometric characteristics of the keyhole, such as shape, size, and depth, in relation to the overall quality and integrity of the weld. This measurement can be determined using machine learning methods such as random forest, which are able to analyze large datasets and identify patterns and correlations between different features and the outcome of the welding process. One of the key advantages of using random forest for feature importance analysis in laser welding is that it is able to handle both continuous and categorical variables, making it well-suited for analyzing the complex and multifaceted nature of the keyhole. Additionally, the algorithm is able to provide a measure of feature importance that is both robust and reliable, as it takes into account the interactions between different features and the overall effect on the welding process. Figure 69 delineates the importance of 22 features as ascertained through the Random Forest methodology. Concurrently, Figure 70 exhibits the results of Random Forest Prediction, with panel A illustrating the Confusion Matrix with a test size of 20%, and panel B showcasing a representative Random Forest decision tree. The process of determining feature importance in laser welding using random forest typically involves the following steps:

1. **Collect and preprocess the data:** This involves acquiring large datasets of images and measurements of the keyhole and laser welding process, and cleaning, formatting, and normalizing the data for analysis.
2. **Train the random forest model:** The dataset is then split into training and testing sets, and the random forest model is trained on the training set using a variety of hyperparameters, such as the number of decision trees and the number of features sampled.
3. **Measure feature importance:** Once the model has been trained, the feature importance can be measured using techniques such as Gini importance, mean decrease in impurity (MDI), or permutation importance (MDA).
4. **Analyze and interpret the results:** The results of the feature importance analysis can then be used to identify the most important geometric characteristics of the keyhole and how they relate to the overall quality and integrity of the weld. This information can then be used to improve the laser welding process and optimize the keyhole geometry for better performance.

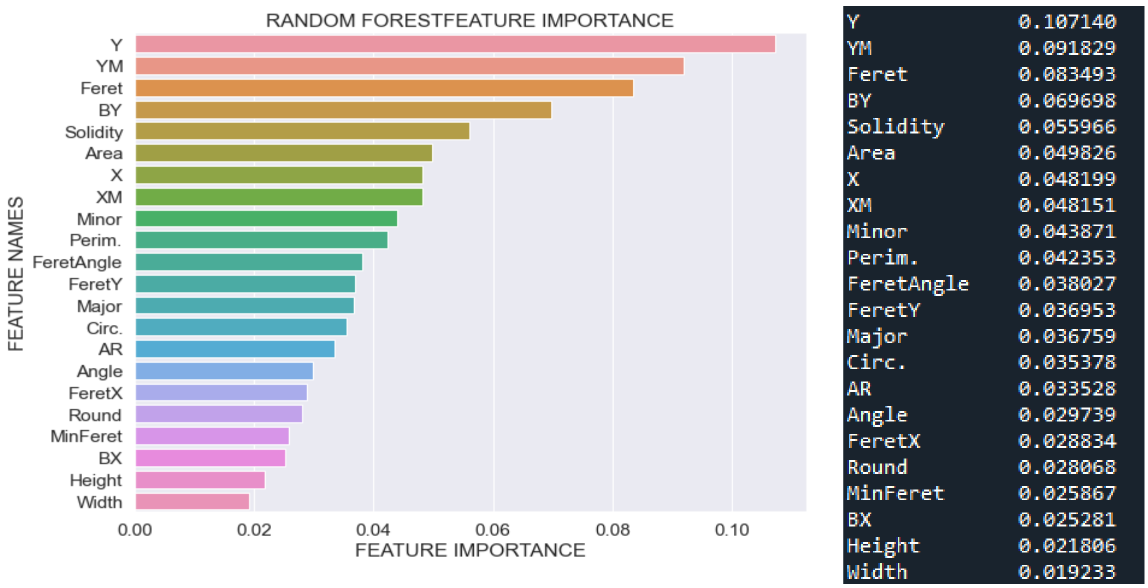
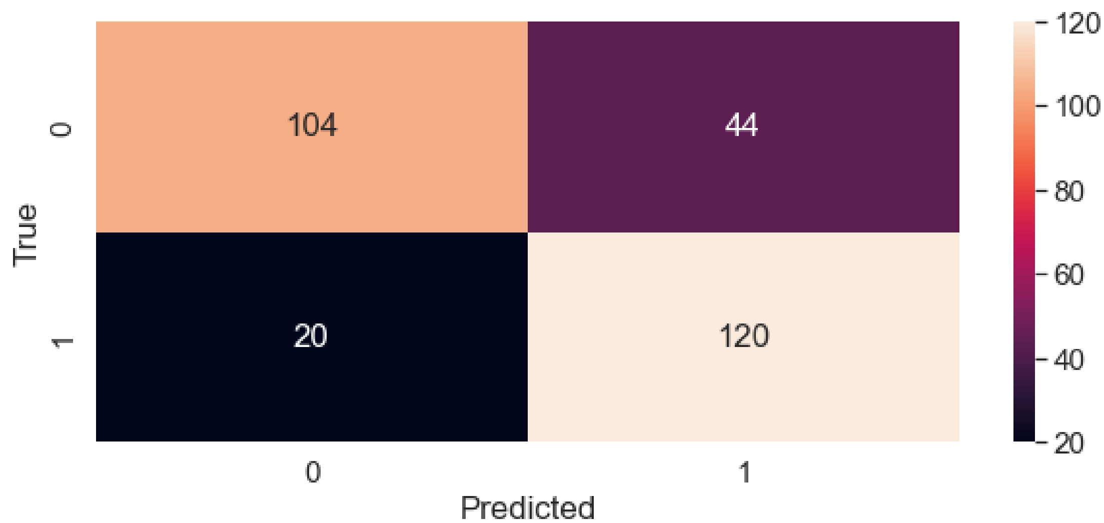
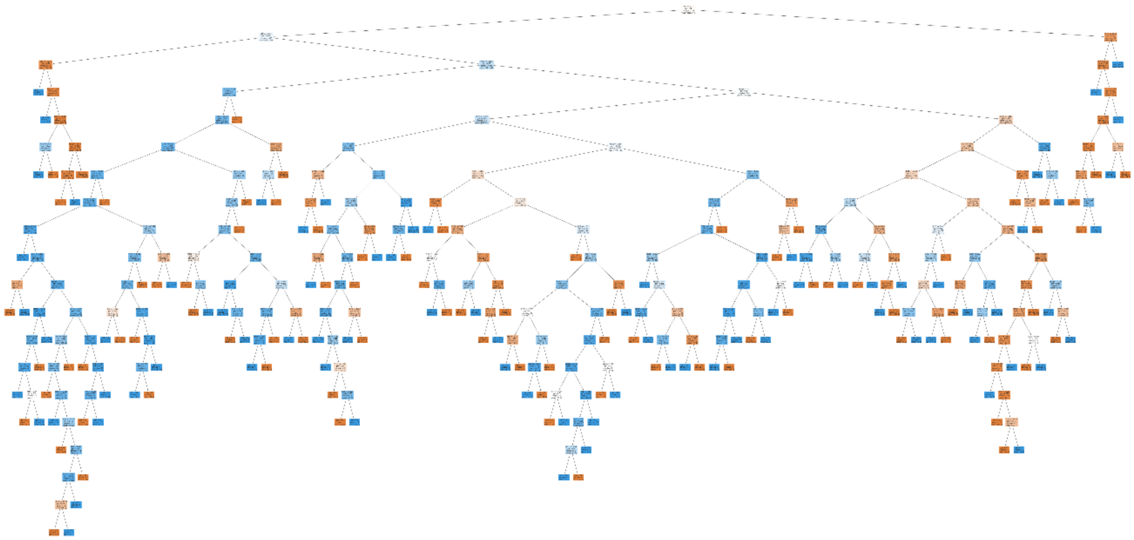


Figure 69. Random forest feature importance analysis



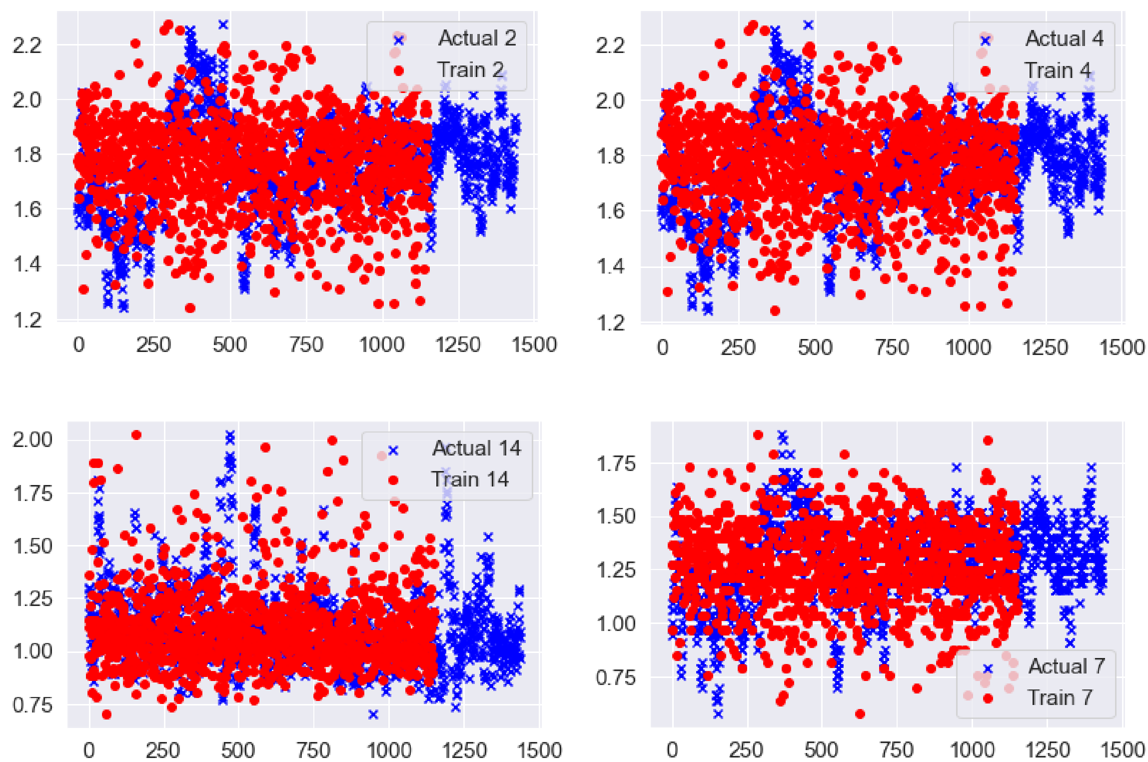
(a)



(b)

Figure 70. Random Forest Prediction. A) Confusion matrix Test size 20 % and b) Random Forest decision tree

An actual vs. predicted model diagram is a type of plot used to visualize the performance of a predictive model. The diagram shows the actual values of the target variable (i.e., what was observed or measured) plotted against the predicted values (i.e., what the model estimated or forecasted). In the case of binary classification (i.e., pass/fail), the diagram might show actual pass instances plotted against predicted pass instances on one axis, and actual fail instances plotted against predicted fail instances on the other axis. The ideal scenario would be for all points to fall along the diagonal line, indicating perfect predictions. However, in practice, the model will make some errors, and the points will deviate from the diagonal line. The diagram can help to visualize the nature and extent of these errors, which can inform model improvements or changes to the data used to train the model. Plotting the actual vs random forest predictive model diagram is a common approach for evaluating the performance of a machine learning algorithm for image processing tasks, such as object detection or segmentation. In this approach, the algorithm is trained on a set of labeled images to learn to recognize specific features or objects, and then it is tested on a separate set of images to evaluate its accuracy and generalization ability. The actual vs predictive model diagram is a scatter plot that compares the true labels of the test images (i.e., the actual values) with the predicted labels generated by the machine learning algorithm. Each point in the plot represents an individual test image, where the x-axis corresponds to the actual label and the y-axis corresponds to the predicted label. If the algorithm is performing well, the points should be close to the diagonal line (y = x), indicating that the predicted labels are similar to the actual labels. This type of evaluation can provide insights into the strengths and weaknesses of the machine learning algorithm, as well as help to identify areas for improvement. However, it is important to note that this approach is just one of many evaluation methods, and it should be used in combination with other techniques, such as cross-validation, to ensure the reliability and robustness of the algorithm. Overall, the actual vs. predicted model diagram is a useful tool for evaluating the performance of a predictive model and gaining insights into how it can be improved (Figure 71).



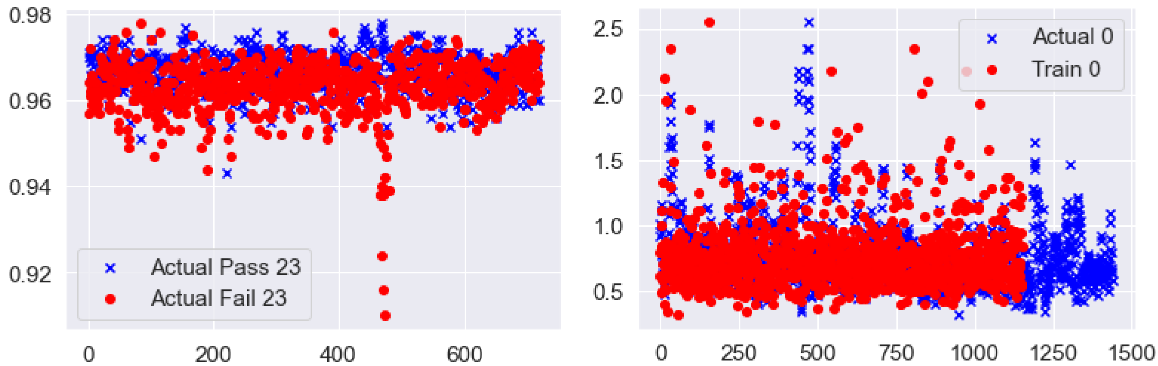


Figure 71. Comparison between actual and predictive model

5.12.3 Model performance report

Table 33 shows the performance metric of the model. Precision measures the accuracy of positive predictions, recall measures the fraction of positive instances that were correctly classified, and F1-score is the harmonic mean of precision and recall. Support indicates the number of samples in each class. The results of the random forest classification model indicate an overall accuracy of 78%, with precision of 0.84 for the "Pass" class and 0.73 for the "Fail" class. The recall score for the "Pass" class is 0.70, while the recall score for the "Fail" class is 0.86. The F1-scores for the "Pass" and "Fail" classes are 0.76 and 0.79, respectively. The precision score for the "Pass" class indicates that when the model predicts a "Pass" result, it is correct 84% of the time. Similarly, the precision score for the "Fail" class indicates that when the model predicts a "Fail" result, it is correct 73% of the time. The recall score for the "Pass" class suggests that the model correctly identified 70% of the "Pass" results, while the recall score for the "Fail" class indicates that the model correctly identified 86% of the "Fail" results. The F1-score provides a balance between precision and recall, with the score for the "Pass" class being 0.76 and for the "Fail" class being 0.79. Overall, the results suggest that the random forest classification model is effective in predicting the occurrence of porosity in keyhole laser welding of overlap aluminum laser welding, with an accuracy of 78%. This indicates that the model is able to correctly classify 78% of the samples in the dataset. The precision, recall, and F1-score metrics suggest that the model performs better at predicting the "Pass" class than the "Fail" class, which may indicate a class imbalance in the dataset. It is important to note that the accuracy of the model could be further improved by increasing the size of the dataset, as well as by fine-tuning the model hyperparameters. Additionally, further analysis of the features used in the model could provide insights into the most important factors contributing to the occurrence of porosity in laser welding. In conclusion, the random forest classification model is a promising approach for predicting the occurrence of porosity in laser welding and could be useful in quality control and process optimization in industrial settings. However, further research is needed to optimize the model and to validate its effectiveness in real-world applications.

Table 33. Performance metric of model

	Precision	**Recall**	**F1-score**	**Support**
Pass	0.84	0.70	0.76	148
Fail	0.73	0.86	0.79	140
Accuracy			0.78	288
Macro avg	0.79	0.78	0.78	288
weighted avg	0.79	0.78	0.78	288

5.13 CONCLUSION

In conclusion, the study investigated the occurrence of porosity in keyhole laser welding of overlap aluminum laser welding. The study explored the use of a random forest classification model to predict the occurrence of porosity in the welding process. The model was trained and tested on a dataset of welding samples, and the performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. The results of the study suggest that the random forest classification model is effective in predicting the occurrence of porosity in keyhole laser welding of overlap aluminum laser welding, with an overall accuracy of 78%. The precision, recall, and F1-score metrics suggest that the model performs better at predicting the "Pass" class than the "Fail" class, which may indicate a class imbalance in the dataset. It is important to note that the accuracy of the model could be further improved by increasing the size of the dataset, as well as by fine-tuning the model hyperparameters. Additionally, further analysis of the features used in the model could provide insights into the most important factors contributing to the occurrence of porosity in laser welding. The study has important implications for quality control and process optimization in industrial settings. The random forest classification model could be used as a tool to identify potential defects in the welding process and to optimize the parameters to reduce the occurrence of porosity. However, further research is needed to optimize the model and to validate its effectiveness in real-world applications.

5.14 REFERENCE

[245] M. Tisza, Development of lightweight steels for automotive applications, in: Engineering Steels and High Entropy-Alloys, Intech Open, 2020.

[246] J. Szyndler, L. Madej, Metal forming methods dedicated for aerospace industry, Computer Methods in Materials Science. 15 (2015) 294–310.

[247] T. Trzepieciński, Recent Developments and Trends in Sheet Metal Forming, Metals (Basel). 10 (2020) 779.

[248] V. Prakash, D.R. Kumar, Performance evaluation of bio-lubricants in strip drawing and deep drawing of an aluminium alloy, Advances in Materials and Processing Technologies. (2020) 1–14.

[249] R. Dwivedi, G. Agnihotri, Study of deep drawing process parameters, Mater Today Proc. 4 (2017) 820–826.

[250] J. Tenner, K. Andreas, A. Radius, M. Merklein, Numerical and experimental investigation of dry deep drawing of aluminum alloys with conventional and coated tool surfaces, Procedia Eng. 207 (2017) 2245–2250.

[251] W.-C. Xiao, B.-Y. Wang, Y. Kang, W.-P. Ma, X.-F. Tang, Deep drawing of aluminum alloy 7075 using hot stamping, Rare Metals. 36 (2017) 485–493.

[252] M. Habibi, R. Hashemi, M.F. Tafti, A. Assempour, Experimental investigation of mechanical properties, formability and forming limit diagrams for tailor-welded blanks produced by friction stir welding, J Manuf Process. 31 (2018) 310–323.

[253] M. Merklein, M. Geiger, New materials and production technologies for innovative lightweight constructions, J Mater Process Technol. 125 (2002) 532–536.

[254] A. Graf, Aluminum alloys for lightweight automotive structures, in: Materials, Design and Manufacturing for Lightweight Vehicles, Elsevier, 2021: pp. 97–123.

[255] F. Findik, Recent developments in explosive welding, Mater Des. 32 (2011) 1081–1093.

[256] D. Ren, L. Liu, Y. Li, Investigation on overlap joining of AZ61 magnesium alloy: laser welding, adhesive bonding, and laser weld bonding, The International Journal of Advanced Manufacturing Technology. 61 (2012) 195–204.

[257] Z.M. Beiranvand, F.M. Ghaini, H.N. Moosavy, M. Sheikhi, M.J. Torkamany, M. Moradi, The relation between magnesium evaporation and laser absorption and weld penetration in pulsed laser welding of aluminum alloys: Experimental and numerical investigations, Opt Laser Technol. 128 (2020) 106170.

[258] S. Janasekaran, M.F. Jamaludin, M.R. Muhamad, F. Yusof, M.H. Abdul Shukor, Autogenous double-sided T-joint welding on aluminum alloys using low power fiber laser, The International Journal of Advanced Manufacturing Technology. 90 (2017) 3497–3505.

[259] A. Aminzadeh, A. Parvizi, M. Moradi, Multi-objective topology optimization of deep drawing dissimilar tailor laser welded blanks; experimental and finite element investigation, Opt Laser Technol. 125 (2020) 106029. https://doi.org/10.1016/J.OPTLASTEC.2019.106029.

[260] R. Lin, H. Wang, F. Lu, J. Solomon, B.E. Carlson, Numerical study of keyhole dynamics and keyhole-induced porosity formation in remote laser welding of Al alloys, Int J Heat Mass Transf. 108 (2017) 244–256.

[261] S. Katayama, Y. Kawahito, M. Mizutani, Elucidation of laser welding phenomena and factors affecting weld penetration and welding defects, Phys Procedia. 5 (2010) 9–17.

[262] J. Xu, Y. Rong, Y. Huang, P. Wang, C. Wang, Keyhole-induced porosity formation during laser welding, J Mater Process Technol. 252 (2018) 720–727.

[263] B. Zhang, K.-M. Hong, Y.C. Shin, Deep-learning-based porosity monitoring of laser welding process, Manuf Lett. 23 (2020) 62–66.

[264] X. Cao, W. Wallace, C. Poon, J.-P. Immarigeon, Research and progress in laser welding of wrought aluminum alloys. I. Laser welding processes, Materials and Manufacturing Processes. 18 (2003) 1–22.

[265] R.S. Velmurugan, T. Dhingra, Intelligent Predictive Maintenance: Industry 4.0, in: Asset Maintenance Management in Industry, Springer, 2021: pp. 113–135.

[266] H. Wang, J. Liu, Y. Xu, X. Wang, N. Ren, X. Ren, Q. Hu, Experimental characterization and real-time monitoring for laser percussion drilling in titanium alloy using transverse electric field assistance and/or lateral air blowing, J Manuf Process. 62 (2021) 845–858.

[267] C. Knaak, G. Kolter, F. Schulze, M. Kröger, P. Abels, Deep learning-based semantic segmentation for in-process monitoring in laser welding applications, in: Applications of Machine Learning, 2019: pp. 10–22.

[268] T.S. Singhal, J.K. Jain, M. Kumar, V. Bhojak, K.K. Saxena, D. Buddhi, C. Prakash, A comprehensive comparative review: welding and additive manufacturing, International Journal on Interactive Design and Manufacturing (IJIDeM). (2023) 1–15.

[269] J. Schindelin, I. Arganda-Carreras, E. Frise, V. Kaynig, M. Longair, T. Pietzsch, S. Preibisch, C. Rueden, S. Saalfeld, B. Schmid, others, Fiji: an open-source platform for biological-image analysis, Nat Methods. 9 (2012) 676–682.

[270] S.M. Hartig, Basic image analysis and manipulation in ImageJ, Curr Protoc Mol Biol. 102 (2013) 14–15.

[271] H. Pirsiavash, D. Ramanan, Detecting activities of daily living in first-person camera views, in: 2012 IEEE Conference on Computer Vision and Pattern Recognition, 2012: pp. 2847–2854.

[272] B. Hamoud, A. Kashevnik, W. Othman, N. Shilov, Neural Network Model Combination for Video-Based Blood Pressure Estimation: New Approach and Evaluation, Sensors. 23 (2023) 1753.

[273] X. Ran, H. Chen, X. Zhu, Z. Liu, J. Chen, Deepdecision: A mobile deep learning framework for edge video analytics, in: IEEE INFOCOM 2018-IEEE Conference on Computer Communications, 2018: pp. 1421–1429.

[274] Q. Huynh-Thu, M. Ghanbari, Temporal aspect of perceived quality in mobile video broadcasting, IEEE Transactions on Broadcasting. 54 (2008) 641–651.

[275] M.D. Abràmoff, P.J. Magalhães, S.J. Ram, Image processing with ImageJ, Biophotonics International. 11 (2004) 36–42.

[276] U. Guide, T. Ferreira, W. Rasband, ImageJ 1.44 The ImageJ User Guide 1.44, 2011.

[277] T.K. Ho, Random decision forests, in: Proceedings of 3rd International Conference on Document Analysis and Recognition, 1995: pp. 278–282.

[278] E.M. Kleinberg, Stochastic discrimination, Ann Math Artif Intell. 1 (1990) 207–239.

[279] A. Cutler, D.R. Cutler, J.R. Stevens, Random forests, Ensemble Machine Learning: Methods and Applications. (2012) 157–175.

[280] B. Mahesh, Machine learning algorithms-a review, International Journal of Science and Research (IJSR). 9 (2020) 381–386.

[281] I.V. Vamsi, N. Abhinav, A.K. Verma, S. Radhika, Random forest based real time fault monitoring system for industries, in: 2018 4th International Conference on Computing Communication and Automation (ICCCA), 2018: pp. 1–6.

[282] B. Gregorutti, B. Michel, P. Saint-Pierre, Correlation and variable importance in random forests, Stat Comput. 27 (2017) 659–678.

[283] A. Fisher, C. Rudin, F. Dominici, All models are wrong but many are useful: variable importance for black-box, proprietary, or misspecified prediction models, using model class reliance, ArXiv Preprint ArXiv:1801.01489. 1 (2018).

CONCLUSION GÉNÉRALE

Cette étude exhaustive sur le soudage au laser des alliages d'aluminium, dans le contexte de l'Industrie 4.0, a abordé la collecte de données critiques comme les paramètres thermiques et la géométrie du bain de soudure via des technologies de pointe telles que les caméras thermiques et haute résolution, radiographie et 3D. Elle a intégré des modèles d'apprentissage automatique avancés, tels que Random Forest (RF), pour analyser ces données et prédire les défauts de soudage, tels que la porosité et les distorsions. Les avancées technologiques réalisées permettent des améliorations significatives dans la surveillance en temps réel et l'optimisation des processus de soudage, abordant efficacement les défis de gestion de la porosité et des distorsions thermiques. Le nouveau modèle proposé combine la surveillance par capteurs et l'analyse par apprentissage automatique, marquant une tendance vers une gestion plus intelligente des processus de soudage. Cette recherche souligne l'importance de l'innovation continue et ouvre la voie à des explorations futures pour une caractérisation plus précise et une meilleure qualité de soudage, illustrant l'impact profond de l'intégration de l'IA et des technologies avancées dans l'amélioration des processus de soudage au laser des alliages d'aluminium. En somme, cette étude offre une contribution substantielle à la compréhension et à l'amélioration des processus de soudage au laser, plaçant la technologie et l'innovation au cœur de l'avenir de la fabrication industrielle. Elle récapitulera les objectifs spécifiques qui ont été atteints et les principales conclusions de chaque chapitre.

Chapitre 1 : Vers une usine intelligente de flans soudés au laser en aluminium (ALWB) basée sur l'industrie 4.0 ; examen critique et nouveau modèle intelligent

Le premier chapitre de cette étude a jeté les bases théoriques en examinant l'influence révolutionnaire de l'Industrie 4.0 sur les processus de fabrication contemporains, se concentrant spécifiquement sur le soudage laser des alliages d'aluminium. Il a identifié et discuté les défis critiques associés à cette technique, tels que le contrôle de la porosité et la minimisation des distorsions, soulignant ainsi l'impératif d'intégrer des innovations technologiques pour adresser ces problèmes. De plus, ce chapitre a articulé l'objectif principal de la recherche : développer une approche intégrée exploitant les progrès de l'Industrie 4.0 pour accroître substantiellement la qualité et l'efficacité du soudage. Par conséquent, il a mis en exergue l'importance de fusionner les technologies avancées avec les techniques de fabrication établies afin de satisfaire les demandes de production actuelles, illustrant la synergie entre innovation technologique et pratique manufacturière.

Chapitre 2 : Analyse bibliométrique de l'intelligence artificielle et du suivi en temps réel de la technologie du soudage à l'ère de l'industrie 4.0

Ce chapitre détaille une analyse bibliométrique sur l'application de l'intelligence artificielle (IA) dans le soudage, en se concentrant particulièrement sur la surveillance en temps réel. Il révèle un intérêt croissant pour l'utilisation de l'IA afin d'optimiser le contrôle de qualité et d'améliorer les processus de soudage grâce à des technologies avancées. Cette étude met également en lumière les défis associés à l'implémentation de l'IA dans les pratiques de soudage, incluant la complexité des données et le besoin de compétences spécialisées. Les résultats soulignent l'impact positif potentiel de l'IA sur le soudage tout en indiquant les obstacles à surmonter pour intégrer pleinement les innovations de l'Industrie 4.0.

Chapitre 3 : Numérisation 3d en temps réel de flans soudés au laser en aluminium 5052-h32 ; caractérisation géométrique et de soudage

Ce chapitre illustre une avancée dans l'optimisation du soudage laser des alliages d'aluminium 5052-H32 via la numérisation 3D pour une caractérisation géométrique et de soudage précise en temps réel. L'intégration de cette technologie a facilité la détermination des conditions opérationnelles optimales pour réduire les distorsions thermiques et la porosité. L'analyse a identifié les distorsions supérieures à ±3 mm comme un seuil critique pour la qualité du soudage, nécessitant des ajustements pour assurer la conformité aux standards de qualité. Cette découverte promeut une amélioration significative des techniques de soudage en offrant une compréhension approfondie de l'impact de la dynamique du soudage laser sur les propriétés des assemblages soudés.

Chapitre 4 : Analyse expérimentale du soudage laser à fibres superposées pour les alliages d'aluminium : reconnaissance de la porosité et inspection de la qualité

Ce chapitre dévoile une étude approfondie sur la reconnaissance de la porosité dans les soudures laser d'aluminium à recouvrement, combinant des techniques expérimentales et analyses statistiques. Utilisant la radiographie numérique pour une visualisation précise des défauts et analysant l'impact des profils des faisceaux laser sur la porosité, cette recherche a permis de comprendre les mécanismes de formation de la porosité et d'identifier les paramètres critiques l'influençant. Des avancées dans la minimisation de la porosité ont été réalisées par l'optimisation des paramètres de soudage, comme l'énergie du laser et la vitesse de soudage, améliorant ainsi la qualité et la fiabilité des joints soudés pour diverses applications industrielles.

Chapitre 5 : Surveillance en temps réel de la porosité du soudage laser de l'aluminium à l'aide de l'apprentissage automatique basé sur les caractéristiques de la morphologie 3D du trou de serrure

Ce chapitre clôt l'étude en mettant en lumière l'intégration de l'apprentissage automatique pour le contrôle en temps réel de la porosité lors du soudage au laser, via l'analyse des caractéristiques morphologiques 3D du trou de serrure. Grâce à l'utilisation de caméras haute vitesse pour la collecte de données du bain de soudure et à l'application d'un modèle de Random Forest pour la prédiction de porosité, cette approche représente une avancée notable. Les résultats illustrent l'efficacité de cette méthode pour la détection précise de la porosité en temps réel, révélant l'impact profond de l'IA sur l'amélioration des processus de soudage au laser. Cette innovation promet une amélioration significative de la qualité des soudures, offrant un mécanisme efficace pour l'ajustement des paramètres de soudage et la minimisation des défauts, conforme aux visions de l'Industrie 4.0.

En conclusion, cette étude apporte une contribution significative à la compréhension des processus de soudage au laser des alliages d'aluminium en intégrant l'Industrie 4.0, offrant une vision globale des avancées technologiques et des méthodologies innovantes pour surmonter les défis de fabrication et améliorer la qualité et l'efficacité de la production.

RECOMMANDATIONS POUR LES TRAVAUX FUTURS

En se basant sur les résultats et les conclusions de cette thèse, voici quelques recommandations pour les travaux futurs :

1. Élargir l'étude à d'autres alliages d'aluminium : bien que cette thèse se soit concentrée sur l'alliage d'aluminium 5052-H32 et AA 6061-T6, il serait intéressant de répliquer les expériences avec d'autres alliages pour voir si les résultats sont similaires ou s'ils varient en fonction des propriétés du matériau.

2. Étendre la surveillance en temps réel à d'autres paramètres : cette thèse a montré comment l'apprentissage automatique peut être utilisé pour surveiller la porosité de la soudure en temps réel. Il serait intéressant d'étendre cette surveillance à d'autres paramètres, tels que la température, la pression et la vitesse, pour voir comment cela peut aider à améliorer la qualité de la soudure.

3. Utiliser l'apprentissage automatique pour optimiser les paramètres de soudure : bien que cette thèse ait utilisé l'apprentissage automatique pour surveiller la qualité de la soudure, il serait également intéressant d'utiliser cette technique pour optimiser les paramètres de soudure afin d'améliorer la qualité de la soudure dès le début du processus.

4. Développement de nouveaux processus de fabrication laser: Le développement de nouvelles technologies de fabrication laser permettra de produire des pièces plus complexes et plus précises. Par exemple, le développement de la fabrication additive basée sur le laser, telle que la fusion sélective par laser, la stéréolithographie et la fusion de lit de poudre, peut être exploré pour des applications industrielles.

5. Application de l'analyse en composantes principales (PCA) : La PCA est une méthode de réduction de la dimensionnalité qui permet de transformer les données en un ensemble de variables non corrélées appelées composantes principales. Cette

technique peut être appliquée à divers domaines tels que l'analyse de données, la reconnaissance de formes, la bio-informatique et l'analyse d'image.

6. Mise en œuvre de méthodes non supervisées: Les méthodes non supervisées sont des techniques d'apprentissage automatique qui ne nécessitent pas d'étiquetage des données. Elles peuvent être utilisées pour explorer des données de fabrication complexes, détecter des anomalies, segmenter des images et des vidéos, et effectuer d'autres tâches de traitement de données.

En résumé, l'exploration de nouvelles technologies de fabrication laser, l'application de l'analyse en composantes principales et la mise en œuvre de méthodes non supervisées peuvent aider à améliorer l'efficacité et la qualité des processus de fabrication. Ces domaines offrent des opportunités passionnantes pour la recherche future et peuvent conduire à des améliorations significatives dans l'industrie manufacturière.

RÉFÉRENCES BIBLIOGRAPHIQUES

Aminzadeh, A., Karganroudi, S. S., Meiabadi, M. S., Mohan, D. G., & Ba, K. (2022). A Survey of Process Monitoring Using Computer-Aided Inspection in Laser-Welded Blanks of Light Metals Based on the Digital Twins Concept. Quantum Beam Science 2022, Vol. 6, Page 19, 6(2), 19.

Aminzadeh, A., Parvizi, A., & Moradi, M. (2020). Multi-objective topology optimization of deep drawing dissimilar tailor laser welded blanks; experimental and finite element investigation. Optics & Laser Technology, 125, 106029.

Aminzadeh, A., Rahmatabadi, D., Pahlavani, M., Moradi, M., & Lawrence, J. (2023). Smart Laser Welding: A Strategic Roadmap Toward Sustainable Manufacturing in Industry 4.0. Sustainable Manufacturingin Industry 4.0: Pathways and Practices, 41–56.

Buongiorno, D., Prunella, M., Grossi, S., Hussain, S. M., Rennola, A., Longo, N., Di Stefano, G., Bevilacqua, V., & Brunetti, A. (2022). Inline Defective Laser Weld Identification by Processing Thermal Image Sequences with Machine and Deep Learning Techniques. Applied Sciences 2022, Vol. 12, Page 6455, 12(13), 6455.

ElMaraghy, H., Monostori, L., Schuh, G., & ElMaraghy, W. (2021). Evolution and future of manufacturing systems. CIRP Annals, 70(2), 635–658.

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2021). Substantial capabilities of robotics in enhancing industry 4.0 implementation. Cognitive Robotics, 1, 58–75.

Ma, D., Jiang, P., Shu, L., Gong, Z., Wang, Y., & Geng, S. (2033). Online porosity prediction in laser welding of aluminum alloys based on a multi-fidelity deep learning framework. Journal of Intelligent Manufacturing.

Pereira, T., Barreto, L., & Amaral, A. (2017). Network and information security challenges within Industry 4.0 paradigm. Procedia Manufacturing, 13, 1253–1260.

Ren, Z., Fang, F., Yan, N., & Wu, Y. (2021). State of the Art in Defect Detection Based on Machine Vision. International Journal of Precision Engineering and Manufacturing-Green Technology 2021 9:2, 9(2), 661–691.

Sharma, A., & Pandey, H. (2020). Big Data and Analytics in Industry 4.0. Advances in Science, Technology and Innovation, 57–72.

Stavridis, J., Papacharalampopoulos, A., & Stavropoulos, P. (2018). Quality assessment in laser welding: a critical review. International Journal of Advanced Manufacturing Technology, 94(5–8), 1825–1847.

Zhang, B., Hong, K. M., & Shin, Y. C. (2020). Deep-learning-based porosity monitoring of laser welding process. Manufacturing Letters, 23, 62–66.