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Machine Learning Driven Prediction, Optimization and Control in Wire Arc Additive Manufacturing: A Comprehensive Review

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Abstract - Industry 4.0 has led to an implementation of machine learning which has become a breakthrough in various fields by facilitating more efficient data processing, simulating the machine learning process and generalizes the knowledge from existing data to make predictions which in result improvises the system accuracy. In advanced manufacturing processes, ML plays an important role in enhancing process efficiency, optimizing various input parameters, reducing experimental works along with stable quality. Wire arc additive manufacturing is a metal additive manufacturing technique which produces near net shape components with few challenges like parameter optimization and defects. Incorporating ML into WAAM provides a better solution in predicting output parameters and optimizing input parameters. This review consolidates the recent studies on using ML techniques in WAAM. It highlights their application in predicting response parameters, Geometric parameters, mechanical properties, microstructures and input optimization. Comparative analyses show the effectiveness of various algorithms along with their strengths and limitations. This study suggests the future research directions by analysing the recent accomplishments in the available literature, it aims to integrate ML and WAAM to highlight its potential for process modelling, overall process optimization and prediction.

Keywords: Machine Learning, Wire arc additive manufacturing, Process optimization, Parameter Prediction,

1 INTRODUCTION

Wire arc additive manufacturing (WAAM) is a type of direct energy deposition process which produces a three-dimensional component as shown in Figure 1 [1]. WAAM is seen as one of the best ways to fabricate metal parts that can have properties that are comparable or superior than those made by traditional methods like forging and casting [3]. Due to its poor surface finish, the fabricated component is near net shape. The high deposition rate, energy efficiency, low manufacturing cost, and ability to fabricate large, dense components are the advantages of WAAM for modern manufacturing [1,2]. Despite these advantages, wire arc additive manufactured products have challenges in microstructures, Surface roughness, mechanical properties and geometric parameters [1-8].

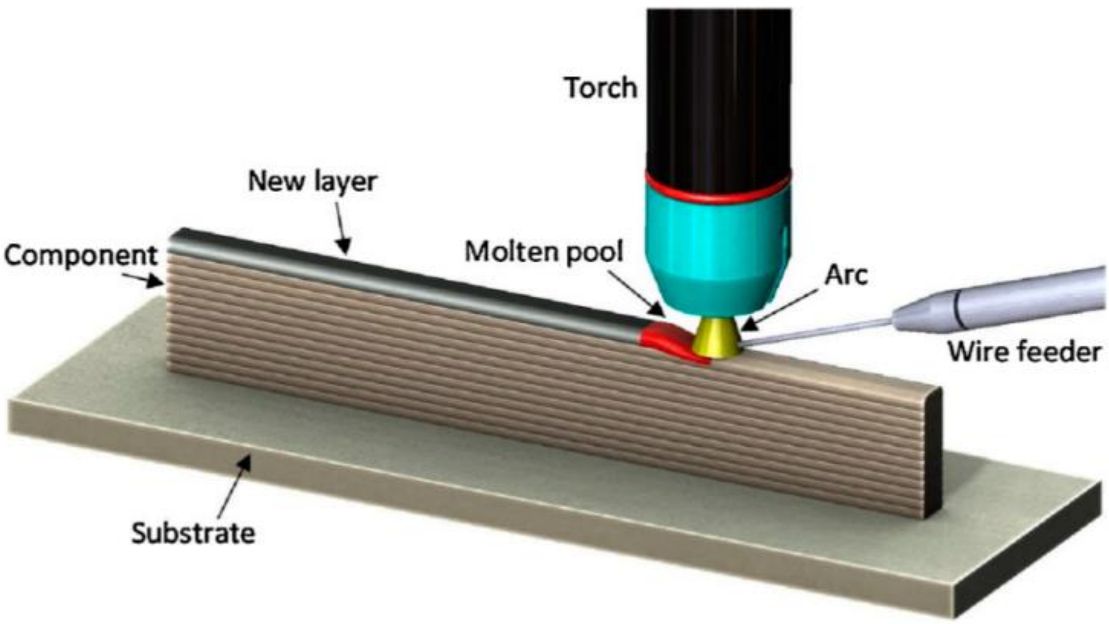

Fig. 1. Wire arc additive manufacturing

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To overcome the challenges, the WAAM process parameters should be controlled and optimized. Machine learning is being implemented in machining operations to increase precision, accuracy, efficiency and productivity. The incorporation of ML in WAAM can change traditional manufacturing methods. It allows for data-driven optimization and better build quality [4]. Machine learning models are extensively used in prediction and optimization of process parameters of WAAM. By capturing non-linear features from machining signals, machine learning greatly improves the accuracy of surface roughness predictions [5].

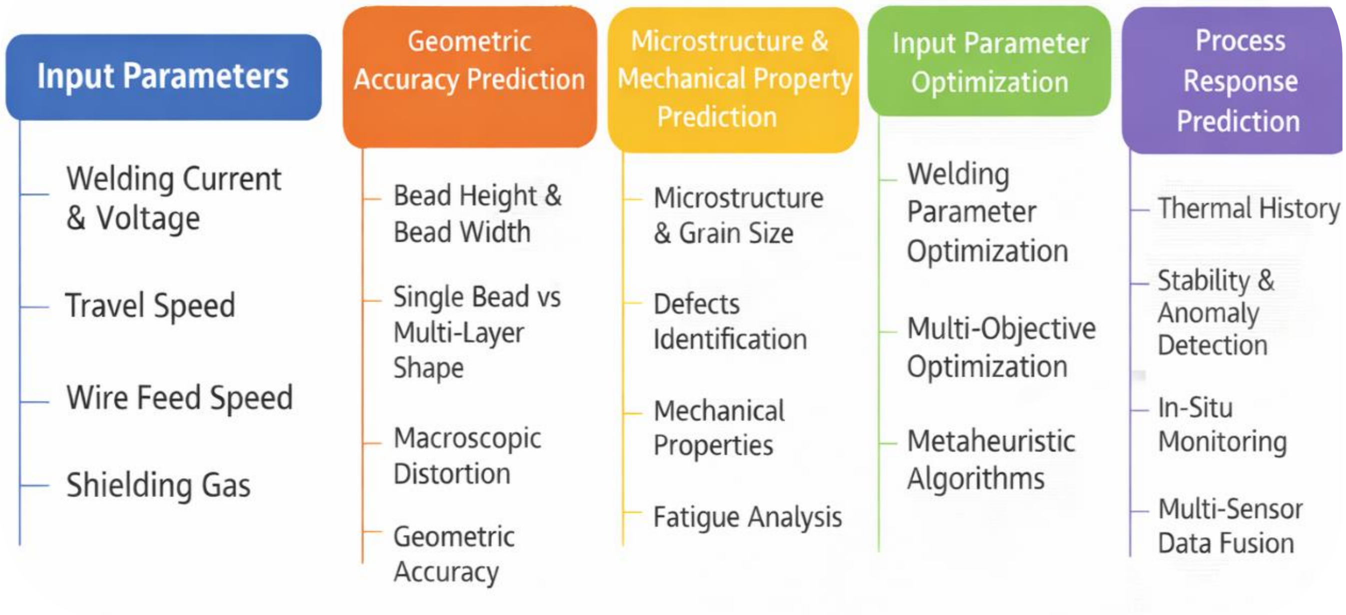

Fig. 2. Research domains in Wire Arc Additive Manufacturing (WAAM)

Artificial Neural network (ANN), Linear Regression (LR), Support Vector Regression (SVR), Random Forest (RF) and K-Nearest Neighbours are the most commonly used ML models to predict the response parameters and geometric parameters of a wire arc additive manufactured component [1,2,6,7]. Convolution Neural network (CNN), XGBoost, RF are the extensively used ML models in analysis and prediction of microstructure, mechanical strength and heat treatment of the component [8]. In order to reduce experimental trials, Input parameters are optimized with ML models such as Particle swarm optimization (PSO), Teaching Learning based Optimization (TLBO) and Response surface methodology (RSM) [9].

Although there are several existing studies on application of machine learning in WAAM, the findings are spread across different problem areas. A detailed review is needed to consolidate these works and provide a clarity on the effectiveness of various machine learning approaches. This review categorizes the applications of ML in WAAM into four main areas: (i) predicting process response parameters, (ii) predicting geometric accuracy, (iii) predicting microstructure and mechanical properties, and (iv) optimizing process parameters. Additionally, a comparison of commonly used ML algorithms is included, along with a discussion on new trends and future research directions in the field.

Figure 2 shows an overview of the main research areas in Wire Arc Additive Manufacturing (WAAM) discussed in this review. It emphasizes the importance of basic process input parameters, including welding current, voltage, travel speed, wire feed speed, and shielding gas. These factors influence geometric accuracy, microstructure, mechanical properties, and process response during deposition. Additionally, studies that focus on optimizing input parameters for better build quality and process stability are included. This framework acts as a guide for organizing and summarizing the existing literature.

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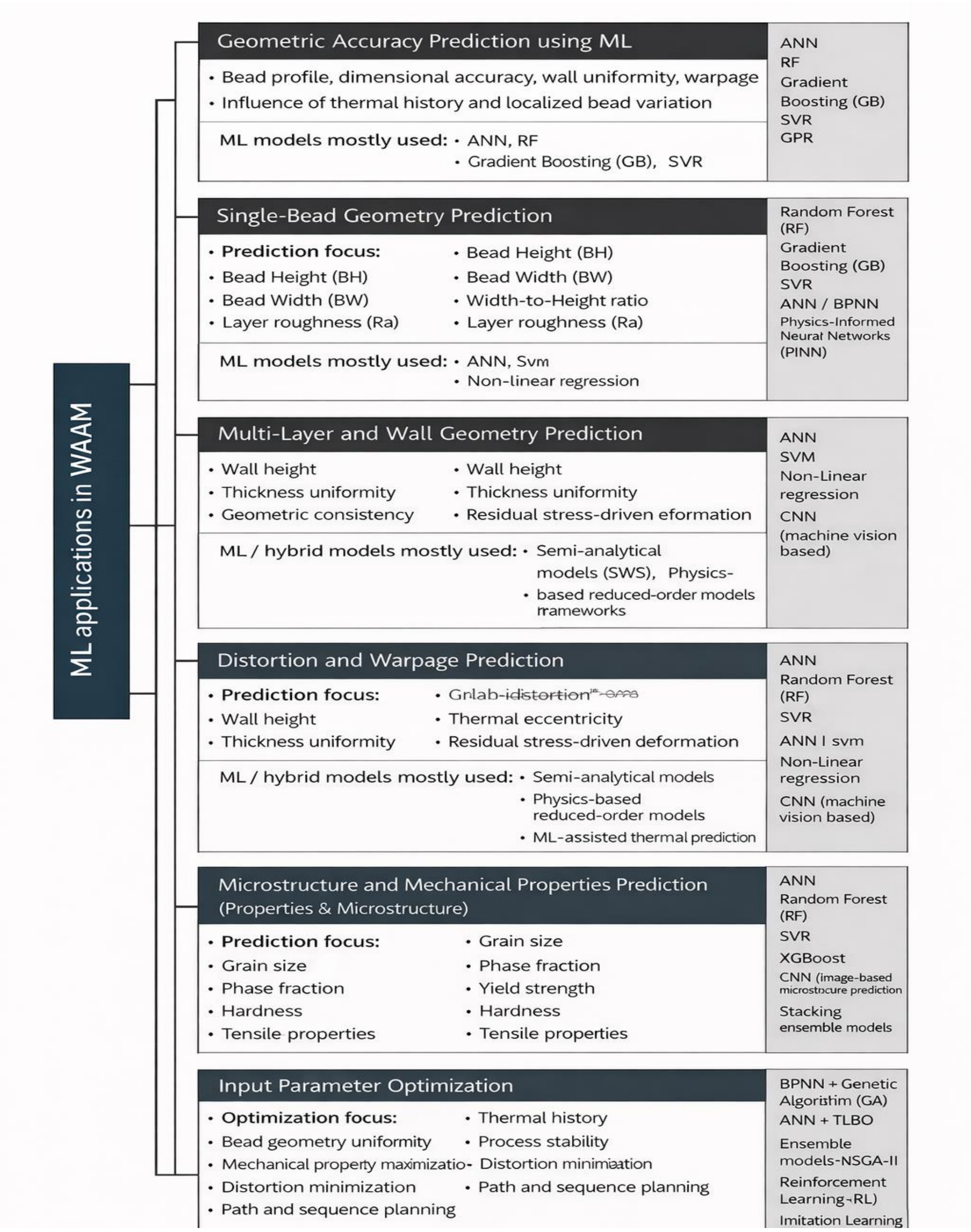

Fig. 3. Machine learning applications in Wire Arc Additive Manufacturing (WAAM) for prediction and optimization.

Figure 3 below displays a concatenated view of machine learning (ML) use in Wire Arc Additive Manufacturing (WAAM), indexed by the prominent prediction, as well as optimization problems that exist in the literature. This concatenated view indicates the various machine learning model usages for geometry accuracy prediction for single-beam, multi-layer, and wall geometry, distortion, as well as warpage predictions, microstructure, and mechanical property predictions, predictions for defects, as well as mechanical degradation, input variables for optimization, predictions for process response variables. In these concatenated views, the most popular machine learning approaches for each problem statement can be seen, including the more traditional regression, ensemble methods, up to the more recent learning paradigms like physics-informed learning, as well as reinforcement learning. This serves as a roadmap for the comprehensive review that has been discussed in 2-5 sections.

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2. GEOMETRIC ACCURACY PREDICTION USING ML

Geometric accuracy is one of the most important and challenging aspects of Wire Arc Additive Manufacturing (WAAM). The combined effects of thermal history and localized bead variation result in macroscopic defects such as distortion and poor surface finish. Data-driven modelling is widely used to predict basic dimensions, like bead profile, and complex final geometry, including wall uniformity and warpage.

2.1 Single-Bead Geometry Prediction.

The majority of research focuses on predicting the fundamental single-bead dimensions Bead Height (BH) and Bead Width (BW) as these directly affect the build quality of subsequent layers. The schematic representation of single-bead deposition in Wire Arc Additive Manufacturing (WAAM) is shown in Figure 4. As the arc heat source moves along a predetermined path, a metallic wire is continuously fed into it, where it melts and deposits onto a substrate. Process variables like welding current, voltage, wire feed speed, and travel speed control the final bead geometry, which is defined by parameters like bead height and bead width. Predicting geometric accuracy in multi-layer and multi-bead WAAM structures requires an understanding of single-bead formation.

The ability of prediction models to manage the process's intrinsic non-linear parameter relationships is usually the basis for their classification.

Tree-based ensemble methods, like Random Forest (RF) and Gradient Boosting (GB), have shown a strong ability to capture the complex relationship between welding parameters current, speed, and feed rate and bead dimensions The efficiency of boosting techniques was demonstrated by Xiong et al. [10], found that GB had the lowest prediction error for bead height (BH) and bead width (BW) when compared to Support Vector Machine (SVM) and RF. Similarly, Sharath P. Subadra et al. [6] and A. Yaseer et al. [11] confirmed that RF accurately predicts bead geometry and, importantly, layer roughness (Ra value of 0.957) when weaving paths are included. Irfan et al. [12] also used a Backpropagation Neural Network (BPNN) as a model for geometric outputs like the width-to-height ratio, laying the groundwork for future optimization studies.

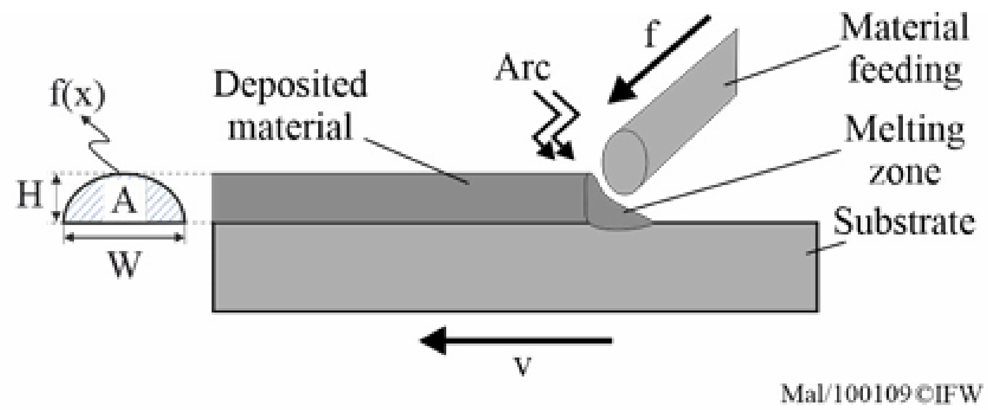

Fig. 4. Schematic representation of single bead geometry [7]

Simpler and effective regression models have been widely used. Support Vector Machine (SVM) Regression has proven to be very effective, especially when working with segmented data. Won-Jung Oh et al. [13] successfully applied SVM to predict and control BH/BW with remarkable accuracy, showing low average errors of 0.36% for BH and 1.28% for BW by analyzing data from the arc strike and middle deposition zones. B. Denkena et al. [7] compared multiple models (ANN, SVM, GPR, LR) and created a multi-stage ANN pipeline that achieved prediction accuracies of R^2=0.82 for width and R^2=0.76 for height, which provided necessary input data for dexel-based process planning. A. Rashid et al. [14] pioneered the use of a Physics-Informed Neural Network (PINN) framework to predict BH/BW. By including governing heat transfer equations in the network, the PINN model demonstrated higher accuracy compared to purely data-driven networks. It also stayed efficient in terms of computation. This represents a significant improvement in reliable geometric prediction.

2.2 Multi-Layer and Wall Geometry Prediction.

When using multi-layer structures, models must consider the combined effects of heat buildup, temperature between layers, and variations between layers. The change in Wire Arc Additive Manufacturing from single-layer deposition to multi-layer wall formation is shown in Figure 5. Bead shape, layer height, and wall geometry are all greatly impacted by heat accumulation and shifting

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thermal conditions caused by successive layer deposition in multi-layer builds. Controlling overall wall height, thickness uniformity, and geometric consistency takes precedence over predicting individual bead dimensions as the build height increases. When applying single-bead strategies to multi-layer and wall-type structures, this increased complexity emphasizes the need for sophisticated modeling and prediction techniques.

The focus changes from bead height and width to overall wall height, thickness consistency, and feature accuracy. Neural networks are the preferred tool because they can model complex, multi-variable, and sequential relationships. Dingyi Wang et al. [15] used an artificial neural network to the issue of bead shape in corner structures and achieved very high accuracy ($R^2 > 0.99$). This shows that machine learning can effectively predict non-linear toolpaths. Additionally, Kim et al. [1] used an SVM model not only for prediction but also to optimize the specific geometric feature of the bead's center angle. This shows a shift from simple description to targeted control. A key new trend is the integration of process physics. V. Panagiotopoulos et al. [16] created non-linear regression equations to estimate nominal wall thickness and average layer height based on experimental data which confirmed that high R^2 values are possible for geometrically consistent 'Class A' prints.

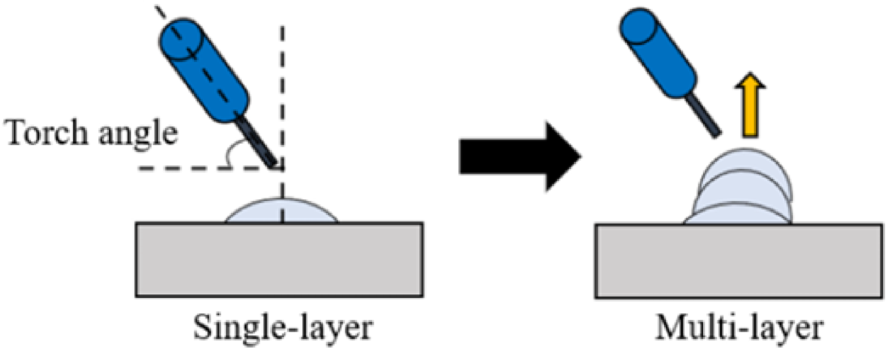

Fig. 5. Deposition strategy for multi-layer [1]

For real-time control needed in multi-layer builds, machine vision combined with deep learning provides a strong solution. Zhang et al. [17] created a machine vision framework that uses a Convolutional Neural Network (CNN) along with U-Net segmentation to extract bead geometry from deposition images with more than 95% accuracy. This real-time data enables immediate adjustments to process parameters to reduce over-fill and under-fill issues. Similarly, Nguyen et al. [18] used an ANN for adaptive toolpath planning in rib-web structures. They predicted void length with high precision, achieving less than 1 mm error. This allows for continuous, corrected Eulerian paths that significantly improve geometric accuracy and efficiency. The process parameters chosen by the SVM classification were used in multi-layer deposition experiments. Figure 6 shows that experimental findings demonstrated that the SVM classifier's performance in relation to the torch's angle and travel speed was appropriate for multi-layer deposition.

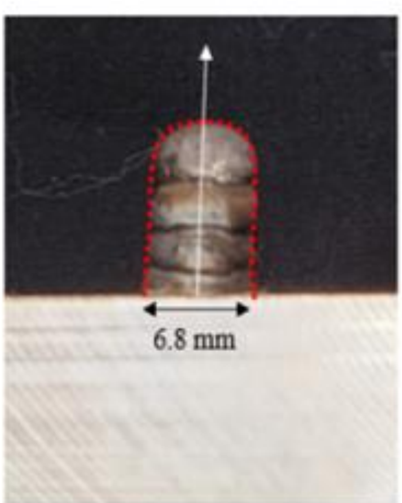

Fig. 6. Results of multi-layer deposition showing best bead angle [1]

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2.3 Distortion and Warpage Prediction.

Predicting macroscopic distortion, which is the final difference between the part and its intended CAD geometry, requires models that can account for long-range thermal effects and residual stress buildup. Directly predicting this final distortion using only experimental data is tough because of the large domain size and complexity. Zhao et al. [19] tackled this issue by using a Simplified WAAM Simulation (SWS), a semi-analytical model, to predict thermal field distribution and a distortion-related measure known as thermal eccentricity. By focusing on predicting a measure closely linked to distortion instead of the distortion itself it could accurately forecast the final distortion of the substrate plate without the high computational cost of full Finite Element (FE) analysis. This approach successfully combines traditional simulation with modern computational efficiency.

3. MICROSTRUCTURES AND MECHANICAL PROPERTIES PREDICTION

The Final success of WAAM relies on achieving the right material properties. These properties are closely connected to thermal history and defect formation. Machine learning offers valuable tools to understand these complex relationships. This advancement is helping the field move toward predicting quality.

3.1 Properties and Microstructure Prediction.

A primary application involves mapping complex process conditions, or inputs, to resulting material characteristics, or outputs. Artificial Neural Networks (ANN) and ensemble models excel in this area. Sahoo et al. [20] showed how effective ANN, Random Forest (RF), and Support Vector Regression (SVR) are in linking process-induced variations, such as heat input and cooling rate, to microstructural evolution, including grain size, and the resulting yield strength. ANN demonstrated superior predictive ability.

In a similar study, Chen et al. [21] used Random Forest (RF) and Extreme Gradient Boosting (XGBoost) to predict microstructural features, like phase fractions and grain size distribution, as well as final tensile properties based on dual-deposition process parameters, outperforming a Deep Neural Network (DNN).

Xiaohan Wang et al. [22] relied on a range of models, including CNN, XGBoost, RF, and Decision Trees, to predict Wire Arc Additive Manufacturing (WAAM) microstructure from macro images, with CNN achieving 95% accuracy, and mechanical properties from processing conditions, where XGBoost served as the best regression model. A typical Convolutional Neural Network (CNN) framework used for image-based prediction tasks in WAAM is shown in Figure 7. Through a series of convolution and pooling layers, the network extracts hierarchical spatial features from input images. These features are then flattened and sent through fully connected layers for the final prediction. Accurate material property prediction from visual data is made possible by these architectures, which are especially good at capturing intricate microstructural patterns and defect-related features.

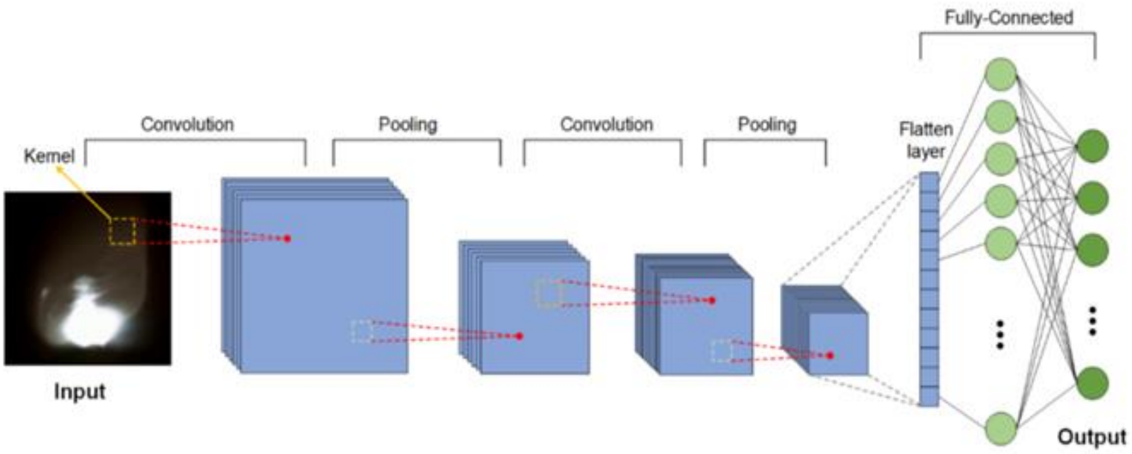

Fig. 7. Convolutional Neural Network (CNN) architecture used for image-based feature extraction and prediction of microstructure and material properties in WAAM [22]

Parand Akbari et al. [23] provided a framework to benchmark and predict general mechanical properties, such as yield strength and hardness, emphasizing the creation of highly accurate and understandable models. Additionally, R. Mamedipaka et al. [8] utilized a stacking ensemble model to examine how heat input affects microstructure, mechanical properties, and corrosion behavior, finding that lower heat input led to better hardness and strength.

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3.2 Defect Detection and Correlation to Mechanical Degradation.

A key challenge is detecting defects like porosity and cracks in real-time and linking these features to mechanical performance, especially fatigue life.

Visual defects can be effectively identified using deep learning. Zhang et al. [24] achieved 94% accuracy in classifying surface flaws like pores and lack of fusion using a CNN-based machine vision system and the research established a direct correlation between lower tensile strength and defects found. X. He et al. [25] achieved 94.38% accuracy in classifying four defect types, such as cracks and poor fusion, from Magneto-Optical (MO) images using a Cost-Sensitive CNN (CSCNN). This demonstrated efficacy in categorizing data with imbalanced defects. Using a Convolutional Neural Network (CNN) for real time quality monitoring, Hae-Won Cho et al. [59] also created a technique for real-time anomaly detection in the WAAM process, specifically for Molybdenum alloy. Anomalies in welding signals, such as voltage and current, are frequently indicative of defects. Unsupervised models, such as Isolation Forest and One-Class SVM, were applied to voltage and current signals by Mattera et al. [26]. With the highest accuracy of 91.9%, linked spectral and statistical features to flaws like humping and spatter.

Using Autoencoder (AE) and Variational Autoencoder (VAE) for anomaly detection from the same signal data, G. Mattera et al. [27] investigated this further. A semi-supervised learning method for real-time anomaly detection in the Inconel 718 Pulsed Transfer WAAM was created by Giulio Mattera et al. [60]. The technique uses Wavelet Transform for enhanced frequency domain feature extraction and abrupt anomaly identification after training an unsupervised deep learning model (residual convolutional autoencoder) on high-quality data, establishing a pattern of "normality." SVM and incremental learning were used by Y. Li et al. [28] to detect defects in arc current and voltage signals.

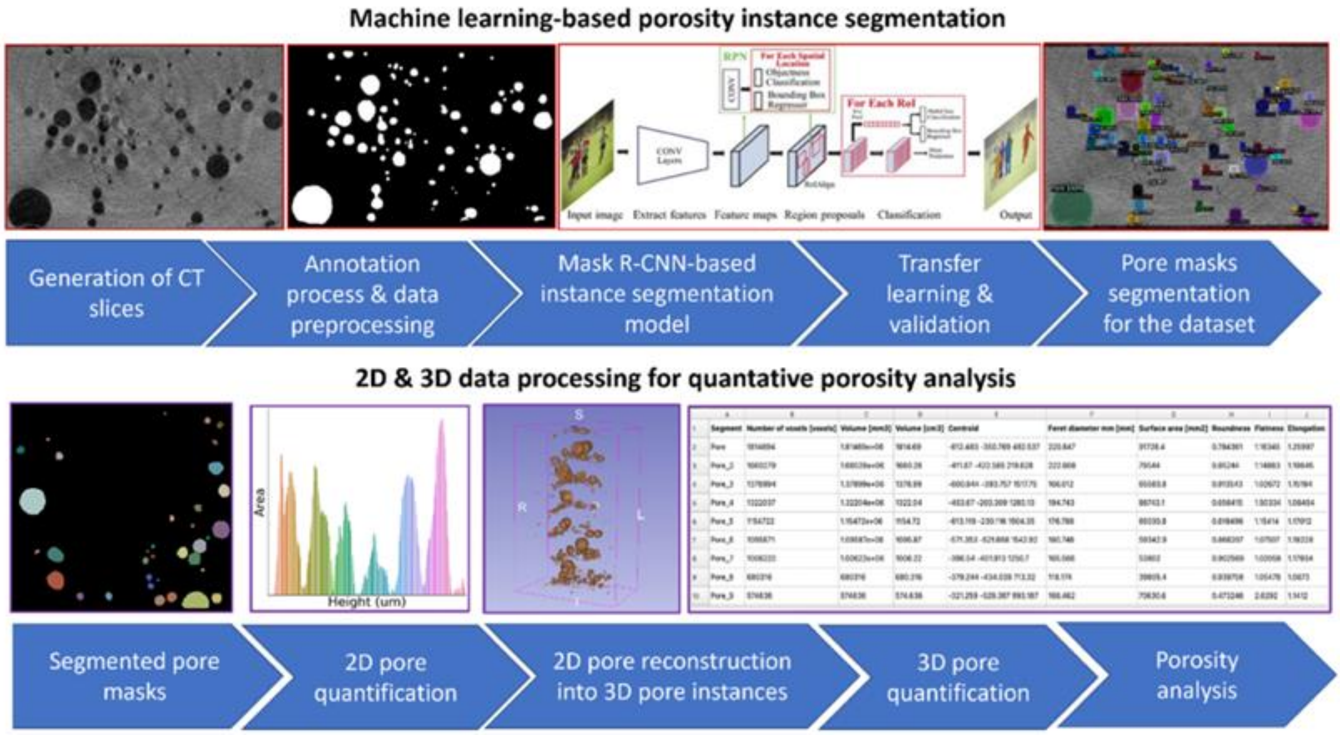

Fig. 8. Machine learning–based workflow for porosity instance segmentation and quantitative 2D–3D porosity analysis in WAAM components [30].

R. Li et al. [29] achieved a high F1 score of 0.9307 by combining Vector Quantization Variational Convolutional Autoencoder (VQ-VCAE) with Isolation Forest to detect anomalies like holes and spatter in real time. The most notable application relates significant structural characteristics and prognoses to internal defects. Yuan Wang et al. [30] systematically analyzed 3D porosities using deep learning and 3D reconstruction from micro-CT slices, providing information essential for property prediction. A typical machine learning-based workflow for quantitative porosity characterization in WAAM components is shown in Figure 8. Mask R-CNN-based instance segmentation is used to identify individual pores after micro-CT slices have been created and annotated. In order to correlate internal defects with mechanical performance, the segmented pores are then reconstructed into 3D instances, allowing for precise quantification of pore size, distribution, and morphology.

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In support of this, Yancen Lu et al. [58] examined the intricate relationship between wire feed speed and travel speed on porosity defects (volume, morphology, and distribution) in WAAM Ti-22V-4Al alloys. Since porosity is a crucial factor in determining final properties, there was a specific use of machine learning techniques for quantitative analysis of the parameter interplay. In order to relate the volume fraction and morphology of X-ray CT porosity descriptors to the anticipated tensile strength and elongation ($R^2 >$ 0.95), Marques et al. [31] used ensemble models such as Gradient Boosting. Crucially, the emphasis also extends to long-term integrity: Yu et al. [32] and T. Zhan et al. [33] concentrated on fatigue. Yu et al. estimated the stress concentration factor and high-cycle fatigue (HCF) life (R^2=0.77–0.85) by combining Support Vector Regression (SVR) with defect parameters. T. Zhan et al. assessed the impact of porosity defects on the fatigue characteristics of WAAM Al-Si-Mg alloy using a neural network. Banglong Yu et al. [57] further demonstrated this prognostic capability by creating a robust prediction model for the high cycle fatigue (HCF) life of WAAM TC17 titanium alloy components. This model explicitly accounts for the negative effects of defects by using Gaussian Process Regression (GPR) to correlate microstructure characteristics and defects (size, location) with the resulting HCF life.

The overall shift from merely monitoring processes to real-time closed-loop control with the goal of attaining zero-defect manufacturing is highlighted in the review by D.R. Gunasegaram et al. [34]. It presents the function of machine learning in WAAM as supporting prognostics, diagnostics, and direction.

4. INPUT PARAMETER OPTIMIZATION

The goal of optimization as shown in Figure 9 is to use predictive models to efficiently search the wide range of parameters and find the best combination of inputs to achieve a specific goal, such as maximum strength, minimum distortion, or optimal geometry. Machine learning models are often paired with metaheuristic algorithms, like Genetic Algorithms, or used in closed-loop control systems, such as Reinforcement Learning.

By combining BPNN with a Genetic Algorithm (GA) for multi-objective optimization of bead geometry in 17-4 PH stainless steel, Irfan et al. [12] improved the predictive power of BPNN. With a PCC of 0.85, experimental validation confirmed that the optimized parameters produced a noticeably more uniform bead profile. The GA minimized a function aimed at a low width-to-height ratio for efficiency and high geometric uniformity. In the same way, metaheuristic and multi-objective optimization methods are essential for property control. In order to improve the mechanical properties of WAAM SS316L, Surner et al. [36] used Teacher Learning Based Optimization (TLBO) to determine the ideal travel speed, wire feed rate, and voltage combination. This resulted in a notable 25.6% increase in Yield Strength (YS). By extending this control to microstructural refinement, Zihao Jiang et al. [47] successfully resolved the inherent trade-off between productivity and material properties by proposing a novel multi-objective framework that uses the NSGA-II algorithm and a physics-informed stacked ensemble model to optimize process parameters for high deposition rate and uniform, fine equiaxed grain structure in AZ31 magnesium alloy.

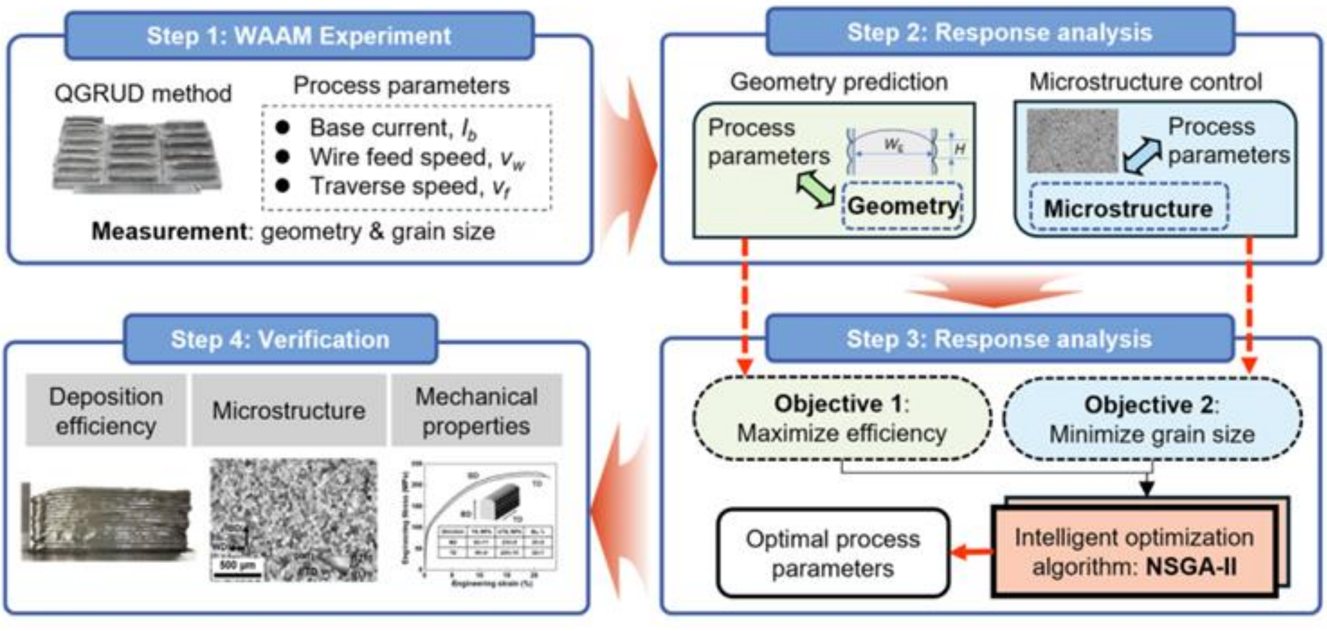

Fig. 9. Machine learning–assisted multi-objective input parameter optimization framework for Wire Arc Additive Manufacturing [47]

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In contrast, M.S. Mohd Mansor et al. [37] employed a number of statistical optimization techniques, such as Taguchi, ANOVA, and RSM, and discovered that the latter two were the most successful in optimizing multiple variables in WAAM. ML helps with strategic path and sequence planning in addition to single-bead optimization. In order to minimize substrate plate distortion, Zhao et al. [19] optimized deposition sequences using the computationally efficient Simplified WAAM Simulation (SWS) predictive model. They discovered an ideal sequence that minimized distortion, which was validated by 3D scanning. Using a Reinforcement Learning (RLTube) framework, Petrik and Bambach [35] implemented more sophisticated control by automatically modifying deposition strategies (wire feed rate and welding speed) in response to a reward function that penalized misalignments. Iason Sideris et al. (2024) [48] built on intelligent path design by introducing an automated framework for path planning optimization that used a Reinforcement Learning (RL) agent for fast paths and a Monte Carlo tree search for thermal response. This allowed for the efficient management of both geometric accuracy and deposition time. Rui Yu et al. [49] demonstrated the ultimate advancement toward fully autonomous WAAM by using imitation learning to automate the intricate Double-Electrode GMAW (DE-GMAW) process. In order to generalize human welding expertise into a robotic surrogate for adaptively controlled DE-GMAW, they employed a Convolutional Neural Network (CNN).

Finally, linking optimization with in-situ detection systems closes the control loop. Liu et al. [38] employed a semi-supervised approach (Autoencoder and One-Class SVM) for early detection of abnormal states, enabling adaptive adjustments of current and voltage to stabilize inputs. André Ramalho et al. [39] introduced a novel process-aware machine learning method to autonomously detect key process instabilities, like humping and porosity, in real-time using melt pool characteristics, achieving over 85% accuracy and enabling immediate corrective optimization actions. The reliance of the field on integrated sensing and ML for real-time control is systematically reviewed by Gaurav Kishor et al. [50], categorize sensing methods and emphasize multi-sensor integration for enhancing process reliability. These diverse and hybrid approaches reinforce the necessity of integrating ML optimization within comprehensive frameworks, such as the Digital Twin (DT) technology systematically reviewed and proposed by Haochen Mu et al. [51], to advance WAAM toward smart manufacturing.

5. PREDICTION OF PROCESS RESPONSE PARAMETER USING ML

This category focuses on using process inputs such as speed and current, along with in-situ monitoring signals like arc voltage and video, to predict responses in the WAAM process. These responses include thermal history, process stability metrics, and the immediate appearance of defects like porosity. These predictions are essential for providing real-time feedback and control.

Thermal history is among the most intricate responses. A novel Physics-Informed Machine Learning (PIML) method was presented by Z. Chen et al. [40] to forecast the temperature field during WAAM. In comparison to conventional Finite Element Method (FEM) simulation, the PIML model achieved high accuracy while significantly reducing the computational cost by directly incorporating physical laws, specifically heat transfer equations, into the neural network training process. Similar to this, Jun Cheng et al. [41] predicted surface waviness based on inputs like wire feed speed, welding speed, and overlap ratio using an ANN model that was optimized with RGPSO for increased hyperparameter prediction accuracy. Based on sensor data, deep learning and statistical techniques are frequently used to forecast stability responses and defects. Mattera et al. [26] examined WAAM stability responses from arc current and voltage signals using a variety of unsupervised models, including One-Class SVM, PCA, Local Outlier Factor, and Isolation Forest. The most dependable method for detecting aberrant deposition responses in real time was Isolation Forest, which achieved an accuracy of 91.9%. In keeping with this emphasis on stability, Sarra Oueslati et al. (2025) [52] examined the use of machine learning (ML) to identify and forecast process instability through sophisticated signal processing on electrical arc signals, confirming the potential of derived monitoring criteria for process state prediction and real-time quality assurance.

In order to predict porosity metrics like volume fraction and size distribution in response to process inputs, Marques et al. [42] employed ensemble models, such as Random Forest and Gradient Boosting. They discovered that Gradient Boosting was the most successful. To further address defect detection via electrical signals, Tianyang Zhang et al. [53] established a dependable in-situ technique by using Continuous Wavelet Transform (CWT) to convert arc voltage into 2D images. This allowed them to train a deep learning model to accurately detect surface oxidation defects in copper alloy WAAM. To fully predict responses, innovative monitoring frameworks employ complex models and multiple data streams. By combining three sensor modalities (electric signals, camera images, and laser profilometer point clouds) with a multi-model machine learning strategy (MLP, YOLOv5, VAE), Mu et al. [43] developed a digital shadow approach for defect detection that effectively identified problems like humping and voids with an F1 score of 0.791. By proposing a robust in-situ monitoring system using a data-fused, concatenated-ensemble learning (CEL) model that integrates multi-sensor data (current, voltage, and thermal) using Convolutional Neural Networks (CNN) for feature extraction, Duck Bong Kim et al. [54] significantly advanced this idea of data fusion. They achieved high classification accuracy (99.4%) for anomalies like lack-of-fusion and porosity. With an F1 score of 86.3%, Song et al. [44] also concentrated on identifying

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surface anomalies like inclusion, porosity, and lack of fusion using a CNN-based autoencoder trained on melt pool video data. In addition, Rongwei Yu et al. [55] demonstrated the effectiveness of deep learning in correcting geometric deviations by introducing an online monitoring system that uses a synchronized infrared thermal imager and a novel Deep Learning model, WAAM-Net, to predict and quantify cladding layer offset in real-time.

Lastly, as a process response, machine learning can forecast final properties and keep an eye on important consumable components. Based on arc-related process data, Hussein et al. [45] created a Random Forest classifier and a Multi-Layer Perceptron (MLP) regressor to forecast the contact tip's wear state, obtaining a R^2 of 0.75. The ANN model achieved the highest accuracy when Sahoo et al. [46] used ANN, RF, and SVR to predict important electromechanical properties, specifically electrical resistivity and tensile strength, as responses to process parameters. The ANN model achieved the highest accuracy at R^2 = 0.97. The Digital Twin (DT)-based architecture, introduced by Mohammad Mahruf Mahdi et al. [56], combines OPC UA for real-time control, 3D visualization, and CNN/DNN-based defect prediction to improve overall geometric accuracy and deposition quality. These real-time predictive models are ultimately essential parts of intelligent control systems, serving as the foundation for comprehensive solution.

6. FUTURE TRENDS

Despite significant progress in the application of machine learning (ML) to Wire Arc Additive Manufacturing (WAAM), several critical challenges and open research gaps remain. Most existing studies are confined to specific materials, narrow process windows, or isolated prediction tasks, which limits model generalizability and industrial relevance. To enable reliable and scalable deployment of ML-assisted WAAM, future research should move beyond offline prediction toward integrated, adaptive, and physically consistent frameworks. In particular, the development of real-time closed-loop control systems that combine multi-sensor data—such as arc signals, thermal imaging, and vision-based monitoring—with fast and robust ML models remains an important research direction. Such systems would allow dynamic adjustment of process parameters during deposition, enabling compensation for thermal accumulation, process drift, and external disturbances, and thereby supporting zero-defect manufacturing.

Another promising direction lies in the integration of physics-informed and hybrid data–physics modeling approaches. While purely data-driven models have shown high predictive accuracy, they often require large datasets and may exhibit limited extrapolation capability. Embedding physical knowledge related to heat transfer, fluid flow, and metallurgical transformations into ML architectures can improve prediction robustness, reduce data dependency, and enhance model interpretability. The combination of experimental data with physics-based simulations offers significant potential for achieving reliable process–structure–property relationships across a wide range of WAAM conditions.

The lack of standardized and openly accessible datasets remains a major bottleneck in advancing ML research for WAAM. Future efforts should focus on establishing benchmark datasets that cover diverse materials, deposition strategies, sensor modalities, and output variables, along with standardized evaluation metrics and validation protocols. Such initiatives would enable fair comparison of ML models, improve reproducibility, and accelerate the development of transferable solutions. In parallel, extending ML-driven prediction and optimization frameworks to multi-material and functionally graded WAAM components represents a largely unexplored but critical research opportunity. These systems introduce additional complexity due to spatially varying thermal histories, microstructures, and mechanical properties, requiring advanced modeling strategies capable of handling strong material and property gradients.

Recent advances in reinforcement learning and autonomous optimization also open new avenues for intelligent WAAM systems. Although still in an early stage, reinforcement learning-based approaches have the potential to enable adaptive parameter tuning and intelligent path planning for complex geometries and varying deposition conditions. Hybrid strategies that combine reinforcement learning with conventional optimization techniques and physics-based constraints may offer a practical pathway toward autonomous and reliable WAAM processes. Furthermore, the development of digital twin frameworks that integrate real-time sensor data, ML models, and physics-based simulations is expected to play a key role in industrial scalability. Such digital representations can support predictive quality control, process optimization, and lifecycle management across different machines and production environments. Addressing challenges related to computational efficiency, model updating, and interoperability will be essential for realizing robust digital twin-enabled WAAM systems.

7. CONCLUSION

This review demonstrates that Machine Learning (ML) has transitioned from simply aiding in parameter estimation to being a vital element for ensuring quality and refining processes in Wire Arc Additive Manufacturing (WAAM). Advancement in research has been noted in four key areas: precision of shapes, forecasting of microstructure and mechanical attributes, observation of reactions during the process, and independent improvement of the process. When it comes to predicting shape accuracy, ML algorithms like Random Forest, Gradient Boosting, and Neural Networks have demonstrated a strong

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ability to predict bead shapes and intricate wall designs. Newer methods that take physics into account, such as PINNs and models that are partially analytical, are delivering greater precision and faster computing than typical finite element methods.

Regarding material qualities and controlling the process, ML methods efficiently connect process settings and information from sensors to how well it performs mechanically, if flaws appear, and how stable the process is. Deep learning designs, notably CNNs and autoencoders, make it possible to spot flaws precisely using visual and signal data, which helps with immediate problem diagnosis. New developments in predicting how a process will react highlight combining different types of data and using physics-aware learning to keep tabs on temperature changes, consistency, and how quickly materials are used up. Furthermore, combining ML with optimization techniques and reinforcement learning has made it possible to have independent, self-regulating control, which is greatly pushing WAAM closer to being a self-correcting, error-free production method that can be used widely in industry.

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Conflict of interest

All authors declare that they have no conflicts of interest.

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