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Integration of the AI and ML Approaches for Prediction Analysis in Welding: Review

David BASSIR [a,b,1]
[a] *IRAMAT, UMR –7065, Université Technologique de Belfort-Montbéliard, 90010 Belfort Cedex, France*
[b] *Centre Borelli – UMR –9010,ENS Université Paris Saclay, 4 Av. des Sciences, 91190 Gif-sur-Yvette, France*

Abstract. Welding techniques are presents in almost all industries from automotive, aerospace, building, etc. Despite the fact that the technology behind welding remain simple, it is very complicated to characterize and predict the final mechanics responses without considering all the process of the welding. In particular when we refer to the fatigue as the main constraints are located at these singularities areas. Such challenges include poorly controlled welding parameters and weld geometry, which lead to weld quality problems. Nowadays, with the recent involvement of Artificial intelligence (AI) and Machine Learning (ML) into the industry 4.0, it was just matter of time before it is applied to welding problems. The potential applications of ML and AI in welding are vast, as it should bring more efficient and streamlined compared to what is used to be in the early 90's. In this review a focus will be done on the recent advanced, and reviews previous investigation on AI applications in welding process control and welding robot control. Quality control of such welds are important when we deal with mass production of sensitive products. The main challenges remain the data acquisition to increase the efficiency of the prediction. Testing are sometime coupled with finite elements simulation for training and testing the ML Perspectives and future challenges regarding the integration and the impact of AI in the welding industry in the era of Industry 4.0.

Keywords. Welding, ML, DL, Prediction, AI, Industry 4.0, Quality control

1. Introduction

Internet of Things coupled and industry 4.0 concepts [1], [2] have revolutionized the data acquisition techniques, sensors, information processing, and digital twin models. It has opened new research paths for many industries including welding [3]–[5]. Welding is a fabrication process that joins materials, usually metals, by melting the workpieces and adding a filler material to create a strong bond when the melted material cools and solidifies. It is widely used in various industries, including construction, automotive, aerospace, shipbuilding, and manufacturing, to join parts and components together permanently.

The process involves heating the materials to their melting point in order to join them using various technics, each suitable for different applications. Some common

[1] David BASSIR, Corresponding author, IRAMAT, UMR –7065, Université Technologique de Belfort-Montbéliard, 90010 Belfort Cedex, France; E-mail: david.bassir@utbm.fr.

welding methods [6], [7] include: 1) Arc Welding: Uses electricity to create an electric arc between an electrode and the workpiece to melt and join the metals. 2) Gas Welding: Involves using a flame from a fuel gas to melt and join metals. 3) Resistance Welding: Uses the application of pressure and electric current to join materials. Spot welding and seam welding are common examples of resistance welding. 4) Laser Welding that uses laser beam to melt and join materials. 5) Electron Beam Welding which use a high-velocity electron beam to melt and join materials. 6) Friction Welding is based on friction generated by workpieces that heat and melt.

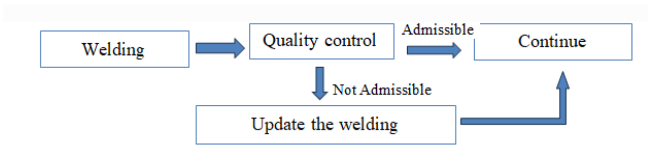

Figure 1. Welding workflow with quality prediction. If the predicted quality of the next welding operation is good, then the welding process continues. Otherwise, necessary measures are required (such as updating the welding parameters).

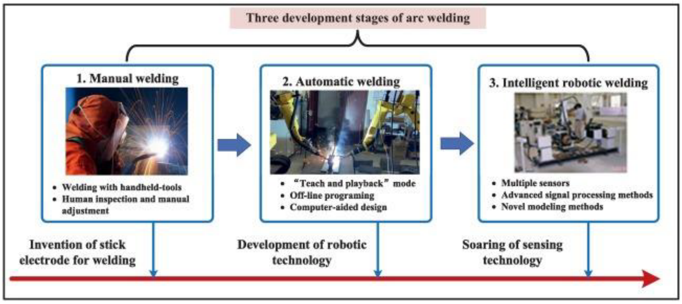

Figure 2. Evolution of the welding process from Manuel to intelligent robotic welding [7].

In general, welding process requires skilled operators, as well as adherence to safety guidelines and precautions, as it involves high temperatures and potentially hazardous fumes. It is also a critical process for the manufacturing and construction industries, enabling the creation of sturdy and reliable structures and components. Properly executed welds can provide strong and long-lasting connections, ensuring the integrity and safety of the finished products. Whatever welding during the process, data acquisition (figure 1) is required for both aspects: Quality control and Prediction. For these purposes, methodology is needed to build experiment platforms to get the welding information data and be able to control the welding process. Quality control of welding is a crucial aspect of ensuring the reliability, safety, and durability of welded products [8]. Proper quality control measures help identify and rectify defects, prevent potential failures [9], and maintain consistent welding standards at whatever stages (figure 2) [8]. ML brough an innovative and efficient solution to overcome these problems. Based on the recent literatures, it is already showing promising advancements for prediction and quality control of welding [10]. Below some recent applications of the ML:

a) Prediction of Welding Parameters: ML models have been used to predict optimal welding parameters based on various inputs such as material type, thickness, joint configuration, and welding process. These predictive models help in optimizing welding processes, reducing trial and error, and achieving higher quality welds.

b) Defect Detection and Quality Control: ML techniques, particularly computer vision and image analysis, have been applied to detect welding defects automatically. These defects may include cracks, porosity, lack of fusion, and other imperfections. By using machine learning algorithms, manufacturers can perform real-time quality control during the welding process, reducing the risk of producing faulty welds.

c) Welding Process Monitoring: ML algorithms are utilized for real-time monitoring of welding processes. By analysing data from various sensors, such as temperature, current, voltage, and gas flow, these models can detect anomalies, predict potential issues, and maintain the stability of the welding process, leading to better quality and consistency in welds.

d) Material Characterization: ML models have been employed to predict material properties based on welding parameters and conditions. This aids in selecting appropriate materials for specific welding applications and ensures the desired mechanical properties of the final weld.

e) Welding Robot Control: ML has been integrated into welding robots and automation systems to enhance their efficiency and accuracy. These models enable robots to adapt to varying conditions and execute welds with precision.

f) Data Integration and Analytics: ML facilitates the integration and analysis of vast amounts of welding-related data, including sensor data, historical welding data, and welding process parameters. By leveraging this data, manufacturers can identify patterns, optimize processes, and make data-driven decisions to improve welding quality.

The effectiveness of ML models heavily relies on the availability of high-quality and diverse data. To stay at the cutting edge of the field, researchers and practitioners continue to explore innovative techniques and collect comprehensive datasets. In the next parts, a short introduction of AI and ML will be presented with the prediction aspects for welding. Finally, challenges and future perspective for the application of welding will be summarized.

2. Artificial Intelligence (AI) & Machine Learning (ML)

AI is a broad field of computer science that focuses on creating intelligent machines capable of performing tasks that typically require human intelligence (figure 3). It can be built using various approaches, such as machine learning, deep learning, expert systems, natural language processing, and more. One of the popular techniques used in AI, especially in deep learning, is the concept of neural networks (NN). They are inspired by the structure and functioning of the human brain and consist of multiple interconnected layers of artificial neurons. This architecture is referred to as a "multilayered" or "deep" neural network. Each layer processes input data and passes it on to the next layer until the output layer produces the final result. The "multilayered" nature of deep neural networks allows them to learn complex patterns and representations from data, making them particularly effective for tasks like image recognition, natural language processing, and decision-making.

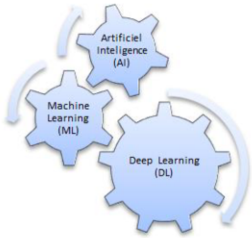

Figure 3. DL is the driving concept for the ML which is one of the AI approaches.

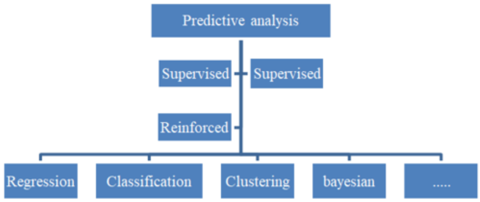

Figure 4. Predictive approaches for data analysis.

ML is categorized into three main types (figure 4): a) Supervised Learning: The algorithm is trained on labeled data, with input-output pairs provided during training. The goal is to learn a mapping from input to output, enabling the algorithm to predict the output for new inputs. b) Unsupervised Learning: The algorithm is given unlabeled data and is tasked with finding patterns or structures within the data without explicit guidance. Clustering and dimensionality reduction are common tasks in unsupervised learning. c) Reinforcement Learning: The algorithm learns through trial and error, receiving feedback from the environment in the form of rewards or penalties. The goal is to learn an optimal strategy or policy to achieve a specific objective. ML algorithms include linear regression, decision trees, random forests, support vector machines, Time Series Forecasting, Anomaly Detection, neural networks, and many others. It often complements data analysis by enabling more sophisticated modeling and prediction tasks, especially in cases where the relationships between variables are complex and not easily captured through traditional statistical methods. Predictive approaches for data analysis involve historical data to build models that can make predictions about future outcomes. These models are trained on existing data, and once they are enough accurate, they can be used for new, data to make predictions.

In summary, data analysis is about exploring and understanding existing data, while ML is about building models that can make predictions or decisions based on data, often leading to automated decision-making or process improvements. Both fields are essential components of modern data-driven approaches to problem-solving and decision-making in particular for welding. It is essential when applying the above approaches to validate and evaluate the models to ensure their accuracy and reliability. Performance metrics such as accuracy, precision, recall, and F1-score are used to assess model performance. In addition, additional check should be taken to avoid overfitting and to maintain the model's generalization capabilities when using to new data.

3. Prediction in Arc Welding

In this part, we focus on the process of Arc welding (figure 2) which is widely used in industries. It has seen numerous applications and advancements with the integration of AI and ML techniques. The combination of arc welding and AI opens up new possibilities for improving welding quality, process efficiency, and overall productivity. Here are some key areas where AI & ML are making an impact in arc welding: 1) Weld Quality Prediction: AI models can analyse various welding parameters and data collected during the welding process to predict the quality of the weld. By considering factors such as voltage, current, arc length, travel speed, and material properties, AI algorithms can identify potential defects or inconsistencies and suggest adjustments to achieve higher-quality welds. 2) Welding Parameter Optimization: AI can be used to optimize welding parameters based on the desired outcomes, material properties, joint configurations, and other factors. These models help reduce trial-and-error processes and minimize wastage, resulting in improved efficiency and cost savings. 3) Defect Detection and Real-time Monitoring: AI-driven computer vision and image analysis techniques can automatically detect welding defects in real-time. By monitoring the welding process continuously, AI systems can identify defects like porosity, cracks, and lack of fusion, allowing for immediate corrective actions. 4) Weld Path Planning for Robotic Welding: AI-powered path planning algorithms enable welding robots to determine the most efficient and effective trajectory for welding a particular joint [11]. These algorithms consider factors such as joint geometry, weld type, and accessibility, leading to precise and accurate welds. 5) Welding Process Control: AI can be used to develop closed-loop control systems for arc welding. By constantly analysing sensor data and making adjustments to welding parameters in real-time, AI-controlled systems can maintain the stability and consistency of the welding process, even in the presence of disturbances. 6) Welding Data Analytics: AI facilitates the analysis of large volumes of welding data, enabling manufacturers to gain insights into trends, patterns, and correlations that were not apparent through traditional methods. This data-driven approach aids in process improvement and decision-making. 7) Welding Automation and Integration: AI plays a crucial role in automating the entire welding process, from planning and parameter optimization to execution and inspection. Integrating AI with robotic welding systems increases productivity, reduces human error, and enhances overall production efficiency. As AI technologies continue to evolve, we can expect even more advancements in arc welding, leading to safer, more efficient, and higher-quality welding processes. However, it's essential to ensure that AI-driven welding systems undergo rigorous testing, validation, and quality assurance to maintain the highest standards of safety and reliability.

4. Future Challenges and Perspectives

As AI, ML and automation technologies (robotic) continue to advance, there role will surely increase in the field of welding. However, Several challenges are to be addressed to fully leverage AI and ML prediction in welding processes:

g) Data Collection and Quality: AI models require vast amounts of data to be trained effectively. In welding, acquiring high-quality data [7] can be challenging due to the complexity of welding processes and the need for specialized sensors and equipment. Ensuring the accuracy and reliability of data collected from various welding scenarios is critical to the success of AI prediction models.

h) Model Training and Generalization: Developing AI models that can generalize across different welding scenarios and materials is essential for practical applications. Creating models that can handle various welding techniques, joint configurations, and materials is a complex task [12], [13] that requires a large and diverse dataset for training.

i) Real-Time Prediction: Welding is often performed in real-time, and any AI prediction system must be capable of making fast and accurate predictions to be useful on the shop floor. Reducing prediction latency and ensuring the AI models can handle real-time data streams is a significant challenge.

j) Robustness and Adaptability: Welding environments can be harsh and dynamic, with variations in lighting, temperature, and other factors that can affect the performance of AI prediction models. Ensuring the robustness and adaptability of AI systems to such changing conditions is crucial for practical implementation.

k) Safety and Certification: In industries where safety is paramount, such as aerospace or nuclear, AI prediction models need to be certified and validated to meet stringent safety standards. Proving the reliability and safety of AI models in welding applications will be a critical challenge.

l) Expert Knowledge Integration: Welding often requires expert knowledge and judgment, especially in complex or specialized applications. Integrating human expertise with AI prediction systems to enhance decision-making and problem-solving will be an important consideration.

m) Data Privacy and Security: Welding data can be sensitive and proprietary, particularly in industrial settings. Ensuring data privacy and security while still leveraging the benefits of AI prediction will be a balancing act for the industry.

n) Cost and Implementation: Implementing AI prediction in welding processes might require significant initial investment in technology, training, and infrastructure. Assessing the cost-benefit ratio and demonstrating tangible benefits will be essential for widespread adoption.

o) Regulatory Compliance: Welding industries are subject to various standards and regulations. AI prediction models need to comply with these regulations, and establishing frameworks for assessing and certifying AI systems in welding applications will be necessary.

Despite the above challenges, AI integration in welding processes holds tremendous potential for improving efficiency, quality, and safety in various industries. With ongoing research and development, many of these challenges can be overcome, paving the way for a smarter and more automated welding industry.

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