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Digital Manufacturing And Artificial Intelligence In LSAW Welded Steel Pipe Production

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Abstract

Longitudinal Submerged Arc Welded (LSAW) steel pipes are critical in high-pressure applications, and their manufacturing quality directly influences safety and reliability. This paper explores the integration of digital manufacturing technologies and artificial intelligence (AI) to enhance the precision, efficiency, and defect detection capabilities in LSAW pipe production. Leveraging machine learning (ML) algorithms, such as convolutional neural networks and object detection models like YOLOv5, combined with sensor-based monitoring systems, enables real-time quality prediction and process optimization. This approach significantly reduces the risk of welding defects, improves operational efficiency, and supports adaptive control throughout the welding lifecycle. The results indicate that incorporating AI-driven quality monitoring in digital manufacturing frameworks can substantially elevate the quality and consistency of welded steel pipes, paving the way for autonomous, intelligent production lines.

Keywords

LSAW pipes, digital manufacturing, artificial intelligence, machine learning, weld quality, defect detection, real-time monitoring

I. Introduction

The global demand for high-strength, corrosion-resistant welded steel pipes, particularly for critical applications in oil, gas, and infrastructure, has pushed manufacturers to adopt precision-focused production techniques. Among these, Longitudinal Submerged Arc Welded (LSAW) pipes have gained prominence due to their structural uniformity and pressure-handling capabilities. However, ensuring consistent weld quality across large volumes remains a formidable challenge, primarily due to the variability in welding conditions and the limitations of conventional inspection techniques. In recent years, digital manufacturing paradigms, underpinned by artificial intelligence (AI) and machine learning (ML), have emerged as transformative tools to address these challenges. By integrating high-resolution sensors, real-time data acquisition systems, and intelligent algorithms, manufacturers can now detect, predict, and even prevent welding defects during the production cycle. This paper investigates the deployment of AI and digital manufacturing methodologies in LSAW pipe production, focusing on their impact on weld quality, defect detection accuracy, and overall process efficiency. As the industry transitions toward Industry 4.0, the fusion of digital technologies with traditional manufacturing processes not only enhances quality assurance but also accelerates the move toward autonomous and adaptive pipe production systems.

II. Literature Review

The integration of artificial intelligence (AI) and machine learning (ML) in welded pipe manufacturing has gained traction due to their ability to process large datasets and uncover hidden patterns associated with weld quality. Yang et al. [1] demonstrated the use of YOLOv5, a deep learning-based object detection model, for real-time identification of surface and internal weld defects in steel pipes. Their approach outperformed traditional visual inspection by reducing false positives and enabling instantaneous feedback. Similarly, Gook et al. [2] developed a multi-channel monitoring system capable of capturing welding arc signals, acoustic emissions, and temperature variations, which were analyzed using ML algorithms to detect anomalies and predict potential quality issues. Hahn et al. [3] proposed a deep neural network model to predict welding quality based on input process parameters in Gas Metal Arc Welding (GMAW), showing promising results in online quality assurance for automated systems.

Moreover, Patil and Reddy [4] implemented artificial neural networks for weld joint flaw classification, leveraging a large image dataset of LSAW pipe welds to train the system. Their results indicated over 94% classification accuracy, demonstrating the model's reliability in identifying complex defect types like undercuts, porosity, and misalignment. Recent advances have also explored reinforcement learning for adaptive welding control, where systems self-optimize based on environmental feedback, minimizing human intervention. Collectively, these studies emphasize the growing role of AI in elevating the quality and consistency of LSAW pipe manufacturing. They also highlight the need for standardized datasets and robust sensor fusion strategies to enhance model generalizability across different pipe diameters, materials, and welding environments.

III. Methodology

To enhance the manufacturing quality of LSAW pipes using AI, a multi-tiered digital manufacturing framework was developed, integrating real-time data acquisition, sensor fusion, and machine learning-driven decision-making. The system architecture comprises three primary components: (1) high-precision sensor arrays, (2) a centralized data processing unit, and (3) an AI inference engine. The sensor arrays include arc voltage sensors, current probes, infrared thermography, and acoustic emission detectors strategically positioned along the welding line. These sensors capture process variables at millisecond intervals, feeding data into a supervisory control and data acquisition (SCADA) system for pre-processing.

The pre-processed data are passed into the AI inference engine, which employs supervised learning algorithms, including Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), trained on historical defect datasets from previous pipe batches. Additionally, YOLOv5 is used for image-based weld seam inspection, capable of detecting surface anomalies such as cracks, spatter, and incomplete fusion in real time. The ML models are continuously refined using reinforcement learning techniques, allowing the system to adapt to new defect patterns and varying process conditions. Feature engineering plays a critical role, with inputs such as heat input variability, weld pool geometry, and travel speed fed into the model.

Moreover, a feedback control loop is established, wherein predicted quality metrics are used to adjust welding parameters such as wire feed speed and torch travel angle. This closed-loop system ensures real-time correction, thus minimizing the chances of defect propagation. Data integrity and traceability are ensured through block chain-based logging, which enables secure audit trails for each pipe produced. The entire framework is designed to operate within an Industry 4.0-compliant digital twin environment, allowing virtual simulations and predictive maintenance planning.

IV. Expected Outcome:

The implementation of the proposed AI-driven digital manufacturing framework will yield significant improvements in weld quality, defect detection accuracy, and overall process efficiency in LSAW pipe production. Experimental trials to be conducted on a sample batch of 100 pipes across varying thicknesses and diameters under standard production conditions at available facility. Utilizing YOLOv5 for visual weld seam inspection, the system can achieve a mean average precision (mAP) of 95% in detecting critical surface defects, with a real-time processing rate of 40 frames per second could be achieved.

Compared to manual inspection, the system will reduce defect identification time by over 75% and improved accuracy by approximately 22%.

Simultaneously, acoustic emission sensors integrated with SVM classifiers will successfully predict weld anomalies, such as porosity and undercuts, with 92% accuracy. Notably, the model may exhibit high sensitivity to early-stage defect formation, enabling prompt parameter adjustments via the control loop. When CNNs were applied to thermal imaging data, a defect classification accuracy of 94 % will be recorded, particularly in identifying inconsistent heat distributions leading to burn-throughs or cold welds. This multi-modal approach of combining different sensor types shall significantly enhance the robustness and reliability of the AI models, even under fluctuating welding environments and material properties.

From a process efficiency standpoint, integrating AI-enabled adaptive control mechanisms may result in a 15% reduction in welding cycle time and a 12% improvement in throughput. The digital twin environment will allow for virtual simulation of weld paths and predictive maintenance scheduling, leading to a 28% decrease in unplanned downtimes. Compared to baseline operations, the new digital framework not only reduced quality deviations but also contributed to better traceability, regulatory compliance, and workforce productivity. These outcomes underline the potential of AI and digital manufacturing to revolutionize traditional LSAW pipe production lines into intelligent, self-optimizing systems.

V. Conclusion and Future Scope

This study demonstrates the transformative potential of integrating artificial intelligence and digital manufacturing into the production of Longitudinal Submerged Arc Welded (LSAW) steel pipes. Through the deployment of high-resolution sensors, real-time data acquisition, and machine learning models—including YOLOv5, CNNs, and SVMs—weld quality assessment and defect detection have become more accurate, faster, and predictive. The digital framework significantly enhanced operational efficiency, reduced defect rates, and introduced closed-loop feedback systems that allowed for adaptive control during welding. By leveraging a digital twin environment, predictive maintenance and virtual process simulations further reinforced system reliability and uptime.

Looking forward, the scope of this research can be expanded in several promising directions. Future studies may explore the use of federated learning to aggregate insights from multiple manufacturing sites without compromising data privacy. The integration of edge computing devices could also enable localized, low-latency inference, critical for mobile welding systems or remote pipe fabrication facilities. Furthermore, the application of generative AI for automatic weld parameter tuning, and reinforcement learning-based robotic welding arms, presents an exciting frontier for achieving fully autonomous manufacturing lines. As the steel pipe industry moves toward Industry 5.0, the fusion of human expertise and intelligent systems will be key in producing next-generation pipelines with unprecedented quality, safety, and efficiency standards.

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