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REVIEW ARTICLE - MECHANICAL ENGINEERING

Towards Digital Twin–Enabled Laser Welding: Opportunities, Challenges, and a Hybrid Framework for Industrial Deployment

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Abstract

The recent advancements in laser welding (LW) technology through the incorporation of Digital Twin (DT) technologies, due to the growing importance of Industry 4.0 and smart manufacturing in the context of automation, precision, and digital fabrication, have made LW one of the world's leading advanced production processes. The DT technologies are expected to provide the necessary integration to facilitate effective real-time monitoring, predictive modeling of process behavior, optimal process control, and adaptive process control capability for welded parts. However, an overall framework for effectively integrating LW technology into the manufacturing environment has yet to be developed. This paper critically reviews recent developments in DT-enabled LW systems and proposes a hybrid framework for successful industrial deployment. For data collection, the authors used a systematic review approach to identify studies published after 2018 that covered various technologies related to DTs applied to welding. The review included consideration of real-time sensing technologies; data fusion using multi-sensor technologies; physically based modeling technologies; artificial intelligence technologies; EDGE-Cloud Computing architectures; and adaptive process control strategies. The findings indicate that developing a physics-informed simulation of the welding process and integrating it with an AI-based prediction model will significantly improve accuracy in assessing weld quality, predicting defect occurrence, and optimizing the process. The integration of EDGE Computing and Cloud Computing with Office & Manufacturing processes supports real-time responses and scalability within the industry. Some of the major challenges identified in the research included data synchronization, interoperability, cybersecurity, computational latency, and explainable artificial intelligence. A hybrid DT framework is proposed to provide an intelligent, autonomous platform for future LW applications in Smart Manufacturing.

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Keywords: Laser Welding (LW); Digital Twin (DT); Artificial Intelligence (AI); CNN-LSTM; Multi-Sensor Integration; Smart Manufacturing; Real-Time Process Control.

1. Introduction

Welding is a fundamental manufacturing process widely used across multiple industrial sectors, including automotive, aerospace, shipbuilding, and electronics. It enables the permanent joining of two or more components, thereby forming a functional assembly that satisfies mechanical, structural, or aesthetic requirements. The welding process used is determined by various parameters, including, but not limited to, geometry, material type, production volume, and the mechanical and thermal properties required of the weld joint. Traditionally used welding processes, such as arc/weld resistance and friction processes, were chosen for their consistent operation and have been well defined by many industrial standards governing their application. However, they lack the precision and efficient control over the welding process and energy consumption. They cannot easily adapt to geometries in welding applications, thereby limiting the production of high-performance parts using Advanced Manufacturing techniques [1].

The advancement of intelligent manufacturing is driving a global industrial revolution, primarily based on the principles of Industry 4.0, moving toward Industry 5.0. Both of these paradigms share the goal of leveraging digital technologies, cyber-physical systems, and real-time data to improve productivity, increase product quality, and promote sustainability through automated weld processes. For these reasons, LW has become increasingly popular in welding applications. LW has several advantages due to its precision and energy density; therefore, it is an excellent method for welding thin metal parts, complex-shaped parts, and dissimilar metals. In addition to the above, the localized, highly concentrated energy input enables rapid welding with minimal heat-affected zones, thereby increasing reliability in high-end applications such as aerospace components, medical devices, and electronic assemblies [2].

Nomenclature and Symbols			
DT	Digital Twins	CAD	Computer-Aided Design
LW	Laser Welding	AI	Artificial Intelligence
AI	Artificial Intelligence	CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory		

As manufacturing processes get more complex, the requirement for advanced tools capable of simulating, predicting, controlling, and optimizing these operations in real time has become increasingly critical. DT technology provides a robust solution to these challenges. A DT is a computer-based representation of a physical product that uses real-time inputs from various sources (e.g., sensors) to model, compare, predict, and analyze product performance, and to explore potential system improvements [3]. LW operations continue to face significant challenges due to insufficient real-time monitoring, a lack of predictive control, and poor integration between physical processes and digital models, despite rapid development in digital manufacturing technologies [4].

Intelligence and smart manufacturing systems are essential for the welding and automation industries. For instance, P. Stavropoulos et al. [1] introduced the fundamental concept of smart manufacturing, grounded in DTs and their integration with Industry 4.0 settings. Fu et al. [2] reviewed the implementation of DT technologies in machining systems with emphasis on machining errors and smart manufacturing optimization.

This review intends to provide a comprehensive foundation for advancing DT-empowered LW systems toward intelligent, adaptive, and industrially deployable smart manufacturing environments. The rationale behind this review is to evaluate how DT can be applied to different methods of welding workflow while investigating how the distinct advantages and requirements of LW can help to create pathways for DT implementation in areas such as monitoring, predictive simulation, operator training, and decision support via the application of DT. In contrast to earlier research, the suggested framework combines real-time adaptive control, hybrid modeling, and multi-sensor data fusion into a single DT architecture. Specifically, the current review has provided a comprehensive assessment of the current research landscape concerning the application of DT in welding processes, with a particular emphasis on LW. Also, the review has utilized a specific methodology for integrating DT technology into the LW process. In this regard, the technical barriers to successful implementation of DT in LW are identified through a synthesis of existing literature, including data collection and processing, model fidelity, cybersecurity, and interoperability and standardization of industrial practices. Through identification of these barriers, there can be a bridging of the existing gap in knowledge to provide actionable results to aid in the development of more intelligent, adaptable, and environmentally sustainable process control of LW systems while enabling future advancements in the areas of digital manufacturing and cyber-physical process control.

The review methodology strongly emphasizes the use of a systematic review to provide a well-structured, thorough approach to reviewing the literature on DT technology in LW systems, thereby ensuring the validity and reproducibility of the analysis. A collection of relevant studies published between 2018 and 2020, sourced from leading computer science databases: Web of Science, Scopus, and IEEE Xplore by means of combinations of various keywords related to the "Digital Twin", "laser welding, "process monitoring", "AI," and "smart manufacturing." This initial search yielded many relevant peer-reviewed articles, which were subsequently filtered according to predetermined inclusion and exclusion criteria. For the study to be considered, it must have been published in English. It should have illustrated an instance of the application of the DT to a welding or manufacturing application. Studies that lack sufficient methodological layout, experimental validation, or technological relevance will be excluded from analysis. Subsequently, a thematic classification strategy was also integrated with the dataset to identify the key characteristics of each selected study, e.g., the modeling strategies, sensor integration, data processing strategies, applications of AI, etc., along with any issues encountered regarding industrial applications, which would ultimately contribute to the identification of both current DT-based welding system limitations, research trends, and technology gaps.

PRISMA was utilized as the methodology to conduct a transparent, systematic, and reproducible process for selecting articles. The PRISMA process was used to identify, screen, assess, and select the most relevant studies on DT technology in LW systems and the intelligent manufacturing environment [5]. Moreover, a critical analysis of the reviewed studies was conducted to underpin the development of an integrated conceptual framework for intelligent LW environments, based on the synthesized findings from the literature and the review. In addition to providing a systematic foundation for future research and industry applications, the overall process was designed to ensure that the state of the art is comprehensively and critically appraised. Fig. 1 illustrates the overall article screening and selection process based on the PRISMA workflow methodology.

2. Literature Review

2.1. Overview of digital twin concepts and applications in manufacturing and welding

The digital counterpart of an entity, created digitally and updated at regular periodic intervals, is referred to as the 'Digital Twin' (DT). By utilizing DT technology, manufacturers can create a virtual representation of their entity, enabling them to continuously collect, integrate, and exchange data with the physical entity. Shell would enable enhanced monitoring, prediction, and control across the full lifecycle of products and processes. Research into the application of DTs has been completed for several welding processes, including friction spot welding, friction stir welding, and arc welding. For example, Maity et al. [6] developed a DT framework for friction spot welding by combining FE modeling with data-driven algorithms to monitor the thermal behavior of the welding process and dynamically adjust process parameters in real time. Similarly, Kuritsyn et al. [7] developed an approach to apply DT to optimize the design of tools used in friction stir welding by incorporating motion-based process conditions to improve weld joint quality while reducing the operational complexity of the process. In addition, Chen et al. [8] developed a DT to produce 3-D temperature fields resulting from the arc-welding process in real time by integrating sensor data with computational process models, enabling continuous adjustments to process parameters. In addition, DT has been developed to detect welding defects, predict anomalies associated with the arc welding process, and support autonomous planning. Zhang et al. [9, 10] and Ji and Mohamad Nor [11] proposed a deep learning-based DT framework for welding quality inspection using acoustic signal analysis. This study used an AI-based classification technique to improve the accuracy of defect identification in welding operations. Two recent publications by Li et al. [12]

and Bao et al. [13] reviewed the previous applications of DT with a focus on the real-time detection of incomplete parts and recognition of anomalies in welding processes, providing evidence that the integration of machine learning technologies with virtual environments offers significant potential for the optimization of welding processes. Based on research by Wang et al. [14], the training and skill assessment of welders using DT technology were improved through VR simulation of welder movement during human-to-machine cooperation. However, DT technologies currently used for monitoring weld quality, assisting operators of the welding process, and for other types of welding have identified multiple gaps in the knowledge base. There is substantial prior research on DT and welding processes, but most of this research has used traditional welding methods; as a result, there have been significantly fewer studies on high-precision welding processes like LW. The majority of previous studies also focused heavily on real-time monitoring and/or simulation of the welding processes in a controlled experimental laboratory environment. It was unable to demonstrate actions to support scalability in manufacturing, connectivity to other systems for interoperability, deployment of adaptive process control, or the application of DT to develop intelligent manufacturing applications. Similarly, few studies have been used to support the generalizability of AI models, their robustness across various operational conditions, and their adaptability to non-nominal geometries. Consequently, targeted research into the implementation of DT technologies in LW is warranted due to the challenges posed by the high energy density, rapid heating and cooling, melt-pool dynamics, and the plasma plume associated with this welding process.

While the literature has addressed the use of DT in the general welding process, there remains an overarching need for a systematic, specific analysis of LW to identify the technological, operational, and human factors critical to implementing DT technologies in the manufacturing environment. The studies utilized in this review represent the progressive evolution of DT development in welding, from basic applications to more complex and specific applications in LW, including real-time monitoring, intelligent process controls, and applications for high-precision manufacturing.

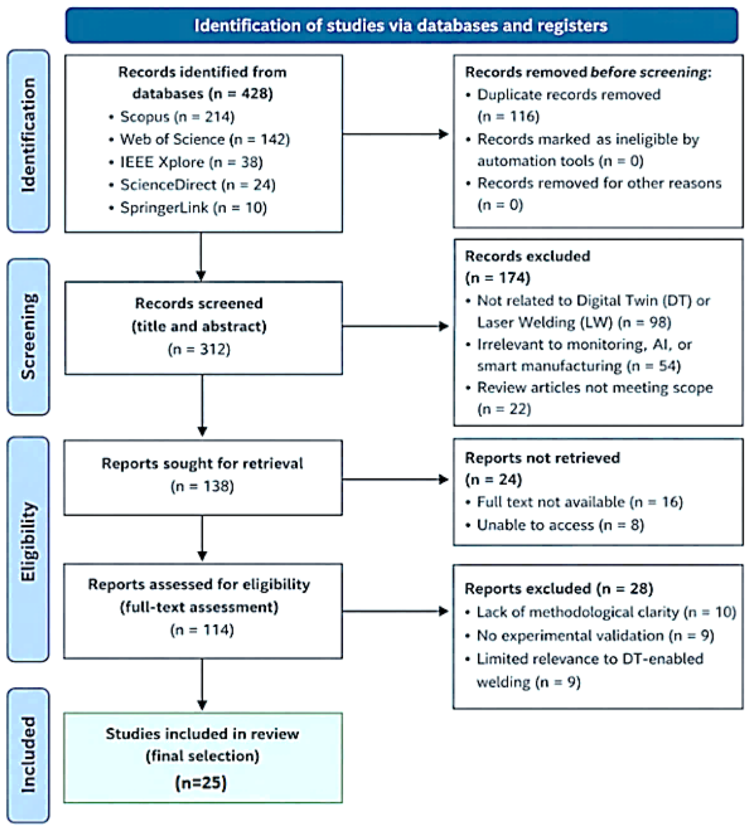

Fig. 1. PRISMA workflow of identification, screening, eligibility, and final inclusion of studies in this methodical review of literature

2.2. Specific advances and opportunities of digital twin in laser welding

The importance of artificial intelligence (AI) and digital modeling in LW has been confirmed by many studies. In fact, research has demonstrated that wire feeding faults can be detected with up to 96% accuracy using an LSTM-CNN neural network. At the same time, a real-time data acquisition system was simultaneously developed to record plasma density, laser intensity, and melt pool temperature [15]. In another study, a hybrid CNN-LSTM model was proposed to localize penetration with 99.8% accuracy and to facilitate acoustic feature extraction of the process [16]. These results highlighted the potential of DT to enhance real-time process monitoring and predictive control. While high detection accuracy was reported, studies focussed on small-scale experiments, and questions remain about scalability to industrial production and robustness under variable operational conditions.

Besides, numerical simulation remains an indispensable tool for understanding the fundamental physical principles of LW and predicting both the origin and the quality of welded joints [17]. Cloud manufacturing integration methods and AI indicate considerable potential for advancing DT in laser-welded sheet materials [18]. Yet, the combination of high-fidelity simulations with real-time sensor data imposes substantial computational requests and may confine practical implementation unless optimized.

Digital twinning is essential to LW through real-time monitoring, optimization, decision support, and predictive simulation. By using Internet of Things (IoT) sensors, it is possible to collect high-resolution data from the welding process to feed into virtual models synchronized with the real weld. Real-time digital representations of the weld process enable continuous assessment of key variables such as power and feed rate [19]. Therefore, the DT models not only generate a digital image of the weld in real time but also highlight potential problems at an early stage, enabling automatic adjustments to maintain weld quality [20]. Despite the advantages of DT for LW, significant challenges remain in sensor data reliability and communication network latency, preventing widespread industrial deployment.

Real-time monitoring is a major component of DT for LW. The integrated Industry 4.0 approach has automated geometric inspections of parts by comparing them to a standard Computer-Aided Design (CAD) model. [21]. The cloud-based 'Inspection 4.0' system will work in combination with DT to provide remote monitoring of processes, enhance the accuracy of automated systems, and provide support for decision making. However, when merging multiple data sources, proper care must be taken to avoid inconsistencies and errors in the virtual representations of the welding process. Numerical simulations are also an important tool for predicting and optimizing the performance of LW processes. The concept of creating a customized production system using 3D lasers to scan parts, incorporating geometric variations into iterative, live simulations to dynamically adjust process parameters and predict the final quality of parts, was recently documented in [22]. In addition, simulation methods that use nominal measurements account for geometric deviations in parts and predict and monitor the final quality of the weld joint [23]. As documented in the previous two examples, they have proven that DT can model, evaluate, and adjust welding conditions dynamically. Maintaining model fidelity under significantly fluctuating process conditions and validating simulation results through experimental means continue to pose numerous challenges. The ability to simulate "what if" scenarios in a simulated environment allows the operator to explore various adjustment scenarios before implementation, thereby determining the optimal conditions to accomplish their tasks. DTs also enable the integration of Artificial Intelligence algorithms to develop reliable performance predictions and forecast the need for preventive maintenance within their processes, thereby improving overall reliability and efficiency. Although success has been demonstrated in the feasibility of DTs, the interpretability and robustness (reliability) of artificial intelligence (AI) models with respect to complex welding processes (real-world) still require additional research and are under-investigated. To improve decision-making capabilities between operators and their processes, Sun et al. (2021) [24] introduced a methodological framework for determining the most efficient process configurations. Operators can use both the Internet of Things (IoT) and augmented reality (AR) technologies/devices to assess their health and physical condition while engaging in LW, thereby incorporating human factors into their respective processes. Furthermore, an innovative approach has been developed that integrates a DT along with AR technologies/devices to assist operators in selecting the most efficient monitoring system for their respective processes. This approach allows users to visualize, simulate, and evaluate different system configurations and, in turn, make informed decisions. Collectively, these innovations will lead to more flexible, efficient, and environmentally sustainable manufacturing processes compared to LW, while demonstrating the ongoing technical and operational challenges that remain in manufacturing for the full-scale deployment of DTs.

2.3. Thermal distribution and behaviour of heat transfer

To achieve the implementation of a DT and to perform real-time monitoring and intelligent/adaptive control of the LW process, an accurate thermal model of the process must be developed, as it is a fundamental and critical precursor to the successful deployment of all three concepts for the LW process. The thermal field present in LW is influenced by both the wide temperature gradients within the workpiece and the highly concentrated heat input surrounding the melt pool. This large temperature variation directly correlates to the continued development of residual stress, characterization of the microstructure, and ultimately, the performance of the completed joint. Fig. 2 illustrates the thermal distribution and heat concentration around the weld zone developed during LW. Fig. 2 also shows that the laser's energy output produces very high thermal gradients, which may significantly affect melt pool formation, the heat-affected zone (HAZ), and cooling rates. Understanding the thermal characteristics of the LW process is important for developing DT models for real-time process monitoring and adaptive optimization [20, 23].

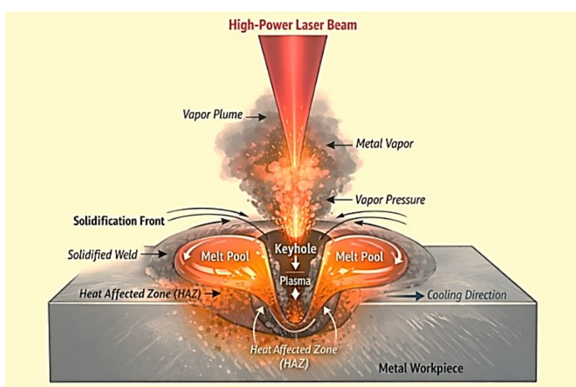

Fig. 2. Temperature distribution and thermal gradients during the LW process based on numerical simulation

Fig. 3 illustrates the thermal distribution (Simulation), showing considerable heat concentration in the keyhole and melt pool areas, as highlighted by the thermal distribution during LW. The temperature differential defined above significantly influences the resulting microstructure and mechanical properties of the welded joint, as well as the joint's heat transport and cooling. Fig. 3 also shows how thermal transfer characteristics, driven by heat input, and the material's response to heat affect weld quality and process stability during welding. If thermal behavior analysis can be incorporated into DT-enabled systems, DT will enable enhanced predictive modeling and intelligent control. This advanced analysis capability will also enable defect prevention in an advanced manufacturing environment.

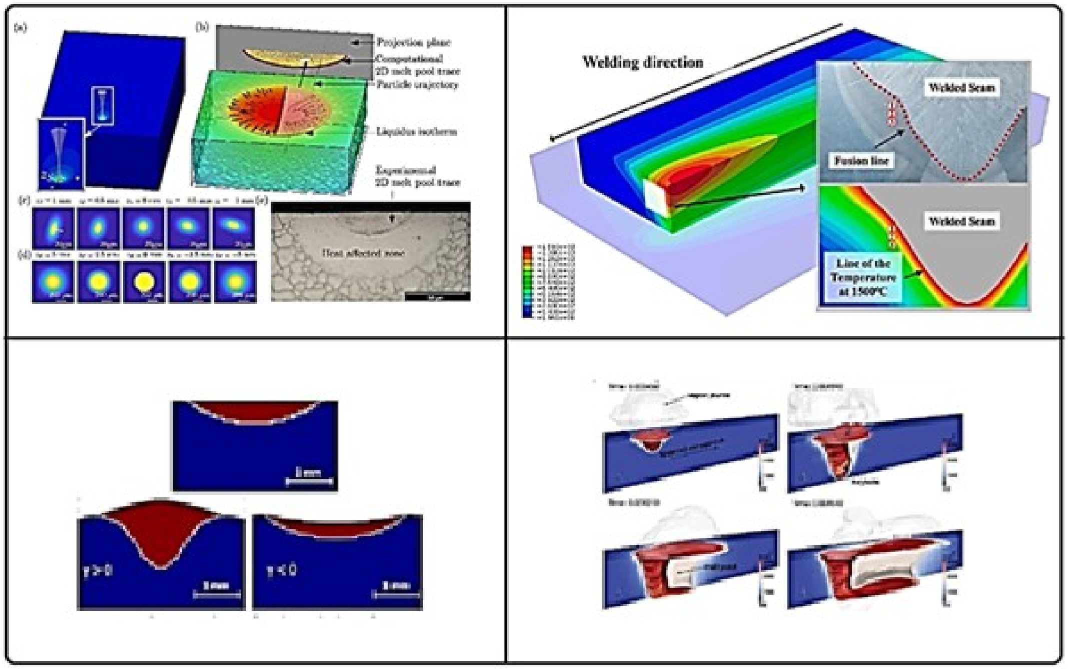

Fig. 3. Illustrates thermal distribution (simulation)

3. Challenges and Industrial Constraints of DT-Enabled Laser Welding

There are still significant technical, computational, operational, and industrial barriers that must be overcome before DT-enabled LW systems can be launched in a mass production environment. The barriers relate to multiple aspects of data management, real-time synchronization, the reliability of artificial intelligence, scalability of computational resources, interoperability across systems, and human-machine interaction. DT Frameworks were used to integrate high fidelity physical modeling for complex thermal and metallurgical phenomena, real-time acquisition of multi-source sensor data, and adaptive optimization of process parameters for improving the quality of welds and the robustness of the process [6,8,15]. This system amalgamation offers opportunities for successful error detection, greater process repeatability, and customized manufacturing - all of which are goals achieved by integrating these aspects into a single DT solution designed around the ideals of Industry 4.0 manufacturing [22]. However, several important problems prevent the widespread industrial use of DTs for LW. One limiting factor, for example, is data management. DTs for LW generate massive amounts of information due to multiple high-frequency Internet of Things (IoT) sensors (e.g., those that monitor laser power, melt pool activity, etc.) that monitor all aspects of the process and provide input to the DT system. DTs require large volumes of historical as well as real-time information from multiple high-frequency IoT sensors that record several parameters of LW activity to function effectively and provide useful information; thus requiring large amounts of digital infrastructure such as, but not limited to, high-performance telecommunications networks and cloud/edge computing architecture for real-time processing, storage, and synchronization of large amounts of information from multiple points needing extreme precision (i.e., loss of data, latency, and uncertainty in the time-sensitive environment can have a detrimental effect on the success of DT based decision-making).

The other major difficulty with DTs is the integration of artificial intelligence (AI) into the DT framework. AI has proven to offer advanced methods for identifying defects, measuring penetration, and predicting process outcomes, using models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks [15, 16]. However, generalizing these approaches has proven very challenging due to their lack of robustness and difficulty in interpreting their outputs, limiting their use in industry. Many AI models are trained using only production-specific datasets and/or controlled laboratory environments, limiting their ability to be used in "real-world" situations where materials, joints, surfaces, and machines have been used for varying amounts of time (age factor) and in a variety of ways. The resulting opacity and lack of adaptability of these systems lead to issues related to trust and the need for certification and validation of safety-critical AI-augmented DT systems used in manufacturingl. When building a predictive DT, it is critical to include high-fidelity numerical simulations. This is particularly important for understanding non-nominal geometries or part-to-part variability [21]. The use of non-nominal geometries has been shown to improve predictive accuracy and quality assessments. Still, it requires extensive computational resources, making it difficult, if not impossible, to integrate into fast-paced production schedules without considering the trade-off between model accuracy and computational speed. As a result, the trade-off between model fidelity and computational speed is a major constraint on deploying DTs in most industrial settings. Connect to DTs in practice, but are not able to accurately predict transient phenomena such as keyhole instability, melt pool oscillation, or steep temperature gradients. As mentioned, a human factor has not been adequately accounted for in the implementation of DTs for LW. The operator involvement, ergonomic interface design, and the human integration factor are critical to successful adoption and operational efficiency. Recent studies on interfaces augmented with technology, skill monitoring, and operator training in the context of DTs have highlighted their potential to integrate human factors into digital manufacturing systems [14, 23]. Failure to take this dimension into account may lead to a negative reaction to change. It could restrict the potential impact of their DT-based solutions even with high levels of technological sophistication. Furthermore, standardization, interoperability, and other regulatory issues continue to be barriers to the integration of DT systems into heterogeneous industrial environments. The lack of cohesive standards creates challenges for data sharing, multi-vendor interoperability, cybersecurity, and the long-term viability of systems. All of the characteristics delineated above are critical to the successful implementation of a sustainable DT deployment [5, 23]. The constraints related to the deployment of DTs are especially critical in the case of LW, as high levels of synchronization between the physical and digital systems are required.

From a technological perspective, there are several areas of promise in the development of systems for the co-evolution of ultra-precision LW robots, intelligent sensing systems, and a DT- driven control platform. Collectively, they have the capacity to support significant improvements in efficiency, quality, productivity, resource utilization, and on-time delivery. Nonetheless, developing a homogeneous and reliable digital ecosystem will require, in a coordinated fashion, the development of calibration, validation, maintenance, and lifecycle management processes for high-speed data streams. The ability to address these issues will determine whether DT technology transitions from experimental demonstrations to viable solutions for industrial LW. Table 1 summarizes and displays information on the main issues, potential impacts in the context of DT-based LW, and associated research directions.

Table 1. Proposed solutions of the DT in LW, research gaps, and consequences

Challenges	Potential consequences	Proposed solutions
Integration of IoT and optical sensors	Increased system complexity; higher installation and maintenance costs. Calibration difficulties and loss of reliability in keyhole and melt-pool measurements.	Development of standardized sensor layouts for LW cells. Automated calibration and sensor health-monitoring. Intuitive user interfaces (AR, VR)
Massive real-time data processing	Risk of system overload and latency in decision-making—difficulties in analyzing high-frequency images and signals in due time, leading to late defect detection.	Use of cloud and edge computing architectures. Implementation of data-flow optimization and compression algorithms. Design of modular and scalable DT architectures.
Adaptation to industrial constraints	Variations in material, geometry, and environment reduce model robustness and predictive accuracy when moving from the lab to the shop floor.	Use of non-nominal simulations, including 3D scans and real geometric deviations. Strengthening of multiphysics and hybrid (model-based + data-driven) approaches.
Maturity of artificial intelligence tools	Lack of transparency in AI decisions—difficulties for operators and quality engineers to interpret predictions and alarms.	Development of explainable AI models for defect and penetration monitoring. Extensive validation with industrial data. Hybrid algorithms combining rules and learning.
Standardization and interoperability	Difficulty integrating heterogeneous sensors, robots, and control systems into industrial LW lines. Risk of rapid obsolescence and vendor lock-in.	Development of open standards and communication protocols for welding DT. Design of integrated, modular platforms that ensure interoperability and long-term upgradability.
Human–machine interaction and operator skills	Under-use of DT functionalities, operator overload with complex dashboards, and resistance to change	Design of ergonomic HMIs focused on key laser-welding indicators. AR-based training and guidance. Continuous upskilling programs involving operators in DT projects

4. Critical Analysis of Reviewed Studies

The studies reviewed have reported outstanding advancements in DT technologies for LW, including artificial intelligence, thermal modeling, real-time monitoring, and adaptive process control. However, it appears that the methodologies employed, the validation of the studies, the extent of their application in industry, the extent of sensor integration, and the manner in which computational scalability has been assessed vary significantly across virtually all of the reviewed studies. For this reason, a comparison of the studies was warranted to facilitate an evaluation of their respective strengths/weaknesses and the associated implementation issues. Table 2 provides a comparative summary of a selection of recent application-oriented literature on the use of DTs in welding processes, including an overview of significant contributions, the types of welding processes, the methodologies used in the studies, and the applicable limitations. This comparison reveals the need for integrated, scalable, and real-time DT frameworks in LW and enables the detection of existing research gaps [15, 18]. Additionally, the bulk of current DT implementations in welding processes remain fragmented, with limited integration between sensing, modeling, and control components, according to the analysis of the evaluated research. The inability of DT systems to perform well in industrial settings, where fast data processing and synchronization are crucial, stems from this lack of integration [15].

In this regard, it can be stated that the lack of a cohesive, interoperable architecture is the main drawback of existing DT-based welding systems, rather than the performance of individual models or sensors. The success of DT systems is influenced not only by component accuracy but also by the level of functional interaction between the physical and digital environments [18].

To address these issues, this research proposes a hybrid architecture that uses edge-cloud computing, multi-mode data acquisition based on the physical dimensions (sensor array), and hybrid physics/AI models. This approach will enable real-time monitoring of the LW operation and adaptive process control, as well as facilitate a better understanding of complex behaviors during LW, such as key holing and melt pool dynamics [23].

From an industrial perspective, implementing an integrated DT framework will significantly enhance predictive maintenance strategies, reduce the risk of defects, and improve production reliability. To accomplish this, an effective data infrastructure, standardized communication methods, and a user-friendly interface for human-machine interaction are required [15, 8].

Future research should focus on improving the implementation of advanced control strategies such as reinforcement learning, enhancing data synchronization methods, and refining modeling interpretability. An important development direction for the next generation of DT-enabled welding systems is to incorporate sustainability parameters, such as energy consumption and environmental impact [23-26].

Table 2. Critical comparison of reviewed DT-enabled welding studies

Ref.	Main Objective	Methodology	Dataset / Experimental Setup	Validation Approach	Advantages	Limitations
[15]	Welding penetration monitoring	CNN-LSTM hybrid model	Acoustic emission signal dataset	Experimental validation	High prediction accuracy	Limited industrial scalability
[17]	Multi-sensor welding monitoring	Sensor fusion system	Multi-sensor welding data	Real-time experiments	Improved monitoring reliability	High computational complexity
[11]	Welding quality inspection	Acoustic signal analysis with AI	Controlled welding experiments	Laboratory-based validation	Efficient defect classification	Limited adaptive control capability
[8]	Thermal modeling in friction stir welding	DT thermal simulation	Thermal distribution analysis	Simulation-based validation	Improved thermal prediction	Limited real-time industrial implementation
[14]	Human-robot interactive welding	DT-enabled robotic welding framework	Robotic welding environment	Experimental robotic setup	Enhanced process automation	Limited interoperability analysis

5. Conceptualizing a digital twin framework for Laser Welding

The framework proposed in this study is shown in Fig. 4. It combines standardized multi-sensor data acquisition, advanced data processing, hybrid physics and AI modeling, a standardized, interoperable DT platform, and ergonomic human-machine interfaces to provide real-time monitoring, control, and optimization of the LW process.

5.1. Physical system and data acquisition layer

The system consists of an integrated layer that combines different types of sensors found in a manufacturing plant, which is known as the production environment. In addition, the system provides data other than just the optical camera images generated by the camera systems used to monitor the laser fusion system, including the temperature of the molten pool, the temperature gradient of the molten pool, as well as the acoustic signature produced during the occurrence of both stable and unstable process conditions. The molten pool also produces a spatially distributed plasma signature, providing a time- and space-dependent representation of the part geometry via 3D scanning. The implementation of a standardized and localized multi-sensor integration method (e.g., multi-sensor integrated environment) rather than traditional single sensor environments (or laboratory-based setups) allows the integrated sensor system to contain both automatic calibration and sensor health monitoring capabilities to reduce long-term sensor drift for the collected data due to the long-term nature of the data.

5.2. Data processing and standardization layer

The second integration layer processes the original data streams collected in the first layer, which have high-frequency sampling rates and various non-uniformities. It requires data pre-processing (i.e., data cleaning), temporal synchronization, and data normalization. The second data integration layer will also establish algorithms to reduce data computation and memory requirements for storing the data, while preserving the data in its original (i.e., raw) multi-physical, heterogeneous format to accurately reflect the current state of the LW process. The resulting data streams are synchronized, cleaned, and standardized, rendering them directly usable by the DT's physics-based and data-driven models.

Fig. 4 shows an example of the suggested DT architecture for LW, which combines edge and cloud computing with multi-sensor data collection. The technology uses hybrid models that combine AI-driven methods with physics-based strategies to provide precise, real-time, adaptive control during the welding process. Furthermore, the general design of the suggested DT framework for LW is built as a multi-layered system that facilitates adaptive control, prediction, and real-time monitoring of the welding process. The framework generates a synchronized virtual representation of the LW process by combining physical process data with sophisticated computer models.

The final integration layer processes the finished raw data streams generated by the previous two integration tiers to provide real-time data that links to the connected cloud location for multiple users through an edge computing framework and multi-cluster architecture. The multi-cluster architecture will be needed to improve system performance by reducing both system latency and the potential for any one cluster within the system to experience an excess data load, which are two of the primary barriers to implementing the industrial DT technology, A mixed edge-cloud computing architecture is leveraged to provide seamless integration of multiple technologies, such as communication, synchronization, and filtering while providing low latency and scalable architectures.

A three-layer architecture has been created to support the operator user interface and assist in decision-making and improving process visibility. The operator user interface comprises all user interactions for operating the LW system, including dashboard displays, alert systems, and augmented reality (AR) tools. The integrated architecture will ensure better interoperability, scalability, and real-time response for industrial LW applications and overcome key challenges with current DT implementations.

5.3. Potential strategies for validation and benchmarking

The frameworks presented above are conceptual. However, many methods are available to validate these frameworks to demonstrate their industrial viability and performance if they are employed in a future study. They could be validated through experimentation using LW, multi-sensor monitoring systems, thermal imaging, acoustic emission analysis, and AI-driven predictive models. In addition, the proposed DT architecture can be compared to current monitoring and control systems regarding the accuracy of predictions, computational efficiency, real-time responsiveness, defect detection capability, adaptive process control, and scalability within the industry. Furthermore, the validation studies for future research could be based on simulation-based validation, hardware-in-loop architectures, and/or industrial pilot programs to evaluate interoperability, data synchronization efficiency, and reliability during real manufacturing conditions.

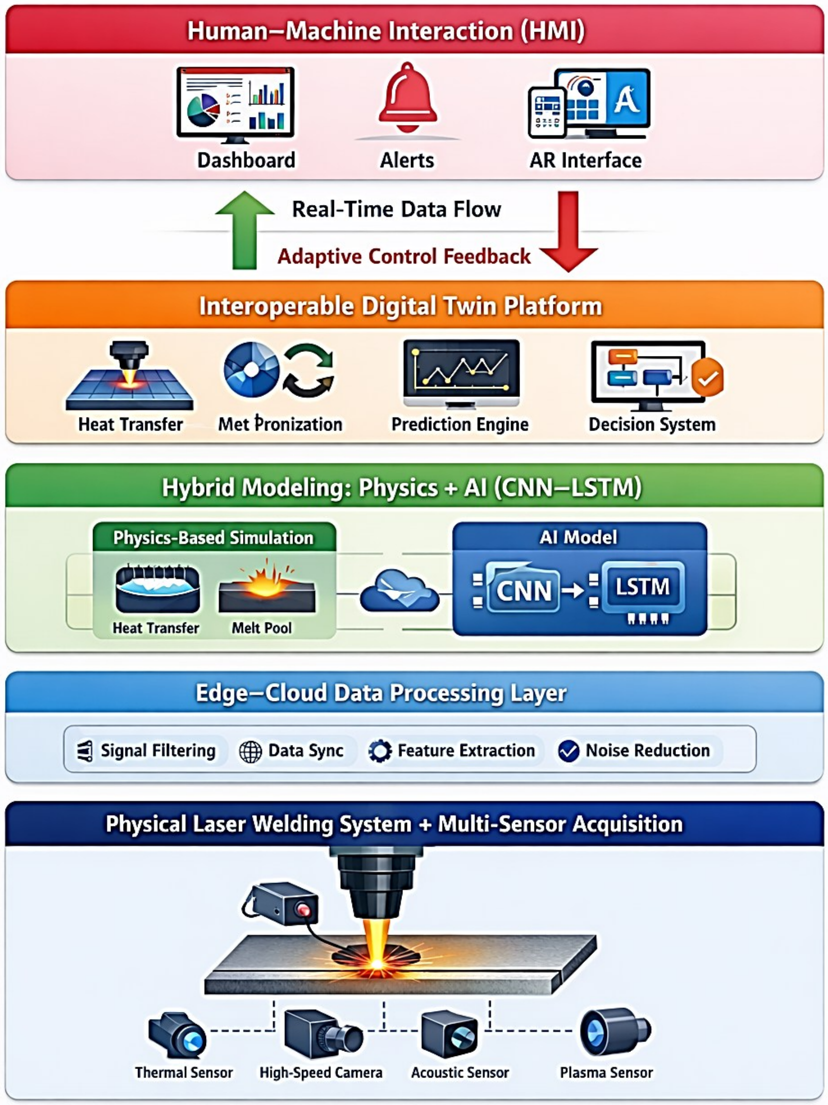

Fig. 4. Proposed DT architecture for LW with multi-sensor data acquisition, edge-cloud processing, hybrid physics-based and AI-driven modeling, and real-time adaptive control

5.4. Hybrid modeling layer: Physics-based and AI models

The third layer includes hybrid modeling, combining physics-based models with data-driven artificial intelligence (AI) techniques to enable hybrid prediction. Physical laser-welding phenomena, such as heat transfer, melt-pool dynamics, and solidification, are modeled using multiphysics numerical simulations. Non-nominal simulations will also be used to model the actual geometries with deviations from the nominal models. Convolutional and Long Short-Term Memory (LSTM) neural networks will be used in parallel to generate predictive models. The CNNs will be used to extract features from the optical and acoustic sensor signals; the LSTMs will be used to model the process's temporal evolution. The combined methods above will capture some of the nonlinearities in the LW process, which are very difficult to model using physics-based approaches. The bidirectional interaction between physics-based and data-driven predictive models will improve the robustness and interpretability of all predictions, thereby providing real-time quality indicators, probable defect predictions, and performance and drift predictions for the process.

5.5. Interoperable and modular digital twin platform

Layer four is where the interoperable and modular DT platform resides. The DT is built according to open standards and industrial communication protocols; this design minimizes vendor lock-in, ensuring long-term scalability and providing feedback mechanisms that send adaptive control signals back to the physical process for closed-loop optimization. Therefore, the DT platform will provide operational recommendations, automatically adjust welding parameters, and provide secure interfaces to integrate with production systems.

5.6. Ergonomic human-machine interaction layer

Layer five focuses on creating ergonomic human-machine interfaces for the key indicators of LW. This layer consolidates synthetic performance metrics, model-generated alerts, and process contextual information into intuitive dashboards and augmented reality tools to assist with operator training, provide real-time support, and improve skills. The use of explainable AI concepts helps operators understand why a decision from the DT was made, ultimately increasing their acceptance and trust in the system. Outcomes from this layer include simplified dashboards, contextual instructions, and decision-support tools, all of which will help the technology achieve a higher level of industrial adoption. The hybrid modeling approach, which combines the strengths of data-driven and physics-driven models, is perhaps the most innovative aspect of the proposed framework. AI techniques offer greater capability to capture nonlinear relationships, enabling more accurate real-time predictions; meanwhile, physics-based models are highly interpretable and reliable for describing thermal and metallurgical phenomena. Combining both methodologies into a single DT platform greatly enhances the forecast accuracy, adaptability, and reliability of the overall system.

An edge-cloud processing, real-time control, hybrid modeling, and DT framework for LW is provided, and multi-sensor data is shown in Fig. 5. The physics-based and artificial intelligence models were used to process sensor data, predict accurately, and synchronize in real time. A feedback control system and a user interface guarantee stable operation, enhanced weld quality, and better process transparency. Furthermore, the proposed design provides a flexible platform for integrating advanced technologies such as edge intelligence, reinforcement learning, and sustainability-oriented performance metrics. The framework's flexibility enables it to adapt to the industry's evolving needs and facilitates the transition to fully autonomous, intelligent welding systems.

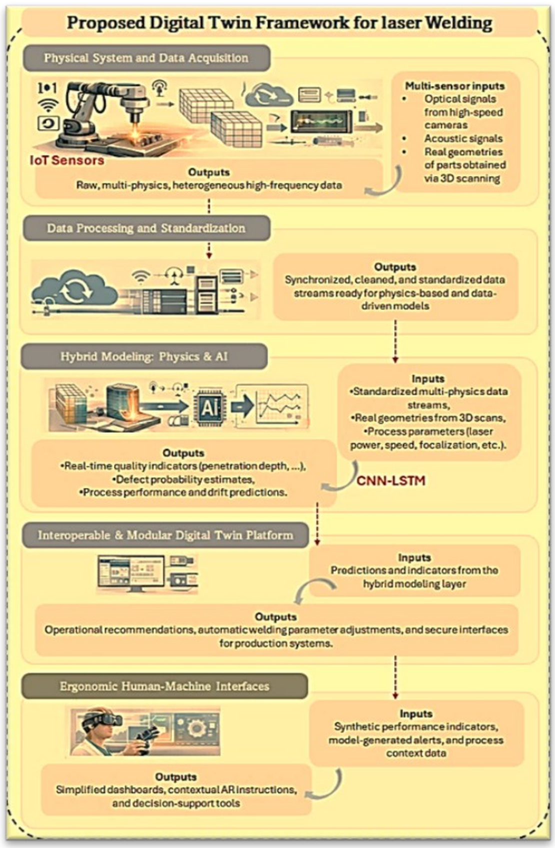

Fig. 5. The proposed DT framework for LW

6. Conclusions

Intelligent systems that can use data flows from a product's full life cycle via the digital thread are essential in today's industrial environment. The use of advanced technologies, such as DTs would improve the efficiency, sustainability, and performance of LW, a significant manufacturing process. This paper reviewed the literature on the application of the DT concept in relation to LW. The results demonstrated that DTs can be used to provide real-time process monitoring, optimize LW parameters, improve LW performance, and deliver both technical and environmental benefits. This review identified challenges and opportunities for further development in data management, modeling fidelity, and the human–machine interface (HMI) that hinder the widespread use of DT-based systems in manufacturing. Thus, the integration of DT technologies into LW is relatively new, has limited practical use, and has not yet fully leveraged the advancements enabled by DT. In this respect, the framework presented in this paper is the first step in creating a structured methodology for integrating DT/LW. Future research will detail and validate the framework technically, eventually test it in an industrial setting, and couple it with advanced control systems. Further research should also fully integrate environmental and energy-related measures, which will be critical in developing the next generation of smart production systems. To support the future development of intelligent welding systems, further research will also focus on the experimental validation of the proposed framework, the implementation of advanced control techniques, and the embedding of sustainability indicators.

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