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Smart laser welding; a strategic roadmap toward sustainable manufacturing and industry 4.0

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ABSTRACT

Industry 4.0 & the Internet of Things have revolutionized every manufacturing process, and the welding industry is far from this huge breakthrough. Big data and real-time monitoring as critical elements of the fourth industrial revolution are the essential parts of all manufacturing sectors, especially laser welding**.** Therefore**,** optimizing and controlling manufacturing processes using Industry 4.0 components such as the internet of things, sensor-based monitoring, big data analytics, etc., are considered critical approaches towards sustainable, efficient, and defect-free manufacturing. In this regard, this chapter has argued intelligent laser welding and analyzed sustainable manufacturing challenges by using optimization approaches. It recommends possible concerted effort and reveals how laser welding and Industry 4.0 strategies can integrate, assist, and synchronize each other.

Keywords: Industry 4.0; Laser welding 4.0, Smart manufacturing, Sustainable manufacturing; Digital twins

1. Introduction

Industry 4.0 is the fourth significant period in the industry since the beginning of the Industrial Revolutions. It defines a way to make the transition from dominant machine production to digital production. It transforms the production and management systems in every industry and every country into smart ones. In short, connecting the digital world to the physical aspect of the industry using the growing capabilities of the Internet of Things (IoT) and other technologies can be described as the Fourth Industrial Revolution [1]. On the other hand, this course associates with the emergence of new technologies in robotics, artificial intelligence, blockchain, nanotechnology, quantum processing, biotechnology, the Internet of Things, and automobiles, which can facilitate their launch, further prosperity, and expansion in various fields. The concept of "industry 4.0" has recently been introduced and accepted in the academic world and the manufacturing community. However, the shift from the third industrial revolution to the world of Industry 4.0 demands comprehensive study towards understanding irreversible transformations. The standards of this new industrial revolution need to be well understood, and a clear roadmap must be developed and implemented to achieve a successful change. There are various elements and factors in these changes that also stimulate social influences. The Internet of Things is one of these instrumental requirements that allows machines to communicate and creates a cheaper production environment.

The second important motivation and advantage of these transformations is "automation," in those systems act only to be influenced by each other's performance [2]. On the other hand, some sensors [3], and cyber-physical-systems (CPS) are other critical parts of this evolution and provide accessible communication between machines and surrounding environment. When different aspects of Industry 4.0, including CPS, IoT, machine-to-machine (M2M) communications, and automation, come together, it becomes easier to build compatible, robust, and agile systems with exceptional capacities. This transformation enables the communication of machines with human operators, leading to creating a new construction vision based on four fundamental concepts of 1. intelligence, 2. products, 3. communication, and 4. information network.

Like the other three industrial revolutions, the fourth industrial revolution has affected various manufacturing industries, including welding processes, and this has become important for achieving the desired efficiency and effectiveness in production. It is natural that manufacturers that cannot immediately adapt to modern market demand either go out of business or incur higher costs in the future.

Nowadays, welding is an advanced technique that is used in all aspects of industries and modern life. Laser welding (LW) has been an essential technology in numerous businesses such as IT, manufacture, healthcare, and beauty since Einstein's establishment of the theoretical foundations in 1917. With the development of laser applications in material processing methods, laser welding has always been considered a new process in various industries [4–6]. Technologies such as scanning, and deposition welding have led to the development of laser welding methods in multiple sectors such as the automotive and aerospace industries. Although in the '60s60's there were attempts to use lasers in welding, the '70s70's can be considered the beginning of laser welding in various industries. Solid-state pulsed lasers were the first lasers used in laser welding for applications such as spot-on sensitive electronic or precision mechanical components. With the progress of laser beam production resources and technological advances in laser beam conduction, laser welding has also undergone dramatic changes. With the increasing use of sheet metal industries, new technologies to improve product quality and reduce costs and operating time have become significant. Since welding plays a vital role in producing metal products, new laser welding methods instead of traditional welding methods increase the quality of products. It also reduces the number of operations after the welding process in various industries. Recently, Aminzadeh et al [7], used a real-time monitoring technique to define the distortion and deviation in aluminum laser-welded blanks via a 3D laser scanner.

For this reason, this process is prevalent in the industry and is an attractive option. Although laser welding imposes complex processes in process control and data connectivity, it offers numerous unparalleled advantages like speed, technology, and costs. Compared with traditional fabrication processes, including resistance spot welding or conventional ARC welding, laser welding or primarily fiber laser welding provides easy operation. It is straightforward to learn with a fast-learning curve, improves energy efficiency and machine lifetime. It causes a smaller ecological footprint, more economical maintenance requirements, less environmental contamination, less high-volume production time. However, a lack of a road map in the Twins model, metaheuristic approaches, and machine learning towards potential advancements is a gray area in manufacturing sectors. Therefore, this chapter aims at introducing the use of big data (BD) and AI-ML in designing digital twins (DTs) or DT-based systems for laser welding applications by highlighting the current state-of-the-art deployments.

2. Real-time monitoring for smart welding

The technology of Laser Welding (LW) as a permanent connection technique has notable potential for industrial applications. As compared to conventional welding methods, LW shows advantages of productivity, versatility, effectiveness, deeper penetration, less distortion, and higher welding velocity [8]. However, LW is an almost complex fabrication process in which achieving acceptable joint quality is affected by several process variables and other factors such as defects in the microstructure of the base material, contamination of the workpiece surface, and changes in laser beam properties. Such defects alter the welded elements' mechanical characteristics, resulting in an increased risk of fatigue of the part. Therefore, ensuring the quality of the welded joint is a must for use in industry. For this purpose, quality monitoring is considered critical in modern production systems and is usually applied in three stages before, during, and after the process [9].

Since laser welding inputs (controllable and uncontrollable), noises, and disturbances alongside the welding circumstances affect the outputs, a promising method of producing the desired results is in demand to guarantee that all noises are dismissed or lessened; therefore, the welding process conditions maintain at their standard levels.

One way of ensuring the mentioned conditions is monitoring the principal inputs means welding parameters and other influential welding conditions that may deviate from standard levels/constants or even change completely. Simple changes would be enough for some deviations of welding conditions or input parameters from desired levels or constants. For instance, adjusting the torch position can remove the error due to deviation between the actual weld seam and the torch's trajectory. Or, if welding's current becomes lower than its desired value, action will be taken to increase its level to the needed constants. These mentioned corrections are straightforward because they are applied just to some individual welding conditions and variables.

However, some errors are related to the complex difficulties from unknown sources and cannot be corrected by changing individual parameters; therefore, dealing with these conditions needs smart and in-process control and monitoring.

2.1. Intelligent laser welding monitoring

Due to its smaller heat-affected zone, higher operation speed, and precision, LW has recently become a widely employed joining technology in different industries, ranging from the assembly line of the vehicle's production to micro-electric elements in the electronic industries. Faster, reliable, and economical detection of defects in industry and manufacturing processes is one of the chief concerns. Therefore, several developed systems with the ability of online inspection have recently been introduced to improve welded components' quality plus reduce costs. Generally, non-destructive weld quality monitoring is classified into three main categories: 1. pre-process, 2. post-process, and 3. in-process [10,11] figure 1.

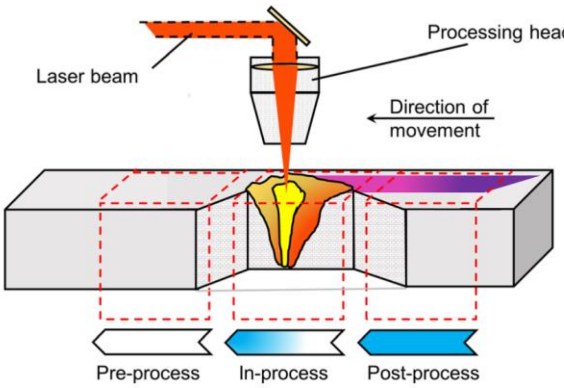

Figure 1. Three monitoring stages. [12]

Pre-process inspection is ideal for adjusting the system prior to starting the welding; however, there are some limitations due to part fit-up problems. This scanning process focuses mainly on the issues of seam tracking and the gaps between the components that will be welded to each other. The pre-process

monitoring ensures a reliable joint by adjusting the beam spot to focus on the center gaps. In other words, preconditions assure a correct weld line position and, therefore, a sound welding condition.
In welding with smaller, higher-speed, and advanced laser beam spots that are more accurate, the precise position of the beam is more vital. For this purpose, seam tracking sensors with the ability to operate both off-line and in a closed control loop can be used to inspect and detect the seam position and helps operators in modifying the part dimensions, weld line position, and clamping tolerances.

Second, post-process inspection focuses on the final product's global quality before its delivery to the customer. Although some problems of the produced elements can be corrected by using post-processing inception, this detection method is sometimes considered distractive because it cannot recover the defective components that have already been fabricated.

In this regard, modern manufacturing systems are considered online monitoring as in-process inspection during laser welding. Adding a quality control system to a laser welding machine increases productivity by quickly identifying and reducing the resulting number of defects in a process. Process monitoring can support the identification of defective welds. However, as it often lacks complete reliability, such detection is usually only indicative. Some of the defects are easy to detect online during the process, mainly if generated at the surface, while others are challenging to observe, particularly internal imperfections. To define the process condition correctly, characterizing and discovering different types of welding defects is necessary. In this chapter, online monitoring is considered a core of sustainability in laser material processing. Three classifications of the monitoring process, which were mentioned in this section, are shown in Table 1.

Table 1. Three monitoring stages, equipment, signals and objectives. [13]

Stages	Equipment	Monitoring signals	Objective
Pre-process	Machine vision Laser triangulation	Optical signal	Seam tracking Gap measuring
In-process	Fusion sensors Laser 3D scanners	Optical signal Acoustic signal Electrical signal Thermal signal Ultrasonic signal	Welding stability Defect detection Pool monitoring Keyhole monitoring Feature prediction Feedback control
Post-process	Machine vision NDT methods Metallurgical test Laser triangular	Optical signal Acoustic emission	Defect classification Weld geometry

2.2. In-process monitoring for sustainable manufacturing

Online/in-process monitoring is the first step to achieve cloud manufacturing and an intelligent decision base for each system. The ever-increasing demands for a product with improved characteristics and quality produced at higher rates put an undue burden on online monitoring improvements during the automatic welding process. With no online monitoring devices and sensors, flaws will remain undetected, which can cause costly correction or repair situations.

Recently, some employed devices, such as laser-triangulation cameras, help operators with online and in-situ control and monitoring the weld bead dimension and geometry. [14].

This inspecting/monitoring method has been successfully applied in several sheet metals processes, including vehicles' production lines or tailor-welded blanks. [6,7]. However, this procedure is not capable of detecting internal flaws, and therefore cannot be employed in some of the fabrication processes, like remote laser welding. Other monitoring techniques, such as coaxial, optical radiation detection [15], coaxial visual detection [16], paraxial sound [17], temperature detection [18], plasma radiation, and charge detection [19], have been developed for Laser Process Control System (LPCS) that can be used alone or in combination with 3D laser triangulation inspection camera.

As mentioned before, the data transition is the linking chain in any intelligent system, and in this regard, the Internet of Things sensor plays a vital role in smart factories. With the ability to transfer real-time data and take corrective and preventive measures instantly, IoT helps to reduce the maintenance time, facilitate online inspection and monitoring, and optimization of production systems.

3. Robots in welding

Technavio Research has recently reported the day-by-day growth of robotics due to the development of Industry 4.0. The concept of robotics in Industry 4.0 is creating intelligent industrial sectors by which production lines would benefit from smart systems and IoT and avoid disturbances [20]. Robots are beneficial in operating different tasks from monitoring the machines' conditions, analyzing, diagnosing, predicting the failures to moving heavy objects [21]. They are also helpful in assembling products, treating dangerous materials, painting and cutting and shaping warehouses, polishing, etc. Kuka robots are examples of industrial robots used in material treatment, loading or unloading, spot, laser and arc welding, and palletizing or depalletizing. They are capable of delivering real-time data through IoT. The fast development of smart manufacturing with the help of artificial intelligence, known as AI, makes the traditional offline programming and teaching-playback modes obsolete since they cannot adapt themselves to the flexible and fast modes of modern manufacturing. In this regard, intelligent and automated industrial welding robots have been introduced and added to production lines with the aim of enhancing efficiency.

4. Smart decisions in manufacturing

Too often, intelligence factories leverage the universal shop floor data collection provided by intelligent manufacturing equipment, connected sensors, and a wealth of IoT devices to improve the performance of industrial operations significantly. Nevertheless, data transmission and big computing involve reorganizing the entire organization as operations and information technology congregate.

Traditionally, C-suite executives think about better and faster decision-making because from their point of view, it’s up to them, the leaders. However, now, smart manufacturing’s ability to deliver data efficiently and quickly to the decision point is changing such long, slow-moving traditional trends of decision making. Sustainability is defined as ongoing growth in economic and social fields with a less negative impact on the environment.

Intelligent manufacturing ensures obtaining all of the three aspects of sustainable development together with the help of Industry 4.0 components, including real-time transferring data, reducing waste and the loss of material, enhancing productivity, cutting down costs and the time of processes, and dealing with the labor force challenges. In modern manufacturing systems, a researcher uses metaheuristic approaches and artificial intelligence in divers' applications to define and optimize the influence of process parameters.

4.1. Metaheuristic Approaches for modeling and optimization of laser welding

In general, manufacturing sectors, researchers, and engineers encounter increasing complexity problems from several technical, social, and scientific sectors. Those challenges could be timeconsuming as optimization tasks, frequently global optimization ones. To this end, some novel solutions should be applied to tackle these challenges and improve the efficiency of a production system. Metaheuristics approaches are one of the incredible answers for this problem [22]. From a mathematical perspective, a metaheuristic is a method for designing, finding, producing, or selecting a heuristic that may present an adequately good solution to an optimization problem.

A metaheuristic is a developed method of providing a satisfying solution to issues of optimization and formally considered as an iterative generation process with the ability to guide a subordinate heuristic and is an asset to learning, discovery, or problem-solving by experimental and particularly trial-and-error methods and combining effectively different theories for investigating and using the search space. Learning approaches are used to structure information to get near-optimal solutions. Overall, Genetic Algorithms (GA), Particle Swarm Optimization, Differential Evolution, Cross-Entropy, Simulated Annealing, and Hybridization are the most frequent approach in this concept. Here, genetic algorithm is introduced as the most popular method between researchers, Figure 2. With optimized welding input parameters, it is now possible to get better welding geometry, microstructure, and tensile strength. Today, industrial processes are looking forward to optimizing their process parameters using the mentioned methods.

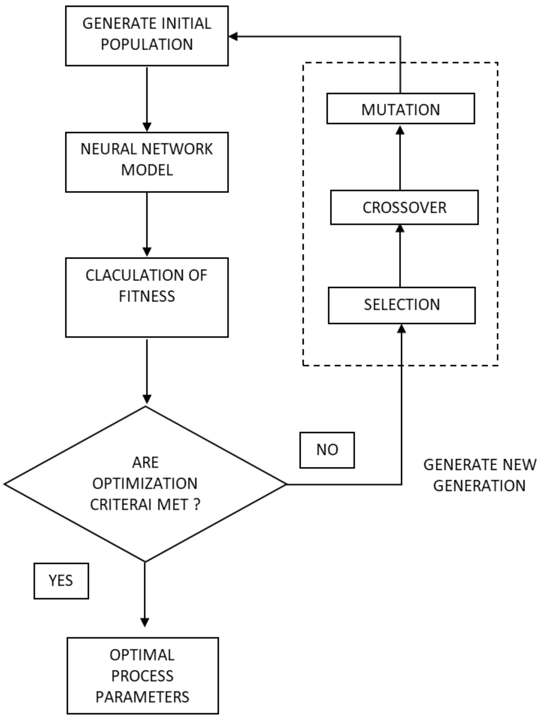

Figure 2. Flow chart for the optimization parameters using Genetic Algorithms [23].

4.2. Artificial intelligence and machine learning

Artificial intelligence (AI) is based on training/learning algorithms, including machine or deep learning, in combination with large sets of data obtained from sensors or other intelligent devices. The data wh are well-defined representations of the surrounding environment and phenomena. Machine learning (ML) is typically shorthand for “traditional machine learning,” which usually excludes deep learning, where humans use expertise to manually select features and train models. As a new concept of the non-destructive method (NDT), smart inspection tends to be in real-time. Due to the automation characteristic of laser welding and sensing methods and the development of machine learning (ML) and

artificial intelligence (AI) tools, smart in-process inspection is applied to achieve a perfect welding quality, improve economic efficiency, and increase productivity by reducing quality defects.
All the online parameters conditions are captured by sensors and sent to the cloud; the cloud will make the best decision to set the input parameters based on the objective criteria. Artificial intelligence (AI), as a core of every intelligent system, plays a vital role in intelligent welding systems and manufacturing processes. In this method, a computer system mimics human cognitive processes by training the system to perceive its environment, make decisions, and take action. In this regard, standard ML techniques include decision trees, support vector machines (SVM) [24], and ensemble methods are applied in different manufacturing sectors. Furthermore, deep learning can be defined as a subset of ML models that are based on the human brain's neural pathways, and the term deep refers to the complicated neural layers connecting the input and output. This model aims to train algorithms that generalize features for predicting outcomes, but these algorithms are not explanatory. With regards to the inherent characteristics of the welding process, it consists of uncertain and nonlinear processes, which are affected by various factors where complex physical and chemical reactions occur; therefore, it is difficult to rely on experience or simple mathematical rules to establish accurate models. Recently, ML has been applied to solve this issue. Several techniques, instruments, and procedures have been expanded and implemented in different applications as ML has grown into an independent field, Table 2.

Table 2. Real-time monitoring and smart decisions in laser welding

Method	Input parameters	Output	Material	Optimization method	Reference
A lightweight deep learning algorithm for inspection of laser welding defects on safety vent of power battery	2-classifications and a 7-classifications dataset by ourselves. (Image processing 34537 images from the production line)	Defect detection	Lithium-ion battery	convolutional neural network (CNN)and the technique of transfer learning	[25]
Real-time penetration state monitoring using convolutional neural network for laser welding of tailor rolled blanks	laser welding monitoring platform and a penetration state diagnosis unit (Image processing)	Diagnosing the penetration state during the laser welding of a TRB (Tailor rolled blanks)	AISI 304 austenitic stainless steel	convolution neural network (CNN).	[26]
Deep-learning-based porosity monitoring of laser welding process	coaxial high-speed camera and labeled with the porosity attributes measured from welded specimens.	porosity monitoring	6061 Aluminum alloy	A convolutional neural network (CNN)	[27]

Supervised deep learning for real-time quality monitoring of laser welding with X-ray radiographic guidance	Hard X-ray radiography, acoustic emission signals.	momentary events during the laser welding process,	AA5005 aluminum alloy	deep convolutional neural network (CNN), graphics processing units (GPU)	[28]

5. Digital Twins, big data and connection interfaces in laser welding 4.0

Recently, the digital Twin or device shadow as a part of industry 4.0 is getting more and more attention between all industries and academic fairs. More precisely, digital twinning is one of the top ten technology trends in the last couple of years due to its high applicability in the industrial sector. As this trend unfolds, manufacturing processes play a crucial role and are becoming increasingly digital. Generally, a digital twin, as a link between digital models and simulations with real-world data, creates new possibilities for improved creativity, competitive advantage, and human-centered design. A complete real-time presentation of the state of the intelligent manufacturing system is a challenge; however, the emergence of a digital twin has made it possible to solve this problem. Undeniably, digital twin solutions, a near-real-time digital image of a physical object, and real-time monitoring are the most common in the ear of intelligent technologies. Frequently, it is considered as part of the intelligent fabrication process. However, it can be employed in any field, such as production, training and education, marketing and business, transportation, energy, power, electronics, human and healthcare, sports and games, networking, and communications. Production systems can observe, monitor, and control physical processes, produce a digital twin within the physical world, obtain and collect real-time data/information from the surrounding environments, analyze and simulate the conditions, and finally make decisions based on real-time communication and collaboration with humans. Integrating the digital twin into intelligent manufacturing makes construction processes smarter, efficient, and more available. Sustainable and smart manufacturing includes sustainable, intelligent manufacturing facilities, systems, and services assisting and supporting each other. Smart manufacturing equipment has two dimensions: intelligent manufacturing unit and line. A twin model unit and the line could be simulated in real-time condition, and all reports are considered in design, production, logistics, and sales. The following diagram, Figure 3, shows the advanced progress in the digital twins' concept, especially in manufacturing science and technology.

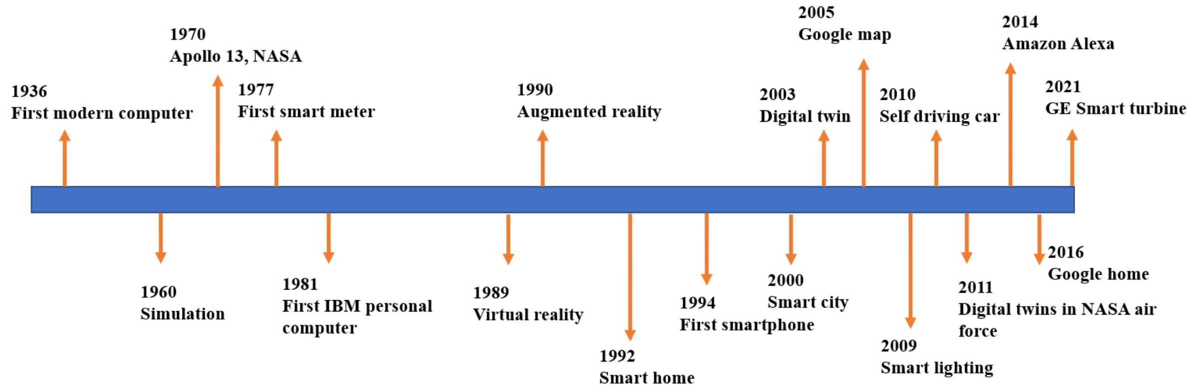

Figure 3. Evolutionary trend of Digital Twin concept.

6. Sustainable and intelligent manufacturing

In the Industry 4.0 age, smart production and manufacturing processes have drawn attention due to the demand for sustainable development. Smart manufacturing has to consider sustainability features. Its facilities, such as laser beam welding and industrial robots, should be more intelligent, supporting their combination toward the smart manufacturing closed-loop to perform different tasks. The systems of Intelligent manufacturing show a diversified trend, and a growing number of them are being developed for particular responsibilities and applied to actual products; therefore, they can significantly improve the level of intelligence. Current services in intelligent manufacturing are investigated and developed, and the sustainable collaborative manufacturing system platform integrates consumers, specialists, and businesses and presents personalized services. From a lifecycle view, the intelligent manufacturing system is classified into three aspects: framework, enabling technology, and sustainable, smart manufacturing.

The enabling technology of sustainable and intelligent manufacturing consists of digital twin-based, big-data-driven, artificial intelligence-driven, and Internet of Things (IoT)-driven. A twin model is proposed as the framework of digital twin-driven sustainable, intelligent manufacturing, especially for the laser welding process, Figure 4.

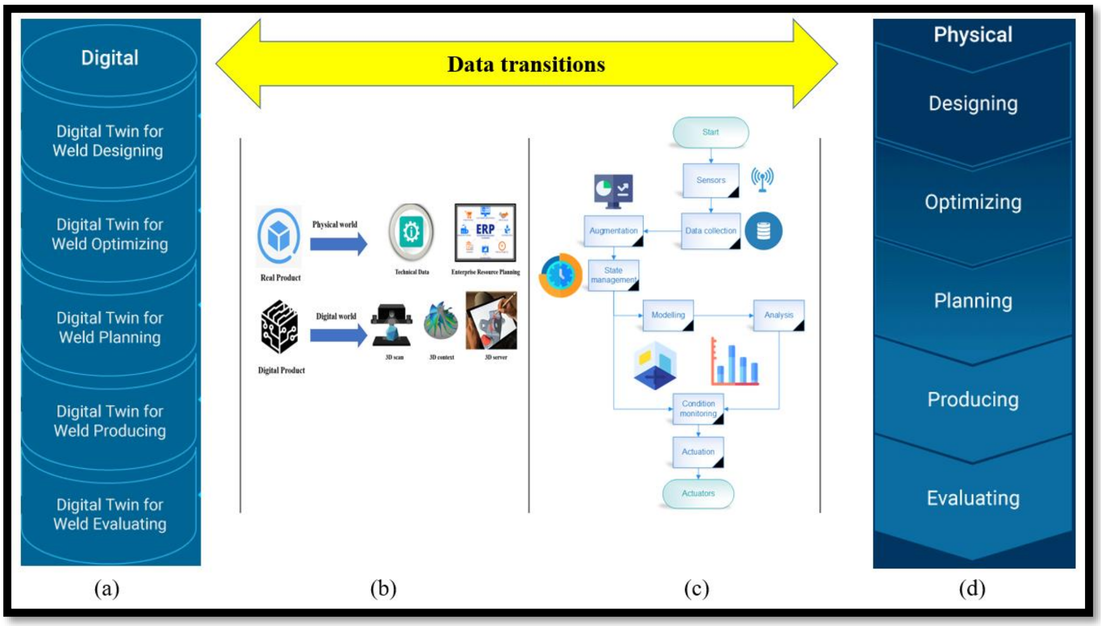

Figure 4. Digital twin model. a) Digital stage, b) simulation and inspection, c) monitoring stage d) physical stage.

Primarily, sustainable and intelligent digital twin-driven consists of basic sustainable and smart manufacturing principles and platforms. The data of the primary platforms comes from the equipment layer of the platform, which includes equipment, unit, production line, and production workshop. After the platform collects the data from the device layer, it combines cloud computing, AI, IoT, and other technologies to examine environmental, economic, and social factors comprehensively. It combines humans, equipment, and technology to provide virtual and physical prototyping data. Sensors may be included in the physical welding processes to verify the digital twin for improving numerical simulations' accuracy compared to the actual measurements in the physical welding tests. The role of digital twins in the optimization of the welding is obtaining the welding process window and assisting in optimizing and monitoring the biological welding processes. The integration of Machine learning and AI into the digital twins can lead to the improvement in autonomous decision-making capabilities.

Digital twins will predict every possible root cause of the welding issues. Simultaneously, machine learning and AI will automatically recognize the issues and make decisions to solve the problems, correct errors, or indicate failures.
Interactions connect all the welding digital twins through the whole welding lifecycle, from the designing stage to optimization, planning, production, and evaluation. This makes the quality evaluation of the welded structures possible during the first stage of designing and through all other production phases. What can ensure the improvement in the welding process stability and the quality of the weld are the interactions and connections between the physical aspects of the welding with digital twins via AI and machine learning.

7. Challenges and barriers

Industry 4.0 and smart manufacturing paradigm is defined by integrating physical and information flows into manufacturing processes via intelligent cyber-physical systems. However, significant inevitable challenges lie in the transition of current industrial sectors to meet industry 4.0 demands [21,29]. Owing to this transition, the need for higher customized complex products leads to competition among companies in bringing industry 4.0 into their manufacturing process, which imposes grave challenges in developing infrastructures and needed skills. The fourth industrial revolution enhances the communication between cyber and physical environments, resulting in a considerable amount of data and information, which is the backbone of intelligent manufacturing. Due to different types of machines working in a specific industry, abundant data, heterogeneous in nature, and in various types are produced. Utilizing this big released data to its full potential is of great importance in a business-oriented and competitive world [29–31]. Since many manufacturers lack reliable analytical devices and facilities, they are not fully prepared and ready to cope with and get insights into such a massive volume of data. But before explaining some limitations companies have to overcome and address in implementing industry 4.0, there is a major "acceptance challenge". It means most industrial authorities are reluctant to accept intelligent manufacturing methods and technologies due to their lack of awareness of the benefits they will bring to them. Therefore, persuading industries to come to use such innovative facilities is a challenge [29,32].

Regarding big data analytics, when working at their most total capacities, for example, during online monitoring of welding process, machines produce enormous data via sensors or other monitoring devices, which impose a considerable burden on the network, sometimes leading to pocket loss. On the other hand, collecting, storing, and transmitting high-speed, high-volume data often fails due to the low memory of sensors. Therefore, strengthening the wireless network infrastructures and adopting high-tech devices are strongly needed [33]. However, failing to address the maintenance condition of such intelligent, delicate machines, which may get damaged by moisture, dust, physical impacts, industrial heat, etc. (like those during welding processes), is colossal. Moreover, the installation process of these machines, including proper device replacement, calibration, error testing, and configuration, may result in business downtime and process breaks and should be considered an obstacle [21,29,34].
In the way of interpreting this massive amount of flowed data, there are some challenges as follows:

1. High-volume data received by high speed and varied types should be processed and classified based on its type. For example, in online monitoring of laser welding, optical, thermal, ultrasonic, and other types of utilized sensors' outputs are different from each other which should be put in various categories.
2. It should be determined which collected data is proper and critical and must be separated from a less critical and reliable one. There should be a distinguishing line between the data affected by noise and others which are not affected.
3. There are various analytical models, such as Descriptive, Diagnostic, Predictive and Prescriptive, etc. Deciding on which method would be appropriate for analyzing the data is another challenge faced by manufacturers.

4. After analyzing the data, there is a need for synchronizing and sharing appropriate information between the different business units.
5. Finally, putting the data into a presentable format for further evaluation and prediction.

Before going to the problems IoT and robots bring to industries in adapting to Industry 4.0, a challenge of personnel requirement has to be addressed [29,35]. By not adjusting their employees toward appropriate skills, enterprises will be at the risk of falling behind other competitors. On the other hand, employees need to get proper training and certificates due to installed up-to-date IT and control systems. It is predictable that in addition to scientific knowledge, a welding engineer needs to get a proper understanding of cloud-computing, big data analytics, and different software for simulation or, in general, computer and programming skills. They need to get the assistance of software developers, automation, and IT specialists and define for them what program or software they acquire.

During the online monitoring of welding, for example, engineers and operators have to interpret and analyze the data and decide on further actions. That means They need the skills of processing and analyzing data and statistics. In this automated world, 3D visualization of engineers and operators using robots and other complicated structures would be a great asset.

Some technical qualifications and needed skills of employees in smart industries of the future are summarized in Table 4.

Table 4. Technical qualifications and needed skills that personnel in the age of industry 4.0 must, should and could have, respectively.

Must (Requirements with the highest priority that must be met)	**Should (Requirements with higher priority compared to Could items but less importance to Must ones)**	**Could (Requirements that are not desirable but are not indispensable)**
Knowledge of computer and information technology	Management knowledge	Programming and encoding knowledge
Skills of processing and analyzing the data and information	General skills and knowledge in technologies	Specialist skills and knowledge of technology
Knowledge in statistical science	Specialist skills of production line and processes	Knowledge of legal regulations
Knowledge in process and organizational structure (setting up machines and reconfiguration)	Awareness of data protection and cyber-security systems	-
Ability of adopting new communicating methods, IT systems and IoT	-	-

The new wave of IoT brings new challenges, especially in the cybersecurity field, by increased density of released data. However, before getting into this topic, attention should be paid to low-cost, high-speed access to the Internet, that is, implementing new wireless infrastructures [32,36].

Cybersecurity assures valuable data and information from cyber-attacks and risks that have expanded. However, any stakeholder utilizing IoT has the potential of being the victim of misusing or unapproved access to its stored data. Therefore, the security of cyberspace is one of the primary and prioritized concerns by legislatures and businesses that should be addressed. To accomplish the higher capability of IoT, securing the data against dangers and vulnerabilities is highly needed. For example, IoT uses smart sensors to automatically sense the surrounding environment and exchange data and information among devices and gadgets. These gathering data devices are the ones most threatened by cyberattacks [21,29,37].

Security Vulnerabilities that are weaknesses, flaws, or errors found within a security system and have the potential of being threatened are related to different IoT architecture layers.

The first layer is sensing or perception, one that consists of physical sensing and detecting devices. This layer's common threats are:

- Unapproved access because of physical assault.
- Lack of Confidentiality, most deployed sensors lack designed-in protection against physical manipulation.
- Visual availability of physical parts puts them in danger of being captured and stolen.
- Noisy data, that is, the data contains some incorrect information due to vast distances of transmission.
- Malicious code bringing potential damages to files and cause information theft and software failures.

The network or system layer stands as the second layer responsible for a remote and wired connection between network devices, servers, and other smart objects. It is also used for processing and transferring the data sent by sensors and is susceptible to the following threats:

- A Denial-of-Service (DoS) attack, the most frequent cyber-attack, makes the machine or network inaccessible by forcing them to shut down and sending them failure and fake messages.
- Routing attacks in which attackers send error messages by creating routing loops.
- Transmission threats contain data exploitation, interrupting, and blocking.
- Data breach, which occurs when data or information is taken or stolen without the authorization of a system's owner.
- Network congestion means the reduced quality of service due to a network carrying more data than it can handle.

The third layer is the one that manages the essential services for clients or applications and can be threatened by the following attacks:

- Manipulation, which is an alternation in data and information by attackers.
- Unauthorized access, which is an abuse of data and services due to unapproved access.
- DoS attacks like what happens for the system layer.
- Spoofing that is the act of disguising a communication from an unknown source as being from a known, trusted source.

And the final layer is application one, also known as the interface layer, and conveys application services to consumers and specifies the shared communications protocols. Common threats of this layer are:

- Configuration vulnerability**,** a flaw in security settings, like failing to auto-encrypt files and false in remote hubs.
- Malicious code attacks, like those, happen for the sensing layer.

- A phishing attack, a type of social engineering attack often used to steal user data, including login credentials and credit card numbers.

Digitalization is significantly changing the work environment, and automation is expected to be seen more in workplaces than before. From simple software scripts capable of automating a wide range of digital processes to sophisticated employed robots that can perform an ever-growing number of manual tasks, automation provides industries with new alternatives and solutions. However, despite the many advantages of automation, there are different concerns associated with this high-speed automation. The total cost of shifting from a conventional workforce to a robotic one and bringing automation into a working environment from purchase to installation and maintenance create obstacles, especially for smaller businesses with limited financial sources. Therefore, business owners have to consider these considerable expenses before investing in the automation of their systems. In addition, loss of employment because of the widespread use of robots is predicted to happen shortly and will bring social issues. Another problem caused by industry 4.0 and automation is an increased demand for complex and modern customized products that manufacturers find challenging to balance automation and repetition while maintaining high-quality products and increasing flexibility.

Although laser welding is one of the most preferred fabrication methods, there are still some difficulties and challenges in employing this welding process and should be considered when integrating industry 4.0. The HAZ (heat-affected zone), loss of alloying elements, porosity, and other defects such as cracks and insufficient penetration welds affect the resultant mechanical properties like the formability of the welded structure and an acceptable combination of input variable can control these failures. The challenge of obtaining the optimum combination of variables through a large number of experiments and a huge volume of data and deciding on which types of data to be analyzed should be addressed. Another challenge of the digitalization of laser welding is online monitoring. For this purpose, programming skills, knowledge of different software, and a secured transferring network to receive data from sensors and changing them into readable data are needed [38].

8. Conclusion and Future research opportunities

Regarding the fact that enhanced welding quality and efficiency is a crucial part of intelligent manufacturing, in this chapter, the
expansion of smart sensors, latest gadgets, and AI-based ways of real-time inspection and monitoring of welding quality are reviewed in detail:

1. In-process welding inspection is a perfect real-time monitoring procedure since the data obtained through it can be applied for adjusting welding conditions in real time.
2. Inspection monitoring devices are classified and reviewed.
3. The AI-based techniques and systems employed in welding monitoring are reviewed.

AI has high potential to process and mine the data and is an asset in achieving multiple monitoring objectives. Therefore, a developed smart quality evaluation system becomes the most impressive and challenging one.

Toward future research, smart monitoring will concentrate on three features:

- An innovative acquisition platform of various welding signals
- In-depth study of signs
- Feedback control of welding variables

However, to be more precise, the entire process of welding inspection and monitoring remains humanized. With regards to the various welding methods and their applications in repairing, fabrication of medical gadgets, computer devices and components, micro-welding, automotive, aerospace, and electronic industry,
seam welding is a novel topic in this concept which is considered in modern manufacturing.

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