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Review

A Survey of Process Monitoring Using Computer-Aided Inspection in Laser-Welded Blanks of Light Metals Based on the Digital Twins Concept

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Abstract: The benefits of laser welding include higher production values, deeper penetration, higher welding speeds, adaptability, and higher power density. These characteristics make laser welding a superior process. Many industries are aware of the benefits of switching to lasers. For example, metal-joining is migrating to modern industrial laser technology due to improved yields, design flexibility, and energy efficiency. However, for an industrial process to be optimized for intelligent manufacturing in the era of Industry 4.0, it must be captured online using high-quality data. Laser welding of aluminum alloys presents a daunting challenge, mainly because aluminum is a less reliable material for welding than other commercial metals such as steel, primarily because of its physical properties: high thermal conductivity, high reflectivity, and low viscosity. The welding plates were fixed by a special welding fixture, to validate alignments and improve measurement accuracy, and a Computer-Aided Inspection (CAI) using 3D scanning was adopted. Certain literature has suggested real-time monitoring of intelligent techniques as a solution to the critical problems associated with aluminum laser welding. Real-time monitoring technologies are essential to improving welding efficiency and guaranteeing product quality. This paper critically reviews the research findings and advances for real-time monitoring of laser welding during the last 10 years. In the present work, a specific methodology originating from process monitoring using Computer-Aided Inspection in laser-welded blanks is reviewed as a candidate technology for a digital twin. Moreover, a novel digital model based on CAI and cloud manufacturing is proposed.

Keywords: real-time monitoring; Computer-Aided Inspection (CAI); laser welded blanks (LWBs); digital twin (DT); Industry 4.0

1. Introduction

The transportation industry has dedicated a lot of engineering effort and innovative research into reducing the weight of its products. Air pollution and emission of greenhouse gases from the transportation sector have had detrimental environmental and health effects for decades. For this reason, governments have enacted restrictive regulations on automotive industries to prevent and control the spread of vehicular emissions. Strict regulations have led car manufacturers to look for different solutions and new technologies to solve the problem. One of the strategies that has been adopted in this field is to reduce the weight of cars, leading to fuel consumption and carbon dioxide emission reduction.

Given that the body and other exterior components are a large portion of the car's weight, using light metal structures such as aluminum alloys in automobiles is an effective way to lessen the overall car weight. Aluminum alloys are known for their superior properties, such as strength-to-weight ratio, heat resistance, and corrosion resistance. Laser welding is an effective method of joining materials with high accuracy, good flexibility, and low distortion [1]. However, laser welding of aluminum structures is associated with a range of difficulties due to excessive heat dissipation, the hydrogen solubility of molten aluminum, and an oxide layer inclusion. Manufacturers are motivated by Computer-Aided Inspection (CAI) to ensure high product quality and avoid production defects, which requires automated, rapid, and accurate inspection [2]. CAI commonly refers to automated inspection, among other computer-aided applications extensively used in different industries [3]. By using manufacturing standards and geometric dimensioning and tolerancing (GD&T) criteria, CAI is not only able to detect laser welding defects but also to compensate for these shortcomings. Advances in scanning technology, digital cameras, and controllers have led to a significant increase in real-time monitoring of laser welding processes. A digital twin (DT) aims to build a digital replica of a physical system in a virtual space, such that the digital replica represents the same elements and the same dynamics of a physical system. DT systems can be very helpful for understanding, analyzing, and improving a product, service system, or production [4]. DT systems can also be used to inspect the process, to enable visualization of the impact of variations [5]. Integration of real-time monitoring and real-time simulation in a laser welding process ultimately leads to adopting a DT in laser welding processes. To communicate data, information technology advancements, like the Internet of Things (IoT) and Augmented Reality (AR), can be implemented to link the physical system and its digital twin [6]. Real-time data collection, data analysis, and physics-based simulation are basic phases in defect detection aimed at avoiding the occurrence of defects, and improving the quality of this cutting-edge technology. Thus, a critical review of monitoring technology for the laser welding process is provided. Kong, et al. [7] utilized spectrographic monitoring to control the laser welding process of galvanized high strength steel in two cases, with zinc coating and without zinc coating, in a lap joint configuration. Considering zinc vapor signals as the process feedback, welding defects were identified by the presence of spatters induced by zinc vapor at the faying surface. A series of experiments were conducted to investigate the effects of laser welding parameters on the keyhole dynamics and weld pool, using a high-speed charge-coupled device (CCD) camera with a green laser as an illumination source. The results revealed that welding quality strongly depends on zinc vapor at the faying surface; a higher depth of penetration was also observed in the case of removing the zinc coating. Sebestova, et al. [8] monitored Nd: YAG laser welding by measuring plasma spectral emission lines to calculate the plasma electron temperature. They found a relationship between electron temperature and depth of penetration, which can be used as a controller to identify welding defects and achieve desired penetration depth. Liu, et al. [9] studied laser hot-wire welding of butt joints to assess the molten pool dynamics and the stability of the welding process. A high-speed CCD camera and a spectrometer were used for real-time monitoring of the process through visualization of the molten pool and calculation of the electron temperature according to the Boltzmann plot method. Research established that the contribution of a hot wire facilitates the formation of a molten pool, though laser beams were not able to make the molten pool in butt joints with a large gap. Harooni, et al. [10] conducted real-time spectroscopic monitoring of laser welding of AZ31B magnesium alloy in lap joint configuration. Spectroscopic analysis was performed to study the correlation of the oxide layer on welding sheets and the generation of defects in the interface of overlapped sheets. In addition, a high-speed CCD camera, assisted with a green laser as an illumination source, was employed to monitor the molten pool and the keyhole dynamics due to the oxide layer. The results confirmed that the existing oxide layer on magnesium sheets leads to the generation of pores in the interface area. Blecher, et al. [11] utilized inline coherent imaging for real-time monitoring of keyhole depth in five different alloys. A comparison of real-time keyhole depth measurements and metallographic depth measurements proved that the proposed method was capable of time measurement of keyhole depth except for aluminum alloys. Luo, et al. [12] improvised the acoustic signal monitoring of laser welding by offering a plane microphone array with a time delay recognition. They concluded that the welding process could be monitored and justified using the suggested method even with background noises in the working environment, which had been an obstacle to traditional acoustic signal monitoring. Mirapeix, et al. [13] proposed plasma optical spectroscopy to identify aluminum in the laser welding of Usibor1500 tailor-welded blanks. The estimation of aluminum was done by the line-to-continuum method in real-time. A correlation was identified between aluminum content in real-time monitoring and off-line tests like macrographs or tensile tests. However, the correlation found in the tensile specimen test at lower aluminum contents was not clear because it was affected by other parameters like seam geometry. Recently, our research team developed a new automatic technique to address the distortion in real-time monitoring of aluminum laser-welded blanks [14,15]. The research also provided experimental and numerical investigation of different types of key process parameters and their impact on production quality in automobile applications [16–19]. Wang, et al. [20] developed a real-time monitoring system for disk laser welding based on the feature selection method for pattern recognition, and the Support Vector Machine (SVM) and Back-Propagation (BP) neural network for pattern classification. Images of the plume and spatters were processed, and a sequential forward floating selection (SFFS) algorithm was used for detecting the optimal feature subset. The classification accuracy of BP and SVM were very close to one other; however, the accuracy of SVM reached the maximum of 98.43 using 10 features. It should be noted that the overall processing time remained a challenge for the proposed method. In another study, Wang, et al. [21] used a combination of a Support Vector Machine and a Pearson product-moment correlation coefficient to characterize disk laser welding quality. High-speed photography was employed for image processing, and the area of the plume, the number of spatters, and the horizontal coordinate of the plume centroid were selected among six features to establish an SVM model with 93.58% classification accuracy. The authors concluded that the proposed monitoring system could be used for real-time monitoring of high-power laser welding. De Bono, et al. [22] evaluated two different monitoring methods of laser welding: optical-based and laser interferometry monitoring methods. The optical-based method investigated photodiodes signals of butt welding, and the laser interferometry monitoring took advantage of the In-Process Depth Meter (IDM) sensor from Precitec in stake welding. Photodiode data obtained at the wavelengths between 600 and 850 nm deduced defects correlated to laser power and joint contamination and gap. However, for detecting defects like porosities and cracks, photodiode data need to be decomposed by orthogonal empirical mode decomposition (OEMD) theory. The data acquired by the IDM sensor established a correlation between the IDM signal and the keyhole depth. Chen, et al. [23] employed an SVM model for real-time monitoring in high-power disk laser welding using 15 features of the metal vapor plume and spatters. A high-speed camera was used to capture laser-induced metal vapor for image processing. SVM classification using seven features reached a remarkably accurate 95.93% by 10-fold cross-validation. The authors suggested that the centroid, perimeter, average grayscale value, and quantity of the spatters were critical to improving welding quality. Pasinetti, et al. [24] proposed in-line monitoring of the laser welding process by a smart vision system based on the Industrial Internet of Things (IIoT) approach, to make an interconnection and remotely control the process. Two different setups were used to fulfill two goals. The first setup, called seam tracking, was targeted to keep the laser welding in an optimal position. The second setup, called the keyhole monitor, aimed to detect incomplete keyhole penetration. The researchers suggested that the architecture used enables remote monitoring of multiple welding units from a central unit. Lei, et al. [25] developed a multi-information fused modeling system for predicting weld waist width and the weld back width by a combination of Principal Component Analysis (PCA), genetic algorithm (GA), and neural networks (NN). Images were acquired by a modified optical fiber laser coaxial monitoring system, and pre-processed by the PCA algorithm to effectively remove the redundancy of extracted information. Two morphological features, in addition to laser power and welding speed, were selected as input parameters of the NN. GA was used to optimize the architecture of the NN. Considering the low errors of the developed model, and the short processing time of less than 90 m, the authors proposed that it could be used for real-time monitoring of the laser welding process. Zhang, et al. [26] employed a multiple-optical-sensor system to integrate with a Deep Belief Network (DBN) that was optimized by a genetic algorithm for online monitoring of the high-power disc laser welding process. The multiple-optical-sensor system was able to deliver effectively a thorough insight into the laser welding process. A deep learning model based on the DBN demonstrated more than 10% higher average accuracy compared to the back-propagation neural network (BPNN) model. Haubold [27] offered a monitoring system for remote laser welding using two parallel processing algorithms customized for identifying spatter number and size. The reproducibility of spatter formation was investigated at four different settings of process parameters for ten repetitions. Although a correlation between spatter number and the corresponding standard deviation was established, no resolution for reduction of spatter size and number was made. Shevchik, et al. [28] developed a hybrid monitoring system for data acquisition and processing applied to titanium laser welding. The monitoring system included optical and acoustic sensors combined with machine learning (ML) techniques. M-band wavelets transformation was utilized to decompose optical and acoustic signals, and the normalized energy of the frequency bands was extracted. The Laplacian graph Support Vector Machine (LapSVM) was used to correlate the extracted features with welding quality. The proposed method displayed more than 85.9% classification accuracy, which is notable given the low cost of data preparation. Accordingly, the researchers claimed that the hybrid monitoring system could be used for the industrialization of laser welding monitoring, and they also raised some concerns about sensors selection rather than sensors combination. Zhang, et al. [29] put forward a vision-based monitoring system for laser welding of tailor rolled blanks (TRB) through coaxial visual monitoring and Convolution Neural Network (CNN) processing algorithms. The monitoring system was dedicated to evaluating the penetration quality of the laser welding of TRB. Four statuses for the penetration state were considered for the creation of an image dataset to train and validate the CNN. They advised that with the 2 ms latency of the CNN for TRB, the proposed monitoring system could be effectively employed for real-time monitoring applications. Gonzalez, et al. [30] introduced ConvLBM to monitor laser deposition and welding processes based on medium wavelength infrared (MWIR) imaging. ConvLBM employed a Convolution Neural Network (CNN) to obtain features from MWIR. ConvLBM estimated dilution for the laser deposition process due to its significance on the quality of the process. Defect characterization was also achieved for the laser welding process by ConvLBM for three different materials, proving the adaptability of the monitoring method for different applications. Kaewprachum, et al. [31] employed an infrared camera for real-time monitoring of the laser welding process to apprehend fast dynamic heating phenomena. The images were captured and analyzed to reveal the effects of laser power and welding speed on the average molten pool temperature and the width of the molten pool. Infrared camera measurements were validated by microscopic measurements, and a good correspondence was observed, especially at high powers. Papacharalampopoulos, et al. [32] employed a methodology as a candidate for process-level digital twins (DTs) in laser welding. A simplified laser welding paradigm capable of displaying temperature profiles was studied to assess the employed methodology. The proposed digital twin approach consisted of decomposing spatial domains, adaptation to accuracy, adaptation to measurements, and estimation of inner state, providing intuitiveness to the operator, and real-time function. The methodology was adopted to solve linear partial differential equations, and was validated following measures ensuring the operational performance of a DT.

To the best of the authors' knowledge, the present work is the most comprehensive attempt to present a DT for laser-welded blanks. A virtual system of the physical laser welding system has been developed using CAI to monitor, quality control, and optimize the laser welding process. The developed DT resides in the cloud, and it continuously communicates with physical and virtual systems to provide appropriate commands to operating processes and machines in real-time. In this DT, an evaluation of different aspects of laser welding qualities has been made in order to give a product license to laser-welded blanks.

2. Quality Control Based on 3D Geometrical Inspection

For developing a DT, the raw data of a physical system is collected to extract inspection features and analyze the physical system in real-time. Computer-Aided Inspection (CAI) can help to identify defects and abnormalities occurring in the geometry of a physical system. A 3D scan measurement is one of the CAI tools which provides non-contact, non-destructive, and accurate measurements of a physical system. In other words, it is a 3D geometric inspection technology using data acquisition and data pre-processing to obtain the size and shape of a physical part to display the part in digital space in three dimensions. The 3D scanning provides an opportunity to immediately detect where the digital replica does not match with the 3D CAD model. Three-dimensional scanning is a viable option for the quality control of geometrical features of special welding jigs and fixtures. Using 3D scanning, it is possible to identify where deviations occur, and to measure them instantly. To better understand Geometric Dimensioning and Tolerancing (GD&T), manufacturing standards such as ASME Y14.5 and ISO-GPS have been developed in the era of automation. In addition, as part of its standards and requirements, the American Society of Mechanical Engineers (ASME) also established rules, definitions, defaults, and recommended practices. According to the ASME, parts and workpieces should be evaluated in a free state. Therefore, it is necessary to consider the compliance and deformation of non-rigid parts during the inspection. In response, definitions for geometric dimensioning and tolerancing of non-rigid parts have been developed, based on the ASME Y14.5 and ISO standards. Figure 1 presents the types and tools of CAI algorithms. In fact, inspection 4.0 aims at intelligent inspection by illustrating the basic work that can be implemented. Based on the compliance behavior and inspection parameters, a digital inspection protocol can be implemented onto the cloud, and the appropriate machine and inspection method will be selected. This novel aspect will be presented in the upcoming parts of this article. Generally, components are designed to fit into the right material and mechanical properties based on rigid and non-rigid concepts in computer-aided modeling.

Regarding the compliance behavior of parts, rigid and non-rigid parts, CAI algorithms are developed. CAI is primarily used for comparing the reference geometry, computer-assisted design (CAD), with measured data, scan models [34]. Due to gravity and/or residual stress, some mechanical components often have different shapes in the free-state position compared to the state-of-use position. To make it possible to inspect different types of parts, different registration methods have been developed to classify workpieces into rigid and non-rigid ones. Furthermore, rigid registration is the primary step in computer-assisted inspections of non-rigid parts. In conventional CAI software, it is assumed by default that any data entered into the software is from a rigid part. Therefore, any deviation between the input data and the nominal CAD model should be considered a potential manufacturing defect [35]. Rigid registration has the primary goal of bringing CAD and scan models into a common coordinate system without deforming either model. The model is translated and rotated using an optimal transformation matrix without affecting its shape [36]. Initial CAI approaches were introduced using a rigid registration algorithm with Iterative Close Points (ICP) [37]. The ICP algorithm is known as one of the most robust and efficient rigid registration approaches. Although various methods have been developed over the years—including those described by researchers [38,39]—in different domains, such as aeronautic inspections, the ICP algorithm remains a widely used registration approach [40], thanks to its statistically robust and reliable method of registering. A CAD and a scan of a workpiece that is not presented in the same coordinate systems are shown in Figure 2a, and the ICP algorithm applies the best geometrical fit in Figure 2b. In this regard, the closest point in the reference set (CAD) is first identified for every point the point cloud set contains. The transformation matrix (rotation and translation) is then calculated, to move the CAD model towards scan data. This iteration is repeated until the best geometrical fit is obtained.

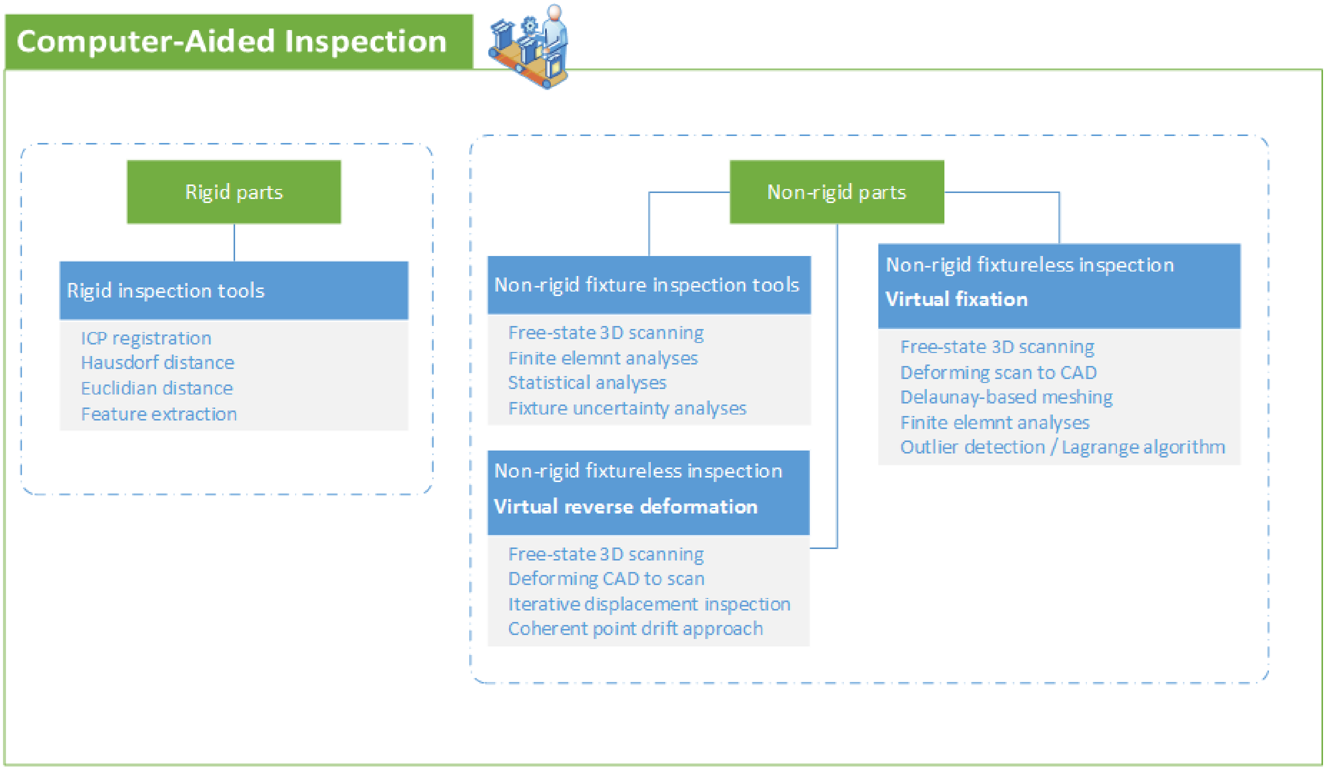
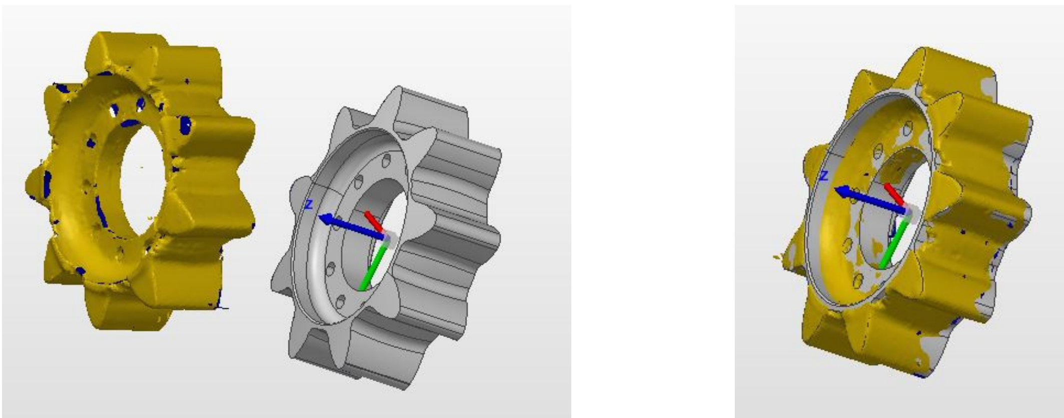


Figure 1. Computer-Aided Inspection methods and tools [33].



(**a**) (**b**)

Figure 2. CAD and scanned models (**a**) before registration (**b**) after rigid registration using ICP algorithm [33].

Each iteration of the ICP registration minimizes the distance between the two models by estimating and computing the transformation matrix that combines translation and rotation. The Hausdorff distance is the main tool in this algorithm [41]. A distance measure is taken between the CAD mesh and the point cloud data acquired by scanning. In other words, it is the maximum distance between every point of a non-empty set and some point of another non-empty set. Equation (1) illustrates this, where d_H (X, Y) is the Hausdorff distance and (X, Y) are the two non-empty subsets.

$$d_H(X,\ Y) = \max\{sup_{x\in X}inf_{y\in Y}d(x,y), sup_{y\in Y}inf_{x\in X}d(x,y)\} \tag{1}$$

The ICP algorithm has undergone a lot of improvements and upgrades, as it is one of the most powerful and widely used algorithms. The ICP algorithm was also modified and developed to decrease calculation time [42]. This method proposes a robust solution by applying random sampling to the point clouds. The algorithm also knew the minimization strategy [43] or measured the transformation in a way that minimizes its error. By using the corresponding points in previous iterations of the ICP algorithm, and searching only in the immediate neighborhood of those points, the closest points search was significantly improved in terms of speed [44]. In addition, some techniques have been used to improve the efficiency and speed of the registration process [45]. A variation of the algorithm has also been implemented to enhance the conversion of the sets by taking color information from the workpieces. Even though not all scanners are able to capture the color information from workpieces, this algorithm can still be used. There have been many variants of the algorithm explored and many improvements made by the ICP algorithm [43].

Since non-rigid workpieces have so much more parameters to consider, rigid registration needs to be accompanied by non-rigid algorithms, to take into consideration the part's deviation in its free state [46]. Scanning models cannot be compared to CAD models due to the flexible deformation of parts in a free state. CAI methods can resolve this problem for non-rigid parts where defects (e.g., geometric deviations from the CAD model) are separated from the deformations caused by the compliance or flexible deformation of non-rigid parts. Typically, non-rigid parts are dimensioned and inspected with over-constrained inspection fixtures to compensate for the flexible nature of these components and to ensure that the measurement setup accurately reflects the part's assembly functionality.

3. Verification and Validation of the Methods in CAI

All Computer-Aided Inspection methods cited are based on scan data and computational calculations. It follows that verification and validation of the calculations are imperative due to this aspect of the methods. Both rigid and non-rigid inspection methods are prone to uncertainty in computational simulations and measurement errors due to inaccuracies in data acquisition devices. Due to the technical limitations of devices, optical effects (such as light fraction and reflectivity of surfaces), or the inaccessible features of some parts, scanners are inaccurate. The results of CAI are influenced by these noisy data. Simulation models can be assessed for accuracy, reliability, and robustness by applying verification and validation (V&V) approaches [47]. Validation evaluates the consistency of computed simulation results compared to the actual ones, while verification measures the accuracy of the solution to a problem using a computational model. All numerical methods, including CAI methods, must be thoroughly verified and validated because of various sources of uncertainty in computer codes and simulations. Validating the result of a numerical approach concerning input noise aims at evaluating a computational model's robustness. An effective computational model should be able to produce satisfactory results despite the presence of noises in the input. A robust approach can still produce acceptable results for noise-containing input data compared with noise-free input data. Typically, the input noise in CAI methods comes from measurement noise that is inherent to measuring data acquisition devices. Thus, it is necessary to study the robustness of CAI methods, given the noise generated by scanning devices. A first development model will be generated based on the CAI method, and real feedback will be received during the production process. Furthermore, by combining the concepts of physical and simulation, the human and machine interface theory can make a powerful and self-learning device.

This smart connected modeling is the trigger for Industry 4.0 and intelligent manufacturing by developing a digital twin model.

4. Digital Twins (DT)

Industry 4.0 is the latest revolution in the industrial era, and refers to the digitization of manufacturing by merging physical and virtual (digital) worlds. Digital twins (DTs) are a strategy within Industry 4.0, operating on the virtualization principle [48]. DTs are digitalized integrated systems to monitor, analyze, and simulate the behavior of a physical system. DTs are composed of three main components: the physical system, the virtual system, and the communication layer that connects these two systems. The communication layer is a linkage for data storage, data processing, and data mapping functionalities [49]. The data from the physical and virtual systems must be stored and processed in the communication layer. In this regard, the communication layer needs to be capable of transmitting a big amount of data (big data) in addition to easy fault detection characteristics. Internet of Things (IoT) technology can be used to make interactions between different layers of the integrated systems for real-time data transmission. IoT effectively maintains two-way synchronization of physical and virtual systems, to keep the virtual system updated and to provide real-time control commands for the physical system. The physical system changes are reflected in the virtual system; in other words, the virtual system is updated by employing feedback from the physical system. Real-time control commands are made based on the past and present conditions of the physical system to take care of the consistency of the manufacturing process and the quality of manufactured parts [50]. The constant synchronization between physical and virtual systems through the communication layer ends up in a real-time quality control platform which is also supported and updated by the physical system. As illustrated in Figure 3, all sorts of information originating from physical and virtual systems—GD&T standards, historical data, customer feedback, and fabrication protocols—are communicating with the cloud network to provide enough material to make decisions. Continuous and online communication between different physical and virtual data providers is only made possible by the ability of IoT [51] to transmit large volumes of data.

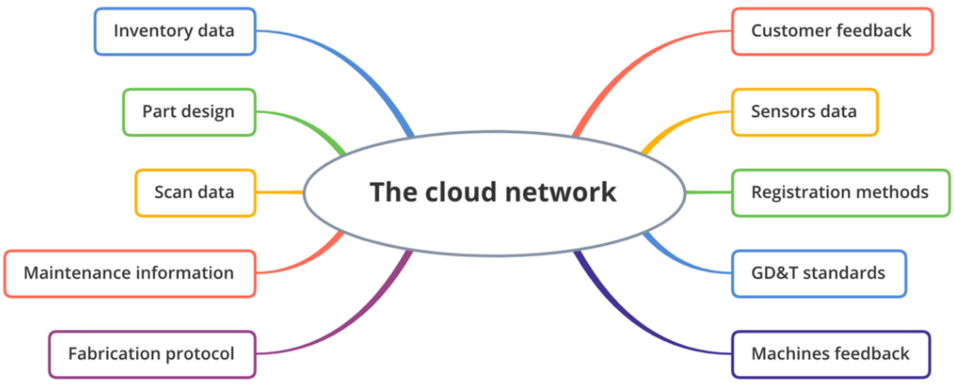


Figure 3. The cloud network in a 4.0 manufacturing factory.

Smart welding is heading inevitably toward the Industry 4.0 paradigm. A schematic of the DT model designed for intelligent laser welding leading to a product license for laser-welded blanks is presented in Figure 4. In this DT, all data from the physical system, including seam tracking, in-process depth meter, and weld inspect data, are communicating with the cloud to update and support the cloud. There is a two-way network of interactions between consequent stages of physical and virtual twins, to transfer and update information, guaranteeing high-quality laser seam according to standards, process command, and specifications defined in the cloud. The application of DTs might facilitate the provision of production licenses for parts manufactured in different production sites, with no need to re-inspect the parts.

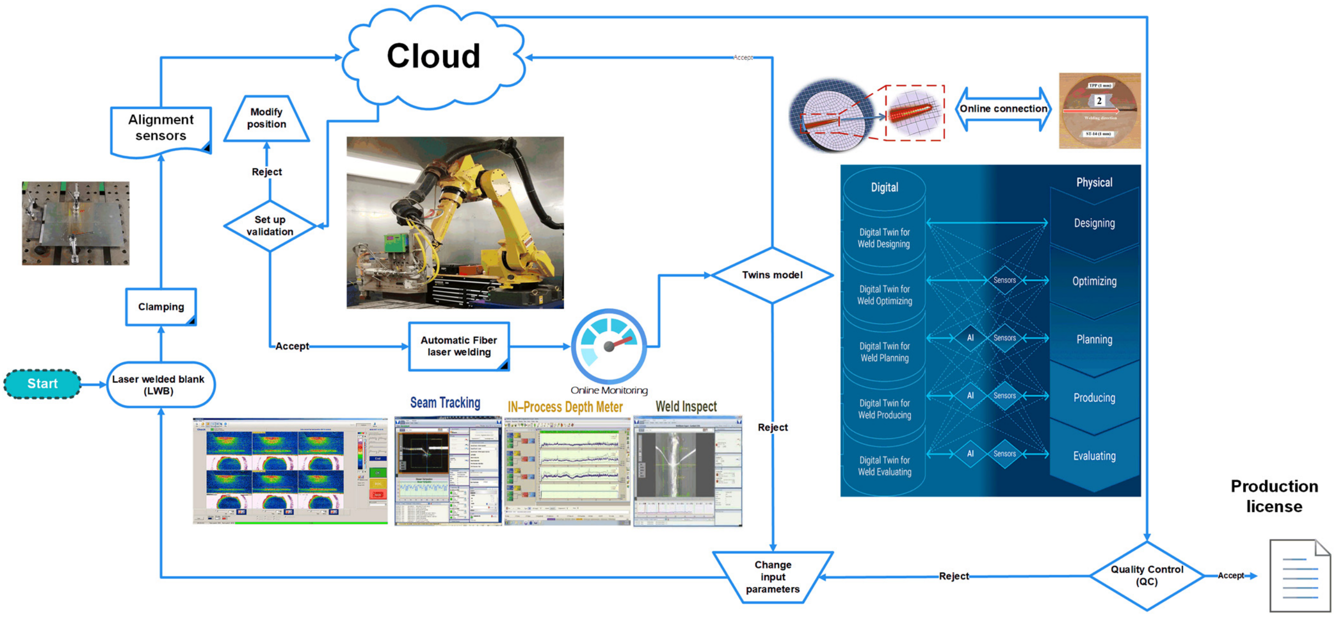


Figure 4. Digital twins model for Inspection 4.0 of laser-welded blanks.

In general, digital twins are efficient platforms for predicting every machine and device's performance, due to their intelligent data processing capability. In a virtual model or DT, physical models of machine operations will be combined with sensor data collected and processed from real assets during real-world operations. In this regard, operators of laser welding machines will benefit from being able to predict structural failure and to plan maintenance activities more effectively. This strategy will result in reduced maintenance costs and operational downtime during welding. As shown in the following model, aluminum sheets are prepared before welding to ensure there is no contamination on the surface. Then, the clamping procedure is adjusted to apply an equivalent force on the surface of the plates. To do so, alignment sensors are used to define the error, and the results are sent to the cloud for future action. By using the validation method, all the process parameters are set, and acceptance/rejection outcomes will be considered, to make a cloud-based smart decision based on the DG&T criteria. If the alignment has been accepted, automatic laser welding will start, and real-time monitoring will be done (seam tracking, in-process depth penetration, weld inspection, etc.). Using sensors and artificial intelligence, digital platforms and physical operations communicate data simultaneously. A cloud platform should be able to process big data and refine it based on pass/fail production criteria. Finally, a license will be issued for the quality assessment of each production. It is worth mentioning that this model can be used in mass production as well as remote manufacturing platforms in any location throughout the world. Thus, this model can be considered the first step toward cloud manufacturing and connected production which can be remotely accessible anytime.

5. Summary and Future Scopes

Investigation of the digital twins market reflects the challenges that have hindered cost-efficient application of digital twins (DTs) in manufacturing. Some of these challenges are due to the complex physics of manufacturing processes and production uncertainties, which in turn leads to difficulties in capturing physical phenomena by a virtual replica. The desire is to set up data-driven digital twins based on a hierarchical structure without any conflict between the physical and virtual systems, which entails appropriate communication and collaboration between them. However, the development of digital twins is still costly due to the restrictions of communication platforms. The ability to predict, prevent and resolve problems and faults also requires the proper implementation of data analysis, decision making, and problem-solving techniques.

In this regard, an overview of computer-aided process monitoring was reviewed, based on the digital twins concept for lightweight laser-welded metals. Different types of 3D geometric inspection, Computer-Aided Inspection (CAI) methods, and tools in the manufacturing industry, are presented and compared in this paper. CAI approaches address automated inspection challenges and requirements for different types of manufactured parts. The development of this process is essential in the production cycle of a part, and therefore should not be ignored. In addition, as moving further toward Industry 4.0, its concepts ought to be incorporated into geometric inspections allowing a comparison between nominal data (CAD model) with respect to a manufactured part, to determine whether it meets specifications without having to apply human judgment. An automated cloud-based Inspection 4.0 is therefore applied. Another objective is to propose an automated production cycle that does not require human intervention. This survey presents an agile approach allowing automation of the laser-welded blanks process. Applying CAI, the process is automated along with the implementation of its DTs. This original model allows remote monitoring of the process, increasing its precision by removing human intervention, increasing productivity, and providing a proper decision-making tool. The challenge now is to integrate artificial intelligence to delegate all redundant work to the machines, and have them provide feedback and auto-maintenance at some point. More research is also needed to develop cost-effective digital twins so that these solutions can meet Industry 4.0 requirements.

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