metals

*Review*

# Advances in Robotic Welding for Metallic Materials: Application of Inspection, Modeling, Monitoring and Automation Techniques

**David Curiel [1], Fernando Veiga [1,2,*], Alfredo Suarez [2,3] and Pedro Villanueva [1]**

1 Department of Engineering, Campus Arrosadía, Public University of Navarre, Los Pinos Building, 31006 Pamplona, Spain
2 TECNALIA, Basque Research and Technology Alliance (BRTA), Parque Científico, Parque Científico y Tecnológico de Gipuzkoa, 20009 Donostia-San Sebastián, Spain
3 ADDILAN Fabricación Aditiva S.L., Eguzkitza 1, 48200 Durango, Spain
* Correspondence: fernando.veiga@unavarra.es; Tel.: +34-658174709

**Abstract:** The robotic welding manufacturing of metal parts is a very important process, especially in heavy industries such as shipbuilding, oil and gas, automotive, and aerospace. There is a great variety of different techniques for manufacturing by robotic welding, and the welding operations are always in a constant process of evolution, as any advance can be significant to avoid defects during the welding process. Although a great deal of research work has been carried out in recent years, thanks to which results and reviews have been presented on this subject, the main aim of this publication is to define and review works that show the advances in the main inspection, modeling, monitoring, and automated operations during the welding process to avoid, or predictively identify, any possible defect in order to obtain an optimum degree of quality in the welding.

**Keywords:** welding; robotic; inspection; modeling; monitoring; automation



**Citation:** Curiel, D.; Veiga, F.; Suarez, A.; Villanueva, P. Advances in Robotic Welding for Metallic Materials: Application of Inspection, Modeling, Monitoring and Automation Techniques. *Metals* **2023**, *13*, 711. https://doi.org/10.3390/met13040711

Academic Editors: João Pedro Oliveira and Xiangdong Gao

Received: 3 March 2023
Revised: 3 April 2023
Accepted: 4 April 2023
Published: 5 April 2023



## 1. Introduction

Welding is a manufacturing process in which two parts are joined by means of filler material and, thanks to the fusion process, a weld pool is obtained, which, when cooled, will transform it into a fixed joint. Among the various types and classifications of welding, this publication is going to focus on robotic welding, in which an industrial robot is capable of carrying out welding activities autonomously.

An industrial robot can be defined as a multifunctional manipulator controlled and programmed to perform several tasks, capable of moving materials, parts, or tools according to variable trajectories for use in industrial automation applications. In other words, industrial robots are multifunctional and reprogrammable to be able to fulfill different functions. Due to all this, the main characteristics to be taken into account in industrial robots are degrees of freedom (number of axes), speed of action, weight to be supported, space of the work area, and level of programming.

Focusing on robotic welding, welding can take place thanks to the inclusion of material by means of an electrode, a laser, or electric arcs that reach temperatures that melt the metals. In order to carry out the welding, support material must be included, such as rotating tables or similar, that allows the welding parts to be positioned from different angles, a power supply, and software for programming the tasks.

In addition, robots must be equipped with a suitable welding tool at their tip, which usually consists of electrodes capable of creating electric arcs to weld the metal parts. A classification of robotic welding can be established as follows:

1. Robotic arc welding, which is the subject of this publication, is a high-powered electric arc created between the electrode and the point where the metal parts to be

welded meet. Very high temperatures are generated, which melt and join the materials together. There are several subtypes, including:

- Gas Metal Arc Welding (GMAW): a process that uses an arc between a continuous filler metal electrode and the weld pool, which is carried out under an externally supplied gas shield and without the application of pressure.
- Gas Tungsten Arc Welding (GTAW): an arc is used between the electrode and the weld pool in which a non-pressurized shielding gas is used (the addition of filler metal is optional).
- Plasma Arc Welding (PAW): high temperatures are generated, which melt the metal parts at the joining points through the use of ionized gas [1].
- Flux-Cored Arc Welding (FCAW): an arc is used between a continuous filler metal electrode and the weld pool; this process is used with flux shielding contained within the flux-cored electrode, with or without an additional shield of externally supplied gas and without the application of pressure.

2. Robotic laser welding is when energy is generated by a high-performance laser that is focused on a small burning spot. Due to the high-density energy generated, the workpiece is melted, and the components are welded together.

The use of robotic welding by companies, especially in the automotive, aeronautical, naval, and construction sectors, generates a series of advantages, among which the following stand out:

1. Reduction in production costs with a high return on investment, increasing the competitiveness of the company [2,3].
2. An increase of more than 80% in production times, as robots operate long shifts and offer a higher work output [4].
3. Increased quality of the final product by reducing defects and welding with greater precision [5].
4. Robots are adaptable to multiple products, processes, and needs.

An important characteristic to consider when robotic welding is the metal material; although all metals can generally be welded, each metal is unique, with well-defined characteristics and properties. The principles that determine the weldability of each metal include electrode material, cooling rate, shielding gases, and welding speed. Once the metals to be used have been chosen, it is necessary to determine which welding process is most suitable for that metal, as different metals require different welding methods. Consideration should also be given to trying to apply as much symmetry to the weld bead geometry as possible [6] as well as to adaptively define the trajectories between layers by means of analyzing whether there are previously deposited layers [7]. Within metallic materials, a classification can be made according to their weldability index:

1. Ferrous metals: their main component is iron; they are characterized by high tensile strength and hardness. Steel and cast iron stand out.
2. Non-ferrous metals: metals whose composition does not include iron. These include:
    - Heavy metals (density $\geq$ 5 kg/dm$^3$): tin, stainless steel, copper, zinc, lead, chromium, nickel, cobalt, and tungsten.
    - Light metals (density between 2–5 kg/dm$^3$): titanium.
    - Ultralight metals (density < 2 kg/dm$^3$): magnesium, aluminium, and beryllium.

Another important feature good for welding is to have the main operating parameters under control, such as current, voltage, welding speed, temperatures, gas flow, and torch angle, because if they are not well regulated, welding defects may occur, including spatter [8], porosity [9], cracks [10], lack of fusion [11], undercuts [12], and depth of penetration. All these defects and incorrect parameter settings have an influence on the quality of the weld, so it will be necessary to check the welds to detect possible defects by means of visual inspections and non-destructive tests (penetrating liquids, ultrasonic methods, radiography, and magnetic particles) [13] (see Figure 1). All these inspection and defect issues will be developed in more detail in Section 2.

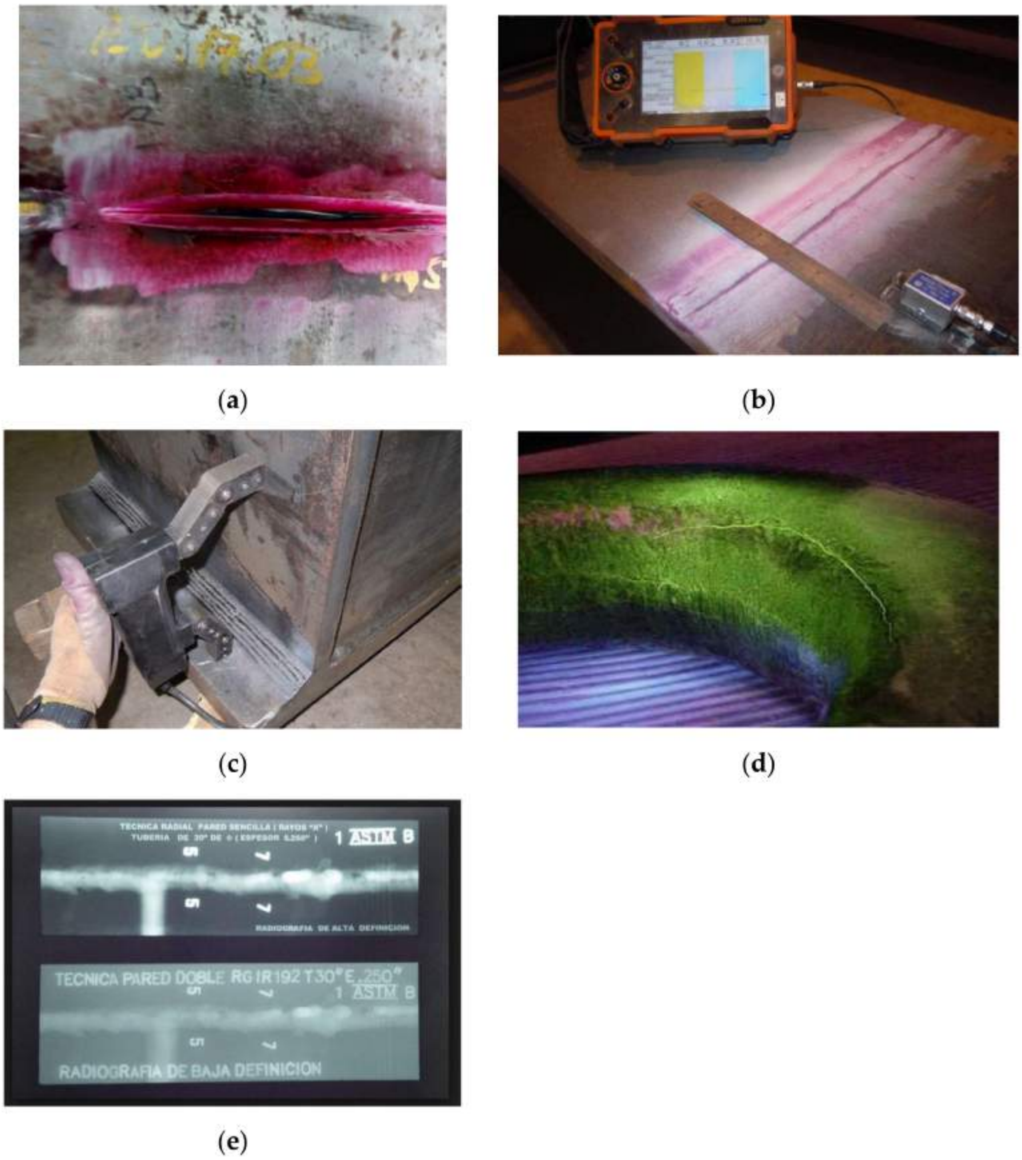



**Figure 1.** Non-destructive testing inspection: (**a**) penetrating liquids, (**b**) ultrasonic methods, (**c**,**d**) magnetic particles, and (**e**) radiography.

In order to try to prevent defects from appearing in the weld, several types of different technological tools are now available (e.g., modular software interfaces [14] and neural networks [15]) that allow the designer to simulate and model the best patterns and/or maps for the welding sequence [16] and to analyze the possible changes and defects that may appear through mathematical formulations (e.g., finite elements, regression analysis, algorithms, Gaussian hypothesis). These tools and formulations will be implemented in Section 3.

In recent days, additive manufacturing (AM) [17], often referred to as 3D printing, is essentially a transformative approach to traditional industrial manufacturing that simply adds layers of material to create strong, lightweight components. One of the integrated solutions is direct energy deposition which uses filament and arc as a generator. This application of welding in additive manufacturing is generating great interest in the scientific community and industry. For example, Figure 2 shows the application of additive manufacturing by welding a part on a robot.

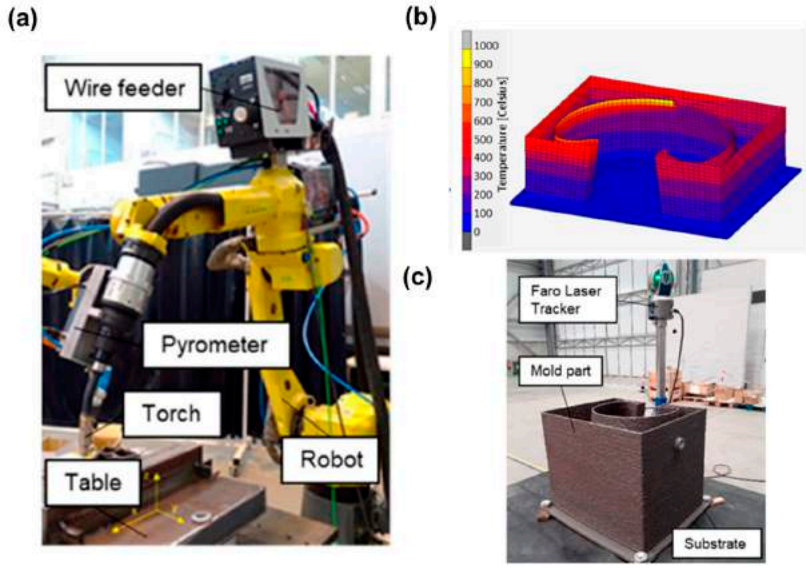



**Figure 2.** Set-up of the (**a**) robotic system for the manufacture of parts with GMAW-based WAAM, (**b**) model for the temperature estimation, and (**c**) measurement of the deformation in the final part (edited from [18]).

Once the welding parameters have been determined and modeled, it is necessary to ensure that they remain within acceptable limits throughout the welding process. For this purpose, direct or indirect control and monitoring are used, thanks to the use of vision techniques (e.g., cameras, smart cameras), sensors [19] (e.g., sound, vision, integrated vision, radiation, spectral, infrared or inductive) or sensor fusion [20], which read the parameters or variables referred to depending on the type of sensor and the type of parameter to be measured, in order to be able to analyze and control them through the appropriate software and thus incorporate them into the automated system [21]. This control and monitoring process will be explored in more depth in Section 4.

In Section 5, we will develop the subject of automation, which is composed of a set of components that, once the parameters and variables of the process have been captured, compare them with predetermined average values, adjusting these characteristics in real time when necessary. The efficiency of automation in industrial welding processes is beyond doubt [22], especially in repetitive operations, as satisfactory results are always obtained thanks to the reduction of defects and costs and the improvement in productivity and quality.

Robotic welding is a widely used technique for improving the quality, efficiency, and safety of welding processes. However, robotic welding faces many challenges, such as variations in workpiece geometry, joint location, and thermal distortion. To overcome these challenges, various sensing technologies have been developed and applied to enable intelligent robotic welding systems that can adapt to changing conditions and monitor weld quality. This review covers some of the main topics related to robotic welding applications, such as inspection of welding performance, modeling of welding processes, monitoring techniques and their application, automation of welding processes, synthesis, and conclusion. The review aims to provide an overview of the current state-of-the-art and future trends in this field.

## 2. Inspection of Welding Performance

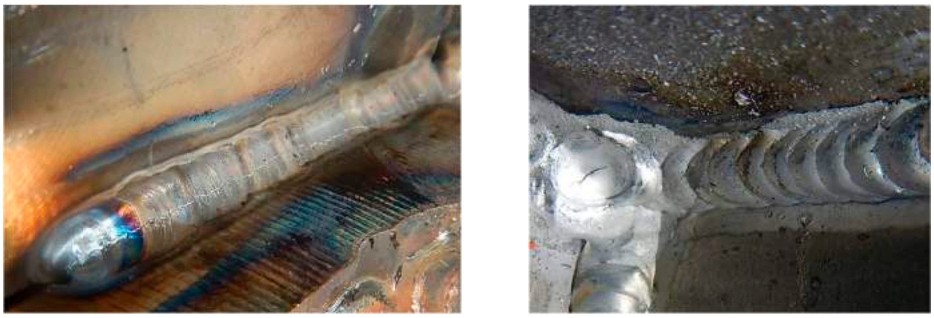
In order to succeed in making a good weld, before carrying it out, it is necessary to start by studying what type of metals we define to create new parts [23], what type of arc is the most appropriate for those materials and thicknesses we have [4], and to define exactly the characteristics of the operating parameters which correspond to the type of welding arc chosen [24], including current, voltage, welding speed, temperatures, gas flow, and torch angle. If these parameters are not correctly defined and regulated, it directly influences the reduction of the efficiency of the process, which can be more than 15% [25], lower quality than desired [26], a reduction in the useful life of the weld due to the reduction in mechanical properties [27], and the generation of defects which would have to be corrected a posteriori, accompanied by serious economic and productive damage. For this reason, it is necessary to compare, control, and relate these input parameters with the characteristics of the weld at the end of the weld, including geometry and dimensions [5], in order to know whether the weld has been carried out successfully.

Once the most appropriate arc welding with its corresponding parameters has been defined, we must bear in mind that during the welding process, unforeseen events may occur that may produce various defects in the weld. Before carrying out the welding operations, it is advisable to calibrate the robot itself and the system to be used [28] and to take into account the availability of a classification of the quality of the weld [29] as well as a classification of possible defects that may appear. These classifications, generally based on databases or neural networks, have a very high degree of accuracy in the detection of defects by means of machine learning algorithms or decision tree algorithms [30] to establish a correlation between current and voltage signatures [31] through radiographic image processing based on ANFIS adaptive networks [32]. A real-time defect classification during the welding process has been achieved based on the combined use of principal component analysis and an artificial neural network (ANN) [15,33] or through deep learning and digital radiography and an optimized convolutional neural network (CNN) [34].

To perform these defect classifications, we will study the most common defects that occur during welding, and how to detect and identify them:

1. Cracks: among the defects that can occur in welding, the most critical is when cracks occur. These appear when the load or stress applied to a part exceeds its resistance (see Figure 3). Cracks can be categorized as "hot cracking" (when the metal is solidifying) or "cold cracking" (when the metal has cooled to room temperature). The methods used to detect cracks are usually precise and leave no room for doubt. For example, there are methods using eddy currents [35], thermography using a high-power infrared light source [36], a system that analyses acoustic emission using sensors [37], an ultrasonic laser [38], and a real-time X-ray imaging system has been developed to detect them [10].
2. Porosity: one of the most recurrent defects when welding is the creation of pores, which are caused by bad use of the materials, the process itself, or external contaminants that are in the base metal, which causes the gas to be trapped in the molten metal and as solidification occurs, this gas is emitted outwards and the pore appears. There are numerous and varied reasons behind the formation of these pores, including issues with nozzles, guns, torches, electrodes, gas flow, incorrect usage, and humidity. Figure 4 exemplifies the situations in which porosity appeared in welds as a result of non-compliance with the conditions of protection, cleaning, or drying of the materials involved in the welding process.

To avoid porosities in the weld, it is necessary to anticipate their appearance and predict whether these pores will appear as the welding process progresses when the material starts to cool. This can be done through real-time monitoring of the welding process using methods such as analysis of the welding voltage signal through deep neural networks (DNN) [39], analysis of the arc sound signal [40], monitoring of optical plasma spectroscopy [41], monitored analysis of thermal images [42], and monitoring of voltage and current through control chart and probability density distribution [43]. The collection of these data is carried out by statistical analysis of arc current where voltage, current, and wire feed speed signals are recorded [44]. Another method is through statistical analysis of process parameter optimization (current, travel speed, gas flow rate, and torch angle) to create a porosity index [9].



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

**Figure 3.** Cracks: (**a**) longitudinal surface crack produced in the weld metal by excessive clamping between plates with different thicknesses (thicknesses of 40 mm and 100 mm) and welded with TIG process without properly preheating the plates; (**b**) transverse crater crack produced in the weld metal by an abrupt interruption of the arc causing tensile stresses across the weld surface.

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

**Figure 4.** Porosity: (**a**) surface porosity uniformly distributed along the weld seam is produced because the displacement angle is too large (excessive slope); (**b**) porosity occurred because the gun is too far away from the workpiece or the voltage has been insufficient at the welding distance.

3. Undercuts: it is the gap that forms when the metal melted by the electric arc does not completely fill the connection area between the weld and the base material. Undercuts also occur when welding current and welding speed are not well matched. The main reason for this is that the arc heat is too high; for example, the current is too high, and the strip speed is too low (see Figure 5); tests under different currents and welding speeds [12] attest that these parameters have to be adjusted so that undercuts do not occur.
4. Spatter: Welding spatter consists of molten metal droplets that are dispersed or splashed during the welding process. In order to avoid spatter, it is necessary to check that the components used in welding are in optimum condition for use [45]and that the welding parameters are correct (current, voltage, arc length, and angle, feed rate–as seen Figure 6, where an example of non-compliant welding can be observed. Thanks to computer vision, a spatter index has been created to predict the appearance of spatter [8].
5. Anode patterns: discoloration along the seam produced by heat during thermal changes such as heating and cooling. It is important to note that depending on the parameters of the welding process, oxides might appear, and the material could break down. This would drastically reduce the quality and life of the weld.
6. Lack of fusion and poor penetration: lack of fusion occurs when there is no fusion between the weld metal and the surface of the base material; poor penetration is similar when the weld bead does not fully penetrate the full thickness of the material [46]; both processes can occur when the welding current is too low, or its travel speed is too fast [30], as seen in Figure 7. Several methods have been developed to detect such defects: by real-time monitoring of the arc pool temperature [47], by real-time optical analysis and a sub-pixel algorithm [48], by studying arc acoustics [11], by camera

vision systems to create maps that are fed into neural networks [49], and through ultrasonic detection [50] or monitoring through infrared sensors [51,52].


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

**Figure 5.** Undercuts caused by using a higher current than necessary (**a**,**b**).

**Figure 6.** Spatter produced by the use of inadequate wire feed rate.

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

**Figure 7.** (**a**) Lack of fusion due to improper handling of the gun, applying the arc heat unevenly; (**b**) incomplete fusion as a result of the weld pool being ahead of the electric arc, preventing proper fusion.

One of the keys to detecting possible defects is to study various characteristics of the weld through the parameters of the welding process:

1. Welding arc sound: this is a consequence of the modulation in amplitude of the current by the arc voltage in the welding process, which can represent the behavior of the sequence of short circuits and ignitions of the arc voltage, thereby opening up the possibility of acoustically detecting disturbances. With this, the weld quality can be controlled [53–55] even with the monitored use of algorithms [30], through acoustic signals [56], or by monitoring parameters to control defects such as weld penetration [11] and weld porosity [40].
2. Weld pool: the working place where the base metal has reached its melting point and is ready to be melted with filler material; for the success of the welding process, it is essential to control the parameters of this pool, as it has a direct effect on the quality of the weld bead geometry. To control the pool parameters, the best option is monitoring [57] to successfully predict the shape of the molten pool. Additionally, camera-based vision systems [58] to create maps that are fed into neural networks [49],

along with acoustic detection [50], detecting undercuts under different welding currents and speeds [59], and real-time control of the pool [60] are alternative methods that can be used.

3. Bead geometry: the main characteristics to be defined and controlled in the bead geometry are width, height, and penetration; all of them will clearly influence the quality of the final weld result [5,27]. A key factor that greatly influences bead geometry is the right choice of shielding gas [3,61]. In order to know if the geometry is appropriate, different techniques are used for its control, such as sensors [22,23,62], sensor fusion [63], and infrared detection for parameter monitoring [52,64]. In addition, it must be taken into account that, thanks to computer vision systems and intelligent detection and control systems, material waste and energy consumption can be reduced by more than 10% in the bead geometry fabrication process [65].

With the descriptions of the defects previously made and the different characteristics of the welding through the parameters of the welding process, it is clear that the main objective is to detect any type of defect in real time through a detection system that tells us about any possible defect of those mentioned above. Moreover, real-time sensing and control should also be considered as it helps to overcome deviations from nominal welding conditions. This is achieved by optimizing welding parameters through real-time sensing and feedback control [66], all of which depend on process properties/capabilities, process innovations, predictive models, numerical models for fluid dynamics, numerical models for structures, real-time sensing, and dynamic controls [67]. Throughout this section, examples have been described that include the detection of defects in real time, but they can also be completed with the following examples: parameter monitoring [68], radiographic inspection [69], and spectroscopy signal [70], depending on the frequency band [71].

In addition to the examples of detecting single defects described in this section, there are methods available that allow for the simultaneous detection of multiple defects, such as cracks, porosity, undercuts, splashes, anode patterns, lack of fusion, and poor penetration. These methods include parameter monitoring [72,73] and computer vision analysis of radiographs [74]. By utilizing these methods, it is possible to improve the efficiency and accuracy of defect detection in various industries.

To all this, the authors must add that all the inspections shown in this section are visual inspections that have been carried out without destroying the parts and the weld, being able to be assimilated as non-destructive tests to detect defects [13], and all of this, with the premise of ensuring quality [75], either through a classification [29] or by estimating it using artificial intelligence algorithms [76].

## 3. Modeling of Welding Processes

In the previous section on inspection, the main defects and the most important characteristics of a weld have been described in depth. To prevent any defect from appearing, we must take advantage of the various current technological tools, such as the various types of neural networks with their modular software interfaces, which, thanks to machine learning and deep learning, can study any parameter of the weld. Once the required parameter data is available, mathematical formulations (finite elements, regression analysis, algorithms, and Gaussian hypothesis) will be used to simulate and carry out the corresponding modeling. For this purpose, we will define the following:

1. Modular software interface: interconnection between independent systems or between a computer system and its human user, which is composed of different functionalities or modules and which is designed following a strategy. Ideally, all available modules should be used to cover the control of the entire welding process [14], and even from the beginning of the CAD design to the finished part [77].
2. Neural Network: A neural network is a method of artificial intelligence that teaches computers to process data in a way that is inspired by the way the human brain does. It uses a type of machine learning process called deep learning, which uses nodes or neurons interconnected in a layered structure that resembles the human brain; they

can learn and model relationships between input and output data that are non-linear and complex. An artificial neural network [78] consists of artificial neurons working together to solve a problem. Artificial neurons are software modules called nodes, and artificial neural networks are software programs or algorithms that essentially use computer systems to solve mathematical computations.

3. Machine learning is an artificial intelligence technique that gives computers access to very large data sets and teaches them to learn from this data. Machine learning software finds patterns in existing data and applies them to new data to make intelligent decisions. They require human intervention for machine learning software to work well enough; a data scientist manually determines the set of relevant features for the software to analyze. An example of machine learning is relating arc sound to weld quality through various parameters (current, voltage, and travel speed) to create a weld classification through algorithms [30].
4. Deep learning: a data scientist provides raw data to the software, which obtains new features itself and learns independently. It can analyze unstructured data sets and solve more complex problems. Some examples of deep learning are:
   - Studying the 3D surface of the weld pool to create maps of the depth of penetration, which were fed into a neural network and create a classification of the penetration in the pool [49].
   - A digital radiography method is used to detect defects through an optimized convolutional neural network (CNN) [34].
   - Interactions between the arc and electrodes predict the shape and depth of the weld pool [79].
   - Performing a classification of defects in the weld bead [23].

In order to carry out the most accurate modeling possible or to detect possible defects in the weld, we must start by collecting as much data as possible on the parameters to be analyzed. Once all the data has been obtained, they must be analyzed by using the following mathematical formulations (let us look at some examples):

1. Finite element (FE): used to inspect through the ultrasonic laser defects such as cracks, porosity, undercuts, [38] or thermo-mechanical behavior [80]; another practical example is calculating the Von Mises stresses in the regions close to the weld bead with their corresponding distribution [80], as shown in Figure 8.
2. Regression analysis: used to predict the evolution of the weld pool through imaging [57] or through the current to control its width [81] or to adjust the bead geometry [82].
3. Gaussian hypothesis: uses the current density distribution to model metal transfer [83].
4. Algorithms, mainly developed in:
   - Weld pool: modeling current and weld velocity [84], pool width [85], pool size through imaging [60], and molten metal flow on the surface [12].
   - Bead geometry [63]: metal transfer modeling [86], and current and voltage modeling [64].

   In addition, the algorithms can also be used for the following:
   - Robot [28] and tool [87] trajectory control to avoid deviations before the start of welding operations and to avoid possible dimensional errors.
   - Detection of defects [87] in the weld: an image transformation algorithm for defect extraction that creates a pattern recognition method for automatic defect identification [74], and a sub-pixel algorithm to detect defects, oxidation, and the lack of penetration [48], detect in-line faults such as porosity, undercuts, lack of fusion, and spatter through temperature signal based algorithm [72], defect classification [31], detect defects in bead geometry, poor penetration, and porosity according to frequency band [71].

- Assessing weld quality through voltage [88]: an optimization algorithm through plasma spectroscopy analysis technique [75], an artificial intelligence algorithm based on current and voltage parameters [76], correlating weld quality with current and voltage [31], and on-line weld quality through voltage variance parameter algorithm [89], and algorithms for real-time inspection of quality [71].

5. Numerical formulations: other than the above, such as numerical models to control the keyhole [58] and the welding arc [43,90].

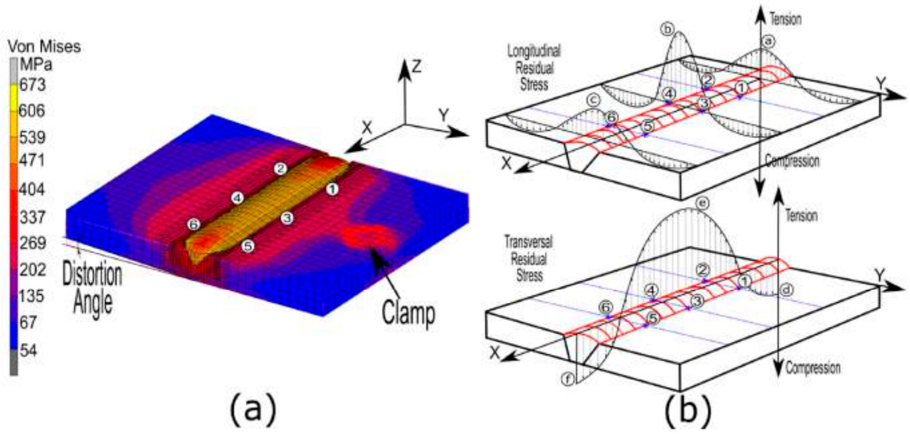



**Figure 8.** (**a**) Von Mises stresses obtained from the FE model of a butt joint with a single V-groove for the first specimen studied; (**b**) theoretical distribution of longitudinal and transverse stresses for welding any butt welded joint with single V-groove (Reprint from [90]).

Once the data has been analyzed with one of the mathematical formulations, to study and improve the modeling technique, we can rely on the various neural networks with their modular software interfaces; look at Table 1 for several examples:

**Table 1.** Various uses for improved modeling through neural networks.

| Neural Network Type | Processes | References |
|---|---|---|
| General | Real-time weld quality inspection for defect detection thanks to current, voltage, and welding speed parameters | [15] |
| Artificial | Through algorithms to predict weld deposition efficiency using arc sound signal, current, and voltage | [91] |
| Artificial | Development of intelligent systems for welding process automation | [92] |
| Artificial | For automatic real-time defect detection and classification based on the combined use of principal component analysis | [33] |
| Deep | For real-time porosity defect prediction and detection based on the voltage signal | [39] |
| Probabilistic | For defect detection using laser-induced plasma electrical signals | [93] |
| Associative Memory | For automatic weld quality classification based on an associative memory neural network created by the characteristics of the electrode displacement signal | [29] |

To further improve the arc welding efficiency and the joint quality, a secondary energy field/source is usually applied to assist the conventional arc welding process. Modeling, sensing, and control of such arc welding processes are efficient and powerful ways for process modification and development and a complete understanding of the underlying interaction mechanism of the auxiliary energy and the welding process [94].

Once the welding process has started, the modeling of as many parameters as possible must be as efficient and fast as can be achieved, and for this, it must be done in real time to detect any possible defect in order to be able to correct it and evaluate the quality of the weld on the spot. To this end, we must tend towards dynamic modeling, which models the weld through the parameters derived from dynamic equations (such as the melting speed equation [95]), and towards simple but effective modeling in real time, through monitoring, in which, for example, the wire feed is modeled by monitoring the width of the weld bead [62].

## 4. Monitoring Techniques and Its Application

It is important to monitor welding parameters during the welding process to ensure that they remain within acceptable limits and to detect any alterations that may result in defects in the weld. Vision techniques, such as cameras and intelligent cameras, and sensors, including sound, vision, integrated vision, radiation, spectral, infrared, and inductive sensors, can be used to read the parameters or variables being measured. These readings can be analyzed in real time through appropriate software to draw conclusions and improve precision, reliability, and efficiency [21].

When alterations to the parameters and predefined modeling procedures are detected, the system should be able to respond, if possible, in real time. Communication between the sensors and control and monitoring systems is necessary to allow for this response. The consequences of alterations to the parameters can result in defects in the weld, and examples of such defects can be studied using the selected detection methods listed in Table 2.

**Table 2.** Different methods of defect detection through process parameters.

| Defect | Method of Detection | Parameter for Detection | References |
|---|---|---|---|
| Porosity | ultrasonic based sensor | the characteristic parameters | [96] |
| Porosity | monitoring of images | temperature of the upper surface of the melt pool | [97] |
| Porosity | monitoring | output parameter | [41] |
| Porosity, Cracks, lack of fusion, undercuts | monitoring | Intensity | [72,73] |
| Lack of penetration | monitoring | spectroscopy signal | [70] |
| Lack of penetration | optical analysis of the plasma spectrum | electronic plasma temperature | [48] |
| Lack of penetration | monitoring | arc voltage signal | [88] |
| Emissions (sound and light) | monitoring | welding arc | [98] |
| Tracking defects | monitoring by a sensor using spectrometry | electronic temperatures | [99] |
| In the molten pool | monitoring | acoustic signals | [100] |
| defect classification (based on a decision tree algorithm) | monitoring and control | current and voltage | [31] |

To detect the aforementioned defects, sensors need to be inserted in real time around the welding process, and their presence can alter the behavior of the metal transfer and, consequently, uneven quality [20], as well as increase the cost of production.

### *4.1. Bead Tracking, Weld Dimension, and Defects Monitoring and Control*

Bead tracking and weld dimension control are essential tasks for ensuring the quality and accuracy of robotic welding processes. Bead tracking involves detecting the position and geometry of the weld seam using various sensors, such as laser, vision, or arc sensors. Weld dimension control involves adjusting the welding parameters, such as wire feed rate and voltage, according to the feedback from the sensors and the desired weld bead shape.

These techniques enable robotic welding systems to perform autonomous and flexible welding operations in different industrial scenarios. There are several types of sensors, among which the most important are [19] as follows:

- Arc: they do not require additional equipment in the welding area. This is why they can be used where operating space is limited. Their operation is based on the variation of the signal obtained from the voltage or current of the arc and can adjust the distance between the torch and the workpiece [101].
- Optical: they allow the observation of the behavior of the welding group and transmit the output of the welding process to the control model as an input signal [102], among which the following stand out:
    - Vision cameras: to determine process stability and weld quality [58].
    - Multi-view cameras: to evaluate weld bead properties [103].
    - Speed cameras: for monitoring deposition height and molten pool temperature [104].
    - High-speed cameras: for a precise understanding of physical phenomena during welding [105].
    - CCD (Charged Coupled Device) cameras: for coating height measurement [106].
    - CMOS cameras (Complementary Metal Oxide Semiconductor; superior imaging to CCD cameras): for allowing better visualization of the molten pool, which improves the ability to assess weld bead quality [107].
    - Spectroscopy: for facilitating the detection of defects [108], such as porosity [41], defects in the weld pool [99], or in the bead [70].
- Infrared:
    - To automatically identify defects [42].
    - To control the welding process through the parameters of the bead geometry and the torch position [51].
    - To control the pool temperature and penetration depth [47].
    - To check the weld pool from the front [109].
    - To check bead geometry, melt pool [110], and penetration depth [52].
    - For general weld monitoring [111].
- Sounds, among which the following stand out:
    - Acoustic: thanks to a dynamic microphone, the acoustic signal is studied by means of the frequency response curve, and the metal transfer modes can be classified [56].

Ultrasonic: these generally have good resolution and can provide accurate data such as in situ monitoring for porosity [96].

### *4.2. Metal Transfer and Weld Pool or Keyhole*

Metal transfer and weld pool or keyhole are two important phenomena that occur during fusion welding processes. Metal transfer refers to the mode of transferring molten electrode material across the arc gap to the weld pool. A weld pool or keyhole is the molten region of the base metal that forms under the action of a heat source. The keyhole is a cavity in the weld pool that is maintained by vapor pressure and surface tension forces. The metal transfer and weld pool or keyhole dynamics affect the quality and geometry of the weld bead, as well as the heat transfer, fluid flow, phase change, and cooling rate in the welding process.

Sensors for fusion monitoring in welding are devices that can collect and analyze data from the welding process to detect defects such as lack of fusion, porosity, cracks, and so on. Fusion monitoring is important for ensuring the quality and reliability of welded joints, especially for applications that require high precision and strength [21]. In addition, global information is extracted from the interrelated data given by each sensor. Let us look at some applications:

- The sensor fusion monitoring system is one of the basic pillars for the additive process to evaluate the quality of the parts and detect possible defects such as high residual stress, deformations, porosity, and cracks [112].
- Through data collected from arc, optical, and sound sensors, it is possible to quantify the processing of the welding arc and to search for the presence of porosity [113].
- By implementing an artificial neural network to sensor fusion, the following elements are improved [92]:
    - Computer vision based on photogrammetry.
    - Process monitoring using fuzzy logic.
- Weld bead tracking through sensor fusion can be fed to the robot controller to instruct it in determining the weld seam trajectory [114].

All this extensive explanation of sensors and their possible fusion with each other for monitoring purposes serve to control as much as possible the welding process and, consequently, the final quality of the weld. In order to achieve optimal welding quality, the best option is to monitor the welding process in situ and on the spot; let's look at an example where the main objective is to evaluate the quality by monitoring in situ:

- Thanks to two algorithms related to the characteristics of the arc voltage signal: time and frequency. Such algorithms are able to detect a lack of penetration, burn-through, and defects caused by lack of gas [88].
- To detect changes in weld quality automatically, based on the statistical parameter of voltage variance [89].
- To direct the directed energy deposition of metals [115].
- To detect defects in weld bead geometry [48].
- Through welding parameters (voltage and current) the following can be found:
    - Thanks to the information extracted from the signal characteristic [68].
    - Via an artificial intelligence algorithm [76].
    - Through machine learning algorithms to correlate arc sound with quality [30].
- Quality control thanks to a fusion system of voltage, current, and temperature sensors, a rotary encoder, and a CCD camera. Thanks to a data acquisition (DAQ) module integrated into the software, the captured data can be stored and visualized [116], as shown in Figure 9.

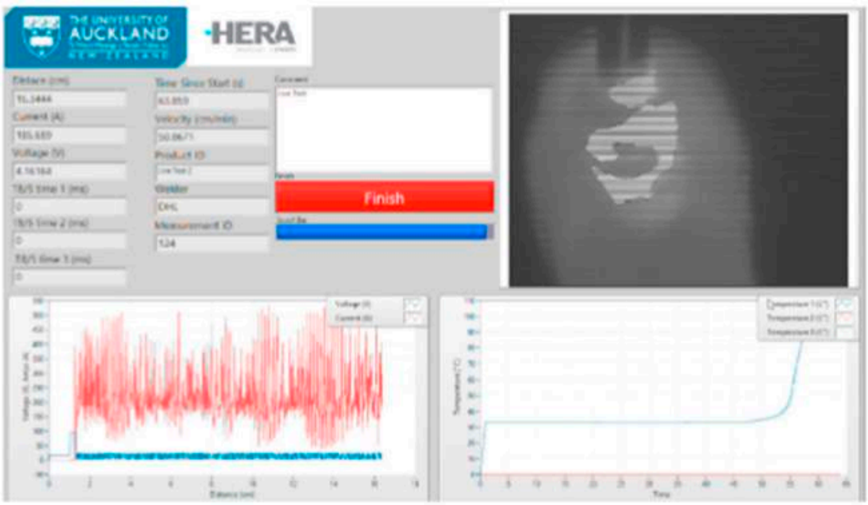



**Figure 9.** The interface features of the front panel view (reprinted with permission from [116] 2020 © the author(s)).

It should be noted that if welding quality can be controlled in real time from the beginning of the welding process by monitoring different types of sensors, material and energy savings of more than 10% can be achieved in manufacturing [65].

## 5. Automation of Welding Process

Automated robotic welding is the set of computerized elements or processes which, thanks to the most advanced technological applications and a controlled discipline based on the use of electromechanical systems, manages to minimize or even eliminate human participation in the robotic welding process and obtain a series of global benefits from the process, such as reduction of time, costs, effort, resources, human error, and welding defects, thereby optimizing plant space and clearly improving productivity and quality. Furthermore, prior to the automated welding operation and before moving on to the design phase, a series of important characteristics must be defined for this process as follows:

1. Type of welding to be used. Data obtained that depends on the type of material to be welded and its resistance.
2. The number of parts to be welded, size, and weight. This influences the degree of complexity of the welding tooling and the range and trajectory of the robot.
3. The thickness of the sheets.
4. Amount of weld to be applied.
5. Cycle time of the process.

Once these characteristics have been defined, it is convenient to have virtual tools to simulate the welding process, which will allow us to check the feasibility of the process and validate the phases of the design. By means of simulation, the process can be reproduced in a virtual 3D environment, as seen in Figure 10, in order to optimize the space in the factory, the use of its resources, and operation times, reducing start-up costs and avoiding possible surprises in the implementation phase. Once the design has been validated, it has to be implemented for weld fabrication.

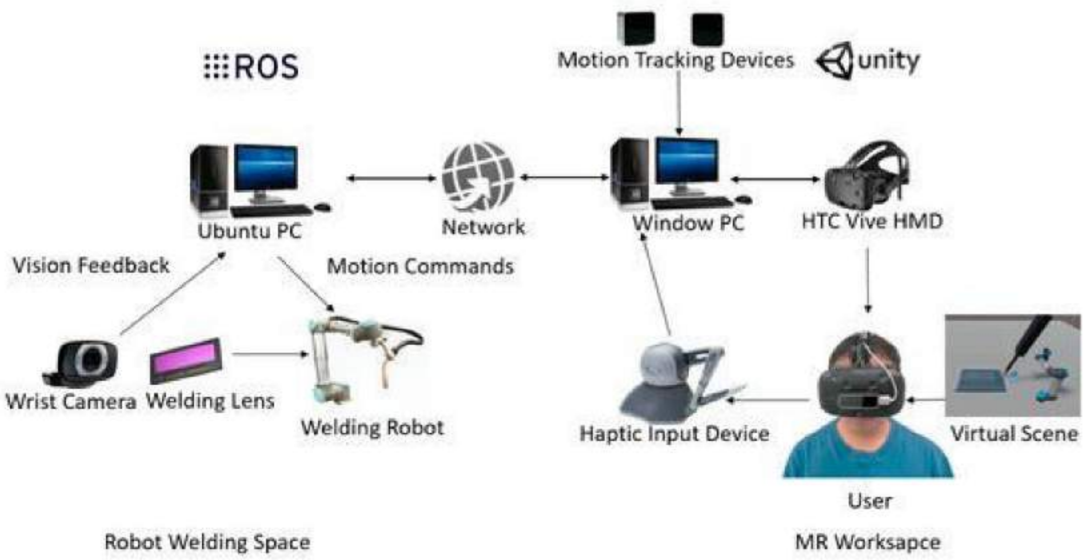



**Figure 10.** The communication scheme of the MRVF tele-welding hardware apparatus (reprinted from [117]).

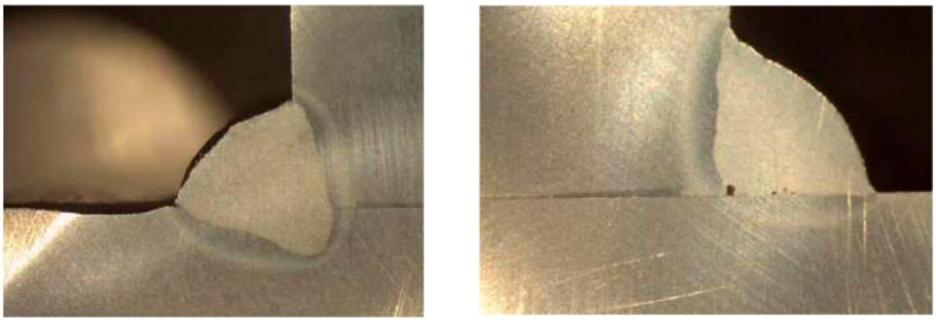
Once the welding process has been automated, software must be available to guide the process in order to control and measure it, then extract data for evaluation and improvement. With all these concepts, implementing automation in welding only represents gains and benefits, so automating is a safe and profitable option. However, there are also a number of problems, among which the most common of which are as follows [22]:

- The need to compensate for inaccuracies in workpiece fixtures.
- Variations in the dimensions of the workpiece.
- Imperfect edge preparation.
- Thermal distortions in the process.

Such problems can be effectively solved with the use of sensory feedback signals from the weld joint. Therefore, the various existing sensors, already explained in Section 4, play an important role in automated robotic welding processes, which, among other functions, mainly have to track the joint, monitor the weld quality during the process, and take into account the variation in joint location and geometry. In addition, various sensors can be used for the detection and measurement of various process characteristics and parameters, such as joint geometry, weld pool, and location, and for on-line process control. The following items are some of the utilities realized in automation:

- Automatic controllers have been developed for the layer-by-layer arc deposition process. As a result, a software interface has been implemented to adjust the parameters of an automatic controller [14].
- The development of a versatile and easily automatable process for the development of optimal weld joint characteristics by controlling the pulse parameters [27].
- Developing intelligent systems for the automation of the welding process for the implementation of an artificial neural network, used to improve computer vision based on photogrammetry and sensor fusion monitoring using fuzzy logic [92].
- Development of an automated additive manufacturing software system based on robotic arc welding from CAD to the finished part [77]. The system contains several modules, including bead modeling, cutting, deposition path planning, weld fitting, and post-process machining.
- Monitoring, control, and the framework of an automated system [21]. A framework for the sensor-based feedback monitoring and control system is proposed to improve its accuracy, reliability, and efficiency in order to identify and reduce defects.

With the automation process, manufacturing times, energy consumption, and possible defects during the welding process are reduced, thus increasing productivity and, most importantly, improving the quality of the weld, the final product, and customer satisfaction. Figure 11 shows the difference and improvement in quality through the automation of welding processes.



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

**Figure 11.** The aspect of convex fillet weld in cross-section: (**a**) good root penetration, and (**b**) incomplete fusion.

## 6. Robotic Laser Welding and Laser-Arc Hybrid Welding

Laser welding and laser-arc hybrid welding are widely used in various industries because of their advantages, such as high welding speed, low distortion, and small heat-affected zone. However, monitoring and modeling techniques are essential for quality control and optimization of the welding process. In this regard, the following papers have contributed to the advancement of inspection, modeling, and monitoring techniques for laser welding and laser-arc hybrid welding.

In [118], the authors presented a comprehensive study of the dynamics of laser welding keyhole and molten pools at different penetration statuses. They used a combined numerical and experimental approach to investigate the relationship between laser power, welding speed, and the size of the keyhole and molten pool. The study highlights the importance of modeling and simulation in understanding the complex welding process.

In [119], the authors investigated the dynamic features of surface plasma in high-power disk laser welding. They used a high-speed camera to capture the plasma during the welding process and analyzed its spectral characteristics. The study provides insights into plasma behavior and its influence on the welding process.

In [120], the authors proposed a neural network-based monitoring system for high-power disk laser welding. They used plume and spatter signals as inputs to the neural network and achieved high accuracy in detecting welding defects. The study demonstrates the potential of machine learning techniques for the real-time monitoring of welding processes. In [121], the authors reviewed the recent advancements in welding monitoring technology based on machine vision. They discussed the challenges and opportunities in this field and presented several case studies to illustrate the application of machine vision techniques in welding quality control. The study highlights the potential of machine vision for improving the accuracy and efficiency of welding inspection. In [122], the authors proposed a method for detecting tight butt joint welds based on optical flow and particle filtering of magneto-optical imaging. They used a magneto-optical imaging system to capture the magnetic field distribution during the welding process and applied optical flow and particle filtering algorithms to detect the weld seam. The study provides a novel approach to detecting tight butt joint welds, which are difficult to inspect using traditional methods.

The application of laser welding to additive manufacturing is of great importance. Laser metal deposition (LMD) is a popular additive manufacturing technique that uses a laser beam to melt and fuse metal powder or wire, layer by layer, to create three-dimensional (3D) parts. LMD has several advantages over traditional manufacturing techniques, such as the ability to produce complex geometries, reduce material waste, and customize parts. However, the LMD process also poses some challenges, including the need to optimize process parameters, minimize defects, and ensure consistent quality.

In [123], the authors investigated the machining process of Inconel 718 parts manufactured by LMD. They analyzed the microstructure, mechanical properties, and surface roughness of the parts and compared them to those of conventionally manufactured parts. The study revealed that the LMD parts had a refined microstructure, improved mechanical properties, and lower surface roughness than conventionally manufactured parts. However, the LMD parts also had defects, such as porosity, that needed to be addressed. The study highlights the importance of process optimization and quality control in LMD. By analyzing the machining process and identifying the sources of defects, the authors were able to suggest strategies for improving the quality and consistency of LMD parts. The study also demonstrates the potential of LMD for manufacturing high-quality parts with advanced materials, such as Inconel 718, which are difficult to machine using traditional methods.

Overall, these papers demonstrate the importance of inspection, modeling, and monitoring techniques for laser welding and laser-arc hybrid welding. They provide insights into the complex welding process and present novel approaches to quality control and optimization of the welding process.

## 7. Synthesis and Conclusions

Robotic welding is a highly efficient and consistent process that is widely used in many industries. However, even with the use of automated machines, defects can occur during the welding process that may compromise the quality and integrity of the welds. Common defects that can occur in robotic welding include cracks, porosity, undercuts, spatter, anode patterns, lack of fusion, and poor penetration.

To prevent these defects, it is important to take appropriate measures before and during the welding process. This can include choosing the appropriate welding method, materials, and parameters for each application. Further, performing regular inspection, maintenance, and calibration of robotic welding equipment, using proper shielding gas type, flow rate, and nozzle size, cleaning and preparing surfaces before welding, controlling heat input, travel speed, and interpass temperatures, and avoiding excessive stress, distortion, or hydrogen absorption.

In addition, it is important to address each specific defect appropriately. For example, to prevent cracks, proper filler materials should be used, and the weld area should be pre- and post-heated. To avoid porosity, the weld area should be cleaned, and adequate shielding gas flow and pressure should be used. To prevent undercuts, the choice of appropriate welding parameters is absolutely essential, and joint preparation should be done correctly. By taking these measures, defects can be prevented, and high-quality welds can be achieved using robotic welding.

Throughout the sections on inspection, modeling, monitoring, and automation, it is clear that there is a close interrelation between all of them, which means that if we want to carry out automated welding with the highest possible quality and no defects, we must take into consideration each and every one of the relevant aspects of each one of them.

In order to be able to carry out good automated welding, we must have programmed in advance the appropriate development of the modeling to be carried out so that once the welding process has begun, it is monitored in situ by various types of sensors, which will, when connected to software and neural networks, control the process parameters, predicting whether the final weld is optimal or may have a defect. If the prediction of the modeling during welding is that it may lead to a defect, this modeling must act to correct the process parameters to avoid the occurrence of any type of defect.

The conclusion is that the objective of this robotic welding production process for metallic materials is to carry out welding with excellent quality, as symmetrical and perfect as possible, optimizing times in the manufacturing processes. Operations must be carried out with consideration for the workers, materials, and energy consumption to reduce costs and generate the greatest possible economic benefit. We must also remember to respect the environment and prevent accidents by attending to the prevention of occupational hazards and focusing our attention on future cutting-edge services. Some examples of the latter are intelligent systems, big data analysis, artificial vision, and technological updating to be connected to the network (IoT).

## 8. Challenges and Future Directions

One of the main global challenges for the future in automated welding is to be able to develop software that brings together the entire welding process from start to finish. For this, it is essential to have sufficiently developed programs and applications that can simulate this sequence before starting the manufacturing process. Creating these simulations will be a major challenge but will lead to very safe methods for carrying out welding without defects.

Another of the main global challenges for the future to be promoted is the change towards intelligent welding processes, and this involves a major development and control of the characteristic parameters of the process in each phase as follows:

1. Inspection: applying the most advanced technologies for detecting any defects, if possible, in the previous stages.
2. Modeling: tending towards simple and dynamic modeling but with real-time effects.
3. Monitoring: use of artificial vision systems to model parameters through predictive control algorithms. Furthermore, the data sent by the different sensors used in this monitoring is transferred to controllers that are displayed on mobile devices or workstations that can be studied anywhere in the world. The integration of the "internet of things" in welding manufacturing is poised to revolutionize the industry, bringing increased efficiency and productivity to the forefront.
4. Automation: developing intelligent systems.

**Author Contributions:** Conceptualization, F.V., A.S. and P.V.; Investigation, F.V., A.S. and D.C.; Methodology, F.V. and D.C.; Project administration, P.V. and A.S; Supervision, A.S.; Validation, D.C., P.V. and A.S.; Writing—original draft, D.C.; Writing—review and editing, F.V., D.C., P.V. and A.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** The data presented in this study are available on request.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References


1. Wu, C.S.; Wang, L.; Ren, W.J.; Zhang, X.Y. Plasma Arc Welding: Process, Sensing, Control and Modeling. *J. Manuf. Process.* **2014**, *16*, 74–85. [CrossRef]
2. Silva, R.J.; Barbosa, G.F.; Carvalho, J. Additive Manufacturing of Metal Parts by Welding. *IFAC-PapersOnLine* **2015**, *48*, 2318–2322. [CrossRef]
3. Mvola, B.; Kah, P. Effects of Shielding Gas Control: Welded Joint Properties in GMAW Process Optimization. *Int. J. Adv. Manuf. Technol.* **2017**, *88*, 2369–2387. [CrossRef]
4. Kah, P.; Latifi, H.; Suoranta, R.; Martikainen, J.; Pirinen, M. Usability of Arc Types in Industrial Welding. *Int. J. Mech. Mater. Eng.* **2014**, *9*, 15. [CrossRef]
5. Tasic, P.; Hajro, I.; Hodzic, D.; Pandzic, A. Prediction of Geometry of Pulsed GMAW Fillet Welded Joints of Structural Steels. *Ann. DAAAM Proc.* **2020**, *31*, 444–452.
6. Uralde, V.; Veiga, F.; Aldalur, E.; Suarez, A.; Ballesteros, T. Symmetry and Its Application in Metal Additive Manufacturing (MAM). *Symmetry* **2022**, *14*, 1810. [CrossRef]
7. Curiel, D.; Veiga, F.; Suarez, A.; Villanueva, P. Methodology for the Path Definition in Multi-Layer Gas Metal Arc Welding (GMAW). *Symmetry* **2023**, *15*, 268. [CrossRef]
8. Bidanda, B.; Rubinovitz, J.; Raman, S. Development of a Spatter Index for Automated Welding Inspection Using Computer Vision. *Comput. Ind. Eng.* **1989**, *16*, 215–224. [CrossRef]
9. Kuppusamy, A.; Rameshkumar, K.; Sumesh, A.; Premkumar, S. Gas Metal Arc Welding Process Parameter Optimization to Reduce Porosity Defect in a Longitudinal Seam Welding of Pressure Vessels. *SAE Int. J. Mater. Manuf.* **2019**, *13*, 61–80. [CrossRef]
10. Boateng, F.T.; Ewert, U.; Kannengiesser, T.; Zscherpel, U.; Griesche, A.; Kromm, A.; Hohendorf, S.; Redmer, B. Real-Time Radiography for Observation of Crack Growth during GTA Welding. *Weld. World* **2016**, *60*, 931–937. [CrossRef]
11. Pal, K.; Pal, S.K. Monitoring of Weld Penetration Using Arc Acoustics. *Mater. Manuf. Process.* **2011**, *26*, 684–693. [CrossRef]
12. Zong, R.; Chen, J.; Wu, C.S.; Padhy, G.K. Influence of Molten Metal Flow on Undercutting Formation in GMAW. *Sci. Technol. Weld. Join.* **2017**, *22*, 198–207. [CrossRef]
13. Schmid, M.; Bhogaraju, S.K.; Liu, E.; Elger, G. Comparison of Nondestructive Testing Methods for Solder, Sinter, and Adhesive Interconnects in Power and Opto-Electronics. *Appl. Sci.* **2020**, *10*, 8516. [CrossRef]
14. Bonaccorso, F.; Cantelli, L.; Muscato, G. An Arc Welding Robot Control for a Shaped Metal Deposition Plant: Modular Software Interface and Sensors. *IEEE Trans. Ind. Electron.* **2011**, *58*, 3126–3132. [CrossRef]
15. Nele, L.; Mattera, G.; Vozza, M. Deep Neural Networks for Defects Detection in Gas Metal Arc Welding. *Appl. Sci.* **2022**, *12*, 3615. [CrossRef]
16. Pattanayak, S.; Sahoo, S.K. Gas Metal Arc Welding Based Additive Manufacturing—A Review. *CIRP J. Manuf. Sci. Technol.* **2021**, *33*, 398–442. [CrossRef]
17. Dilberoglu, U.M.; Gharehpapagh, B.; Yaman, U.; Dolen, M. The Role of Additive Manufacturing in the Era of Industry 4.0. *Procedia Manuf.* **2017**, *11*, 545–554. [CrossRef]
18. Casuso, M.; Veiga, F.; Suárez, A.; Bhujangrao, T.; Aldalur, E.; Artaza, T.; Amondarain, J.; Lamikiz, A. Model for the Prediction of Deformations in the Manufacture of Thin-Walled Parts by Wire Arc Additive Manufacturing Technology. *Metals* **2021**, *11*, 678. [CrossRef]
19. Kah, P.; Layus, P.; Hiltunen, E.; Martikainen, J. Real-Time Weld Process Monitoring. *Adv. Mater. Res.* **2014**, *933*, 117–124. [CrossRef]
20. Alfaro, S.C.A. Sensors for Quality Control in Welding. *Soldag. E Inspecao* **2012**, *17*, 192–200. [CrossRef]
21. Xia, C.; Pan, Z.; Polden, J.; Li, H.; Xu, Y.; Chen, S.; Zhang, Y. A Review on Wire Arc Additive Manufacturing: Monitoring, Control and a Framework of Automated System. *J. Manuf. Syst.* **2020**, *57*, 31–45. [CrossRef]
22. Kah, P.; Shrestha, M.; Hiltunen, E.; Martikainen, J. Robotic Arc Welding Sensors and Programming in Industrial Applications. *Int. J. Mech. Mater. Eng.* **2015**, *10*, 1–16. [CrossRef]
23. Tang, S.; Wang, G.; Zhang, H.; Wang, R. An Online Surface Defects Detection System for AWAM Based on Deep Learning. In *2017 International Solid Freeform Fabrication Symposium*; University of Texas at Austin: Austin, TX, USA, 2017.
24. Palani, P.K.; Murugan, N. Selection of Parameters of Pulsed Current Gas Metal Arc Welding. *J. Mater. Process. Technol.* **2006**, *172*, 1–10. [CrossRef]
25. Haelsig, A.; Kusch, M.; Mayer, P. New Findings on the Efficiency of Gas Shielded Arc Welding. *Weld. World* **2012**, *56*, 98–104. [CrossRef]
26. Wu, B.; Pan, Z.; Ding, D.; Cuiuri, D.; Li, H.; Xu, J.; Norrish, J. A Review of the Wire Arc Additive Manufacturing of Metals: Properties, Defects and Quality Improvement. *J. Manuf. Process.* **2018**, *35*, 127–139. [CrossRef]
27. Pal, K.; Pal, S.K. Effect of Pulse Parameters on Weld Quality in Pulsed Gas Metal Arc Welding: A Review. *J. Mater. Eng. Perform.* **2011**, *20*, 918–931. [CrossRef]
28. Silva, R.H.G.; Galeazzi, D.; Schwedersky, M.B.; Mendonça, F.K.; Bonamigo, A.V.; Marques, C. An Adaptive Orbital System Based on Laser Vision Sensor for Pipeline GMAW Welding. *J. Braz. Soc. Mech. Sci. Eng.* **2021**, *43*, 358. [CrossRef]

29. Zhang, H.; Hou, Y.; Zhao, J.; Wang, L.; Xi, T.; Li, Y. Automatic Welding Quality Classification for the Spot Welding Based on the Hopfield Associative Memory Neural Network and Chernoff Face Description of the Electrode Displacement Signal Features. *Mech. Syst. Signal Process.* **2017**, *85*, 1035–1043. [CrossRef]
30. Sumesh, A.; Rameshkumar, K.; Mohandas, K.; Babu, R.S. Use of Machine Learning Algorithms for Weld Quality Monitoring Using Acoustic Signature. *Procedia Comput. Sci.* **2015**, *50*, 316–322. [CrossRef]
31. Sumesh, A.; Nair, B.B.; Rameshkumar, K.; Santhakumari, A.; Raja, A.; Mohandas, K. Decision Tree Based Weld Defect Classification Using Current and Voltage Signatures in GMAW Process. *Mater. Today Proc.* **2018**, *5*, 8354–8363. [CrossRef]
32. Zapata, J.; Vilar, R.; Ruiz, R. An Adaptive-Network-Based Fuzzy Inference System for Classification of Welding Defects. *NDT E Int.* **2010**, *43*, 191–199. [CrossRef]
33. Mirapeix, J.; García-Allende, P.B.; Cobo, A.; Conde, O.M.; López-Higuera, J.M. Real-Time Arc-Welding Defect Detection and Classification with Principal Component Analysis and Artificial Neural Networks. *NDT E Int.* **2007**, *40*, 315–323. [CrossRef]
34. Naddaf-Sh, M.-M.; Naddaf-Sh, S.; Zargarzadeh, H.; Zahiri, S.M.; Dalton, M.; Elpers, G.; Kashani, A.R. 9—Defect Detection and Classification in Welding Using Deep Learning and Digital Radiography. In *Fault Diagnosis and Prognosis Techniques for Complex Engineering Systems*; Karimi, H., Ed.; Academic Press: Cambridge, MA, USA, 2021; pp. 327–352, ISBN 978-0-12-822473-1.
35. Yusa, N.; Janousek, L.; Rebican, M.; Chen, Z.; Miya, K.; Chigusa, N.; Ito, H. Detection of Embedded Fatigue Cracks in Inconel Weld Overlay and the Evaluation of the Minimum Thickness of the Weld Overlay Using Eddy Current Testing. *Nucl. Eng. Des.* **2006**, *236*, 1852–1859. [CrossRef]
36. Broberg, P. Surface Crack Detection in Welds Using Thermography. *NDT E Int.* **2013**, *57*, 69–73. [CrossRef]
37. Karlsson, L. Crack Detection in Welding Process using Acoustic Emission. Master's Thesis, Mälardalen University, Västerås, Sweden, 2010.
38. Zeng, Y.; Wang, X.; Qin, X.; Hua, L.; Xu, M. Laser Ultrasonic Inspection of a Wire + Arc Additive Manufactured (WAAM) Sample with Artificial Defects. *Ultrasonics* **2021**, *110*, 106273. [CrossRef] [PubMed]
39. Shin, S.; Jin, C.; Yu, J.; Rhee, S. Real-Time Detection of Weld Defects for Automated Welding Process Base on Deep Neural Network. *Metals* **2020**, *10*, 389. [CrossRef]
40. Yusof, M.F.M.; Kamaruzaman, M.A.; Ishak, M.; Ghazali, M.F. Porosity Detection by Analyzing Arc Sound Signal Acquired during the Welding Process of Gas Pipeline Steel. *Int. J. Adv. Manuf. Technol.* **2017**, *89*, 3661–3670. [CrossRef]
41. Valdiande, J.J.; Rodriguez-Cobo, L.; Cobo, A.; Lopez-Higuera, J.M.; Mirapeix, J. Spectroscopic Approach for the On-Line Monitoring of Welding of Tanker Trucks. *Appl. Sci.* **2022**, *12*, 5022. [CrossRef]
42. Sreedhar, U.; Krishnamurthy, C.V.; Balasubramaniam, K.; Raghupathy, V.D.; Ravisankar, S. Automatic Defect Identification Using Thermal Image Analysis for Online Weld Quality Monitoring. *J. Mater. Process. Technol.* **2012**, *212*, 1557–1566. [CrossRef]
43. Thekkuden, D.T.; Santhakumari, A.; Sumesh, A.; Mourad, A.-H.I.; Rameshkumar, K. Instant Detection of Porosity in Gas Metal Arc Welding by Using Probability Density Distribution and Control Chart. *Int. J. Adv. Manuf. Technol.* **2018**, *95*, 4583–4606. [CrossRef]
44. Wei, E.; Farson, D.; Richardson, R.; Ludewig, H. Detection of Weld Surface Porosity by Statistical Analysis of Arc Current in Gas Metal Arc Welding. *J. Manuf. Process.* **2001**, *3*, 50–59. [CrossRef]
45. Fleischmann, R. How to Maintain Your GMA Gun. *Weld. J.* **2013**, *92*, 44–47.
46. Trelles, J.P. Formation of Self-Organized Anode Patterns in Arc Discharge Simulations. *Plasma Sources Sci. Technol.* **2013**, *22*, 025017. [CrossRef]
47. Alfaro, S.C.A.; Franco, F.D. Exploring Infrared Sensoring for Real Time Welding Defects Monitoring in GTAW. *Sensors* **2010**, *10*, 5962–5974. [CrossRef] [PubMed]
48. Mirapeix, J.; Cobo, A.; Conde, O.M.; Jaúregui, C.; López-Higuera, J.M. Real-Time Arc Welding Defect Detection Technique by Means of Plasma Spectrum Optical Analysis. *NDT E Int.* **2006**, *39*, 356–360. [CrossRef]
49. Liang, Z.; Gao, X.; Zhang, K.; Wang, D.; Wang, L. Penetration State Identification from Stereo Image Pair of Weld Pool in GMAW Process by Deep Learning. In Proceedings of the 2022 IEEE 18th International Conference on Automation Science and Engineering (CASE), Mexico City, Mexico, 20–24 August 2022; pp. 1151–1156.
50. Carlson, N.M.; Johnson, J.A. Ultrasonic Sensing of Weld Pool Penetration. *Weld. J.* **1988**, *67*, 239s–246s.
51. Nagarajan, S.; Banerjee, P.; Chen, W.; Chin, B.A. Control of the Welding Process Using Infrared Sensors. *IEEE Trans. Robot. Autom.* **1992**, *8*, 86–93. [CrossRef]
52. Banerjee, P.; Govardhan, S.; Wikle, H.C.; Liu, J.Y.; Chin, B.A. Infrared Sensing for On-Line Weld Geometry Monitoring and Control. *J. Eng. Ind.* **1995**, *117*, 323–330. [CrossRef]
53. Saini, D.; Floyd, S. An Investigation of Gas Metal Arc Welding Sound Signature for On-Line Quality Control. *Weld. J.* **1998**, *77*, 172S–179S.
54. Cayo, E.H.; Alfaro, S.A. Indirect Estimation of the GMAW Weld Quality Using Acoustic Sensing. *Weld. World* **2009**, *53*, 71–76.
55. Pal, K.; Bhattacharya, S.; Pal, S.K. Prediction of Metal Deposition from Arc Sound and Weld Temperature Signatures in Pulsed MIG Welding. *Int. J. Adv. Manuf. Technol.* **2009**, *45*, 1113. [CrossRef]
56. Poopat, B.; Warinsiriruk, E. Acoustic Signal Analysis for Classification of Transfer Mode in GMAW by Noncontact Sensing Technique. *Songklanakarin J. Sci. Technol.* **2006**, *28*, 829–840.
57. Wang, Y.; Zhang, C.; Lu, J.; Bai, L.; Zhao, Z.; Han, J. Weld Reinforcement Analysis Based on Long-Term Prediction of Molten Pool Image in Additive Manufacturing. *IEEE Access* **2020**, *8*, 69908–69918. [CrossRef]

58. Liu, Z.M.; Cui, S.; Luo, Z.; Zhang, C.; Wang, Z.; Zhang, Y. Plasma Arc Welding: Process Variants and Its Recent Developments of Sensing, Controlling and Modeling. *J. Manuf. Process.* **2016**, *23*, 315–327. [CrossRef]
59. Suryakumar, S.; Karunakaran, K.P.; Bernard, A.; Chandrasekhar, U.; Raghavender, N.; Sharma, D. Weld Bead Modeling and Process Optimization in Hybrid Layered Manufacturing. *CAD Comput. Aided Des.* **2011**, *43*, 331–344. [CrossRef]
60. Smith, J.S.; Balfour, C. Real-time Top-face Vision Based Control of Weld Pool Size. *Ind. Robot Int. J.* **2005**, *32*, 334–340. [CrossRef]
61. Khalid, N.; Zamanhuri, P.Z.N.M.; Baharin, F.A.S. A Study of Weld Defects of Gas Metal Arc Welding with Different Shielding Gasses. *ARPN J. Eng. Appl. Sci.* **2017**, *12*, 2006–2011.
62. Kwak, Y.-M.; Doumanidis, C.C. Geometry Regulation of Material Deposition in Near-Net Shape Manufacturing by Thermally Scanned Welding. *J. Manuf. Process.* **2002**, *4*, 28–41. [CrossRef]
63. Alvarez Bestard, G.; Absi Alfaro, S.C. Measurement and Estimation of the Weld Bead Geometry in Arc Welding Processes: The Last 50 Years of Development. *J. Braz. Soc. Mech. Sci. Eng.* **2018**, *40*, 444. [CrossRef]
64. Doumanidis, C.; Kwak, Y.-M. Multivariable Adaptive Control of the Bead Profile Geometry in Gas Metal Arc Welding with Thermal Scanning. *Int. J. Press. Vessels Pip.* **2002**, *79*, 251–262. [CrossRef]
65. Xiong, J.; Zhang, G.; Qiu, Z.; Li, Y. Vision-Sensing and Bead Width Control of a Single-Bead Multi-Layer Part: Material and Energy Savings in GMAW-Based Rapid Manufacturing. *J. Clean. Prod.* **2013**, *41*, 82–88. [CrossRef]
66. Cheng, Y.; Yu, R.; Zhou, Q.; Chen, H.; Yuan, W.; Zhang, Y. Real-Time Sensing of Gas Metal Arc Welding Process—A Literature Review and Analysis. *J. Manuf. Process.* **2021**, *70*, 452–469. [CrossRef]
67. Zhang, Y.M.; Yang, Y.-P.; Zhang, W.; Na, S.-J. Advanced Welding Manufacturing: A Brief Analysis and Review of Challenges and Solutions. *J. Manuf. Sci. Eng.* **2020**, *142*, 11. [CrossRef]
68. Chen, S.; Sun, T.; Jiang, X.; Qi, J.; Zeng, R. Online Monitoring and Evaluation of the Weld Quality of Resistance Spot Welded Titanium Alloy. *J. Manuf. Process.* **2016**, *23*, 183–191. [CrossRef]
69. Zou, Y.; Du, D.; Chang, B.; Ji, L.; Pan, J. Automatic Weld Defect Detection Method Based on Kalman Filtering for Real-Time Radiographic Inspection of Spiral Pipe. *NDT E Int.* **2015**, *72*, 1–9. [CrossRef]
70. Zhang, Z.; Yu, H.; Lv, N.; Chen, S. Real-Time Defect Detection in Pulsed GTAW of Al Alloys through on-Line Spectroscopy. *J. Mater. Process. Technol.* **2013**, *213*, 1146–1156. [CrossRef]
71. Warinsiriruk, E.; Mahfudianto, F. Design the Feature Extraction for Real Time Inspection of Welding Quality. In Proceedings of the 2018 3rd Technology Innovation Management and Engineering Science International Conference (TIMES-iCON), Bangkok, Thailand, 12–14 December 2018.
72. Ancona, A.; Lugarà, P.M.; Ottonelli, F.; Catalano, I.M. A Sensing Torch for On-Line Monitoring of the Gas Tungsten Arc Welding Process of Steel Pipes. *Meas. Sci. Technol.* **2004**, *15*, 2412–2418. [CrossRef]
73. Shaloo, M.; Schnall, M.; Klein, T.; Huber, N.; Reitinger, B. A Review of Non-Destructive Testing (NDT) Techniques for Defect Detection: Application to Fusion Welding and Future Wire Arc Additive Manufacturing Processes. *Materials* **2022**, *15*, 3697. [CrossRef]
74. Liu, Y.; Li, X.; Ren, D.; Ye, S.; Wang, B.; Sun, J. Computer Vision Application for Weld Defect Detection and Evaluation. *Autom. Opt. Insp. Ind. Theory Technol. Appl. II* **1998**, *3558*, 354–357.
75. Mirapeix, J.; Cobo, A.; González, D.A.; López-Higuera, J.M. Plasma Spectroscopy Analysis Technique Based on Optimization Algorithms and Spectral Synthesis for Arc-Welding Quality Assurance. *Opt. Express* **2007**, *15*, 1884–1897. [CrossRef]
76. Zhao, D.; Wang, Y.; Lin, Z.; Sheng, S. An Effective Quality Assessment Method for Small Scale Resistance Spot Welding Based on Process Parameters. *NDT E Int.* **2013**, *55*, 36–41. [CrossRef]
77. Ding, D.; Shen, C.; Pan, Z.; Cuiuri, D.; Li, H.; Larkin, N.; van Duin, S. Towards an Automated Robotic Arc-Welding-Based Additive Manufacturing System from CAD to Finished Part. *Comput. Aided Des.* **2016**, *73*, 66–75. [CrossRef]
78. Chiroma, H.; Abdullahi, U.A.; Abdulhamid, S.M.; Abdulsalam Alarood, A.; Gabralla, L.A.; Rana, N.; Shuib, L.; Targio Hashem, I.A.; Gbenga, D.E.; Abubakar, A.I.; et al. Progress on Artificial Neural Networks for Big Data Analytics: A Survey. *IEEE Access* **2019**, *7*, 70535–70551. [CrossRef]
79. Murphy, A.B. A Perspective on Arc Welding Research: The Importance of the Arc, Unresolved Questions and Future Directions. *Plasma Chem. Plasma Process.* **2015**, *35*, 471–489. [CrossRef]
80. Yang, Q.; Zhang, P.; Cheng, L.; Min, Z.; Chyu, M.; To, A.C. Finite Element Modeling and Validation of Thermomechanical Behavior of Ti-6Al-4V in Directed Energy Deposition Additive Manufacturing. *Addit. Manuf.* **2016**, *12*, 169–177. [CrossRef]
81. Wang, Y.; Xu, X.; Zhao, Z.; Deng, W.; Han, J.; Bai, L.; Liang, X.; Yao, J. Coordinated Monitoring and Control Method of Deposited Layer Width and Reinforcement in WAAM Process. *J. Manuf. Process.* **2021**, *71*, 306–316. [CrossRef]
82. Bead Geometry Prediction for Robotic GMAW-Based Rapid Manufacturing through a Neural Network and a Second-Order Regression Analysis. *Springer*. Available online: https://link.springer.com/article/10.1007/s10845-012-0682-1 (accessed on 21 November 2022).
83. Wang, G.; Huang, P.G.; Zhang, Y.M. Numerical Analysis of Metal Transfer in Gas Metal Arc Welding. *Metall. Mater. Trans. B Process Metall. Mater. Process. Sci.* **2003**, *34*, 345–353. [CrossRef]
84. Wu, C.; Meng, X.; Chen, J.; Qin, G. Progress in Numerical Simulation of Thermal Processes and Weld Pool Behaviors in Fusion Welding. *Jixie Gongcheng Xuebao J. Mech. Eng.* **2018**, *54*, 1–15. [CrossRef]
85. Xia, C.; Pan, Z.; Zhang, S.; Li, H.; Xu, Y.; Chen, S. Model-Free Adaptive Iterative Learning Control of Melt Pool Width in Wire Arc Additive Manufacturing. *Int. J. Adv. Manuf. Technol.* **2020**, *110*, 2131–2142. [CrossRef]

86. Doumanidis, C.; Kwak, Y.-M. Geometry Modeling and Control by Infrared and Laser Sensing in Thermal Manufacturing with Material Deposition. *J. Manuf. Sci. Eng.* **2000**, *123*, 45–52. [CrossRef]
87. Bhatt, P.M.; Kulkarni, A.; Kanyuck, A.; Malhan, R.K.; Santos, L.S.; Thakar, S.; Bruck, H.A.; Gupta, S.K. Automated Process Planning for Conformal Wire Arc Additive Manufacturing. *Int. J. Adv. Manuf. Technol.* **2022**, *119*, 3545–3570. [CrossRef]
88. Zhang, Z.; Chen, X.; Chen, H.; Zhong, J.; Chen, S. Online Welding Quality Monitoring Based on Feature Extraction of Arc Voltage Signal. *Int. J. Adv. Manuf. Technol.* **2014**, *70*, 1661–1671. Available online: https://link.springer.com/article/10.1007/s00170-013-5402-2 (accessed on 21 November 2022).
89. Adolfsson, S.; Bahrami, A.; Bolmsjö, G.; Claesson, I. On-Line Quality Monitoring in Short-Circuit Gas Metal Arc Welding. *Weld. J.* **1999**, *78*, 59S–73S.
90. Lostado Lorza, R.; Corral Bobadilla, M.; Martínez Calvo, M.Á.; Villanueva Roldán, P.M. Residual Stresses with Time-Independent Cyclic Plasticity in Finite Element Analysis of Welded Joints. *Metals* **2017**, *7*, 136. [CrossRef]
91. Bhattacharya, S.; Pal, K.; Pal, S.K. Multi-Sensor Based Prediction of Metal Deposition in Pulsed Gas Metal Arc Welding Using Various Soft Computing Models. *Appl. Soft Comput.* **2012**, *12*, 498–505. [CrossRef]
92. Alfaro, S.C.A.; Drews, P. Intelligent Systems for Welding Process Automation. *J. Braz. Soc. Mech. Sci. Eng.* **2006**, *28*, 25–29. [CrossRef]
93. Huang, Y.; Hou, S.; Xu, S.; Zhao, S.; Yang, L.; Zhang, Z. EMD- PNN Based Welding Defects Detection Using Laser-Induced Plasma Electrical Signals. *J. Manuf. Process.* **2019**, *45*, 642–651. [CrossRef]
94. Wang, L.; Chen, J.; Wu, C.S. Auxiliary Energy-Assisted Arc Welding Processes and Their Modelling. *Sens. Control. Sci. Technol. Weld. Join.* **2021**, *26*, 389–411. [CrossRef]
95. Bingul, Z.; Cook, G.E. Dynamic Modeling of GMAW Process. *Proc. IEEE Int. Conf. Robot. Autom.* **1999**, *4*, 3059–3064.
96. Slotwinski, J.A.; Garboczi, E.J. Porosity of Additive Manufacturing Parts for Process Monitoring. *AIP Conf. Proc.* **2014**, *1581*, 1197–1204. [CrossRef]
97. Khanzadeh, M.; Chowdhury, S.; Tschopp, M.A.; Doude, H.R.; Marufuzzaman, M.; Bian, L. In-Situ Monitoring of Melt Pool Images for Porosity Prediction in Directed Energy Deposition Processes. *IISE Trans.* **2019**, *51*, 437–455. [CrossRef]
98. Cayo, E.H.; Alfaro, S.C.A. Applicability of Monitoring of Electric Arc Emissions for Quality Control in MAG-S Process. *Soldag. E Inspecao* **2011**, *16*, 341–349. [CrossRef]
99. Alfaro, S.C.A.; de Mendonça, D.S.; Matos, M.S. Emission Spectrometry Evaluation in Arc Welding Monitoring System. *J. Mater. Process. Technol.* **2006**, *179*, 219–224. [CrossRef]
100. Grad, L.; Grum, J.; Polajnar, I.; Slabe, J.M. Feasibility Study of Acoustic Signals for On-Line Monitoring in Short Circuit Gas Metal Arc Welding. *Int. J. Mach. Tools Manuf.* **2004**, *44*, 555–561. [CrossRef]
101. Cook, G.E.; Strauss, A.M.; Lammlein, D.H.; Fleming, P.A. 2—Arc Sensors in Weld Monitoring. In *Real-Time Weld Process Monitoring*; Zhang, Y., Ed.; Woodhead Publishing Series in Welding and Other Joining Technologies; Woodhead Publishing: Sawston, UK, 2008; pp. 15–44, ISBN 978-1-84569-268-1.
102. Saeed, G.M.; Song, H. 3—Optical Sensors in Welding. In *Real-Time Weld Process Monitoring*; Zhang, Y., Ed.; Woodhead Publishing Series in Welding and Other Joining Technologies; Woodhead Publishing: Sawston, UK, 2008; pp. 45–73, ISBN 978-1-84569-268-1.
103. Addamani, R.; Ravindra, H.V.; Chethan, Y.D. Assessment of Weld Bead Mechanical Properties During Destructive Testing Using Image Processing by Multivision Technique. *Lect. Notes Electr. Eng.* **2019**, *545*, 265–275. [CrossRef]
104. Song, L.; Bagavath-Singh, V.; Dutta, B.; Mazumder, J. Control of Melt Pool Temperature and Deposition Height during Direct Metal Deposition Process. *Int. J. Adv. Manuf. Technol.* **2012**, *58*, 247–256. [CrossRef]
105. Ogawa, Y. High Speed Imaging Technique Part 1—High Speed Imaging of Arc Welding Phenomena. *Sci. Technol. Weld. Join.* **2011**, *16*, 33–43. [CrossRef]
106. Davis, T.A.; Shin, Y.C. Vision-Based Clad Height Measurement. *Mach. Vis. Appl.* **2011**, *22*, 129–136. [CrossRef]
107. Yamane, S. Tracking the Welding Line in Lap Welding Using Pattern Matching. *ISIJ Int.* **2020**, *60*, 1752–1757. [CrossRef]
108. Valdiande, J.J.; Martínez-Minchero, M.; Cobo, A.; Lopez-Higuera, J.M.; Mirapeix, J. On-Line Monitoring and Defect Detection of Arc-Welding via Plasma Optical Spectroscopy and LIBS. *Spectrochim. Acta Part B At. Spectrosc.* **2022**, *194*, 106474. [CrossRef]
109. Bicknell, A.; Smith, J.S.; Lucas, J. Infrared Sensor for Top Face Monitoring of Weld Pools. *Meas. Sci. Technol.* **1994**, *5*, 371. [CrossRef]
110. Veiga, F.; Suarez, A.; Aldalur, E.; Artaza, T. Wire Arc Additive Manufacturing of Invar Parts: Bead Geometry and Melt Pool Monitoring. *Meas. J. Int. Meas. Confed.* **2022**, *189*, 110452. [CrossRef]
111. Vilarinho, L.O.; Mota, C.P.; Machado, M.V.R.; Finzi Neto, R.M. Near-Infrared Vision System for Arc-Welding Monitoring. *Soldag. Inspeção* **2013**, *18*, 1029–1037.
112. Li, Y.; Su, C.; Zhu, J. Comprehensive Review of Wire Arc Additive Manufacturing: Hardware System, Physical Process, Monitoring, Property Characterization, Application and Future Prospects. *Results Eng.* **2022**, *13*, 100330. [CrossRef]
113. Pringle, A.M.; Oberloier, S.; Petsiuk, A.L.; Sanders, P.G.; Pearce, J.M. Open Source Arc Analyzer: Multi-Sensor Monitoring of Wire Arc Additive Manufacturing. *HardwareX* **2020**, *8*, e00137. [CrossRef] [PubMed]
114. Rout, A.; Deepak, B.B.V.L.; Biswal, B.B. Advances in Weld Seam Tracking Techniques for Robotic Welding: A Review. *Robot. Comput. Integr. Manuf.* **2019**, *56*, 12–37. [CrossRef]
115. Tang, Z.-J.; Liu, W.-W.; Wang, Y.-W.; Saleheen, K.M.; Liu, Z.-C.; Peng, S.-T.; Zhang, Z.; Zhang, H.-C. A Review on in Situ Monitoring Technology for Directed Energy Deposition of Metals. *Int. J. Adv. Manuf. Technol.* **2020**, *108*, 3437–3463. [CrossRef]

116. Hamzeh, R.; Thomas, L.; Polzer, J.; Xu, X.W.; Heinzel, H. A Sensor Based Monitoring System for Real-Time Quality Control: Semi-Automatic Arc Welding Case Study. *Procedia Manuf.* **2020**, *51*, 201–206. [CrossRef]
117. Su, Y.-P.; Chen, X.-Q.; Zhou, T.; Pretty, C.; Chase, G. Mixed Reality-Enhanced Intuitive Teleoperation with Hybrid Virtual Fixtures for Intelligent Robotic Welding. *Appl. Sci.* **2021**, *11*, 11280. [CrossRef]
118. Feng, Y.; Gao, X.; Zhang, Y.; Peng, C.; Gui, X.; Sun, Y.; Xiao, X. Simulation and Experiment for Dynamics of Laser Welding Keyhole and Molten Pool at Different Penetration Status. *Int. J. Adv. Manuf. Technol.* **2021**, *112*, 2301–2312. [CrossRef]
119. Wang, T.; Gao, X.D.; Katayama, S.; Jin, X.L. Study of dynamic features of surface plasma in high-power disk laser welding. *Plasma Sci. Technol.* **2012**, *14*, 245–251. [CrossRef]
120. Gao, X.; Sun, Y.; Katayama, S. Neural Network of Plume and Spatter for Monitoring High-Power Disk Laser Welding. *Int. J. Precis. Eng. Manuf. Green Technol.* **2014**, *1*, 293–298. [CrossRef]
121. Fan, X.; Gao, X.; Liu, G.; Ma, N.; Zhang, Y. Research and prospect of welding monitoring technology based on machine vision. *Int. J. Adv. Manuf. Technol.* **2021**, *115*, 3365–3391. [CrossRef]
122. Gao, X.; Mo, L.; You, D.; Li, Z. Tight Butt Joint Weld Detection Based on Optical Flow and Particle Filtering of Magneto-Optical Imaging. *Mech. Syst. Signal Process.* **2017**, *96*, 16–30. [CrossRef]
123. Ostra, T.; Alonso, U.; Veiga, F.; Ortiz, M.; Ramiro, P.; Alberdi, A. Analysis of the Machining Process of Inconel 718 Parts Manufactured by Laser Metal Deposition. *Materials* **2019**, *12*, 2159. [CrossRef] [PubMed]