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Automatic Control of the Weld Bead Geometry

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Abstract

Automatic control of the welding process is complex due to its nonlinear and stochastic behavior and the difficulty for measuring the principal magnitudes and closing the control loop. Fusion welds involve melting and subsequent solidification of one or more materials. The geometry of the weld bead is a good indicator of the melting and solidification process, so its control is essential to obtain quality junctions. Different sensing, modeling, estimation, and control techniques are used to overcome this challenge, but most of the studies are using static single-input/single-output models of the process and focusing on the flat welding position. However, theory and practice demonstrate that dynamic models are the best representation to obtain satisfactory control performance, and multivariable techniques reduce the effect of interactions between control loops in the process. Also, many industrial applications need to control orbital welding. In this chapter, the above topics are discussed.

Keywords: arc welding, feedforward decoupling, multivariable control, weld bead geometry, welding control

1. Introduction

All fusion welds involve the melting and subsequent solidification of the base metal. The geometry of the weld bead is a good indicator of the melting and solidifying process. Generally, weld inspection starts by evaluating this weld bead geometry and is followed by further inspection of the mechanical properties and metallurgical structures [1]. Many resources and time are employed in the final inspection of the weld bead, which is conducted when the part is finished. At that time, the problem usually has no solution or the solution is very expensive. This is one of the reasons why the control of the weld pool geometry is imperative to improve the quality in the weld and to reduce the cost of welded components.

Research and development in this area have increased in the last five decades, starting from simple control methods and analogical devices, as shown in [2], to complex algorithms and digital devices and computers, as shown in [3, 4]. But, in the literature analyses made in [5], it is possible to observe that most of the cases (90%) of the developments work in horizontal position and only 10% work in orbital welding, despite the importance of orbital welding for the industry. It is important to note that this type of welding imposes strong challenges in the use of sensors due to orbital movement (which can be quite irregular) around the piece. The main challenges are in the size and portability of the sensor, flexibility in the
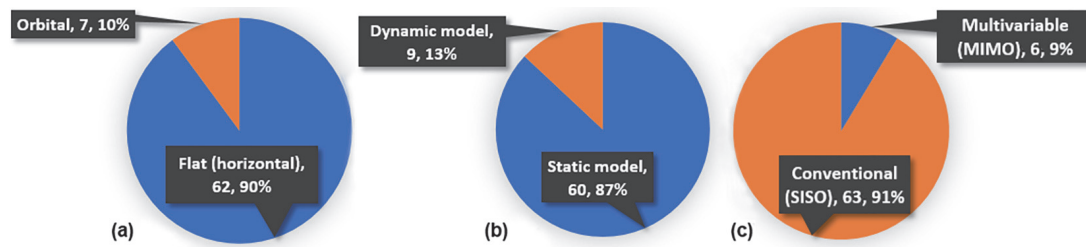
Figure 1.
Statistical information of publications about control systems of the weld bead geometry: (a) welding positions; (b) model types; (c) control type.

communication lines, continuous changes in position and lighting conditions (for optical sensors), and the effects of the force of gravity. These statistical data are shown in **Figure 1a**.

In addition, most cases apply static models, do not control all parameters of the bead geometry, and do not apply multivariable techniques, as shown in **Figure 1b** and **c**. The dynamic models can be a better representation of the process, producing better prediction results. The research where these models were used represents only 13% of the total, as analyzed in [5]. The black box model approach is widely used. Because of the complex characteristics of the process, a physic model approach is very difficult and needs extensive research and resources.

In this chapter the principal control loops and techniques used for online control of the weld bead geometry are discussed. The more usual variables, control, and techniques to modeling, used in welding power sources and welding robotic systems, are critically discussed. Some examples of singled and multivariable control loops are shown. A decoupling technique for multivariable loops is also explained. The dead time and disturbances that can affect the processes and some techniques to determine them are also explained. A special topic about the embedded systems in the welding process was included.

This chapter aims to create a knowledge base necessary to understand the main control systems in welding processes before addressing more complex control techniques. Its main contributions are the exhaustive literature review that is critically discussed and the solutions provided for the control of each part of the process, especially the control of the weld bead geometry for electric arc welding processes.

2. Control loops in welding processes

A typical automatic closed-loop control is composed of a controller or control system, an actuator system, and a measurement system or sensor, as shown in **Figure 2a**. The controller calculates the control law based on the control error, which is the difference between the set point value and the measurement of the controlled variable. The actuator modifies the process state, based on controller output (manipulate variable), to bring the controlled variable to the desired value. In sequence, to close the loop, the measurement system obtains the value of the controlled variable and sends it to the controller. An open-loop control does not have a measurement system, or the controller does not use its feedback as shown in **Figure 2b**.

The selection of variables to the control loop is a very important task. For this, it is necessary to analyze and quantify the influence of all process variables on the variable to be controlled. A statistical tool to quantify these relationships is the cross-correlation, using experimental data series of these variables and the variable
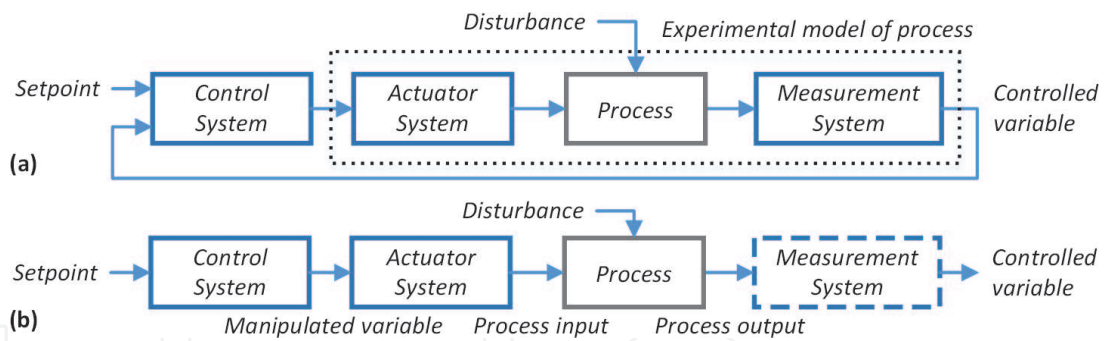
Figure 2.
Representation of a typical automatic control system: (a) closed-loop control; (b) open-loop control.

to be controlled. Other factors must also be considered, such as the actual possibility of modifying each of these variables and how these modifications affect other control loops. These correlations are mentioned in the literature, but often they are not totality quantified, indicating that there is still a wide-open field of research in modeling these processes.

The dead time (transportation lag or time delay) is another important parameter that can be obtained from cross-correlation analysis too [6]. The sampling time for digital control systems must be selected based on the process dynamic, and auto-correlation techniques can be useful.

An important input to be considered on the control loop is the disturbance. This signal (or signals) can affect the process response and must be compensated by the controller. The open-loop controller cannot compensate for the disturbance action because it does not have a feedback signal. An example of disturbance is small variations in the height of the base metal surface product of heat. These variations change the contact tip to work distance and consequently the arc conditions. If the disturbance is measurable, some techniques can be used to improve the response of the controller, as shown in [6].

The model or process can be obtained using white or black box techniques. The first modeling technique required great knowledge of the process and its manufacture parameters to be able to create the equations that satisfactorily describe the process, actuator, and sensor. It is important to keep in mind that these parameters may change during the life of the equipment. Then if you use the parameters defined by the manufacturer, you can make the model inaccurate or useless. Because of this aspect and because of the development of powerful methods and tools for modeling, the black box techniques are more used.

To create a black box model of process for simulation, estimation, prediction, or control purposes, it is necessary that an actuator system and a measurement system modify the state of the process and see its response. With the process input and output values, it is possible to obtain statics or dynamic models of the process, but the actuator and sensor are included in the process model, as shown in **Figure 2a**. This becomes more evident in dynamic models when the dynamic response of the actuator and sensor affects the dynamic of the set. In static models, the use of a different sensor (or actuator), but with the same static gain, does not affect the model.

Other types of control algorithms are the logic control; those are classified as combinational and sequential. The response of the combinational logic algorithm depends on the inputs on current sampling time only, for example, the torch travel limit was reached, the robot must stop, and the arc must close. On sequential control the response depends on the previous sampling time inputs also, for example, in seam tracking control, it is important to know the last positions reached by the torch to calculate the next position.

In welding processes it is possible to find several control loops with different complexities and purposes. Each control loop has a set point or desired value of the controlled variable (supply by the operator or by a higher-level controller), a controlled variable (obtained from measurement system), a manipulated variable (supplied to the actuator by the control system), and disturbances. For example, on GMAW conventional welding power sources with the constant voltage, you can find an arc controller loop that tries to keep the voltage, the wire feed speed controller, and the gas flow controller (commonly included in the sequential logic controller) constant. The more complex processes have other control loops and sequential controllers to generate the arc signal form.

In welding robotic systems, you can find several control loops too but related with the torch or piece position and torch or piece travel. The combination of several controllers makes possible the control of the geometry of the weld bead, for example, a loop that changes the set point of voltage input in the welding power source to control the weld bead width based on profile sensor or video camera. Another example is a control loop that changes the wire feed speed in the welding power source and the welding speed in the welding robot to control the weld bead penetration.

These several controllers and actuators, which modify the same process at the same time to reach the manufacture objectives, will also cause interactions between the loops and its strongly coupled variables. A change in a control loop may affect other loops as disturbance and turns the process unstable. In these cases, a multi-variable control loop must be considered. In the next sections, examples of control loops used in arc welding processes are shown.

2.1 Control of welding speed and seam tracking

If the torch trajectory is known, two open-loop controls can be used to govern the torch movement in two axes of the flat welding robotic system that uses stepper motors as actuator elements. In this system, the X axis is then governed by the welding speed controller and the Y axis by the seam tracking controller. The first loop keeps the welding speed set point, and the second loop applied the torch trajectory correction as shown in **Figure 3**.

The welding speed controller reads a lookup table with the speed set points ($WSsp$) for each torch X position and applies the control signals $SM1$ to stepper motor driver to reach the desired welding speed. These control signals are pulses with a time interval that corresponds to the motor speed (step time), and the pulse count is equivalent to distance traveled. The stepper motor driver sends the signal necessary for each coil to the stepper motor, and the stepper motor generates the rotation movement so that the gear transforms it into linear torch movement. The nT parameter is the time of the sample, made up of the sample time (T) and the sample number (n). The $nT - T$ is the previous sample time.

On the other hand, the seam tracking controller receives the X torch position too and finds the correction to the Y axis on another lookup table. Then, the controller
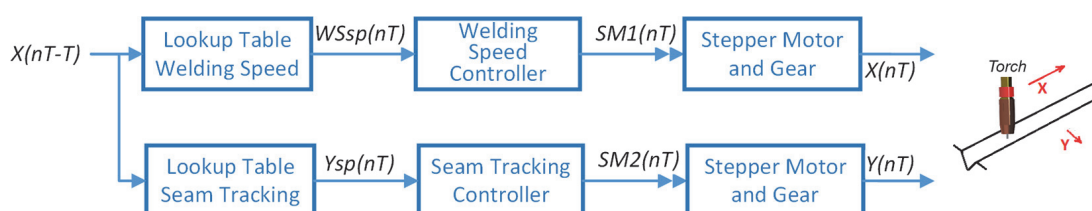
Figure 3.
Blocks diagram of the welding speed and seam tracking control loops.

moves the torch to this *Y* position. These systems do not need feedback because of stepper motor accuracy in normal working conditions.

To reduce the amount of data in the lookup tables, it is possible to save only the significant changes of welding speed and trajectory and hold the last value in the output until the new value is found.

To obtain the correct torch trajectory, the weld joint can be scanned before the welding process starts and the center joint can be calculated in all the points of the torch trajectory. With this data, it is possible to define the correct trajectory for the torch and move the seam tracking stepper motor accordingly.

The seam tracking loop can be transformed on closed-loop, but it is necessary for a profile sensor (e.g., a laser profilometer) to obtain online the joint profile and to make the trajectory analysis. The same control strategy can be used to substitute the lookup table by the algorithm that analyzes the profilometer data. This control strategy is better if the pieces are expected to move or deform during welding, but more calculation resources are needed.
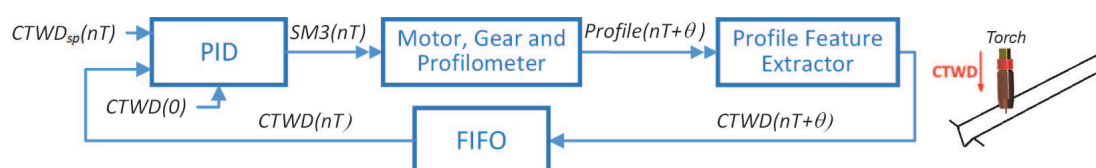
2.2 Control of contact tip to work distance

The contact tip to work distance (*CTWD*) can be controlled in a closed-loop by a proportional-integral-derivative (PID) controller [6]. The CTWD is measured with a laser profilometer and calculated with the algorithm described in the chapter "On-line measurements in welding processes" and compared with the set point (*CTWDsp*). The controller manipulates the step time and the step counter (embedded in the SM3 signal) of the stepper motor associated with the CTWD movement in a robotic flat welding system. The *CTWD*(0) is the initial value for the controller algorithm. **Figure 4** shows this closed control loop.

Due to the advanced position of the sensor, the CTWD measurement is in advanced time (θ). These future values are saved in a memory element that implements a first input-first output list to supply the correct value to the controller. This loop can use the same profile sensor with that of the seam tracking loop when the weld joint is scanned before the welding process starts.

2.3 Control of width, reinforcement, and penetration of the weld bead

The principal variables that affect the bead geometry in the conventional arc welding process are the welding voltage, the welding current, the wire feed speed, the contact tip to work distance, and the welding speed. The most common relation found in the scientific literature shows that increasing the electric current by increasing the wire feed speed, for the same welding speed, results in a greater weld bead depth and welding pools with greater volume and production. An increase in electric current, accompanied by a proportional increase of the welding speed (*wire feed speed/welding speed = constant*), also results in greater penetration, but the welding pool keeps the same volume. Then, the same welding joint volume can be filled (maintaining production) and ensure its integrity by full penetration (good quality) at the same time [7].
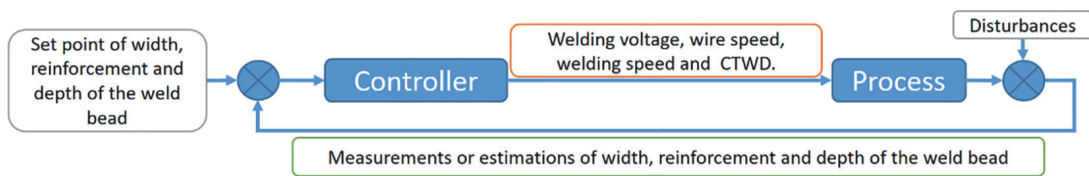

Figure 4.
Blocks diagram of the contact tip to work distance control loop.

On the other hand, laser welding has an additional set of parameters, such as the laser power and optical adjustments of the laser beam, but it is restricted by the availability of the equipment and difficult to make online adjustment in welding parameters. Shortly, the controllable parameters will become diversified, but right now the focus adjustment can be made by changing the position of focus lens inside the laser head. A review of these topics is shown in [8].
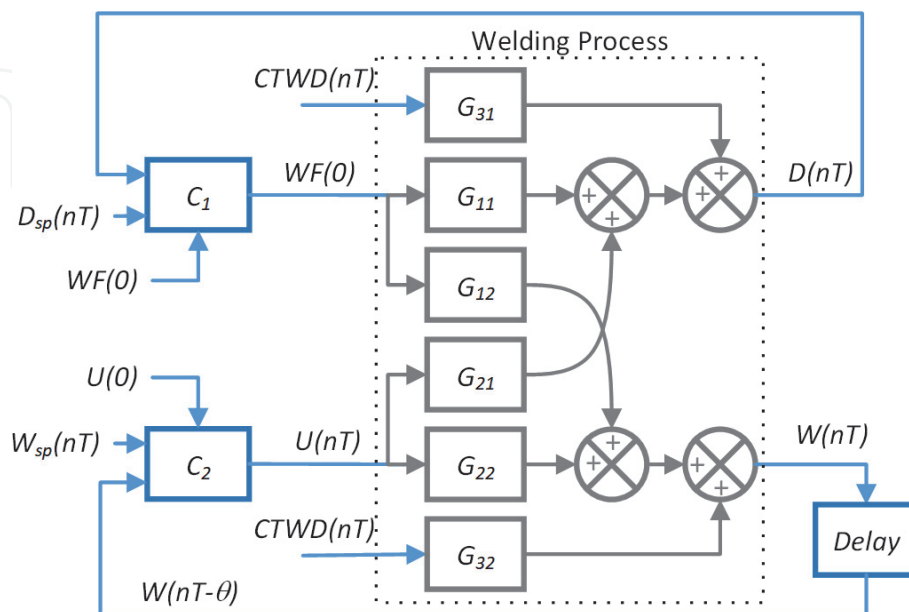
It is important to note that the relations between variables are more complex and multivariable techniques are necessary to describe them. With the multivariable techniques, it is possible to consider the interactions between variables in the process and reduce their effect in the control loop, but the implementation is difficult because of the complexity of the modeling and the control algorithm adjustment. In the literature analysis made in [5], only 9% of the papers use multivariable control loops.

A generic diagram of a multivariable control loop of the weld bead geometry for the GMAW process is shown in **Figure 5**. It used the main variables that affect the process, to control the bead geometry, but it should be noted that due to the interdependence between them, setting the controller parameters and the use of uncoupling become difficult.

The GMAW conventional process can be represented as a multiple-input multiple-output (MIMO) process with three inputs and two outputs, as shown in **Figure 6**. The pairing of controlled and manipulated variables is shown too, and the other variables are considered as disturbances or controlled by other control loops. This selection is based on the bibliographic review and requires the analysis of the relative gains defined in [9].

Figure 5.
Main variables used in the weld bead geometry control in GMAW process.

Figure 6.
Arc welding process represented as a multiple-input multiple-output system, with the depth and width of the weld bead controlled by PID algorithms.

It is important to note that the orbital welding adds more complexity to control, due to the effect of gravity on the transfer of material, the weld pool, and the weld bead formation, in addition to other requirements. So, it is important to consider the orbital angle as a measurable disturbance.

Control strategies proposed in [5] are based on a PID controller improved with a decoupling method, a Smith predictor, and a fuzzy self-adaptive algorithm. In the PID control strategy, shown in **Figure 6**, the welding voltage (U) and wire feed speed (WF) are manipulated by two independent control loops that control the weld bead width (W) and the weld bead depth (D). The $CTWD$ can be considered a disturbance or a manipulated variable, depending on the control strategy. The quantity of material deposited (deposition rate) is indirectly controlled by the relation between WS and WF, and the weld bead reinforcement depends on the relation between bead width and quantity of material deposited. The values $U(0)$ and $WF(0)$ are initial values of manipulated variables.

The weld bead depth value (D) is estimated using the algorithms described in the chapter "On-line measurements in welding processes," and the weld bead width (W) can be estimated too or measured using a profile sensor. These values are feedback to the controller and the control errors, which are calculated using the set point of the weld bead depth (Dsp) and width (Wsp) values. If a laser profilometer is used, the real width and reinforcement of the weld bead are calculated. Note that the measurements have a dead time (θ) and these values are zero during the first sampling times.

While many control algorithms have been proposed, in which approaches are theoretically elegant, most of the industrial processes nowadays are still controlled by proportional-integral-derivative controllers [10–12]. Conventional PID controllers have been widely applied in industrial process control for about half a century because of their simple structure and convenience of implementation [13]. However, a conventional PID controller can have poor control performance for nonlinear and complex systems for which there are no precise mathematical models. Numerous variants of conventional PID controller, such as self-tuning, auto-tuning, and adaptive PID controllers, have been developed to overcome these difficulties. Several online self-tuning or adaptive algorithms are based on fuzzy inference systems that were developed in [11, 12, 14–19].

The weld bead width measure dead time problem can be solved using a modified Smith predictor as shown in [5]. In the same work, the nonlinear is solved using a fuzzy self-adaptive algorithm for PID tuning. But the control strategy still has a problem, the interdependence between the process variables.

To improve the controller behavior, the decoupling structures can be incorporated for reducing the interaction between the loops. In this case, the decoupling used is based on feedforward control. These decoupling techniques are useful when the process is affected by strong measurable disturbances. This strategy can help improve the behavior of the controller in the face of this disturbance, but it cannot replace the feedback control [20]. The typical feedforward control is shown in **Figure 7**.
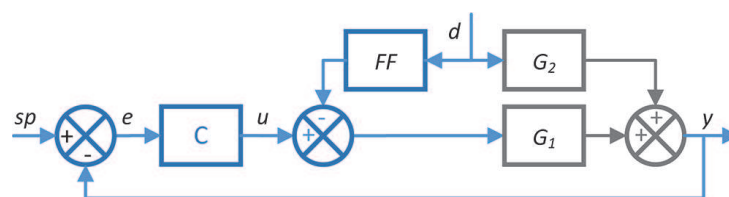
Figure 7.
Typical feedforward control in a single control loop. Adapted from [5].

The feedforward control tries to anticipate the effect of the disturbance (d). The control action is applied directly to the control loop drive element, before the disturbance can affect the controlled variable [6, 20]. Eqs. (1) and (2) usually define the necessary conditions to it, while the feedforward model is obtained in Eq. (3).

$$\frac{\Delta y}{\Delta v} = \frac{G_2(z^{-1})}{1 - CG_1(z^{-1})} + \frac{FFG_1(z^{-1})}{1 - CG_1(z^{-1})} = 0 \tag{1}$$

$$\frac{\Delta y}{\Delta v} = \frac{G_2(z^{-1}) + FFG_1(z^{-1})}{1 - CG_1(z^{-1})} = 0 \tag{2}$$

$$FF = \frac{G_2(z^{-1})}{G_1(z^{-1})} \tag{3}$$

If $G_1(z^{-1})$ and $G_2(z^{-1})$ are quite close to first-order transfer function with delay, as it is shown in

$$G_1(z^{-1}) = \frac{K_1 z^{p_1}}{1 - \alpha_1 z^{-1}} \tag{4}$$

$$G_2(z^{-1}) = \frac{K_2 z^{p_2}}{1 - \alpha_2 z^{-1}} \tag{5}$$

where the terms α_1 and α_2 are related with the sample time (T_s) and process time constants T_1 and T_2, as shown in the next equations,

$$\alpha_1 = e^{-\frac{T_s}{T_1}} \tag{6}$$

,
$$\alpha_2 = e^{-\frac{T_s}{T_2}} \tag{7}$$

then the feedforward transfer function is

$$\frac{\Delta u}{\Delta v} = FF(z^{-1}) = -\frac{K_2 z^{-p_2}(1 - \alpha_1 z^{-1})}{K_1 z^{-p_1}(1 - \alpha_2 z^{-1})} \tag{8}$$

$$\frac{\Delta u}{\Delta v} = FF(z^{-1}) = -K_{FF} z^{(p_1 - p_2)} \frac{1 - \alpha_1 z^{-1}}{1 - \alpha_2 z^{-1}} \tag{9}$$

where

$$K_{FF} = \frac{K_2}{K_1} \tag{10}$$

Sometimes only the steady value is compensated, and the dynamic is depreciated in which case the transfer function of the feedforward block is K_{FF}. This simplifies the modeling work and the model structure. It is important to note that the dead time in the principal channel must be less or equal than the disturbance channel ($p_1 \leq p_2$) for the dynamic compensation to be effective.

If the interactions between loops are considered as disturbances, the same feedforward scheme can be used to decoupling the weld bead width and penetration control loop in our welding process. **Figure 8** shows the block diagram with decouples.

Decouples FF_1 and FF_2 are designed to minimize the interaction between loops and improve the controller behavior. The calculation of the transfer function of decouples is similar to what is explained in the feedforward transfer function. This strategy is similar to inverse decoupling shown in [21, 22].
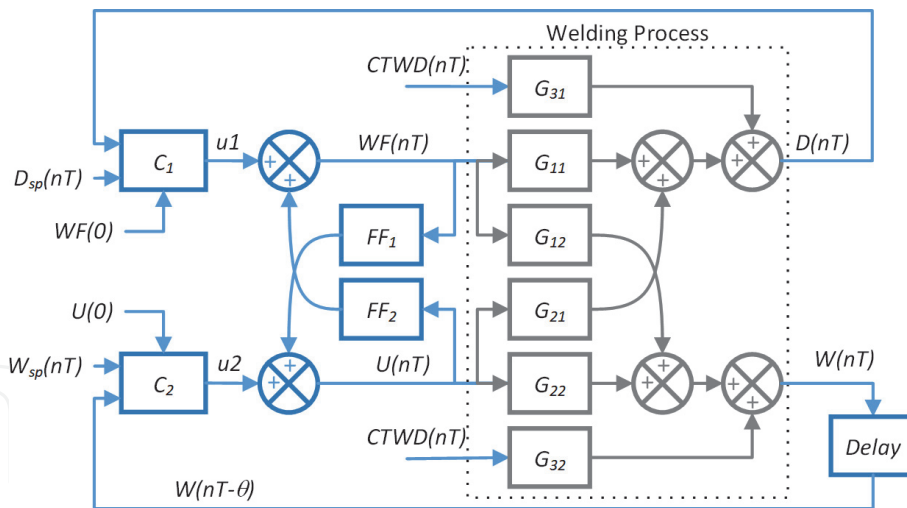
Figure 8.
Weld bead width and depth penetration controller with decouples.

The design and synthesis of PID controllers and fuzzy algorithms in FPGA or microcontroller devices are possible, and the resource consumption is very low, as is shown in [23]. But many other scientific researchers are being developed and tested to solve and improve the control of the welding process. In the next section, some of them will be described.

3. Methods or techniques used for modeling and control of the geometry of weld bead

The welding process is characterized as multivariable, nonlinear, and time-varying, with stochastic behavior and having a strong coupling among welding parameters. For this reason, it is very difficult to find a reliable mathematical model to design an effective control scheme by conventional modeling and control methods.

Due to these characteristics, the use of adaptive techniques has spread in the last decades with favorable results, only overcome by a proportional-integral-derivative controller. The adaptive control has been implemented in some researchers to cope with the problem of the high dependence of process parameters to its operating condition. The main drawback of this method is that it requires online estimation or tuning of the parameters, which is usually a time-consuming operation. The single implementation of PID and low computational resources make it still the most used, as in the rest of industrial applications. A graphic summary is shown in **Figure 9**, and **Table 1** shows the document references analyzed.

Neural networks, fuzzy methods, and their combinations also stand out. Note that the magnificent behavior of the neural network can be clouded by a slow convergence because of the excessive quantity of neurons or hidden layers. Many research efforts use this approach but neglected the need for the quick response of the control system.

Statistical methods, such as the classic autoregressive moving-average and expert systems, are represented too. Other less used techniques include state space, model-free adaptive, first- and second-order model, support vector machine, and finite elements.

3.1 Some scientific research about the geometry control in arc welding processes

Developments in the field of automatic control of the geometry in the arc welding process have been intense in the last four decades. The most representative
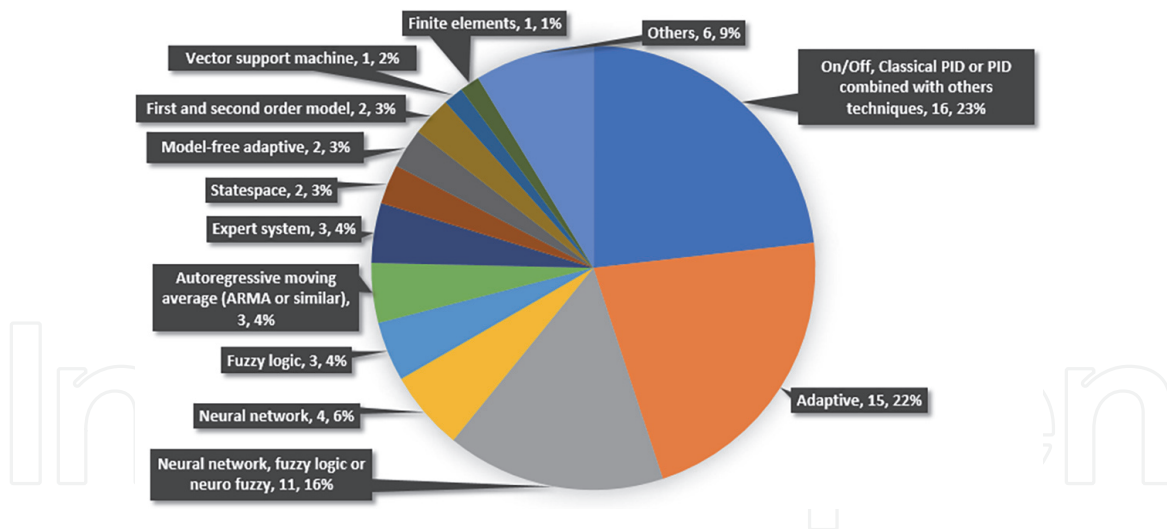
Figure 9.
Graphic summary about the main methods or techniques used for control of the weld bead geometry, including the quantity of references and the percentage they represent in the total papers consulted.

| Control technique or control model	References
On/off, classic PID, or PID combined with other method	[2, 24–37]
Adaptive	[26, 29, 38–50]
Neural network and fuzzy logic or neuro-fuzzy	[3, 4, 51–60]
Neural network	[27, 61–63]
Fuzzy logic	[39, 64, 65]
Autoregressive moving average (ARMA or similar)	[29, 66, 67]
Expert systems	[38, 53, 40]
State space	[1, 68]
Model-free adaptive	[68, 69]
First- or second-order model	[70, 71]
Support vector machine	[64]
Finite elements	[52]

Table 1.
References classified according to the methods or techniques used for control of the weld bead geometry.

research efforts found in the literature are in this area in the last two decades. In this section, some relevant works are discussed in chronological order.

In 1986, Nied and Baheti [46] registered a patent in which a robotic welding system has an integrated vision sensor to obtain images and analyze the welding scene in real-time. It used an adaptive feedback control to assure the full penetration, the weld puddle area, and the maximum width in the TIG process. The adaptive control system determines a puddle geometry error and uses the nominal welding current to change the heat input to the weld pool, regulating the combination of puddle area and width. Arc voltage is modulated to reflect changes in welding current and maintain a constant arc length.

In 1989 Edmund R. Bangs and others [38] registered a patent that described a system for real-time welding adaptive control using infrared images, artificial intelligence (expert system), and distributed processors.

Already in 1990, Andersen designed a control system for the GMAW process [24]. As shown in **Figure 10**, a neural network set point selector defines the start
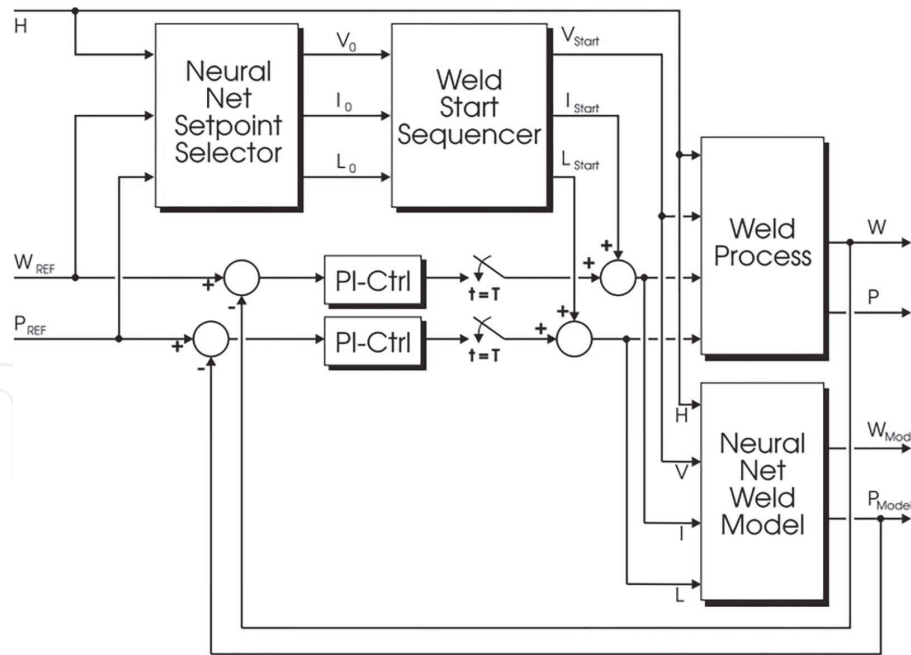
Figure 10.
Control loop proposed for Andersen [24] when the initial set point conditions are defined by neural network and the penetration are estimated. Adapted from [73].

parameters of welding speed (V), current (I), and arc length (L). Another neural network estimates the width (W) and weld depth penetration (P). Two independently closed-loop PIs adjust continuously the start parameters in function of weld bead width and penetration control error. The experimental results are satisfactory. In [72], a similar structure was proposed for the control of weld bead width, without the estimator and using a fuzzy controller. The same philosophy is used in [54] for width and reinforcement control in independent control loops.

Zhang et al. [74] developed an adaptive control of full penetration for GTAW processes, based on the generalized predictive control (GPC) algorithm presented by Clarke [75–77]. The controlled variables are the width and reinforcement of the weld bead, measured by a vision system and a laser stripe. The control or manipulated variables are the welding current and arc length. The sampling interval of the control system was 0.5 s. The process has been described by a moving-average model with a predictive decoupling algorithm. The system is not controlling the penetration directly but has a satisfactory performance in the weld quality control.

Brown et al. [26] developed a control loop with a PID controller and an adaptive dead-time compensator for GMAW processes in a horizontal welding position. The controlled variable is the weld pool width and the welding speed is manipulated. The simulation results show an acceptable response.

A dynamic model, based on neural network, was designed in [53] to predict the maximum backside width in pulsed GTAW processes. Also, a self-learning fuzzy neural network controller was developed for controlling the maximum backside width, and the fuzzy rules were modified online. Another intelligent multivariable controller, type double-input and double-output (DIDO), based on a neuro-fuzzy algorithm and combined with an expert system, was developed to control the maximum backside width and the shape of the weld pool. Experimental results showed the best behavior using the DIDO intelligent controller.

In [55], a neuro-fuzzy controller was designed for the GTAW process. This method overcomes the dependency of human experts for the generation of fuzzy rules and the non-adaptive fuzzy set. The adaptation of membership function and the fuzzy rule self-organization are carried out by the self-learning and

competitiveness of the neural network with three hidden layers. The simulation test got promising behavior.

Chin [28] developed a system for infrared image sense and PID control of the SAW process. Several tests were executed with diverse conditions in the control variables. Similarly, an infrared point sensor (pyrometer) is used in [36] to estimate the weld bead depth in GTAW and SAW processes. The penetration is controlled indirectly (using the infrared emission) by a PI regulator, which changes the welding current in the GTAW process and the welding voltage and welding speed in the SAW process. A satisfactory result is obtained under laboratory conditions.

Moon and Beattie [45] developed an adaptive fill control for multi-torch multi-pass SAW processes. The system measures the joint geometry with laser seam tracking and calculates the total area of the joint, computing by numerical integration based on the actual joint profile. With the area ratio of the joint, the welding current/voltage combination is obtained, and the welding speed is adjusted inversely in proportion to the area to be filled. The control significantly improves weld bead quality. This technology has been used in the manufacture of longitudinal and spiral pipes and pressure vessels.

In [66], two simultaneous but independent control loops are used. The first loop monitors the temperature with an infrared camera and controls the trajectory of the torch. The second loop monitors the geometric profile with the laser stripe and manipulates the welding speed and the wire feed speed. A variable delay Smith predictor is used for reducing the dead-time effect of laser strip sensor, as shown in **Figure 11**. The author tested a SISO closed loop with a PI controller and a MIMO GOSA. The last one obtains the best result.

An H-infinity robust control system in [1] is proposed to control the length and width of the weld pool, manipulating welding current and weld speed. The simulation shows an effective robust method to control processes with large uncertainties in the dynamics. However, the complexity of the H-infinity control algorithm can make the implementation of embedded devices difficult. Also, it needs an effective description of the uncertainties of the welding process dynamics, and it is difficult under conditions of the real processes.

A weld pool imaging system, with a LaserStrobe high shutter speed camera, is used in [58] to obtain contrasting images and eliminate the arc interference. Image processing algorithms, based on edge detection and connectivity analysis, extract information about the weld pool length and width online. A neuro-fuzzy controller, based on human experience and experimental results, manipulate the welding voltage and speed in real-time based on weld pool dimensions. A welding speed closed-loop control is used to reach the set point of the weld pool geometry. The simulation results are satisfactory, but the response may be slow due to the time required for image processing and fuzzy calculation.
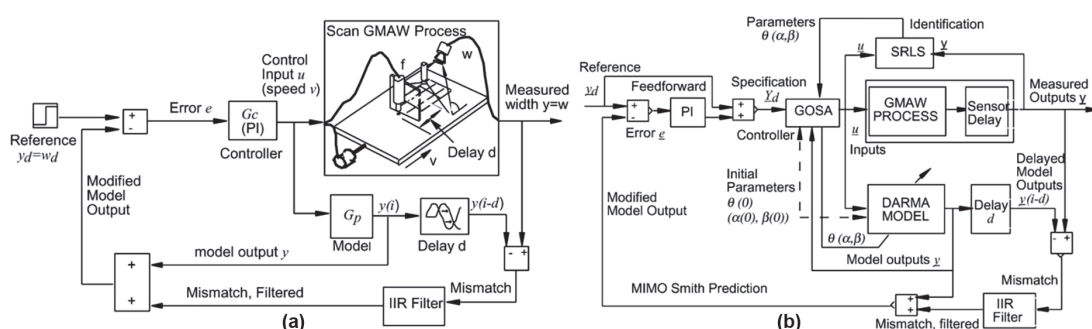
Figure 11.
SISO (a) and DIDO (b) control loops that employ infrared information. Adapted from [66].

In [31], the difficulty to tune the PI controller parameters to achieve the desired performance, across the entire range of the process operation, is shown. Therefore, the design and implementation of more complex controllers are required to obtain better control of the welding process.

A method developed by Casalino in [52] defines an automated methodology for selecting the weld process parameters based on artificial intelligence. While there are many methods available to improve the reliability of traditional open-loop control schemes, these can only be used with a particular welding power source and a specific welding arrangement.

Lu et al. [43] developed a non-transferred plasma charge sensor-based vision system to measure the depth of the weld pool surface in orbital GTAW processes. The sensor measures the welding voltage when the welding current is off and calculates the arc distance by an inversely linear relation. An insulated gate bipolar transistor (IGBT) power module is utilized to temporarily switch off the main power supply. During this period, the large arc pressure associated with the main arc is not present, the depth of the weld pool surface decreases, and the sensor output increases, obtaining the arc measurement. An adaptive interval algorithm controls the depth of the weld pool surface, regulating the main-arc-on period. Four experiments were executed under different conditions and show a satisfactory response.

Smith et al. [34] use two independent PIs to control a pulsed TIG process in a horizontal position. Both controllers use the control error of the top face weld pool width as input. The independent outputs are the welding current and the wire feed speed. The active adjustment of the welding current and the wire feed speed allows compensating variations on the weld pool size. A camera and image processing algorithm measures the top face weld pool width. The controllers and image processing algorithms run concurrently on a PC. The controllers use CAN serial communication protocol to adjust the outputs in two distributed actuator nodes, based on a microcontroller system. A step-change in plate thickness was used to test the controller system. The experimental results produced welds with a more consistent profile when faced with variations in process conditions.

In [63], a three-dimensional vision system is used for obtaining the geometrical parameters of the weld joint. A closed-loop neuronal-network controller is developed to control the width and depth of the weld joint, by regulating the welding voltage, welding speed, and wire feed speed. The neuronal model has two hidden layers with six and four neurons, respectively, as shown in **Figure 12**. The experimental results, using the neural network learning data and the error range of width and depth, are within 3%.

Fuzzy and PID controllers are employed in [65] to control the geometry stability in a GTAW process, by regulating the welding current (ΔI) and wire feed rate (v). A real-time image analysis algorithm was developed for seam tracking and seam gap measuring using passive vision. The control was applied in a teach and playback robotic welding system, which helps the robot track the seam with the gap variation. The quality of the products obtained reached the standard of first-order welding seam (QJ2698-95) in terms of dimensions and soundness, which was verified with an X-ray inspection. **Figure 13** shows the block diagram.

In [78] two SISO subsystems are developed to control a double-electrode GMAW process. The control structure is selected for convenient implementation and design. One system controls the welding current of the main torch by manipulating the wire feed speed. The other system controls the welding voltage of the bypass torch by manipulating the welding current. Two interval models have been obtained, based on experimental data from step-response experiments under different manufacturing conditions. These simple controllers show an acceptable behavior to control this relatively complex process.
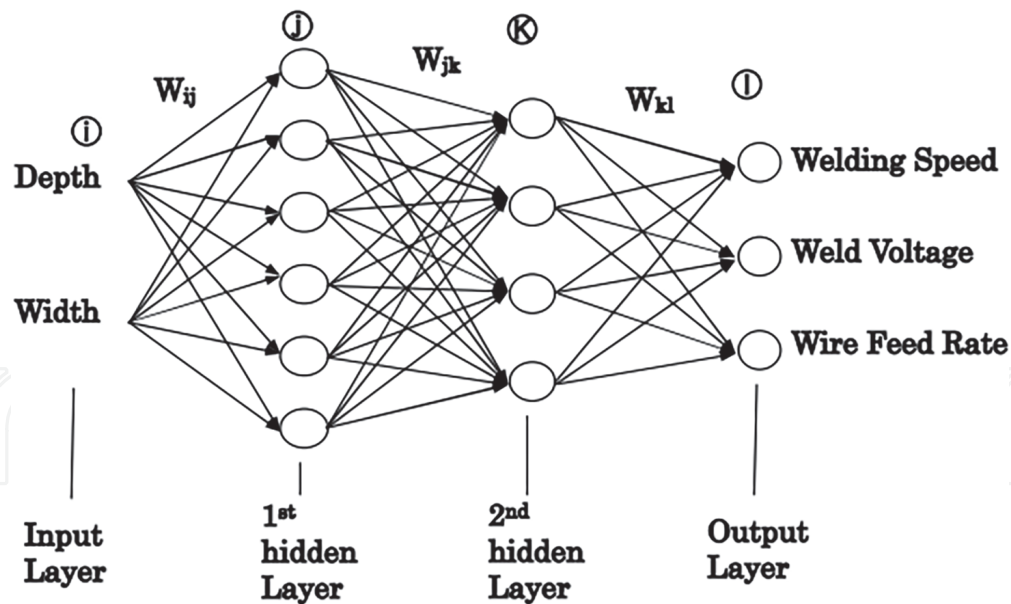
Figure 12.
Neural network to determine welding parameters. Adapted from [63].
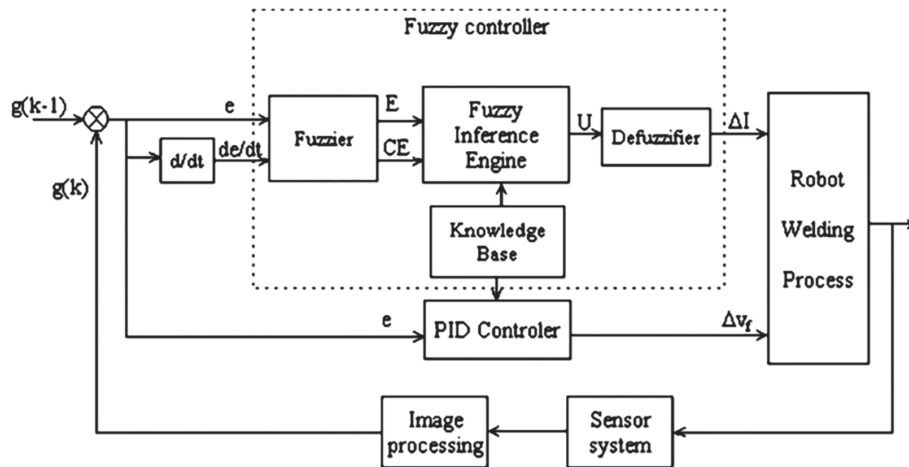

Figure 13.
Block diagram of the geometry stability controller for GTAW process, developed in [65].

Chen solved the full penetration detection, in orbital the GTAW process, with a vision system over the topside pool and a neural network model for estimating the backside weld bead width in [39]. The neural network has 17 neurons in the input layer, 40 in the hidden layer, and 1 in the output. An adaptive controller receives the backside weld bead width, estimated by the neural network, and regulates the peak current. A fuzzy controller received the gap state and controlled the wire feed speed. The experimental results, examined in X-ray, have shown a uniform backside of the weld bead.

An adaptive inverse control based on support vector machine-based fuzzy rules acquisition system is proposed by [64] for pulsed GTAW process. This method extracts the control rules automatically from the process data, using an adaptive learning algorithm and a support vector machine to adjust the fuzzy rules. The controlled variable is the backside weld width, and the manipulated variable is the peak current of the pulse. A double-side visual sensor system captures the topside and backside images of the weld pool simultaneously. The data for model identifying is obtained experimentally. The control is simulated and shows satisfactory results.

Lü et al. [69] developed a MISO algorithm for the control of the width of the weld pool backside in the GTAW process. The vision sensing technology and model-free adaptive control (MFC) are used. The welding current and wire feed speed are selected as the manipulated variables, and the backside width of the weld pool is the controlled variable. The main difficulty was the availability of computational resources to maintain the control period and the image processing speed within acceptable values. It has the disadvantage of using complex optical systems for obtaining the image of the back- and the front side of the weld pool.

In [68] a space state model of the GMAW process is obtained to compare the behavior of three controllers: ARMarkov-PFC (based MPC controller), PI, and feedback linearization based on the PID (FL-PID). The controller outputs are the wire feed motor voltage and the welding voltage. The controlled variables are the welding current and voltage. The simulation results show that the ARMarkov-PFC outperformed other controllers from the viewpoints of the transient response, desired output tracking, and robustness against the process parameter uncertainties but require more computational resources. The FL-PID controller was sensitive to the process parameter variations, presence of noise and disturbance, and results in an improper performance. The PI controller produced an inappropriate transient response and inadequate interaction reduction despite good tracking performance, low sensitivity to parameter variations, and low computational resource requirements.

The main advantages of MPC over structured PID controllers are its ability to handle constraints, non-minimum phase processes, changes in system parameters (robust control), and its straightforward applicability to large, multivariable, or multiple-input multiple-output processes. Despite having many advantages, a noticeable drawback of an MPC is that it requires higher computation capability, as is shown in [79].

The change in arc voltage during the peak current is used in [49] to estimate the weld penetration depth in the pulsed GMAW process. An adaptive interval model control system is implemented, but, contrary to the author's comment, the control accuracy is not good.

Lui et al. [60] developed a model-based predictive control for the orbital GTAW process. The control input is the backside weld bead width, and the outputs are the welding current and welding speed. A nonlinear neuro-fuzzy (ANFIS) model is utilized to estimate the backside weld bead width (related with weld depth penetration) using the front-side weld pool characteristic. **Figure 14** shows a block diagram of this approach.

In [67] the GMAW LAM process is modeled using the recursive least squares algorithm for system identification. An image processing algorithm is employed for obtaining the nozzle to top surface distance. An adaptive controller adjusts the deposition rate and keeps the nozzle to top surface distance constant. The precision range of the control system is limited within ±0.5 mm.

A segmented self-adaptive PID controller was developed in [30] for controlling the arc length and monitoring the arc sound signal in the pulsed GTAW process for the flat and arched plate. The experiments show that the controller has acceptable accuracy.

Lui and Zhang [4] developed a machine-human cooperative control scheme to perform welder teleoperation experiments in the orbital GTAW process. They developed an ANFIS model of the human welder's adjustment on the welding speed. The welder sees the weld pool image overlaid with an assistant visual signal and moves the virtual welding torch accordingly. The robot follows the welder's movement and completes the welding task. The experimental data is used to obtain the model. Later, they transfer this model to the welding robot controller to perform
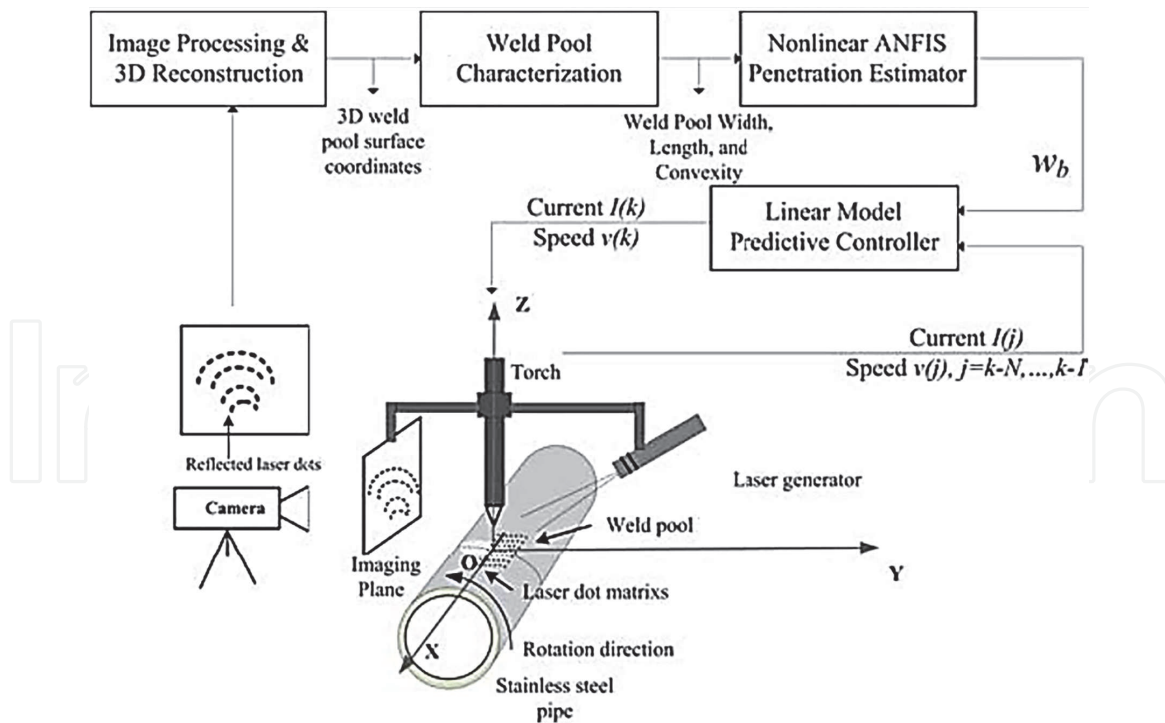
Figure 14.
*Model-based predictive control to orbital GTAW process. Adapted from [60].*

automated welding. The controller receives the three-dimensional weld pool characteristic parameters (weld pool length, width, and convexity) and changes the welding speed.

In other similar work [3], a human intelligence model based on a neuro-fuzzy algorithm is proposed to implement an intelligent controller to maintain a full penetration manipulating the welding current. These works establish a method to rapidly transform human welder intelligence into welding robots by using three-dimensional weld pool surface sense, fitting the human welder response to the information through a neuro-fuzzy model, and using the neuro-fuzzy model as a replacement for human intelligence in automatic systems. In previous works [56, 57], the skilled human welder response to the fluctuating three-dimensional weld pool surface is correlated and compared with a novice welder.

3.2 Embedded devices in welding process control

Embedded systems, especially the FPGA and system on chip (SoC), are used in a multitude of technological processes in various industries, covering hazardous areas such as medical, aerospace, and military or even the most common household appliances. With the increase in processing capabilities of these systems, based on microcontrollers and new processor generation, it is possible to obtain remarkably improved measurement and control systems with the use of advanced algorithms for processing information provided by the sensors. The parallel processing capabilities of the FPGA (into the SoC) allow lower execution times than in processors or microcontrollers. These capabilities are important to estimators based on neural networks (parallel execution) and to control systems in real-time that need to attend several sensors and actuators.

The FPGA has numerous digital inputs and outputs, with the possibility of adding several analogs and other peripherals. Many of them have a hard processor, with one or more cores and various peripherals for communication, video, sound,
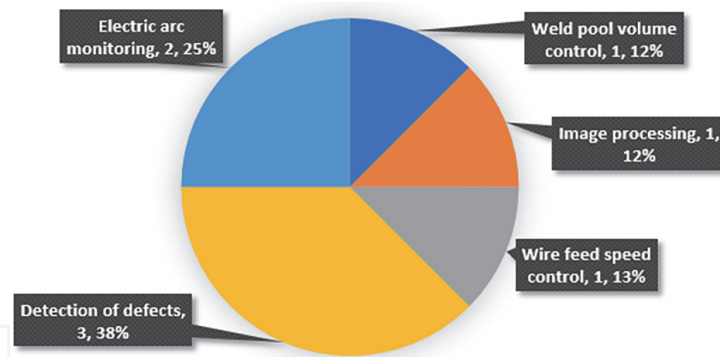
Figure 15.
Graphical summary of the applications of embedded devices in welding processes found in the literature review.

and large random access memory (RAM) capacity, where you can run a standard operating system interconnected with the FPGA. These features and the small size, low power consumption, low heat dissipation, and reconfigurable architecture make it an ideal tool for monitoring and control systems with real-time requirements. For all these good reasons, we must pay special attention to these devices.

The modern welding power sources are controlled by embedded systems. These systems provide communication, data acquisition, and control functions for different welding processes, but their most important specialization is the control of the electric arc, laser signal, and other methods to transfer the energy to the base material. This specialization permitted the substitution of big transformer and switches to select the welding parameters such as the voltage, current, and inductance, by a smaller transformer and high-frequency switching semiconductors governed by a microcontroller. With these changes it was possible to generate various types of waveforms on the output of the welding power source, improving the conventional processes and creating new processes and new control algorithms.

In these systems, the embedded controller emulates the impedance of the old transformer and keeps the set points of welding voltage and current with more accuracy. The configuration of welding parameters, data acquisition, and set point changes can be made using a communication protocol, defined by the manufacturer. The integration with a supervisory or higher control system is possible using this communication protocol.

The literature review does not show an extensive application of FPGA to bead geometry control in the arc welding process. But other works have shown applications related with wire feed control [80], defect detection [81–83], and arc signal monitoring [84, 85]. A graphical summary is shown in **Figure 15**.

4. Conclusions

Based on the literature review and the experimental experience about the control of the welding bead geometry, it is possible to observe the great complexity of the welding process and the many efforts to control it. The proposed solutions range from simple open-loop controllers to complex intelligent control algorithms, highlighting the legendary PID combined with other techniques, adaptive methods, and the neural network and fuzzy algorithms.

Despite the arduous research efforts, few of these algorithms are being applied in the industry, in some cases due to its complexity but others due to commercial interests and its cost of implementation. For these reasons, the control of welding

processes is an open topic for research and especially for the development of feasible solutions to be used in the industry.

Scientific research and the slow but continuous application of its results in the welding industry show a tendency for modeling and control of these processes to be carried out using methods of artificial intelligence. These methods, in addition to including classic artificial intelligence techniques, are incorporating bioinspired algorithms, deep learning techniques, big data and data mining for the analysis of the measurements, the adjustment of the controllers, and even the implementation of the controller itself.

Undoubtedly, the current development of embedded systems and the small and smart sensors is allowing the implementation of many algorithms proposed decades ago and new algorithms that make extensive use of the calculation capabilities of these systems. The use of multivariable control and dynamic models of the process will be possible and will allow a notable improvement in the quality of the welds and the number of parts rejected in the production process.

But the advantages of these technologies will not be accepted and exploited efficiently without adequate training of the technical staff that directs and operates the industries. Many of these modeling and control techniques are still unknown or their advantages are poorly disclosed. This is a problem when it is compared in terms of ease of use and productivity against classical techniques with decades of use in the industry. In this sense, we try to contribute to the dissemination of this knowledge throughout this chapter.

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