WELDING

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Contents

Summary

After a brief definition of various welding processes in Section 1, the problem of model building, required for advanced weld control, is presented in Section 2 for the most typical welding process, the arc welding. This is followed in Section 3.1 by introduction into the control approaches to the welding process, and by presentation of adaptive control in Section 3.2. Applications of intelligent (expert, fuzzy, neural, and neuro-fuzzy) control to the welding process is discussed in Section 3.3 and various sensing elements required for welding process monitoring and control presented in Section 4. In 5 the automated welding using robots is considered and, finally, in 6 the monitoring and inspection aspects of welding discussed.

1. Introduction

Welding is a process of joining metallic parts by coalescence of metals, usually produced by introducing the heat, by electricity, or by gas. In fusion welding the heat introduced generates a molten pool of metal, whereby in solid-phase welding the amount of heat and pressure introduced do not significantly melt the metallic parts. To prevent the rapid oxidation of molten metals in the presence of oxygen, that prevents proper bonding of metallic parts, an inert gas atmosphere - as a protective means - is established around the molten pool of metal. For protection purposes most frequently argon or helium is used.

There are a large number of various welding processes, of which the following are well-known:

- *Arc welding*, particularly the *gas metal arc welding* (GMAW), Figure 1, and *gas tungsten arc welding* (GTAW). These are the most frequently used welding processes in the industrial and manufacturing practice. They rely on the effect of a shielded arc between the metallic work piece and a metallic electrode that uses direct or alternating current to provide the molten metal to the weld joint. In inert gas or carbon dioxide shielded arc welding a tungsten electrode is used for increase of welding efficiency.

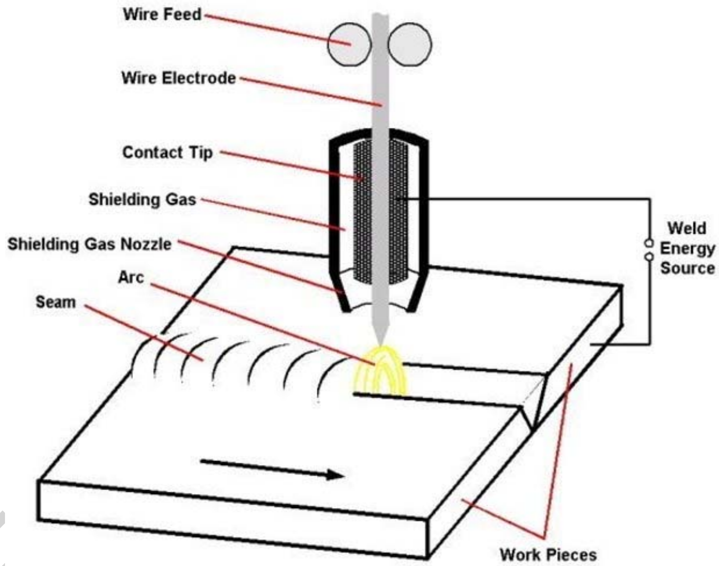

Figure 1: Gas Metal Arc Welding (schematic)

- *Cold welding*, an alternative welding that does not use the heat for producing the joint between the metal pieces but rather an extremely high pressure of above 500 000 pounds per square inch.
- *Diffusion bonding*, based on combined application of pressure and heat to produce a temperature of over 1 000 C degrees for a short period of time.
- *Electron beam welding*, implemented by intensive bombarding the metallic work piece by a dense focused, high-speed electrons accelerated by a voltage of up to 150 kV.
- *Friction welding*, used in joining of metallic pieces, one of which rapidly revolves to produce the required heat that softens the joint interface. For final bond the rotation is stopped and high pressure applied to the joint that in the mean time became plastic.
- *Laser welding*, realized by a strong laser source the focused light energy of which fuses the work pieces together.

- *Plasma welding*, a variant of arc welding in which a hot plasma is the heat provider.
- *Resistance welding*, in which the welding heat is generated by the electrical resistance of the joint to which two electrodes are applied driven by a high-current, low-voltage source (Figure 2).

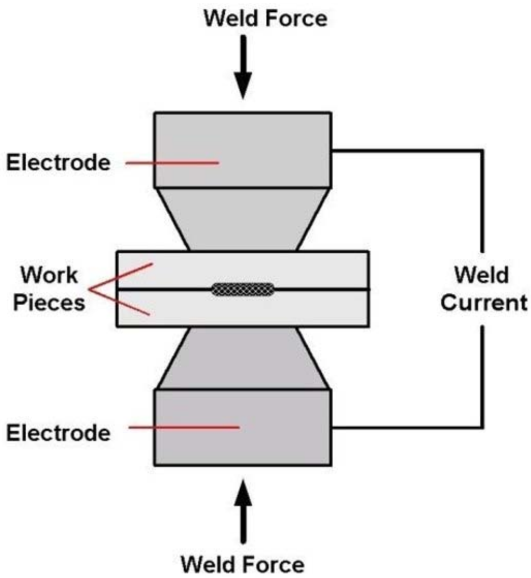

Figure 2: Resistance Spot Welding (schematic)

- *Ultrasonic welding*, accomplished by high-speed vibration of work pieces to be joined (Figure 3).

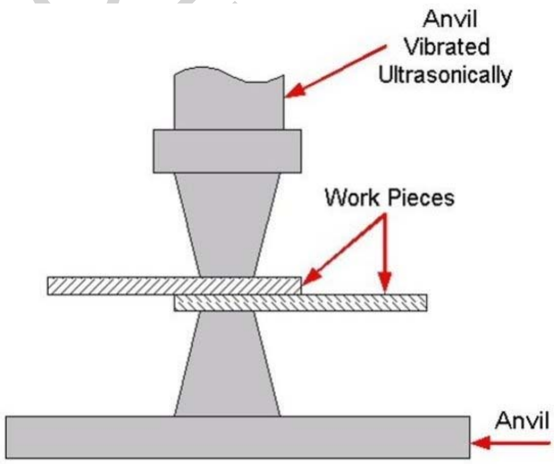

Figure 3: Ultrasonic Welding (schematic)

In the following, predominantly the arc welding, as the most widely used welding art, is considered.

2. Model Building of Welding Process

It is well-known from the modern control theory that the availability of the mathematical model of a process is the major prerequisite for design and use of advanced control algorithms for its control. This means that building of mathematical model of a welding process is the first step in implementation of time-optimal control, maximal material and energy saving control, or of high precision control of a given process. Numerous attempts have been made in building of mathematical models for various welding processes, mainly related to the corresponding heat and fluid flow.

Although the theoretical fundaments of mathematical presentation of welding process, based on heat conduction and other branches of physics, have already been led down in 1940s, and considerably extended middle of 1960s, they have been to complex to be used for on-line process control. As a substitution, statistical methods have been and are still preferred for this purpose. The methods facilitate building of mathematical process models through process identification and parameter estimation, based on experimental data. Besides, statistical and not analytical methods are preferred because the collected experimental data are noise contaminated. The process model built in this way is a black-box input-output model that strictly holds only for the process under experiment.

In welding, due to the process complexity, building the mathematical models from first principles leads to multivariable non-linear system of differential equations that, however, hold for a wide area of application. Such models, before being used for process control, have to be mathematically simplified, usually by linearization that, again, restricts their validity area to a limited region around its operating point at which they have been linearized. The early developed arc welding process models have been in form of first-order non-stationary models, based on welding current and bead width as process variables. Alternatively, also the (continuous and discrete) transfer function matrix models have been developed, based on - for instance in gas metal arc welding - on wire feedrate and travel speed to bead width and height as process variables. In case of discrete-time control implementation, good results have been achieved using for experimental building of process model a second-order transfer function matrix underlying the optimal discrete-time control of wire feedrate and travel speed of the torch.

Modeling of fluid flow in arc welding is particularly complex because it implies a number of different aspects to be considered, such as the surface tension driven flow in weld pool, the forces relevant to fluid flow in the puddle (electromagnetic and gravitational), plasma stream friction, the steep changes in the physical, chemical and mechanical changes in metals, etc. In addition, the interrelation to the simultaneous heat transfer should also be taken into account, so that a set of joint temperature and fluid flow velocity field equations can be derived that represents the actual penetration shape.

When, instead of model building from first principle, i.e. of using fundamental physical laws for this purpose, the use of some formal mathematical methods is preferred, most frequently the *recursive least square method* is selected for system parameter estimation in the rational form as the input/output model

$$Y(z) = [N(z)/D(z)]U(z)\,, \qquad (1)$$

z being the delay operator, and the model parameters, i.e. the coefficients of the numerator and denominator polynomials $N(z)$ and $D(z)$ experimentally determined using the sampled process values. Alternatively, *moving average* model, involving the *weld depression* and the *weld width* as the component of the state vector, is selected. This is based on the fact that the depression and width are main thermal and force weld parameters that can be changed during the welding process by controlling the welding current and the arc length, while selecting a pre-calculated torch speed value. This leads to the two-inputs/two-outputs process description

$$\mathbf{S}(k) = \mathbf{s}_0 + \mathbf{Bu}(k) + \mathbf{e}(k), \qquad (2)$$

where $\mathbf{u}$ is the control vector with the welding current and the arc length as its components, $\mathbf{B}$ is the operator matrix to be determined by experiment, and $\mathbf{e}$ is an error vector.

For simulation purposes a simplified dynamic model of a GMAW process can be built containing as essential system elements the electrical circuit of the system, the consumable electrode, and the welding arc. Denoting the source voltage of the welding arc by V_{Source} and the voltage drop of the electrode-sheath system V_{S}, the dynamic behavior of the system circuit (Figure 4) can be defined by

$$V_{\text{source}} = V_{\text{S}} + V_{\text{A}} + I(R_{\text{C}} + R_0 + R_{\text{W}}) + Ldl/dt, \qquad (3)$$

where V_{A} is the arc voltage for each time step, and I the arc current for the previous time step. The last term in the bracket represents the voltage drop V_{a}, along the anode wire with the resistance R_{W}. In the equation also the effect of the power source inductance L and of its internal resistance R_0 is taken into account, as well as the influence of the nozzle-to-wire contact resistance R_{C}.

Consequently, the thermal model of moving electrode is defined by

$$S = k(T_{\text{P}} - T_{\text{A}})/I_{\text{P}} + j\Phi_{\text{W}} + j5K_{\text{B}}T_{\text{E}}/2e, \qquad (4)$$

where S is a source term, T_{P} the arc temperature, T_{A} the anode tip temperature, j the current density, Φ_{W} the work function of the anode material, K_{B} the Boltzmann constant, T_{E} the electron temperature, and k the effective thermal conductivity at the anode-plasma interface defined as

$$k = (2k_{\text{metal}}k_{\text{plasma}})/(k_{\text{metal}}k_{\text{plasma}}). \qquad (5)$$

A formal direct building of input/output models, based on experimental data has also been carried out using neural networks. This was demonstrated on modeling of an arc welding process in which the variable polarity plasma arc welding takes place, where a [4-10-2] backpropagation network was used to generate the *crown width* and *root width* at network output, based on *torch stand-off*, *forward current*, *reverse current*, and *travel speed* at network input.

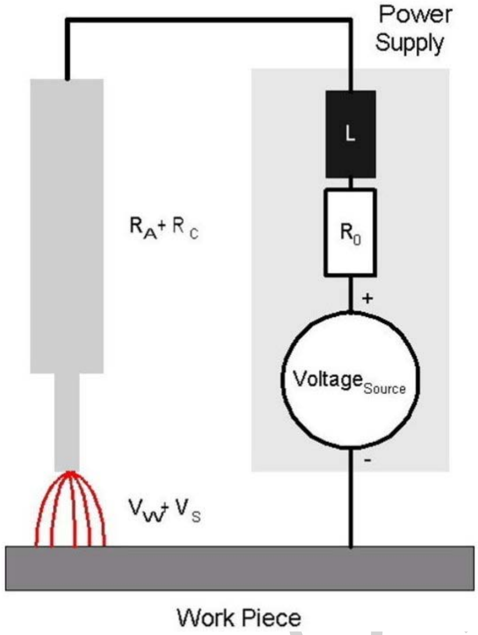

Figure 4: Electric Circuit (schematic)

Finally, welding process modeling using the artificial intelligence approach has also proved to be successful. Both the use of expert systems and of fuzzy logic systems for this purpose has given food experimental results. In both cases a set of linguistic IF-THEN rules has been built, representing the process behavior as understood by a human welding expert. However, the rules elucidated from the expert must be checked for the correctness, completeness, and compatibility, i.e. it has to be found out whether the rules incorporate any contradictory rules pair. To verify this, the model built has to be experimentally verified before being used and, in case of fuzzy logic based models, its membership functions optimally tuned. A better success promises the model building relying on *Sugeno type* of neuro-fuzzy model in which the dynamic process behavior of the process is described by its fuzzy logic part, whereby the shape of membership functions is optimally tuned by its neural part using the collected experimental data.

3. Welding Control

Control of welding processes is a requirement for increased product quality, accelerated operational speed, and reduced production costs by time and energy optimal control. The objectives of the control, however, can be met if the dynamic model of the welding process is well known that, as a rule is not the case. Thus, the implementation of a control strategy has to start with the building of mathematical model of welding process on which the design of the desired control configuration can be based.

3.1. Control Approaches

In the earliest control implementations of arc welding PID controllers have been used for achieving optimal heat and metal transfer from the electrode to the work piece. This was the most simplified welding control approach concentrated on two arc parameters only. Later, a more advanced and more adequate control configuration, the multivariable control, has later been implemented by taking into account the weld geometry and the weld thermal properties and by using different linear and non-linear process models. At the most advanced stage of traditional control application, the *model reference adaptive control* has been implemented, capable to cope with the problem of weld parameters deviations and the changes of environmental conditions. Some of adaptive schemes have also been implemented as conventional controllers with the gain self-tuned in accordance with the pool bead width, the nominal value of the welding current, the sensed weld temperature, etc.

In the today's arc welding facilities the most dominant factors determining the mechanical properties of the weld joint are the pool width, penetration depth, and the reinforcement height (Figure 5). They are thus selected as process variables to be controlled by manipulating the torch power, velocity, and the feed rate as control variables.

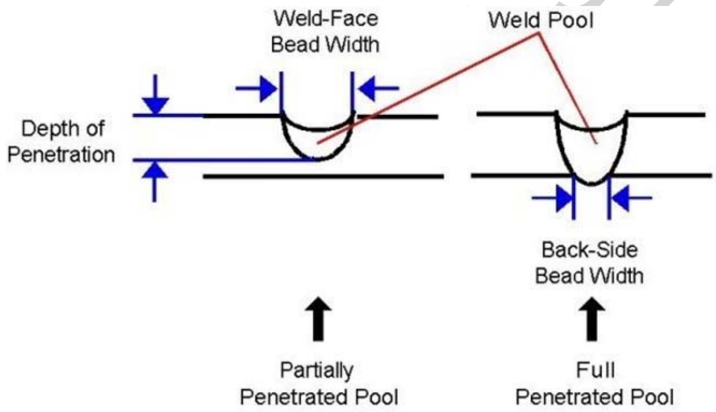

Figure 5: Welding Pool (schematic)

The non-linear behavior of the welding process and its non-stationarity due to the thermal variations, external disturbances and the inhomogeneity of materials to be joined call for adaptive process control, based on an experimentally built mathematical process model, the parameter values of which, in order to track the changing values of process parameters, are to be estimated on-line. This kind of models are usually built using the statistical discrete-time ARMA (Auto-Regressive Moving Average) approach, based on linear relationship in parameter matrix $\boldsymbol{\theta}$ of the form

$$\mathbf{y}(k+d) = \boldsymbol{\theta}\mathbf{x}(k) \qquad (6)$$

with $\mathbf{x}(k)$ as the state vector and $\mathbf{y}(k+d)$ as the delayed output vector of welding process. The parameter matrix $\boldsymbol{\theta}(k)$ is to be estimated using the recursive relation

$$\boldsymbol{\theta}(k) = \boldsymbol{\theta}(k-1) + \gamma\mathbf{x}(k-d)[\mathbf{y}(k)\boldsymbol{\theta}(k-1) + \mathbf{x}(k-d)]^{\mathrm{T}} \qquad (7)$$

where γ is the parameter adjustment gain. Should a linear system's model be built, the matrix-polynomial description

$$\mathbf{A}(q)\mathbf{y}(k) = \mathbf{B}(q)\mathbf{u}(k) \tag{8}$$

could be used, where $\mathbf{y}(k)$ and $\mathbf{u}(k)$ are the output and control vectors of the modeled system and $\mathbf{A}(q)$ and $\mathbf{B}(q)$ the matrices containing the system parameters to be determined experimentally. Based on ARMA model, the *generalized one-step-ahead* control law with the integral square error as the cost function can be applied for adaptive control.

In addition to the control of weld bead geometry also the thermal characteristics of the weld are to be controlled simultaneously because they considerably influence the weld quality. Yet, the task appears to be more complicated because the thermal phenomena are basically distributed in space i.e. they are to be described as *distributed parameter systems*, so that for model-based control of such systems distributed parameter models are required. Some effort have already been maid to build such models, describing the dynamic behavior of thermal characteristics during the weld process, by using the theory of Green's functions but the results achieved, because being mathematically complicated, are not much of practical use for the implementation of a distributed control of welding.

Adaptive control, although being efficient enough to compensate the deviations in process parameters or in environmental conditions, it still belongs to the advanced *traditional* control approach, if not implemented using conventional control technology. With the advent of artificial intelligence technology, development of intelligent control systems has come to agenda, also the development of intelligent adaptive systems.

Intelligent systems are basically knowledge-based systems. They rely on knowledge about the system to be controlled and are capable learn the facts and the relations between them, as well as to infer and reason about the knowledge stored, so that they represent qualitative new systems. Intelligent control systems developed in the last two decades are known as *expert*, *fuzzy*, *neuro*, and *neuro-fuzzy controllers*.

Expert welding controllers are based on the knowledge about the welding process to which also the heuristic knowledge collected by the welding expert as his field experience. The controllers can replace the unskilled or inexperienced human welders and teach them to become welding experts. The controllers are also highly appropriate for automated robotic welding systems used in manufacturing industry.

Fuzzy controllers, as being simplified rule-based expert systems, are particularly appropriate for solving control problems in the cases where only the qualitative system behavior is known. They rely on a set of linguistic fuzzy rules by which the system behavior is qualitatively described and on some defined control decisions to be made in some specific situations. For instance in the arc welding, the required fuzzy rules related set is related to the molten pool width. They enable intelligent control of the pool state.

Neural networks technology, as being capable to directly learn on examples, is appropriate for building of learning systems for modeling and control of dynamic processes. Neural network based systems, when trained by experts, are capable of building mathematical models of dynamic systems and also to learn on-line the corresponding control rules of such systems. In the majority of applications the back-propagation networks are used for this purpose.

Neuro-fuzzy technology, again, combines the advantages of both technologies to produce an improved intelligent system, profiting from the synergetic effect of technology combination. Here, the learning capability of neuro technology helps optimize on-line the shape of the membership functions and values of other parameters of the underlying fuzzy controller. Neuro-fuzzy controllers increasingly applied in automated robotic welding.

It should finally be mentioned that the modern trend in automated welding pays considerable attention to the camera-oriented control configurations and to the *pattern recognition* algorithms for weld quality control.

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Biographical Sketch

Stefan Nordbruch received a Diploma degree in Electrical Engineering at the University of Bremen in 1996. Since 1997 he was with the Institute of Automation of the Department of Physics and Electrical Engineering, University of Bremen, Germany and additional since 2000 with the Friedrich-Wilhelm-Bessel-Institut Forschungsgesellschaft m.b.H., Bremen, Germany. His special interests and experiences are mainly in the area of visual automation of welding processes, which are also the topic of his PhD-thesis. Stefan Nordbruch has a number of contributions on this subject.