Available online at www.elixirpublishers.com (Elixir International Journal)

Mechanical Engineering

Elixir Mech. Engg. 81 (2015) 31702-31708

ISSN: 2229-712X

Modeling and Optimization Approaches used in Welding - A Review

Mir Sadat Ali[1], Ch.Srinivasa Rao[2] and Nageswara Rao[3]

[1]Department of Mechanical Engineering, Centurion University of Technology & Management, Paralakhemundi.
[2]Department of Mechanical Engineering, AU College of Engineering, Visakhapatnam 530 045 Ap, India.
[3]Centurion University of Technology & Management, Paralakhemundi- 761 211.

ARTICLE INFO

Article history:
Received: 11 February 2015;
Received in revised form:
15 March 2015;
Accepted: 6 April 2015;

Keywords
Design of experiments (DOE),
Artificial Neural Network (ANN),
Taguchi,
Optimization of welding process,
Weld bead geometry,
Process parameters.

ABSTRACT

All welding processes are used with the aim of obtaining a welded joint with the desired weld-bead parameters, excellent mechanical properties with minimum distortion. The welding input parameters play a significant role in obtaining excellent mechanical properties with minimum distortion to get a desired weld bead parameters. Usually, the desired welding parameters are determined using traditional methods like welder's experiences, charts and handbooks (preferred values) which are simple and inexpensive. But this does not ensure that the selected welding parameters result in satisfactory welding and this method is not applicable to new welding process. To achive desired weld bead parameters different models were developed to correlate input variables with output variables. Mathematical models to specify the relationship between the input variables and output parameters can be used for optimization. Design of Experiment (DoE) technique has been used to carry out such optimization. Computational network & evolutionary algorithms have also grown rapidly and been adapted for modeling and optimization of welding process parameters to achieve desired properties in the welded joint. In this paper a comprehensive literature review of the application of these techniques is presented. This review shows the correlation and modeling between the input welding process parameters and the output weldment characteristics. The paper also presents the optimization of the different welding processes through the mathematical models and evolutionary algorithm. The use of mathematical models and evolutionary algorithm for the optimization of the different welding processes is discussed in this paper.

Introduction

Welding is a process of permanent joining two materials through localized coalescence resulting from a suitable combination of temperature, pressure and metallurgical conditions. Depending upon the combination of temperature and pressure from a high temperature with no pressure to a high pressure with low temperature, a wide range of welding processes has been developed[1].

Quality of a weld product is evaluated by different parameters like weld bead geometry, deposition rate, hardness etc. These characteristics are controlled by weld input parameters like welding current, welding speed, arc voltage and electrode stick out. Generally, the arc welding processes are substantially nonlinear, in addition to being highly coupled multivariable systems.

Traditionally, for getting a specified welded joint it is required to decide the input process parameters. These input process parameters are chosen by the knowledge of engineer or skill of the machine operator or from the charts or hand books. The formed welded joint is examined with the specified welded joint. So tradional methods are based on the experience and expertise of the operator to achieve the specified welded joint. In order to overcome the scarcely available human expertise various modeling and optimization methods are developed to obtain the desired weldment characteristics. Different mathematical models are developed between the input process parameters and output weldment characteristics. This literature review is done to know the different mathematical models, computational networks and the evolutionary algorithms used in achieving the bead geometry and weld quality. The literature review done is according to the weld joint features. The different welded joint features are shown in Figure: 1.

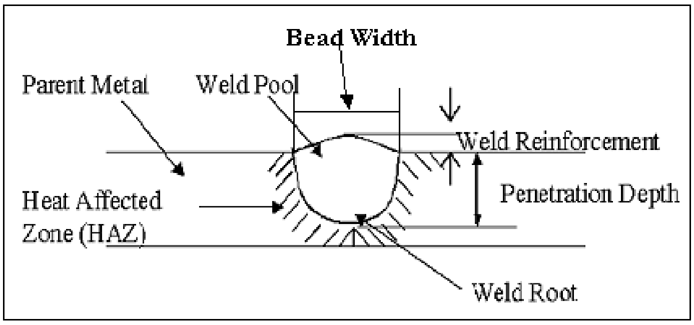

Figure 1

Weld bead geometry

To get the desired quality welds, it is essential to have complete understanding and control over the relevant welding input process parameters in order to obtain the required bead geometry and which is also based on weldability [2]. So, various models to correlate the input variables with output characteristics of the weld have been developed. Fractional factorial techniques, Mathematical modeling, curvilinear regression equations, linear regression equations, response surface methodology, finite element modeling, grey-based Taguchi method and sensitivity analysis were used to model different welding processes.

Tele:
E-mail addresses: sadat.ali@cutm.ac.in

The factorial design method is the most convenient and oldest method used to develop the mathematical model for correlating the input process parameters and output weldment characteristics.

Factorial Design

Ravendra and Parmar [3] has considered the parameters of the FCAW process. The arc voltage, welding current, welding speed, gun angle and nozzle to plate distance as the input process parameters. The fractional factorial technique is used to predict penetration, bead width, reinforcement height, width to penetration ratio and percentage dilution. The developed model is used to predict the bead geometry and to utilize in the automatic control system.

Gupta and Parmar [4] has verified the effect of wire feed rate , open circuit voltage, nozzle to plate distance, welding speed and work piece thickness on the bead penetration, weld width, weld height and dilution in the SAW process. The parent material used was micro alloyed steel in the thickness range of 10 to 16 mm. It was found that the fractional factorial technique used is convenient for the prediction of the main effects and interaction effects of different combinations of welding parameters. The mathematical model developed can be effectively used to predict the weld zone dimensions.

Murugan et al[5] had developed a mathematical model using a five level factorial technique to predict weld bead geometry. Investigation was conducted to find the effect of open circuit voltage, wire feed rate, welding speed and nozzle to plate distance on the depth of penetration, reinforcement, bead width and dilution. Use of SAW process was done for depositing 316L stainless steel on the parent material made of structural steel IS2062. It was found that the voltage and nozzle to plate distance has no effect on bead penetration. But the dilution increases with the increase in voltage. Dilution increases by increasing the welding speed upto a maximum value and after that it decreases with the further increase in welding speed.

Murugan and Parmar[6] had done similar investigation without varying the parent material and the filler material with MIG welding process. Four factors 5 levels factorial technique was used to predict the depth of penetration, bead height, and bead width and percentage dilution. The input process parameters controlled in the determination of weld geometry are open circuit voltage, wire feed rate, welding speed and nozzle to plate distance. It was well demonstrated by [5] and [6] that the factorial technique is an effective method of developing mathematical models to predict weld bead geometry. These mathematical models can be used in a computer program to determine a combination of welding process parameters for a specific set of required weld bead dimensions. Thus, it can be useful technique to utilize in automatic robotic surfacing.

Kim et al [7] had investigated the effect of process parameters like arc voltage, welding current, welding speed and welding angle on the penetration in robotic CO_2 arc welding. The parent material used was SS400 plates of 12mm thickness. Mathematical models were developed using the factorial techniques to predict the desired bead penetration.

Kim et al [8] had employed factorial design to correlate the robotic GMAW process parameters with their responses. The process parameters taken were welding voltage, welding speed and arc current. The response parameters observed were bead width, bead height and penetration. The parent material and the filler wire used was AS1204 Mild steel and adopted bead on plate technique. The models developed using the factorial design was able to predict the responses with 0-25 accuracy.

Linear Regression

Yang et al [9] have used regression equations for modeling the output parameters, bead height, bead width, depth of penetration and melting rates, from the input of SAW process. The input process variables kept under observation are welding voltage, welding current, welding speed and electrode diameter. Positive and negative electrode polarity was used in the investigation process. The parent material used for this study was ASTM A36 steel plate. The developed regression equations were effective in modeling the various features of SAW process.

Starling et al [10] has undertaken GTAW process with magnetic arc oscillation for study. The process parameters observed are welding current, travel speed, bead height and arc deflection current for the output weld bead geometry. The parent material used was AISI 304L stainless steel plates and filler metal used was AWS ER308L, wire of 0.96mm diameter. Statistical experimental design was used to reduce the number of samples to be formed and tested. Experimental results showed that the arc oscillation had little effect on lateral fusion of the joint but oscillation improves bead shape by increasing it's concavity. The linear regression models created for each individual output parameters for all the input process variables was in close agreement with the experimental results.

Yang L.J., Chandel R.S. and Bibby M.J. [11] derived curvilinear (i.e., non-linear) regression equation to study the relationship between correlation coefficients and standard deviation of error in prediction in submerged arc welding. Experimental study to check the feasibility of using linear regression instead of curvilinear regression to model weld features is conducted.

Kim I.S, Son J.S. , Kim I.G. , Kim J.Y. and Kim O.S. [12] determined both linear as well as non-linear multiple regression equations to relate the welding process parameters with the weld bead geometric parameters in robotic CO_2 arc welding. The developed response equations were able to predict the weld bead geometry with sufficient accuracy from the process parameters.

Response Surface Methodology

Murugan and Parmar [13] developed mathematical models using response surface methodology (RSM) to study the direct and interaction effects of SAW parameters (open circuit voltage, wire feed rate, welding speed and nozzle-to-workpiece distance) on the cladding geometry (depth of penetration, height of reinforcement, weld width and dilution %). The process parameters obtained from the developed models were employed to clad IS2062 structural steel plate of 20-mm thickness using 316L stainless steel wire of 3.15 mm diameter. It was concluded that a low dilution of 22.57% can be produced by both high voltage and high welding speed or by low voltage and low welding speed. It was reported that the hardness of the existing martensitic structures at the intermediate mixed zones in overlays was below 400 VHN, due to low carbon content in the cladding.

Gunaraj and Murugan [14] had developed a mathematical model using RSM. The input parameters taken are voltage, wire feed rate, welding speed and nozzle to plate distance. The response parameters observed are penetration, reinforcement, width and percentage dilution of the weld bead in SAW of pipes. Contour graphs relating input parameters to the response factors are plotted. It is observed that all responses decreases with increasing welding speed. When the nozzle to plate distance increases all responses decreases, except the reinforcement which increases. However, an increase in the wire feed rate increases all the responses except the bead width which remains unchanged.

Koleva [15] has conducted investigation on electron beam welding. The input parameters controlled are electron beam power, welding velocity, distance from the main surface of the magnetic lens to the focus point and the distance between the magnetic lens and the sample surface. The output parameters investigated are welding depth and width. The experiment was performed with samples of austenitic steel. Also, the desirability approach was used to find the optimal welding conditions which would lead to the desired depth and width. The author has suggested the use of the developed models for on-line control of the process. This allows the selection of the optimal levels by reducing the time required for testing and minimizing the loss of components.

Gunaraj and Murugan had conducted their study on SAW process. The observations are reported in two parts. In the first part [16] a model was developed to relate the weld bead volume to SAW parameters. The results reveal that, with the increase in welding voltage, penetration reduces, whereas the bead width and dilution considerably increases. Also it was observed that the reinforcement is least when all the SAW parameters were at their upper limits and the wire feed rate was at it's lower limit.

In the second part of their study [17] the total volume of the weld bead was minimized by keeping the other bead parameters as constraints to get good quality welded joint in pipes. The sensitivity analysis was conducted to predict the effect of the bead parameters on the total volume.

In another study Gunaraj and Murugan[18] investigated the effect of SAW parameters on HAZ characteristics. It is observed that the heat input and wire feed rate has a positive effect but the welding speed has a negative effect on the all HAZ characteristics.

Manonmani etal [19] investigated the effect of the laser welding parameters on bead geometry of 2.5mm thick AISI 304 stainless steel. Using the RSM, the relationship between the process parameters and the weld bead parameters is developed. The process parameters considered were beam power, welding speed and beam incidence angle. The effect of these process parameters on penetration, beam width and area of penetration was observed. To verify the performance of the developed model, test run were conducted using intermediate values of the process parameters. The model developed generates accurate results of weld bead parameters. The error percentage between the experimental results and the results produced from the model was between 4.317% to 3.914%. It was demonstrated that with the increase in beam power and beam angle, the depth of penetration and the penetration area increases. Also, as the welding speed increases, the width decreases, whereas the penetration depth and area increase to an optimum value and then decrease with further increases in welding speed. The effect was due to the fact that the effect of key holing was predominant at lower speed and as the welding speed was increased the mode of heat transfer changes from keyholing to conduction type of welding. It was reported that the variation in the bead width was slightly affected by the process parameters.

Koleva[20] conducted experiments in EBW on austenitic stainless steel. RSM was applied to establish relationship between the process parameters and the weld bead characteristics. The input process parameters considered were beam power, welding velocity, focus position, focusing current of the beam and the distance to the sample surface. The weld bead characteristics observed were weld depth, weld width and thermal efficiency. New statistical approaches were proposed to choose the focus position at a condition of maximum thermal efficiency and welding depth.

Benyounis et al. [21] have applied RSM to investigate the effect of laser welding parameters (laser power, welding speed and focal point position) based on four responses (heat input, penetration, bead width and width of HAZ) in CO_2 laser butt-welding of medium carbon steel plates of 5 mm thick. The heat input has an important role in the formation of weld-bead parameters. Welding speed has a negative effect while laser power has a positive effect on all the responses. Again Benyounis et al. [22] have used the previous models [21] to optimize the process. Two optimization criteria were considered; the desirability approach was used to find the optimal conditions in the numerical optimization. It was obbserved that full penetration has a strong effect on the other bead parameters. Also, strong efficient and low cost weld joint could be achieved using the optimal conditions.

Koleva and Vuchkov [22] had investigated the effect of EBW process parameters on weld depth and weld width while welding on stainless steel. The controlled process parameters were beam power, welding velocity and focus position. RSM is applied to improve the quality of the process in mass production. The optimal process parameter values reported were: power 6.5-8 kW, welding velocity 11.667-1.333 mm/s and focus position 78 mm below the sample surface.

Kannan and Murugan [23] had considered the process parameters, welding current, welding speed, nozzle to plate distance and welding torch angle with reference to vertical, on the duplex stainless steel in flux cored arc welding process. The quality was determined in terms of penetration, width, reinforcement and percentage dilution. It was found that the process parameters had a significant effect on the bead geometry of the clad.

Gunaraj and Murugan [24] extended their study to predict the Penetration Size Ratio (PSR) Reinforcement Form Factor (RFF). The 'PSR' is defined as the ratio of bead width to the height of penetration and 'RFF' is defined as the ratio of bead width to the height of reinforcement. In SAW process based on these output parameters the selection of optimum input parameters can be made to obtain the desired bead shape and weld quality.

Artificial Neural Networks (ANNs)

Anderson et al. [25] had explained the concept of neural networks and its implementation technique to model the weld bead geometry with reference to the given input process parameters and vice versa. They used the GTAW process and carried various simulations. They used the experimental data obtained from the GTAW welding input parameters (voltage, current and electrode travel speed) to obtain the following weld bead characteristics: depth of penetration, bead width, bead height and bead cross sectional area. The performance of the data obtained from the neural networks is compared with the data obtained from experimental results. Both are found to be in the close proximity to each other. Also the data obtained is fully comparable to the accuracy achieved by more traditional approaches.

Cook et al. [26] applied the ANN to model the weld bead characteristics of plasma arc welding for the input process parameters. The process parameters selected were torch stand-off, forward current, reverse current and travel speed. The output factors desired were crown width and the root width. The parent material used was 2219 aluminium alloy plates of 6.35 thick and experiments were conducted as bead on plate process. The results confirmed that ANNs are capable tools for modeling and analysis of weld profile data.

Vitek et al. [27] used the ANNs to model the correlation between the weld pool shape to the input process parameters in Nd-YAG laser to the welds of Al- alloy 5754. The weld pool shape parameters considered were penetration, width and cross section area. The process parameters considered were travel speed, average power, pulse energy and pulse duration.

A routine had been developed to convert the shape parameters into a predicted weld profile which was based on the actual experimental weld profile data. The accuracy of the model was excellent. It has been concluded that this approach allows for instantaneous results and therefore, offers advantages in applications where real-time predictions were needed and computationally intensive predictions were too slow.

Juang et al [28] made a comparison between back-propagation and counter-propagation networks in the modeling of the TIG welding process. The input process parameters were: welding speed, wire feed speed, cleaning percentage, arc gap and welding current, while the output features were: front height, front width, back height and back width. The base metal was pure 1100 aluminium with a plate thickness of 1.6 mm. The experimental results, for the TIG welding process, showed that the counter propagation network has a better learning ability than the back-propagation network. However, the back-propagation network has better generalization ability than the counter-propagation network.

Chan et al. [29] have proposed a model to predict the bead width, bead height, penetration and bag length at 22.5^{o}in GMAW process with bead on plate experimentation. The process parameters were: current, voltage, wire travel speed and work piece thickness. Back propagation network (BPN) was used. Results revealed that the weld bead geometry problem can be accurately modeled by using BPN. A new weld bead parameter *l22.5*(length from the origin to periphery at 22.5° from the work piece surface) was defined in this work.

Jeng et al. [30] have used both BPN and learning vector quantization neural networks to predict the laser welding (LW) parameters for butt joints. The input parameters included were workpiece thickness and welding gap, while the output parameters 'responses' were optimal focus position, acceptable welding parameters of laser power, welding speed and weld quality, including weld width, undercut and distortion. All the networks were integrated together to make an accurate prediction model of the laser welding parameters. Therefore, the limitation in the industrial application of LW for butt joints can be reduced through the use of this well established model.

Nagesh and Datta [31] used ANN to model the GMAW process. The input parameters considered for modeling were electrode feed rate, arc power, arc voltage, arc current and arc length. The corresponding output parameters observed are bead height, bead width, depth of penetration and area. The workpiece material was grey cast iron and a mild steel electrode was used. It was showed that there was a small error percentage difference between the estimated and experimental values, which indicates that the neural networks can yield fairly accurate results.

Ridiings et al. [32] have applied neural networks technique to predict the outer diameter of the weld bead shape for three wire, single pass per side, submerged arc, line-pipe seam welds using the following welding process parameters: current, voltage and angle for the three wires as well as the welding speed, stick out and spacing of wires. The affect of each parameter on the shape of the weld bead was investigated in this work. The prediction of the weld bead shape and its variation with respect to different process parameters was determined.

Christensen et al. [33] have developed a multilayer feed forward network for modeling and online adjustment of GMAW process parameters to guarantee a certain degree of quality. In this study, butt joint welding with full penetration of standard steel S135 with 3 mm thickness was carried out. The process parameters were; wire feed speed, voltage, welding speed and gap width while the network inputs were back bead width and back bead height. In open loop control strategy, it has been demonstrated that use of the model to provide high quality welding is feasible and the network training was straightforward and effective. Whereas, in the closed loop experiments a single input and single output control scheme was investigated, it was shown that it was applicable for adaptive control of GMAW with some limitations.

Taguchi Method

Juang and Tarng [34] have adopted Taguchi method to analyze the effect of welding process parameters on the weld pool geometry in TIG welding. The process parameters taken for study were; arc gap, flow rate, welding current and arc travel speed. The bead geometry parameters observed were front and back height of the weld bead, the front and back width of the weld bead. It was experimentally reported that, the four smaller-the-better quality characteristics, 'four responses' of the weld pool in the TIG welding of S304 stainless steel of 1.5 mm in thickness are greatly improved by using this approach.

Lee et al. [35] have used the Taguchi method and regression analysis in order to optimize Nd-YAG laser welding parameters. The parameters considered were nozzle type, rotating speed, title angle, focal position, pumping voltage, pulse frequency and pulse width. It was demonstrated that the laser pulse width and focal position were the laser welding parameters that had the greatest effects on the S/N ratios of the melted length. The optimal welding conditions were obtained at a pulse width of 0.86 ms and a focal position of 3.18 to 3.35 mm. Furthermore, confirmation experiments were conducted at the optimal welding conditions.

Pan et al [36] have optimized laser butt welding of a thin plate of magnesium alloy using the Taguchi method. The effect of Nd- YAG laser welding parameters (shielding gastype, laser energy, conveying speed, laser focus, pulse frequency and pulse shape) on the ultimate tensile stress were studied. Their result indicated that the pulse shape and energy of the laser contributed most to thin plate butt welding. It was found that the optimal combination of welding parameters for laser welding were argon as a shielding gas, a 360 W laser energy, a work piece speed of 25mm/s, a focus distance of 0mm, a pulse frequency of 160 Hz and type III pulse shape. It was also found that the superior ultimate tensile stress was 169 MPa at an overlap of the welding zone of approximately 75%.

S. Fraley et al [37] through their work shown that Taguchi's method for experimental design is straightforward and easy to apply to many engineering situations, making it a powerful yet simple tool. It can be used to quickly narrow the scope of a research project or to identify problems in a manufacturing process from data already in existence. An advantage of the Taguchi method is that it emphasizes a mean performance characteristic value close to the target value rather than a value within certain specification limits, thus improving the product quality.

S.C. Juang and Y.S. Tarng [38] shown that Taguchi methods deal with designing quality rather than correcting for poor quality, they are applied most effectively at early stages of process development. Also the study highlights some limitations of Taguchi method. The main disadvantage of the Taguchi method is that the results obtained are only relative and do not exactly indicate what parameter has the highest effect on the performance characteristic value. Also, since orthogonal arrays do not test all variable combinations, this method should not be used with all relationships between all variables. The Taguchi method has been criticized in the literature for its difficulty in accounting for interactions between parameters. Another limitation is that the Taguchi methods are offline, and therefore inappropriate for a dynamically changing process such as a simulation study.

A large number of experiments have to be carried out when the number of the process parameters increases. To solve this task, the Taguchi method uses a special design of orthogonal arrays to study the entire process parameter space with only a small number of experiments. Using an orthogonal array to design the experiment could help the designers to study the influence of multiple controllable factors on the average of quality characteristics and the variations in a fast and economic way, while using a signal-to-noise ratio to analyze the experimental data could help the designers of the product or the manufacturer to easily find out the optimal parametric combinations.

A loss function is then defined to calculate the deviation between the experimental value and the desired value. Taguchi recommends the use of the loss function to measure the deviation of the quality characteristic from the desired value. The value of the overall loss function is further transformed into a signal-to-noise (S/N) ratio. Usually, there are three categories of the quality characteristic in the analysis of the S/N ratio, *i.e.* the lower-the-better, the larger-the-better, and the more-nominal-the-better. The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the quality characteristic, a larger S/N ratio corresponds to a better quality characteristic. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio. Furthermore, a statistical analysis of variance (ANOVA) is performed to see which process parameters are statistically significant. The optimal combination of the process parameters can then be predicted. Finally, a confirmation experiment is conducted to verify the optimal process parameters obtained from the process parameter design.

Combination of two Modeling Techniques

Park and Rhee [39] have analyzed the signal of the plasma, or spatter, and bead size, to develop a bead size estimation system using the regression method and a neural networks method. It was found that the relationship is a nonlinear function caused by the penetration state. In contrast, the authors concluded that the regression models were appropriate for estimation when classifying the penetration state as partial penetration and full penetration, whereas, the neural network was a very accurate estimation approach for bead size.

Kim et al. [40] have presented an intelligent algorithm to establish the relationship between GMA CO_2 welding process parameters; (number of passes, arc current, welding voltage and welding speed and bead height), in order to predict the bead height using a neural network and MRA for the robotic multi pass butt welding process of BV-AH32 steel with 12 mm in thickness. Results of the study depicts that all the process parameters would influence the bead height. Also, the developed models were able to determine the welding condition required to achieve the desired bead height, which helped to develop an automatic control system and to establish guidelines and criteria for the most effective joint design.

Kim et al. [41] have used genetic algorithm (GA) and RSM to determine the optimal welding conditions in GMAW process, the base metal was mild steel with a thickness of 5.8 mm. First, the near-optimal conditions were determined through a GA, and then the optimal conditions were determined over a relatively small region by using RSM. The desirability function approach was used to find the optimal conditions. Correlation was formed for the following parameters; wire-feed rate, welding voltage and welding speed to some responses, namely, bead width, penetration and height. From the observations it can be concluded that by combining these two techniques, a good result for finding the optimal welding conditions can be obtained.

Chou[42] has integrated approach comprising the combination of the Taguchi method and neural networks for the optimization of the process conditions for GTA welding was presented. Taguchi method was used for design of experiments and initial optimization with ANOVA for the significance of parameters of GTA welding (Electrode size, Electrode angle, Arc length, Welding current, Travel speed, and Flow rate). The author concluded that the Levenberg–Marquardt back propagation (LMBP) algorithm neural networks represent an easy and quick method to explore a non-linear multivariate relationship between parameters and responses. By using this technique with Taguchi method only, the average depth-towidth ratio in weld bead of GTA welding process for SS304 improved about 11.96% from the initial optimal parameters to the real optimal parameters.

S Kumanan, J Edwin Raja Dhas & K Gowthaman, [43] has presented a novel attempt to carry out the forward (the outputs as the functions of input variables) and reverse (the inputs as the functions of output variables) modeling of the metal inert gas welding (a multi-input and multi-output) process using fuzzy logic-based approaches. The statistical regression analysis was used for the forward modeling efficiently. The developed soft computing-based approaches were found to solve the above problem efficiently.

Conclusion

The Modeling and optimization methods covered in this survey are appropriate for modeling, control and optimizing the different welding process. Rather than concentrating on highly resource intensive welding experiments as in tradition, welding engineers around the globe feels comfortable with modeling & simulation tools to predict the response of welding. By adopting any or combination of these methods to analyze and optimize the welding parameters by systematic design of experiment (DOE), ANOVA and numerical optimization and subsequently their adverse consequences on in-service structural integrity of welded structures can be achieved. Future work should focus on the application of these modeling and optimization techniques to find out the optimal welding combinations for a certain welding process at which the process could be considered safe, environment friendly and economical.

References

[1] R.L. Apps and K. A. Lelson, “Effect of welding variables upon bead shape and size in submerged-arc welding”, Weld. Met. Fabr; 31(11), (1963), pp.453-457.

[2] J. B. Austin, “Electric arc welding”, Am. Tech.soc., Chicago, 1956, pp. 61-62

[3] J. Raveendra and R. S. Parmar, Mathematical models to predict weld bead geometry for flux cored arc welding, J. of Metal construction, Vol. 19, n. 2, January 1987, pp. 31R-35R

[4] V. K. Gupta and R. S. Parmar, Fractional factorial technique to predict dimensions of the weld bead in automatic submerged arc welding, IE(I) Journal-MC, Vol. 70, Nov. 1989, pp.67-75.

[5] N. Murugan, R. S. Parmar and S. K. Sud, Effect of submerged arc welding process variables on dilution and bead geometry in single wire surfacing, J. of Material Processing Technology, Vol. 37, 1993, pp. 767-780.
[6] N. Murugan and R. S. Parmar, effects of MIG process parameters on the geometry of the bead in the automatic surfacing of stainless steel, J. of Materials Processing Technology, Vol. 41, 1994, pp. 381-398.
[7] I. S. Kim, J. S. Son, I. G. Kim and O. S. Kim, A study on relationship between process variable and bead penetration for robotic CO2 arc welding, J. of Materials Processing Tech., Vol. 136, 2003, pp. 139-145.
[8] I. S. Kim, K. J. Son, Y. S. Yang and P. K. D. V. Yaragada, Sensitivity analysis for process parameters in GMA welding processes using a factorial design method, Inter. J. of Machine Tools & manufacture, Vol. 43, 2003,pp. 763-769.
[9] L. J. Yang, M. J. Bibby and R. S. Chandel, Linear regression equations for modelling the submerged-arc welding process, J. of Materials Processing Technology, Vol. 39, 1993, pp. 33-42.
[10] C. M. D. Starling, P. V. Marques and P. J. Modenesi, Statistical modelling of narrow-gap GTA welding with magnetic arc oscillation, J. of Material Processing Technology, Vol. 51, 1995, pp. 37-49.
[11] Yang L.J. , Chandel R.S. and Bibby M.J. , 1993 “An analysis of curvilinear regression equations for modeling the submerged arc welding process”. Journal of material processing technology, vol 37, pp 601-611
[12] Kim I.S, Son J.S. , Kim I.G. , Kim J.Y. and Kim O.S. , 2003, “ A study on relationship between process variables and bead penetration for robotic CO2 arc welding”. Journal of material processing technology, vol 136, pp 139-145
[13] N. Murugan and R. S. Parmar, Effect of welding conditions on microstructure and properties of tupe 316L stainless steel submerged arc welding cladding, Welding Journal, AWS, Vol. 76, n. 5, May 1997, pp. 210-s-220-s.
[14] V. Gunaraj and N. Murugan, Prediction and comparison of the area of the heat-affected zone for the bead-on plates and bead-on-joint in submerged arc welding of pipes, J. of Materials Processing Tech., Vol. 95, 1999, pp. 246-261.
[15] E. Koleva, Statistical modelling and computer programs for optimisation of the electron beam welding of stainless steel, J. Vacuum, Vol. 62, 2001, pp. 151-157.
[16] V. Gunarai and N. Murugan, Prediction and optimization of weld bead volume for the submerged arc process part 1, Welding journal, AWS, October 2000, 286-s – 294-s.
[17] V. Gunarai and N. Murugan, Prediction and optimization of weld bead volume for the submerged arc process part2, welding journal, AWS, November 2000, 331-s – 338-s.
[18] Gunaraj and Murugan, Prediction of heat-affected zone characteristics in submerged arc welding of structural steel pipes, welding journal, AWS, January 2002, 94-s – 98-s.
[19] K .Manonmani, N. Murugan and G. Buvanasekaran, Effect of process parameters on the weld bead geometry of laser beam welded stainless steel sheets, Inter. J. for the Joining of Materials, Vol. 17, n. 4, 2005, pp.103-109.
[20] E. Koleva, Electro beam weld parameters and thermal efficiency improvement, Vacuum J., Vol. 77, 2005, pp. 413-421
[21] K. Y. Benyounis, A. G. Olabi and M. S. J. Hashmi, Effect of laser welding parameters on the heat input and weld-bead profile, J. of Materials Processing Tech., Vol. 164-165, 2005, 978-985.
[22] E. Koleva and I. Vuchkov, Model-based approach for quality improvement of electro beam welding applications in mass production, J. Vacuum, Vol. 77, 2005, pp. 423-428.
[23] T. Kannan and N. Murugan, Effect of flux cored arc welding process parameters on duplex stainless steel clad quality, J. of Material Processing Technology, Vol. 176, 2006, pp. 230-239.
[24] Gunaraj and Murugan, Prediction and control of weld bead geometry and shape relationships in submerged arc welding of pipes, J. of Materials Processing Tech., Vol. 168, 2005, 478-487.
[25] K. Andersen, G. Cook, G. Karsai nad K. Ramaswmy, Artificial neural network applied to arc welding process modelling and control, IEEE Transactions on Industry Applications, Vol. 26, n. 5, Sep./Oct. 1990, pp. 824- 830.
[26] G. Cook, R. J. Barnett, K. Andersen and A. M. Strauss, Weld modelling and control using artificial neural networks, IEEE Transactions on Industry Applications, Vol. 31, n. 6, Nov/Dec. 1995, pp. 1484-1491.
[27] J. M. Vitek, Y. S. Iskander, E. M. Oblow et al., Neural network modeling of pulsed-laser weld pool shapes in aluminum alloy welds, proceedings of 5th Inter. Conf. on Trends in Welding Research, Pine Mountain, GA, June 1-5.1998, ASM Inter., pp.442-448.
[28] S.C. Juang, Y. S. Tarng and H. R. Lii, A comparison between the back-propagation and counter-propagation networks in the modelling of the TIG welding process, J. of Material Processing Technology, Vol. 75, 1998, pp. 54-62.
[29] B. Chan, J. Pacey and M. Bibby, Modelling gas metal arc weld geometry using artificial neural network technology, J. of Canadian Metallurgical Quarterly, Vol. 38, n. 1, 1999, pp. 43-51.
[30] J. Y. Jeng, T. Mau and S. Leu, Prediction of laser butt joint welding parameters using back propagation and learning vector quantization networks, J. of Materials Processing Technology, Vol. 99, 2000, pp. 207-218.
[31] D.S. Nagesh and G. L. Datta, Prediction of weld bead geometry and penetration in shielded metal-arc welding using artificial neural networks, J. of Materials Processing Technology, Vol. 123, 2002, pp.303-312.
[32] G. E. Ridings, R. C. Thomson and G. Thewlis, Prediction of multiwire submerged arc weld bead shape using neural network modelling, J. of Science and Technology of welding and joining, Vol. 7, n. 5, 2002, pp. 265- 279.
[33] K. H. Christensen, T. SØrensen and J. K. Kristensen, Gas metal arc welding of butt joint with varying gap width on neural networks, J. of Science and Technology of welding and joining, Vol. 10, n.1, 2005, pp. 32-43.
[34] S. C. Juang and Y. S. Tarng, Process parameters selection for optimizing the weld pool geometry in the tungsten inert gas welding of stainless steel, J. of Materials Processing Technology, Vol. 122, 2002, 33-37.
[35] H. K. Lee, H. S. Han, K. J. Son and S. B. Hong, Optimization of Nd-YAG laser welding parameters for sealing small titanium tube ends, J. of Materials Science and Engineering, Vol. A415, 2006, pp. 149-155.
[36] J. Lee and K. Um, A comparison in a back-bead prediction of gas metal arc welding using multiple regression analysis and artificial neural network, J. of Optics and Lasers in Engineering, Vol. 34, 2000, pp. 149-158.
[37] S. Fraley, M. Oom, B. Terrien, and J. Z. Date, “Design of Experiments via Taguchi Methods: Orthogonal Arrays, The Michigan Chemical Process Dynamic and Controls Open Text Book, USA, 2006.
[38] S.C. Juang and Y.S. Tarng, and Y. Zhou “Welding Parameter Selection for Optimizing the Weld Pool Geometry in the Tungsten Inert Gas Welding of Stainless Steel”, International Journal of Materials Processing Technology, **122**(2002), pp. 286–290.

[39] H. Park and S. Rhee, Estimation od weld bead size in Co2 laser welding by using multiple regression and neural network, J. of Laser Application, Vol. 11. n. 3, 1999, pp.143-150.

[40] I. S. Kim, J. S. Son, C. E. Park, C. W. Lee and Y. K. D. V. Prasad, A study on prediction of bead height in robotic arc welding using a neural network, J. of Materials Processing Technology, Vol. 130-131, 2002, pp. 229-234..

[41] D. Kim, S. Rhee, and H. Park, Modelling and optimization of a GMA welding process by genetic algorithm and response surface methodology, Int. J. of Prod. Res., Vol. 40, n. 7, 2002, pp. 1699-1711.

[42] Hsuan-Liang Lin & Chang-Pin Chou**,** Optimization of the GTA Welding Process Using Combination of the Taguchi Method and a Neural-Genetic Approach**,** Journal of Materials and Manufacturing Processes Volume 25, Issue 7, 2010, pp. 631-636

[43] S Kumanan, J Edwin Raja Dhas & K Gowthaman, Determination of submerged arc welding process parameters using regression analysis and fuzzy logic, Indian Journal of Engineering & Materials SciencesVol. 14, June 2007, pp. 177-183