An Efficient Algorithm to Develop Model for Predicting Bead Width in Butt Welding

I. S. Kim and J. S. Son

Abstract

With the advance of the robotic welding process, procedure optimization that selects the welding procedure and predicts bead width that will be deposited is increased. A major concern involving procedure optimization should define a welding procedure that can be shown to be the best with respect to some standard and chosen combination of process parameters, which give an acceptable balance between production rate and the scope of defects for a given situation. This paper presents a new algorithm to establish a mathematical model for predicting bead width through a neural network and multiple regression methods, to understand relationships between process parameters and bead width, and to predict process parameters on bead width for GMA welding process. Using a series of robotic arc welding, additional multi-pass butt welds were carried out in order to verify the performance of the neural network estimator and multiple regression methods as well as to select the most suitable model. The results show that not only the proposed models can predict the bead width with reasonable accuracy and guarantee the uniform weld quality, but also a neural network model could be better than the empirical models.

Key Words: Robotic arc welding, Bead width, Process parameters, Neural network, Least square method

1. Introduction

The GMA welding process, sometimes called Metal Active Gas (MAG) welding, is a welding process that yields coalescence of metals by heating with a welding arc between continuous filler metal (consumable) electrode and the workpiece. The continuous wire electrode, which is drawn from a reel by an automatic wire feeder, and then fed through the contact tip inside the welding torch, is melted by the internal resistive power and heat transferred from the welding arc. Heat is concentrated by the welding arc from the end of the melting electrode to molten weld pools and by the molten metal that is being transferred to weld pools. Molten weld pools and electrode wire are protected from contaminants in the atmosphere by a shielding gas obtained from an externally supplied Ar, CO_2, or mixtures Ar with O_2, H_2, He, or CO_2 in various combinations[1].

Process parameters for the GMA welding should be well established and categorized for the robotic welding system. With the increase of automation in arc welding, the selection of welding procedure must be more specific to ensure that adequate bead quality is obtained. Further, to get the desired quality welds, it is essential to have a complete control over the relevant process parameters to obtain the required bead geometry and shape relationships on which is based on capacity of a weldment[2].

Numerous attempts have been reported to develop mathematical models relating process variables and bead geometry for the selection and control of the procedural variables[3-5]. Chandel[6] first applied this technique to the GMA welding process and investigated relationships between process variables and bead geometry of bead-on-plate welds deposited by the GMA welding process. These results showed that arc current has the greatest influence on bead geometry, and that mathematical models derived from experimental results can be used to predict bead geometry accurately.

Recently, Artificial Intelligence(AI) such as expert systems, artificial neural networks, fuzzy logic is a key technique for controlling and monitoring the robotic welding process. Technique of neural network offers potential as an alternative to standard computer techniques in control technology, and has attracted a widening interest in their development and application. Development of the intelligent system for prediction of process parameters for robotic arc welding has been

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Table 1 Chemical compositions of BV-AH 32 steel

C	Si	Mn	P	S	Cr	Ni	Cu	Nb	V	Mo
0.16	0.42	1.5	0.018	0.005	0.03	0.03	0.02	0.003	0.005	0.03

Table 2 Mechanical properties of BV-AH 32 steel

Yield strength (kgf/mm2)	Tensile strength (kgf/mm2)	Elongation (%)	Young's modulus (kgf/mm^2)
41.02	57.35	20	21,740

described in the literature[7-12]. Cook[13] has preliminarily worked at the development of intelligent control systems incorporating ANN(Artificial Neural Network). Also, Srikanthan and Chandel[14] proposed the steps adopted to construct the neural network model for GMA welding and evaluated the proposed neural network model.

The objectives of this study are to investigate the results obtained in a detailed experimental study regarding the effects of process parameters on bead width, to develop a new algorithm involving the use of a neural network as well as multiple regression methods in the prediction of process parameters on bead width for butt GMA welding process, and to finally select suitable model that provided the weld final configuration and properties as output and employed the process parameters as input.

2. Experimental work

A number of problems related to the robotic GMA welding process include the modeling, sensing and control of the process. Statistically designed experiments that are based upon factorial techniques, reduce costs and provide the required information about the main and interaction effects on the response factors.

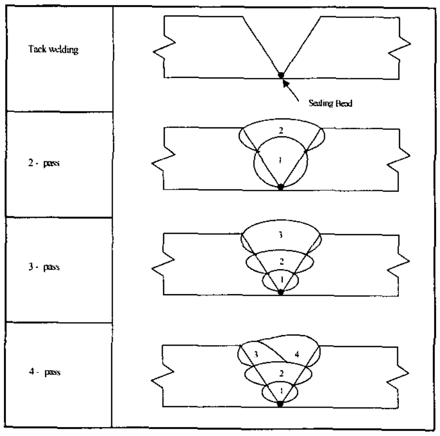

Fig.1 Welding specimen of pass number

Experiments were designed for developing a new model to correlate independently controllable process parameters. The process parameters included in this study were three levels of pass number (2, 3 and 4) shown in Fig. 1, three levels of arc current (170, 220 and 270 A), three levels of welding voltage (23, 26 and 28 V) and 12 to 50 cm/min of welding speed that depends on weld quality. All other parameters except these parameters under consideration were fixed. The welding facility was chosen as the basis for the data collection and evaluation.

The base material used for this study was the BV-AH32 steel with 12 mm in thickness for multi-pass butt welding. Chemical compositions and mechanical properties of BV-AH 32 steel are shown in Tables 1 and 2. This plate was cut into 300×200 mm pieces, and both surfaces were sand blasted to remove dirt and oxides. GMA/CO_2 welding system and an automatic traveling unit were combined to make an automatic process system. The shielding gas composition was Ar 80%, CO_2 20%. Experimental test plates were located in the fixture jig by the robot and the required weld conditions were fed for the particular weld steps in the robot path. With power supply and argon shield gas turned on, the robot was initialized and welding was executed.

This continued until experimental runs were completed. To measure the bead width, the transverse sections of each weld were cut using a power hacksaw from the mid-length position of welds, and the end faces were machined. Specimen end faces were polished and etched using a 2.5% nital solution to display bead width. The schematic diagrams of bead width employed were made using a metallurgical microscope interfaced with an image analysis system[15]. Images are represented by a 256 level gray scale, and the program can be employed to identify bead width. The fractional factorial matrix was assumed to link the mean values of the measured results with changes in the four process parameters for determining bead width. The experimental results were analyzed on the basis of relationship between process parameters and bead width of the GMA welding process. Fig. 2 identifies the major input and output parameters associated with the quality characteristics of a GMA welding process.

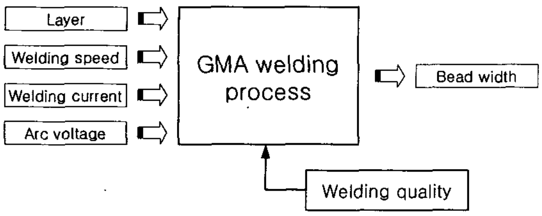

Fig.2 Input and output parameters of the GMA welding process

3. Results and discussion

3.1 Neural network model

Artificial neural network is composed of many nonlinear computational elements operating in parallel. Learning in a neural network means finding an appropriate set of weights that are connection strengths from the elements to the other layer elements. In this study, the back-propagation algorithm of neural networks, which is one of various learning modes, is employed and shown in Fig. 3. The squared error(E_p) and the weight-change equation on the output layer are given :

$$E_p = \frac{1}{2}\sum_k (T_{pk} - O_{pk})^2 \quad (1)$$

$$\frac{\partial E_p}{\partial W_{ji}} = \frac{1}{2}\sum_k \frac{\partial}{\partial W}\left(T_{pk} - O_{pk}\right)^2 = -\sum_k (T_{pk} - O_{pk}) f_k'(net_{pk}) W_{kj} f_j'(net_{pj}) X_{pj} \quad (2)$$

$$W_{kj}(t+1) = W_{kj}(t) + \alpha\delta_{pk} i_{pj} + m\Delta W_{kj}(t-1) \quad (3)$$

$$i_{pj} = \left(\frac{\partial}{\partial W_{kj}}\sum_{j=1} W_{kj} X_{pj} + \theta_k\right) \quad (4)$$

$$\delta_{pk} = T_{pk} - O_{pk} \quad (5)$$

where,

- W_{ji} : the weighting between the interconnection of the i th and j th processing
- α : the learning-rate parameter
- m : the momentum coefficient that increases the speed of convergence for learning the neural networks
- X_{pi} : an input pattern
- $f'(\ )$: a derivative of sigmoid transfer function for each layer
- T_{pk} : a teaching data
- O_{pk} : output data of the neural networks.

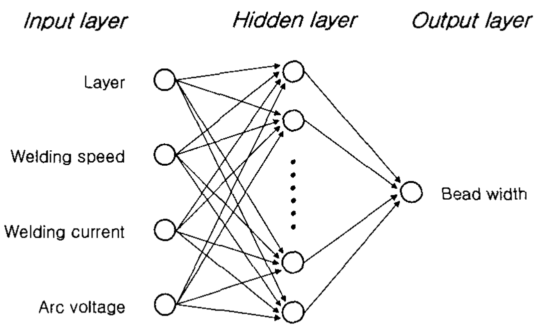

Fig.3 Optimal neural network architecture for predicting bead width

The neural networks were then trained and tested against the hidden examples. The numbers of the samples for training and testing are 54 and 27, respectively. The training process was a lengthy process conducted on a UNIX SUN workstation. With a learning rate of 0.6 and a momentum term of 0.9, the network was trained for 200,000 iterations. During the training process, connection weights increased and decreased as a neural network settled down to a stable cluster of mutually excitatory nodes.

3.2 Development of mathematical models

3.2.1 Linear model

The response variable W can be predicted by linear combination of independent variables as follows :

$$W = k_0 + k_1 \cdot I + k_2 \cdot S_1 + k_3 \cdot S_2 + k_4 \cdot S_3 + k_5 \cdot S_4 + k_6 V \quad (6)$$

where,

- W : bead width
- I : welding current
- S_1 : welding speed for 1 pass
- S_2 : welding speed for 2 pass
- S_3 : welding speed for 3 pass
- S_1 : welding speed for 4 pass
- V : arc voltage
- $k_0 k_1 k_2 k_3 k_4 k_5$: coefficients to be estimated

These analyses were carried out using a standard statistical package program, SAS in the PC[16]. Based on the regression analysis using the least square method from experimental results(bead width) and significance at the 1% level on Fisher's F-ratio that represents the actions and interactions shown to be important, the following equations can be estimated:

2 pass

$$W = -33.292 - 0.105I - 0.405S_2 + 3.250V \quad (7)$$

3 pass

$$W = 26.108 + 0.542S_2 - 0.233S_3 - 0.735V \quad (8)$$

4 pass

$$W = 84.765 + 0.392I - 0.651S_4 - 4.889V \quad (9)$$

3.2.2 Curvilinear model

The relationships between bead width as a dependent parameter and process parameters including pass number, welding speed, welding current and arc voltage as independent parameters can be expressed by following equation,

$$W = c_0 I^{c1} S_1^{c2} S_2^{c3} S_3^{c4} S_4^{c5} V^{c6} \quad (10)$$

The curvilinear equations for multi-pass are is as follows:

2 pass

$$W = 10^{-2.446} I^{-2.093} S_2^{-0.435} V^{6.510} \quad (11)$$

3 pass

$$W = 10^{2.906} S_2^{1.275} S_3^{-0.333} V^{-2.180} \quad (12)$$

4 pass

$$W = 10^{3.261} I^{4.728} S_4^{-0.884} V^{-8.238} \quad (13)$$

To check the adequacy of the developed mathematical models, the standard error of estimate, coefficient of multiple correlation and coefficient of determination for the equations (7)-(9) and (11)-(13) are given in Table 3. According to Table 3, the value of coefficient of multiple correlation of linear and curvilinear equations for 2 pass and 3 pass is higher than those of equations for 4 pass, but all equations are equally useful for prediction of bead width due to small differences.

3.3 Selecting the most accurate model

To ensure the accuracy of the developed bead width models based on a neural network and multiple regression methods and to survey the spread of the values, the experimental and theoretical results using the developed equations were compared in Figs. 4-6. The line of best fit using the plotted points was calculated using the regression. Fig. 4 shows a plot of the measured bead width versus the calculated values for 2 pass, whereas Fig. 5 presents a plot of the measured bead width versus the calculated values obtained using the developed models for 3 pass. However, the calculated values obtained using the neural network model for 4 pass showed better accurate than those of the developed models using multiple regression methods as shown Fig. 6. It is evident from these results that reasonable agreement between experimental and calculated bead width is shown even when the scatter about the calculated results using two empirical equations (linear and curvilinear) for 4 pass is considerable.

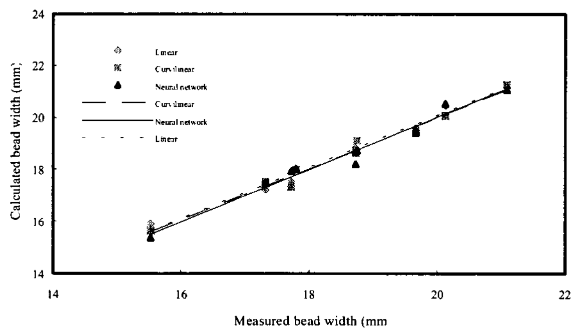

Fig.4 Comparison of measured and calculated results using a neural network and multiple regressions for 2 pass

Table 3 Analysis of variance tests for mathematical models for bead width

Number of equation	Stand error of estimate	Coefficient of multiple correlation	Coefficient of determination (%)
7	0.993	0.987	97.9
8	0.969	0.939	90.3
9	0.881	0.776	64.1
11	0.989	0.979	96.6
12	0.958	0.918	86.8
13	0.805	0.648	43.7

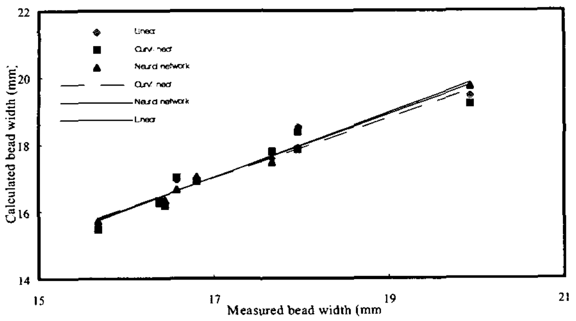

Fig.5 Comparison of measured and calculated results using a neural network and multiple regressions for 3 pass

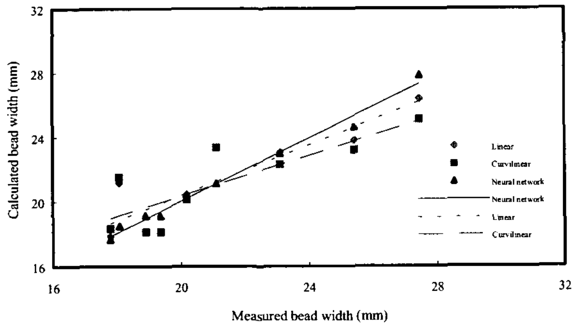

Fig.6 Comparison of measured and calculated results using a neural network and multiple regressions for 4 pass

In order to select the most accurate model, additional experiments were carried out. Table 4 showed process parameters and measured results for the additional experiment. All the predictive equations developed have been compared with their corresponding experimental results. The experimental results and welding conditions including number of pass, welding speed, arc current and welding voltage are employed as the input parameter. Output parameter is the bead width calculated by each model and the corresponding errors of prediction. To choose the most accurate algorithm, the predicted results from the established models are plotted in Fig. 7 together with the experimental results as listed in Table 4. According to Table 4 and Fig. 7, the neural network model gives the best fit to the experimental results and produced better prediction of the bead width than the developed empirical equations.

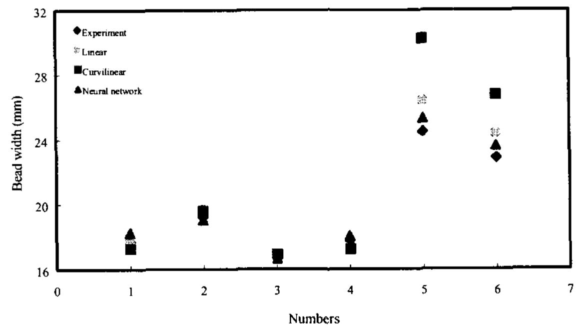

Fig.7 Comparison of measured and calculated results using a neural network and multiple regressions

4. Conclusion

The effects of process parameters on bead width have been studied using the robotic GMA welding process, and the following conclusions have been reached.

1. Process parameters such as number of pass, welding speed, arc current and welding voltage influence bead width for GMA welding process.
2. A neural network model and two regression equations (linear and curvilinear) developed from the experimental data in the course of this work can be employed to conduct a systematic study on the efficient algorithm as well as to control the process parameters in order to achieve the desired bead width. Neural network models are capable of making bead width prediction of the experimental values with reasonable accuracy.
3. The developed models are able to predict process parameters required to achieve desired bead width, to help the development of automatic control system as well as expert system, and to establish guidelines and

Table 4 Process parameters and results for the additional experiment

Trial. No.	No. of pass	Welding current(A)	Welding speed 1(cm/min)	Welding speed 2(cm/min)	Welding speed 3(cm/min)	Welding speed 4(cm/min)	Arc voltage(V)
1	2	250	26	26	-	-	27
2	2	200	22	18	-	-	25
3	3	250	34	34	34	-	27
4	3	200	27	27	22	-	25
5	4	250	37	37	45	45	26
6	4	200	28	28	33	33	24

criteria for the most effective joint design.

In this work, the developed formulae based on experimental results are valid for current process parameters and bead width. It is proposed that these models are extended to shielding gas composition, weld joint position, polarity and many other parameters which are not included in this research.

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