연구논문

신경회로망을 이용한 비드폭 예측

김일수* · 손준식* · 박창언* · 하용훈** · 성백섭**
*목포대학교 기계공학과
**조선대학교 기계공학과

Prediction of the Bead Width Using an Artificial Neural Network

Ill-Soo Kim*, Joon-Sik Son*, Chang-Eun Park*, Yong-Hun Cha** and Bach-Sub Sung**
*Dept. of Mech. Eng., Mokpo National University, Kwangju 534-729, Korea
**Dept. of Mech. Eng., Chosun University, Kwangju 501-140, Korea

Abstract

Adaptive control in the robotic GMA(Gas Metal Arc) welding is employed to monitor information about weld characteristics and process parameters as well as to modify those parameters to hold weld quality within acceptable limits. Typical characteristics are the bead geometry, composition, microstructure, appearance, and process parameters that govern the quality of the final weld.

The objectives of this paper are to realize the mapping characteristics of bead width through the neural network and multiple regression method as well as to select the most accurate model in order to control the weld quality(bead width). The experimental results show that the proposed neural network estimator can predict bead width with reasonable accuracy, and guarantee the uniform weld quality.

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Key Words : Gas metal arc welding, Adaptive control, Artificial neural, Network, Process parameters, Bead width

1. Introduction

Generally the arc welding process is very complicate due to not only the steep changes in the physical, chemical and mechanical properties, but also phase changes in a small weld pool region. A detailed knowledge of the temperature field and bead geometry is important to understand the phenomena of welding process and to develop the improved welding techniques. Therefore the effort of developing relationships between process parameters and bead width is valuable and necessary work.

Robotic arc welding processing generally involves sophisticated sensing and control techniques applied to various process parameters. An overview of modelling and control for robotic arc welding has been given by Cook et. a[1)]. Recently, Artificial Intelligence(AI) such as expert systems, artificial neural networks, fuzzy logic is a key technique for controling and monitoring the robotic welding process. Technique of neural network offers potential as an alternative to standard computer techniques in control technology, and have attracted a widening interest in their development and application. Development of the intelligent system for prediction of process parameters for arc welding has been described in the literature[2-6]. Cook[7] has preliminarily worked at the development of intelligent control systems incorporating ANN(Artificial Neural Network). Andersen[8] has implemented the models by Nunes and Tsai, and carried out comparisons of these models and evaluations against actual welding data.

The objective of the paper is to investigate the results obtained in a detailed experimental study regarding the effects of process parameters such as wire diameter, gas flow rate, welding speed, arc current, and welding voltage on bead width, and to develop a new approach involving the use of neural network and multiple regression methods in the prediction of process parameters on bead width for GMA welding process, and to finally assist guidance in selecting suitable welding conditions for particular tasks.

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 give the required information about the main and interaction effects on the response factors. 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 wire diameters (0.9, 1.2 and 1.6 mm), three levels of gas flow rate (6, 10 and 14 liter), three levels of welding speed (250, 330 and 410 mm/min) and three levels of welding voltage (20, 25 and 30 V). The arc current levels selected for 0.9 mm wire diameter were 90, 190 and 250 A, whereas the levels for 1.2 and 1.6 mm wire diameters were 180, 260 and 360 A. All other parameters except these parameters under consideration were fixed. Fig. 1 identifies the major input and output parameters associated with the quality characteristics of a GMA welding process.

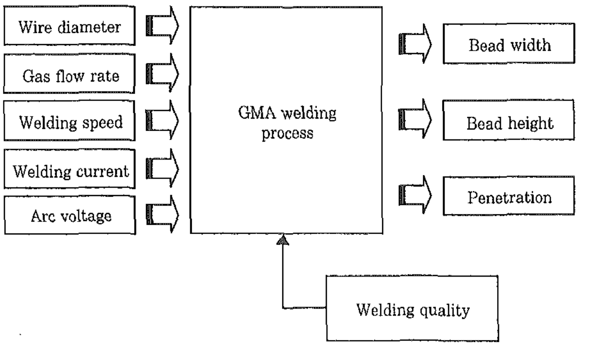

Fig. 1 Input and output parameters of the GMA welding process

The experimental materials was AS 1204 mild steel with chemical composition of C 0.25%, Si 0.4%, P 0.04% and Cu 0.05%. Steel wires with diameters of 0.9, 1.2 and 1.6 mm which have composition of C 0.5%, Mn 1.00-1.50%, Si 0.60-0.85%, S 0.035% max, P 0.025% max and Cu 0.55% max were employed as the welding consumables. The selection of the welding electrode wire was based principally upon matching the mechanical properties and physic. The welding facility was chosen as the basis for the data collection and evaluation. Experimental test plates were located in the fixture jig by the robot controller and the required weld conditions were fed for the particular weld steps in the robot path. With welder and argon shield gas turned on, the robot was initialized and welding was executed.

This continued until the predetermined-fractional-factorial-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. Images are represented by a 256 level Gray scale, and the program[9] 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 five 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.

3. Result and Discussion

3.1 The Neural Network Model

Neural networks have been widely used as a toll to approximate the "true" relationships between process parameters and bead width for GMA welding without imposing any restriction on the parameter space of the model. In other words, a neural network has its fully flexible function that approximation abilities produce a mapping between inputs and outputs, while eliminating a priori non-sample restrictions which are so commonly used to facilitate estimation.

Let us consider the neural network model shown in Fig. 2. Units in the input layer have a linear activation function. The activation rule for a unit in the hidden layer and the output layer is a non-linear monotonic function of the weighted sum of its input. x_i, as follows:

$$y_j = f(\sum_i w_{ji}x_i - q_j) \tag{1}$$

where y_i is the j-the output value, wji are the weights of connections, and qj is a bias.

We used a sigmoidal form for the activation function;

$$f(x) = 1/(1-e^{-x}) \tag{2}$$

The neural network works as a multidimensional non-linear function as a whole, which can be trained to approximate the desired input-output mapping by learning from a set of examples. Backpropagation, which is a kind of gradient-descent method, is widely employed as a learning procedure. The procedure repeatedly adjusts the weight of the connections in the network to minimize a measure of the difference between the actual output vector of the network and the desired output vector.

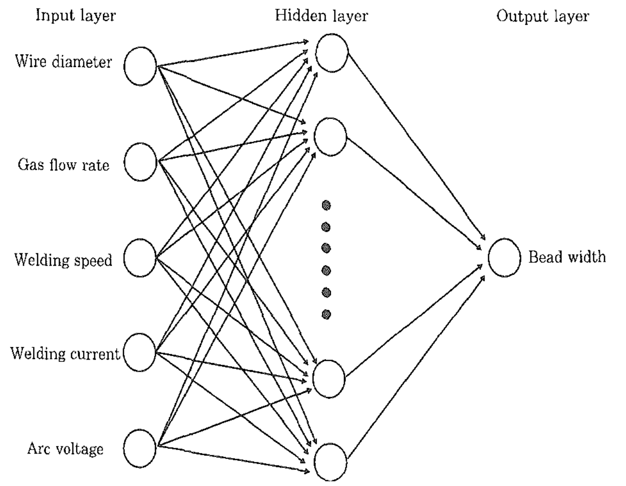

Fig. 2 Optimal neural network architecture for predicting bead width

This difference measure E is defined as

$$E = \frac{1}{2}\sum_c \sum_j (y_{j,c} - d_{j,c})^2 \tag{3}$$

where subscript c is an index over cases (input=output pairs), j is an index over output units, and d_j is the desired output value for y_j.

Each weight is changed by the following rule;

$$\Delta w = -\eta \frac{\partial E}{\partial w} \tag{4}$$

where η is the learning rate.

We used the following rule for accelerating the convergence;

$$\Delta w(n) = -\eta \frac{\partial E}{\partial w(n)} + \alpha \Delta w(n-1) \tag{5}$$

where subscript n indexes the presentation number, and α is a constant which determines the contribution of the past weight change to current weight change.

The neural networks were then trained and tested against the bidding examples. 81 samples were used for training, while 36 samples were employed for testing. 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.

To ensure the accuracy of the neural network model and to survey the spread of the values, Fig. 3 was produced for experimental versus theoretical results using the developed neural network model. The line of best fit using the plotted points was drawn using regression computation. Fig. 3 shows a plot of the measured bead width versus the calculated values obtained using the neural network model. It is evident from these results that the neural network model yields more accurate bead width.

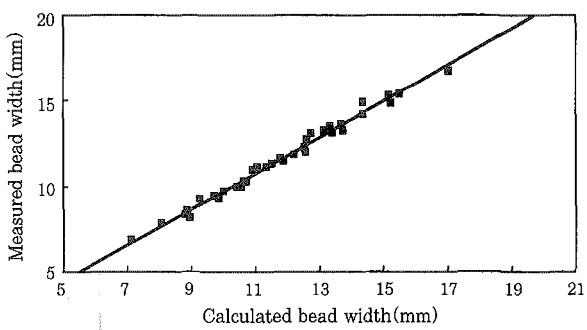

Fig. 3 Comparison of measured and calculated bead width using a neural network

3.2 Development of Mathematical Models

3.2.1 First order model

Suppose that the response variable R can be predicted by linear combination of independent variables such as wire diameter, gas flow rate, welding speed, welding voltage and arc current as follows,

$$R = k_0 + k_1 \cdot D + k_2 \cdot G + k_3 \cdot S + k_4 \cdot I + k_5 \cdot V \tag{6}$$

where R = measure bead width(mm)
D = wire diameter
G = gas flow rate
S = welding speed
I = arc current
V = welding voltage
$k_0, k_1, k_2, k_3, k_4, k_5$ = coefficients to be estimated

Eq.(7) may be represented by the following general statistical form:

$$Y = b_0 x_0 + k_1 x_1 + k_2 x_2 + k_3 x_3 + k_4 x_4 + k_5 x_5 \tag{7}$$

where b′s = estimated k parameter
x_0 = the unit column vector
x_0, x_1, x_2, x_3, x_4 and x_5 = wire diameter, gas flow rate, welding speed, arc current and welding voltage respectively.

All b parameters can be calculated by method of least squares where the basic formula is given as follow:

$$b = (X^T X)^{-1} X^T y \tag{8}$$

where b = the column vector of the estimated parameters : $b_0, b_1, b_2, b_3, b_4, b_5$
X = the calculation matrix
X^T = the transposition of X
$X^T X$ = the variance matrix
y = the column vector of the measured response(bead width)

These analyses were carried out with the help of a standard statistical package program, SAS, using an IBM compatible PC[10]. Based on the regression analysis using least square from experimental results(bead width), the following equations can be estimated:

$$W = -2.3053 + 3.513D - 0.0035G - 0.0179S + 0.0213I + 0.4331V \tag{9}$$

3.2.2 Exponential model

Suppose that the relationship between bead width as a dependent parameter and process parameters including wire diameter, gas flow rate, welding speed, arc current and welding voltage as independent parameters can be expressed by following equation,

$$R = c_0 D^{c1} G^{c2} S^{c3} I^{c4} V^{c5} \tag{10}$$

This equation can be written as,

$$lnR = ln\ c_0 + c_1 lnD + c_2 lnG + c_3 lnS + c_4 lnI + c_5 lnV \tag{11}$$

Thus, the above equation can be expressed by the following linear mathematical form,

$$\eta = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 \tag{12}$$

where η = the logarithmic value of the experimentally measured response (bead width)

β_0, β_1, β_2, β_3, β_4, β_5 = constant to be estimated

x_0 = unit column vector

x_1, x_2, x_3, x_4, x_5 = logarithmic values of wire diameter, gas floe rate, welding speed, arc current and welding voltage.

The procedure used for obtaining the predictive equation for bead width is shown below for the equations:

$$W = \frac{D^{0.3647}\ I^{0.4151}\ V^{0.9273}}{S^{0.4873}\ 10^{0.0097}} \tag{13}$$

To check the adequacy of the mathematical models, the standard error of estimate, coefficient of multiple correlation and coefficient of determination for the equations (9) and (13) are given in Table 1 which indicates that the value of coefficient of multiple correlation of equation (13) is higher than those of equations (9), but all equations are equally useful for prediction of bead width due to small differences. To ensure the accuracy of the developed equations and to survey the spread of the values, two graphs (Figs. 4 to 5) were produced for experimental versus theoretical results using the developed equations. The line of best fit using the plotted points was drawn using regression computation. Fig. 4 shows a plot of the measured bead width versus the calculated values obtained using exponential model, whereas Fig. 5 presents a plot of the measured bead width versus the calculated values obtained using linear equation. It is evident from these results that the mathematical models yields more accurate bead width.

Table 1 Analysis of variance tests for mathematical models for bead width

No. of equation	Standard error of estimate	Coefficient of multiple correlation	Coefficient of determination (%)
9	0.832	0.9697	94.04
13	0.712	0.9810	96.24

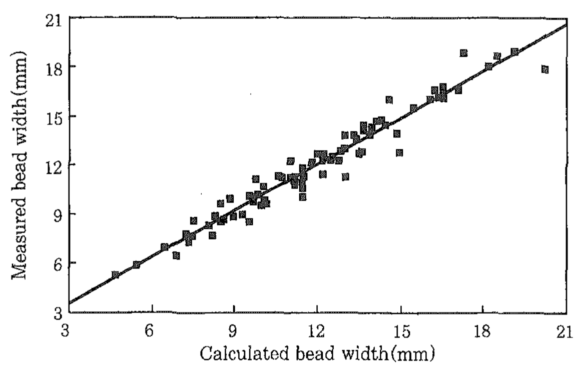

Fig. 4 Comparison of measured and calculated bead width using curvilinear equation

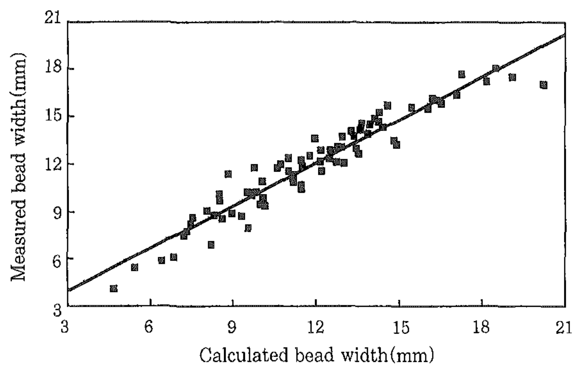

Fig. 5 Comparison of measured and calculated bead width using linear equation

3.3 Selecting the Most Accurate Model

In order to analysis the accuracy of all the developed bead width model based on a neural network and two empirical models, additional experiments ware carried out. Table 2 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 wire diameter, gas flow rate, 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. 6 together with the experimental results as listed in Table 2. As can be seen from Table 2 and Fig. 6, 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. The conclusion from the results of this analysis for the experiment runs show that theoretical results may predict the experiment values with any consistent accuracy.

4. Conclusions

The effects of process parameters on bead width have been studied when bead-on-plate welds are deposited using the robotic GMA welding process, and the following conclusions reached.

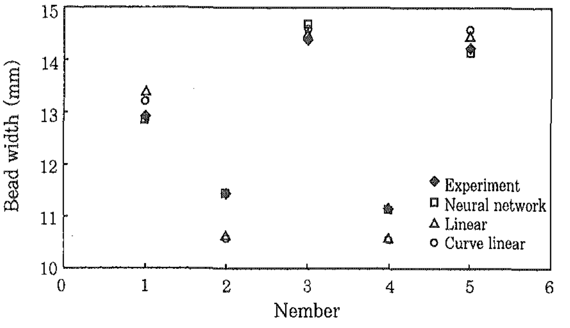

Fig. 6 Comparison of measured and calculation bead width using neural network and multiple regression method

1. Process parameters such as wire diameter, gas flow rate, welding speed, arc current and welding voltage influence the bead width for GMA welding process.
2. A neural network model and two regression equations(linear and exponential)
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 methodology presented in this paper provides an efficient algorithm to establish a general predictive bead width equations to cover the effects of different welding method and work materials. By efficient here, it means that once a the developed model has been determined, the effort for including a new welding method or work materials is only to conduct a typical set of experiments which is much less than establishing a new equation for this particular welding method or work material.

Table 2 Process parameters and results for the additional experiment

Trial. No.	Wire diameter	Gas flow rate	Welding speed	Welding current	Arc voltage	Bead width
1	0.9	6	250	190	30	12.91
2	1.2	6	330	180	25	11.46
3	1.2	10	330	260	30	14.41
4	1.6	10	410	180	25	11.17
5	1.6	14	410	260	30	14.25

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