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A New Technology for Optimization of Bead Height Using ANN

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Abstract

Objective of this paper is to develop a new approach involving the use of an Artificial Neural Network(ANN) and multiple regression methods in the prediction of process parameters on bead height for GMA welding process. Using a series of robotic arc welding, multi-pass butt welds carried out in order to verify the performance of the neural network estimator and multiple regression methods. To verify the developed system, the design parameters of the neural network estimator are selected from an estimation error analysis. The experimental results show that the proposed models can predict the bead height with reasonable accuracy and guarantee the uniform weld quality.

1. INTRODUCTION

Robotic arc welding processing generally involves sophisticated sensing and control techniques applied to various process parameters. An overview of modeling and control for robotic arc welding has been given by Cook et. Al.[1]. 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 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. 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 on bead height, and to develop a new approach involving the use of a neural network and multiple regression methods in the prediction of process parameters on bead height 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 base material used for this study was a 12mm thick BV-AH32 steel for multi-pass butt welding.
This plate was cut into 300×200mm pieces, and both surfaces were sand blasted to remove dirt and oxides. GMA/CO2 welding system and an

automatic traveling unit were combined to make an automatic process system. The shielding gas was composed Ar 80%, CO2 20%. The welding facility at the Intelligent Control Lab. in Mokpo National University was chosen as the basis for 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 height, 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 height. The schematic diagrams of bead height 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 height. The experimental results were analyzed on the basis of relationship between process parameters and bead height 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 height 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. 1. 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;

$$y_i = f(\sum_i \omega_{ji} x_i - \theta_j) \tag{1}$$

where y_i is the output value, ω_{ji} are the weights of connections, and θ_j is a bias,

We used a sigmodal 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. Back propagation, 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.

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 ac 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;

$$\varDelta\omega(n) = - \eta \frac{\partial E}{\partial \omega} \tag{4}$$

where η is the learning rate.

We used the following rule for accelerating the convergence;

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

where subscript n index the presentation number, and 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. 27 samples were used for training, while 6 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.

3.2 Development of Mathematical Models

3.2.1 First order model

Suppose that the response variable H can be predicted by linear combination of independent variables as follows,

$$H = k_0 + k_1 I + k_2 S_1 + k_3 S_2 + k_4 S_3 + k_5 S_4 + k_6 V \tag{6}$$

where H = bead height(mm)

I = Welding current

S_1 = Welding speed in pass no.1

S_2 = Welding speed in pass no.2

S_3 = Welding speed in pass no.3

S_4 = Welding speed in pass no.4

V = Arc voltage

$k_0, k_1, k_2, k_3, k_4, k_5, k_6$:coefficients to be estimated

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 height), the following equations can be estimated:

Pass2

$$H = 7.284 - 0.077C + 0.542S_1 - 0.0449S_2 \tag{7}$$

Pass3

$$H = 21.712 - 1.019V + 0.363S_2 - 0.165S_3 \tag{8}$$

Pass4

$$H = 6.161 + 0.01357C - 0.188V - 0.0685S_4 \tag{9}$$

3.2.2 Exponential model

Suppose that the relationship between bead height as a dependent parameter and process parameters including layer, welding current, welding speed, arc voltage as independent parameters can be expressed by following equation,

$$H = c_0 \cdot I^{c_1} \cdot S_1^{c_2} \cdot S_2^{c_3} \cdot S_3^{c_4} \cdot S_4^{c_5} \cdot V^{c_6} \tag{10}$$

The curvilinear equations is shown below as following :

Pass2

$$H = 10^{11.281}\ C^{-7.845}\ S_1^{5.874}\ S_2^{-0.49} \tag{11}$$

Pass3

$$H = 10^{17.365}\ C^{-16.928}\ S_2^{6.798}\ S_3^{-2.271} \tag{12}$$

Pass4

$$H = 10^{1.877}\ C^{-0.0934}\ S_2^{0.274}\ S_4^{-1.18} \tag{13}$$

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 1 which indicates that the value of coefficient of multiple correlation of linear and curvilinear equations for pass 2 and pass 3 is higher than those of equations for pass 4, but all equations are equally useful for prediction of bead height due to small differences.

3.3 Selecting the Most Accurate Model

To ensure the accuracy of the all the developed bead height model based on a neural network and two empirical models and to survey the spread of the values, three graphs (Figs. 2~4) 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. 2 shows a plot of the measured bead height versus the calculated values for two pass, whereas Fig. 3 presents a plot of the measured bead height versus the calculated values obtained using the developed models for three pass. However, the measured bead height versus the calculated values obtained using the neural network model showed better accurate than those of the developed models using multiple regression methods as shown Fig. 4. It is evident from these results that the developed models yields more accurate bead height.

In order to select the most accurate model, 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 No. of pass, welding speed, arc current and welding voltage are employed as the input parameter. Output parameter is the bead height 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. 5 together with the experimental results as listed in Table 2. As can be seen from Table 2 and Fig. 5, the neural network model gives the best fit to the experimental results and produced better prediction of the bead height 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 height have been studied using the robotic GMA welding process, and the following conclusions have been reached.

1. Process parameters such as No. of pass, welding speed, arc current and welding voltage influence the bead height 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 height. Neural network models are capable of making bead height 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 height 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.

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

No. of equation	Stand error of estimate	Coefficient of multiple correlation	Coefficient of determination (%)
7	0.34	0.923	85.2 (%)
8	0.13	0.991	98.2 (%)
9	0.27	0.886	78.5 (%)
11	0.75	0.916	83.9 (%)
12	0.49	0.974	94.9 (%)
13	0.81	0.842	70.9 (%)

Table 2 Process parameters and results for the additional experiment

Trial. No.	Pass	Welding current	Welding speed 1	Welding speed 2	Welding speed 3	Welding speed 4	Arc voltage
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

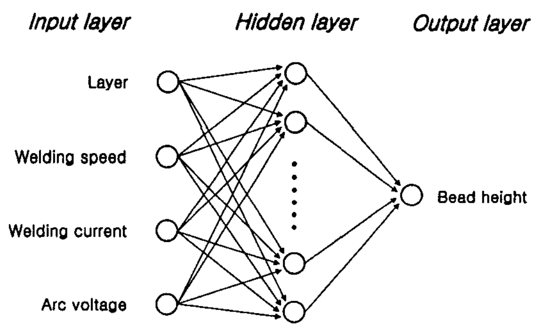

Fig. 1 Optimal neural network architecture for predicting bead height

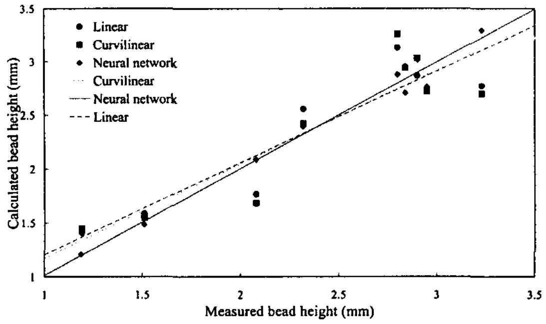

Fig. 2 Comparison of measured and calculated results using a neural network and multiple regressions for pass 2

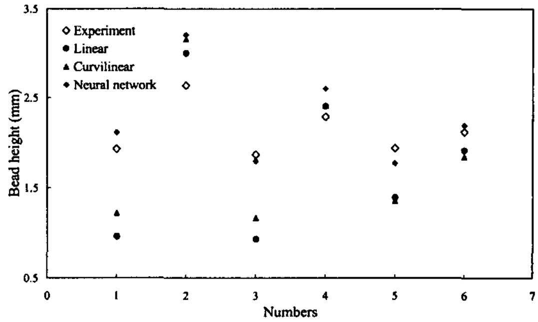

Fig. 5 Comparison of measured and calculated results using a neural network and multiple regressions

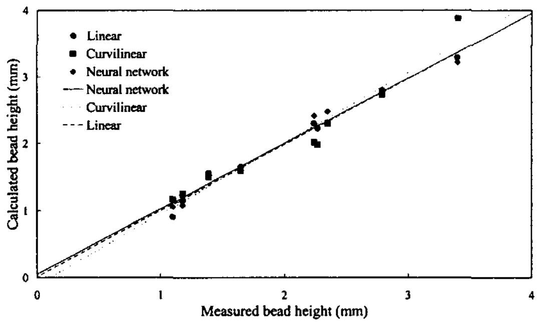

Fig. 3 Comparison of measured and calculated results using a neural network and multiple regressions for pass 3

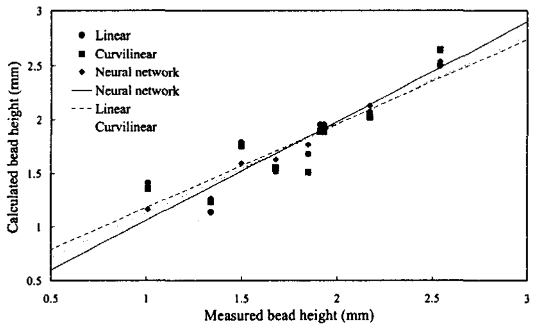

Fig. 4 Comparison of measured and calculated results using a neural network and multiple regressions for pass 4