Developed multiple linear regression model using genetic algorithm for predicting top-bead width in GMA welding process

D.T. Thao*, I.S. Kim*, J.S. Son*, J.H. Seo*

*Department of Mechanical Engineering, Mokpo National University,

16, Dorim-ri, Chungkye-myun, Muan-gun, Chonnam 534-729, South Korea

ABSTRACT

This paper focuses on the developed empirical models for the prediction on top-bead width in GMA (Gas Metal Arc) welding process. Three empirical models have been developed: linear, curvilinear and an intelligent model. Regression analysis was employed for optimization of the coefficients of linear and curvilinear model, while Genetic Algorithm (GA) was utilized to estimate the coefficients of intelligent model. Not only the fitting of these models were checked, but also the prediction on top-bead width was carried out. ANOVA analysis and contour plots were respectively employed to represent main and interaction effects between process parameters on top-bead width.

1. Introduction

It is essential to have a suitable model that establishes the interrelationship between process parameters and bead geometry as welding quality. Research on finding out these relationships is not novel. Datta at el. [1] developed statistical modeling for predicting bead volume of submerged arc butt welds. Also, Gunaraj at el. [2-3] developed mathematical models using the factorial technique for prediction and optimization of weld bead for the Submerged Arc Welding (SAW) process. Gunaraj at el. [4] developed an application of response surface methodology for predicting weld bead quality in SAW of pipes. Lee at el. [5] employed neural network and multiple linear regression methods for prediction of process parameters by prediction of back-bead geometry. Nagesh at el. [6] employed the back-propagation neural networks for prediction of bead geometry and penetration in shielded metal-arc welding.

GA, a stochastic search method, was a powerful tool to solve the optimization problems especially in various welding process. Correia at el. [7] utilized GA as a method to select the near-best values of process parameters based on geometric characteristics. Canyurt [8] developed the Genetic Algorithm Welding Strength Estimation Model (GAWSEM) to estimate the mechanical properties of the welded joint for the brass materials. Correia at el. [9] focused on comparison between GA and response surface methodology in determination of the optimal process parameters in GMA welding process. Cenman [10] employed Genetic Algorithm Welding Current Estimation Model (GAWCEM) and Genetic Algorithm Welding Velocity Estimation Model (GAWVEM) to estimate the welding current and velocity according to the welding environment for the brass material.

In this study, three empirical models: linear, curvilinear, and an intelligent model have been developed. The additional experiments were performed to verify the fitting and the prediction of these models. Graphic displays represent the effects of process parameters on top-bead width. SPSS for Windows, Matlab software and GA tool were utilized to develop these models.

2. Experimental procedure

In this study, the full factorial design was employed, the chosen process parameters were tip gap (T), gas flow rate (G), welding speed (S), arc current (I), welding voltage (V), and the response was top-bead width (W_T). The 150x200x4.5mm mild steel with SS330 materials and steel wire with a diameter of 1.2mm were employed for the experiment. Data collection and evaluation has been carried out using the robot welding facility. To measure the top-bead width as shown in Fig. 1, the specimen was cut transversely from the middle position. In order to assure the precision of the specimen dimension, it was etched by 3% HNO_3 and 97% H_20 nital solution.

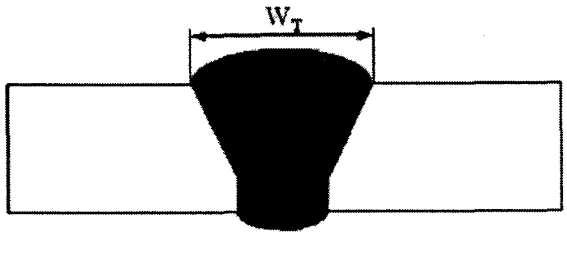


Fig. 1. Schematic diagram for measurement of top-bead width

3. Development of mathematical models

(a) Linear model:

$$Y = k_0 + k_1 T + k_2 G + k_3 S + k_4 I + k_5 V$$

(b) Curvilinear model

$$Y = c_0 T^{c_1} G^{c_2} S^{c_3} I^{c_4} V^{c_5}$$

(c) Intelligent model:

$$Y = c_0 T^{c_1} G^{c_2} S^{c_3} I^{c_4} V^{c_5} + k_0 + k_1 T + k_2 G + k_3 S + k_4 I + k_5 V$$

Y is the measured top-bead width, T tip gap, G gas flow rate, S welding speed, I arc current, V welding voltage. Also, $k_0, k_1, k_2, k_3, k_4, k_5$ and $c_0, c_1, c_2, c_3, c_4, c_5$ are coefficients.

Regression analysis was employed for optimization the coefficients of linear and curvilinear model, whereas GA was employed to search the coefficients of intelligent model

(a) Linear model

$$W_T = 7.5790.494\times T - 0.011\times G - 0.237\times S + 0.295\times I + 0.412\times V$$

(b) Curvilinear model

$$W_T = 3.142 \times T^{-0.496} \times G^{-0.006} \times S^{-0.519} \times I^{0.480} \times V^{0.8}$$

(c) Intelligent model

$$W_T = 6788.6898 \times T^{-1.6559} \times G^{-0.5369} \times S^{-2.8753} \times I^{0.7302} \times V^{1.2293} + \\ + 0.4132 - 0.2065 \times T + 0.0724 \times G - 0.0373 \times S + 0.2148 \times I + 0.3070 \times V$$

The calculated variance test for three developed empirical models listed in Table 1, and the square error of developed models are plotted out as shown in Fig. 2.

Table 1. Variance test for developed empirical models

Model	SSE	Adjusted R Square	Std. Error
Linear	5.0974	0.9530	0.4428
Curvilinear	3.1907	0.9706	0.3503
Intelligent	1.9039	0.9772	0.3085

Not only the additional experiments were performed, but also the accurate prediction of three developed model were plotted out as shown in Fig. 3. It is evident that the fitting and the prediction capabilities of intelligent model are more reliable than linear and curvilinear models.

The developed intelligent model was employed to plot out the effects of process parameters. Fig. 4 shows the main effects of each process parameters. It is clear that the effect of welding speed is very significant.

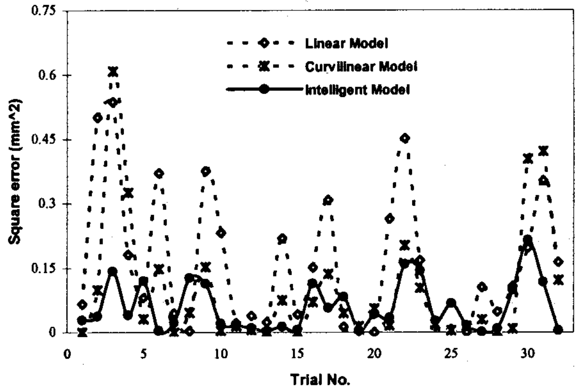


Fig. 2. The fitting of three developed models

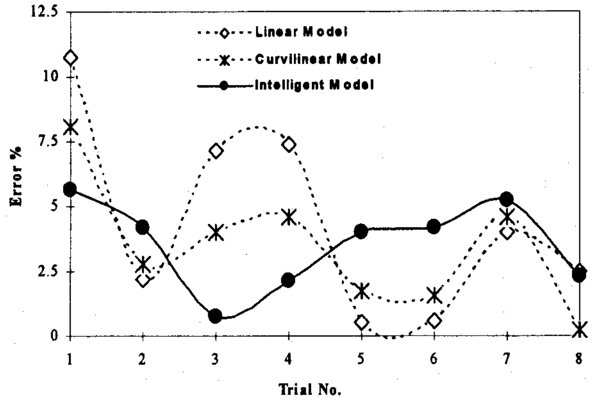
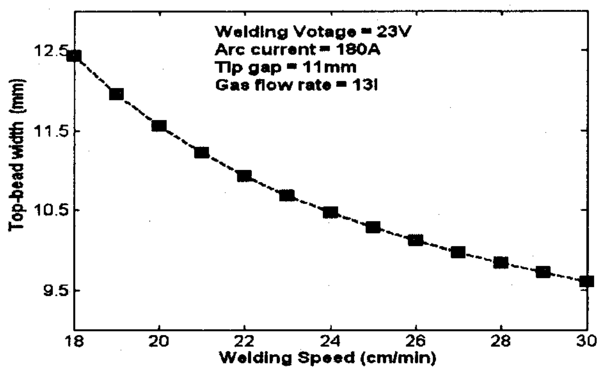
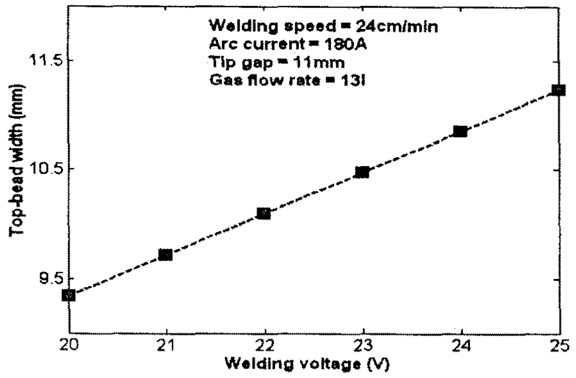


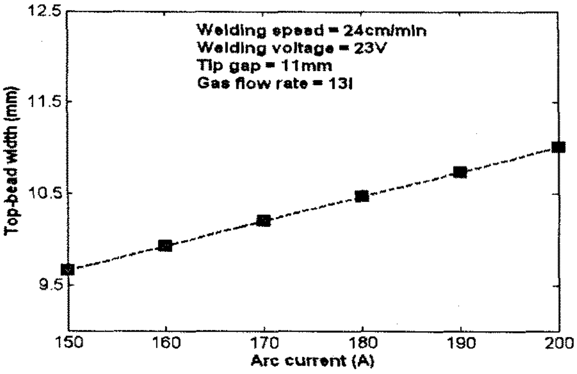
Fig. 3. The accurate prediction of developed models



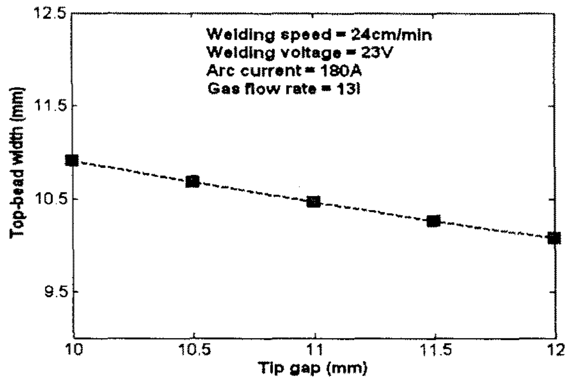
(a) Welding speed



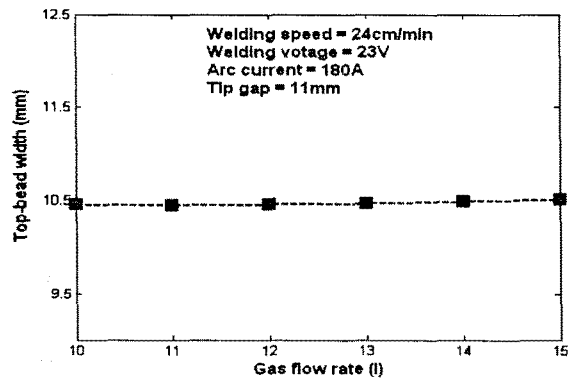
(b) Welding voltage



(c) Arc current



(d) Tip Gap



(e) Gas flow rate

Fig. 4. The effects of main process parameters

4. Conclusions

Within the experimental domain of this study, the following conclusions have been reached:

1) Welding speed has strong significant effect and interaction effects on top-bead width. Welding voltage, arc current also have significant effects, but the effect of gas flow rate is not important.

2) The intelligent model has a reliable fitting and the prediction capabilities on top-bead width and employed to solve optimization problems in GMA welding process.

3) The predicted results from the developed model and graphical representations indicate that the bead geometry can be predicted by using the intelligent model of this study.

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