ARCHIVES of
Computational Materials Science and Surface Engineering

International Scientific Journal published quarterly by the Association of Computational Materials Science and Surface Engineering

2009 • Volume 1 • Issue 4 • 237-244

Interaction model for predicting bead geometry for Lab Joint in GMA welding process

D.T. Thao, I.S. Kim*
Department of Mechanical Engineering, Mokpo National University,
16, Dorim-ri, Chungkye-myun, Muan-gun, Jeonnam 534-729, South Korea
* Corresponding author: E-mail address: ilsookim@mokpo.ac.kr

Received in a revised form 10.07.2008

ABSTRACT

Purpose: The prediction of the optimal bead geometry is an important aspect in robotic welding process. Therefore, the mathematical models that predict and control the bead geometry require to be developed. This paper focuses on investigation of the development of the simple and accuracy interaction model for prediction of bead geometry for lab joint in robotic Gas Metal Arc (GMA) welding process.

Design/methodology/approach: The sequent experiment based on full factorial design has been conducted with two levels of five process parameters to obtain bead geometry using a GMA welding process. The analysis of variance (ANOVA) has efficiently been used for identifying the significance of main and interaction effects of process parameters. General linear model and regression analysis has been employed as a guide to achieve the linear, curvilinear and interaction models. The fitting and the prediction of bead geometry given by these models were also carried out. Graphic results display the effects of process parameter and interaction effects on bead geometry.

Findings: The fitting and the prediction capabilities of interaction models are reliable than the linear and curlinear models and it was found that welding voltage, arc current, welding speed and 2-way interaction CTWD welding angle have the large significant effects on bead geometry.

Research limitations/implications: The these models developed are extended to shielding gas composition, weld joint position, polarity and many other parameters which are not included in this research in order to establish a closed loop feedback control system to minimize possible errors from uncontrolled variations.

Practical implications: The developed models apply real-time control for bead geometry in GMA welding process and perform the Design of Experiments (DOE) analysis steps in order to solve optimisation problems in GMA welding process.

Originality/value: The interaction factors, welding voltage arc current, CTWD welding angle, also imposes a significant effect on bead geometry. With the experimental data of this study, the interaction models have a more reliable fitting and better predicting than that of linear and curvilinear models.

Keywords: Bead geometry; ANOVA analysis; Regression analysis; General linear model; Interaction model

Reference to this paper should be given in the following way:

D.T. Thao, I.S. Kim, Interaction model for predicting bead geometry for Lab Joint in GMA welding process, Archives of Computational Materials Science and Surface Engineering 1/4 (2009) 237-244.

METHODS OF ANALYSIS AND MODELLING

1. Introduction

To get the desired weld quality in robotic GMA welding process, it is essential to know interrelationships between process parameters and bead geometry as a welding quality. Many efforts have been done to develop the analytical and numerical models to study these relationships, but it was not an easy task because there were some unknown, nonlinear process parameters [6]. For this reason, it is good for solving this problem by the experimental models. One of the experimental models was a multiple regression technique that was utilized to establish the empirical models for various arc welding processes [10,12]. Datta *et al.* [1] proposed multiple regression model for predicting bead volume of Submerged Arc Welding (SAW) process. Also, Gunaraj *et al.* [3,4] developed mathematical models using the five-level factorial technique for prediction and optimization of weld bead for the SAW process. And Gunaraj *et al.* [2] employed an application of response surface methodology for predicting weld bead quality in SAW for pipes.

Recently, some researches have been concentrated on using these traditional models with AI (Artificial Intelligence) techniques to solve the problem [7,8,9,11]. Kim *et al.* [7] developed an intelligent system for GMA welding process based on multiple regression and neural network. Li *et al.* [9] studied the non-linear relationship between the geometric variables and welding parameters of SAW process using the Self-Adaptive Offset Network (SAON). Tang *et al.* [11] investigated the relationship between process parameters and the features of the bead geometry for TIG (Tungsten Inert Gas) welding process using a back-propagation neural network. Lee *et al.* [8] developed a mathematical model for prediction of process parameters based on back-bead geometry using multiple regression analysis and artificial neural network. Despite the large numbers of attempts to analyze arc welding process, interaction models to study interrelationships between input and output parameters in the arc welding process are still lacking.

The objectives of this study are to develop the simple and accuracy interaction model to apply real-time control for bead geometry in GMA welding process. To achieve this goal, interaction model based on 25 full factorial design has been developed. The SPSS for Windows [14] was utilized in this study to develop a linear, curvilinear and interaction models. The models were developed and checked the fitting by variance test. The predicted bead geometry given by these developed models were compared with the experimental results based on the additional experiments. Also, graphics display the effects of process parameters and interaction of CTWD and welding angle on bead geometry as welding quality.

2. Experimental procedure

To achieve the objectives of this study, the following basic steps were carefully carried out: selecting process parameters, doing an experimental design, executing the design, and measuring the bead geometry. The chosen process parameters for this study were welding voltage, arc current, welding speed, Contact Tip to Work Distance (CTWD), welding angle, and the response factor was bead geometry.

The most important advantages of full factorial design are that not only the effects of individual parameters but also their relative importance in given process are obtained and that the interactional effects of two or more variables can also be know. In this study, full factorial design with two levels was employed not only to determine the characteristics for the main and interaction effects of the process parameters on the bead geometry as a welding quality, but also to develop empirical models. The chosen welding parameters and their values employed in this study are given in Table 1.

Table 1.
Process parameters and values

Parameter	Symbol	Unit	Values
Welding voltage	*V*	Volt	17, 19
Arc current	*I*	Amp	100, 130
Welding speed	*S*	cm/min	4.5, 5.0
CTWD	*C*	mm	12, 20
Welding angle	*A*	^{o}	55, 65

Table 2.
Chemical compositions of SS400 steel

C	Si	Mn	P	S	Cu	Cr	Ni	Fe
.47	.015	.59	.018	.0058	.04	.08	.5	Bal.

Table 3.
Mechanical properties of SS400 steel

Tensile strength (kg/mm^2)	Yield point (kg/mm^2)	Elongation (%)	Impact value (kg/cm^2)	Hardness (Hv)
45.9	40.4	38	6	126

Table 4.
Chemical compositions of welding wire

Si	C	S	P	Mn
0.41	0.09	0.011	0.012	1.10

Table 5.
Mechanical properties of welding wire

Tensile strength (kg/mm^2)	Yield strength (kg/mm^2)	Elongation (%)	Impact strength (kg/cm^2)
55	44	30	7

The base material used for this study was the 150x200x4.5mm SS400 mild steel. Chemical compositions and mechanical properties of SS400 steel are shown in Tables 2 and 3. The welding wire with a diameter of 1.2mm was utilized for the experiment.

Table 6.
Design Matrix

No	V	I	S	C	A	W	H
1	17	100	4.5	12	55	4.74	1.45
2	17	100	4.5	20	65	4.83	1.60
3	17	100	4.5	12	65	4.71	1.34
4	17	100	4.5	20	55	4.83	1.50
5	17	100	5	12	55	4.61	0.95
6	17	100	5	20	65	4.65	1.22
7	17	100	5	12	65	4.38	0.94
8	17	100	5	20	55	4.38	1.02
9	17	130	4.5	12	55	5.28	1.97
10	17	130	4.5	20	65	5.36	1.88
11	17	130	4.5	12	65	5.16	1.58
12	17	130	4.5	20	55	5.23	1.57
13	17	130	5	12	55	4.87	1.39
14	17	130	5	20	65	4.98	1.31
15	17	130	5	12	65	4.64	1.11
16	17	130	5	20	55	4.77	1.26
17	19	100	4.5	12	55	5.25	1.53
18	19	100	4.5	20	65	5.35	1.46
19	19	100	4.5	12	65	4.91	1.24
20	19	100	4.5	20	55	4.93	1.25
21	19	100	5	12	55	4.72	0.91
22	19	100	5	20	65	4.89	1.06
23	19	100	5	12	65	4.47	0.75
24	19	100	5	20	55	4.63	0.81
25	19	130	4.5	12	55	5.77	1.73
26	19	130	4.5	20	65	5.95	1.71
27	19	130	4.5	12	65	5.42	1.46
28	19	130	4.5	20	55	5.45	1.49
29	19	130	5	12	55	5.23	1.23
30	19	130	5	20	65	5.37	1.28
31	19	130	5	12	65	5.31	1.21
32	19	130	5	20	55	5.25	1.15

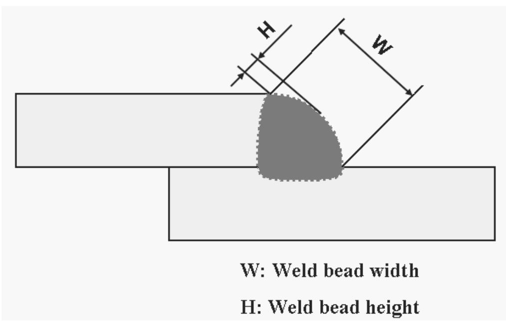


Fig. 1. Diagram for measurement of bead geometry

Also, Tables 4 and 5 represent the chemical compositions and mechanical properties of welding wire. The experiment has been carried out using the robot welding facility for data collection and evaluation.

To measure the bead geometry as shown in Fig. 1, the specimen was cut transversely from the middle position using a wire-cutting machine. In order to assure the precision of the specimen dimension, it was etched by 3% HNO_3 and 97% H_20 nital solution to display bead width. A metallurgical microscope interfaced with an image analysis system and the program [13] can be employed to measure the bead geometry.

Since the experimental design involves five variables at two levels, the full factorial of the type 32 has been applied as shown in Table 6.

3. Development of empirical models

3.1. Weld bead width

Interaction model that includes the interaction term provides a better description of the relationship between the independent and dependent variables. The inclusion of the interaction term will offer a more accurate estimation of the relationship and explain more of the variation in the dependent variable. Generally, with a 25 full factorial design, the full model contains a mean term, 5 main effect terms, 10 2-way interaction terms, 10 3-way interaction terms, 5 4-way interaction terms and the 5-way interaction term. To maximize adjusted R-Squared with the smallest number of independent variables, multiple regression analysis (with Enter, Remove, Forward, Backward, or Stepwise method) can be employed to determine the best fit model. This can be done if the interaction terms had been created beforehand. However, creating these variables can be tedious when analyzing models that contain a large number of interaction terms. In this study, General Linear Model (GLM) was employed to test interaction terms and the fit of the model. This procedure provides regression analysis and analysis of variance for one dependent variable by one or more factors and/or variables. Table 7 is the results of GLM analysis output from this analysis.

The factors of interaction model were chosen based on observed Fisher's values or p values (probability of significant) and adjusted R square from GLM analysis. To determine whether the factors have a significant effect, their p values can be compared with 2 probability level α of 0.05 and 0.01, respectively. If the p value is less than or equal to 0.05 or 0.01 for any independent, it is concluded that that variable does have a significant on the dependence variable. Also, this can be done by compare their F value with Fisher's value [$F_{0.05}$ (df1, df2)] and [$F_{0.01}$ (df1, df2)] from standard F tables.

According to Table 7, at the 95% confidence level, V, I, S, C variables and VI, CA interaction terms were significant on bead width. These factors will significantly increase the predictive power of the interaction model and the following interaction model was chosen with assumption that it was adequate at the 95% confidence level:

$$Y = \beta_0 + \beta_1 V + \beta_2 I + \beta_3 S + \beta_4 C + \beta_5 VI + \beta_6 CA \tag{1}$$

In which, Y is the measured bead width in [mm], Vwelding voltage in [Volt], I arc current in [Amp], S welding speed in [dm/min],C CTWD in [mm], and A welding angle in [^{o}].
Also, $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ are coefficients.

To compare the fitting and predicting of interaction model, the linear and curvilinear models were also been developed as the follow:

Linear model:

$$Y = k_0 + k_1 V + k_2 I + k_3 S + k_4 C + k_5 A \tag{2}$$

Curvilinear model:

$$Y = c_0 V^{c_1} I^{c_2} S^{c_3} C^{c_4} A^{c_5} \tag{3}$$

Where, $k_0, k_1, k_2, k_3, k_4, k_5$ and $c_0, c_1, c_2, c_3, c_4, c_5$ are coefficients to be estimated for the models, respectively.

The values of the coefficients of equations (1,2,3) were calculated by using regression analysis.

For linear model:

$$W = 3.30521 + 0.17125 \times V + 0.01617 \times I - 0.7525 \times S + \\ + 0.01078 \times C + 0.00275 \times A \tag{4}$$

For curvilinear model:

$$W = 0.37446 \times V^{0.60535} \times I^{0.36761} \times S^{-0.71219} \times \\ \times C^{0.03375} \times A^{0.02864} \tag{5}$$

For interaction model:

$$W = 9.68021 - 0.17375 \times V - 0.03783 \times I - 0.7525 \times S - \\ - 0.01756 \times C + 0.003 \times VI + 0.000472 \times CA \tag{6}$$

Table 7.
ANOVA for the model of weld bead width

Source	DF	F	p	Probability level	
				$\alpha = 0.05$	$\alpha = 0.01$
Corrected	7	67.701	.000		
Intercept	1	85727.397	.000	Sig.	Sig.
V	1	100.163	.000	Sig.	Sig.
I	1	200.848	.000	Sig.	Sig.
S	1	120.875	.000	Sig.	Sig.
C	1	6.352	.019	Sig.	Insig.
A	1	.646	.430	Insig.	Insig.
V * I	1	6.916	.015	Sig.	Insig.
C * A	1	38.105	.000	Sig.	Sig.
Error	24				
Total	32				
Corrected	31				

[$F_{0.05}(1,24)$]= 4.2597, [$F_{0.01}(1,24)$] = 7.823, DF: Degrees of freedom

3.2. Weld bead height

Table 8 is the ANOVA analysis output for the weld bead height. As seen in Table 8, at the 95% and 99% confidence level, V, I, S, variables and CA interaction factors were significant on weld bead height and it can be assumed that the chosen interaction model for the weld bead height was adequate at the 95% and 99% confidence level.

Table 8.
ANOVA analysis for the model of weld bead height

Source	DF	F	p	Probability level	
				$\alpha = 0.05$	$\alpha = 0.01$
Corrected Model	6	67.623	.000		
Intercept	1	8805.598	.000	Sig.	Sig.
V	1	16.255	.000	Sig.	Sig.
I	1	90.737	.000	Sig.	Sig.
S	1	251.578	.000	Sig.	Sig.
C	1	2.986	.096	Insig.	Insig.
A	1	.018	.895	Insig.	Insig.
C * A	1	44.166	.000	Sig.	Sig.
Error	25				
Total	32				
Corrected Total	31				

$[F_{0.05}(1,25)] = 4.2417$, $[F_{0.01}(1,25)] = 7.770$

The followings are the developed models for the weld bead height.

Linear model:

$$H = 5.493542 - 0.056875\times V + 0.008958\times I - 0.895\times S + \\ + 0.006094\times C - 0.000375\times A \tag{7}$$

Curvilinear model:

$$H = 36.40916\times V^{-0.81152}\times I^{0.8209}\times S^{-3.30484}\times \\ \times C^{0.09126}\times A^{0.00268} \tag{8}$$

Interaction model:

$$H = 5.455622 - 0.056875\times V + 0.008958\times I - \\ - 0.895\times S + 0.000118\times CA \tag{9}$$

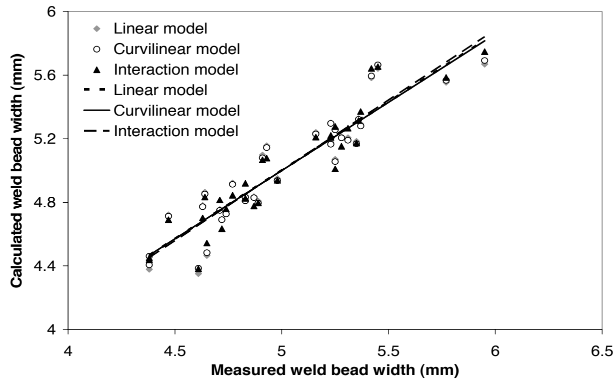
In order to compare the fitting of linear, curvilinear and interaction models, the variance test for all developed equations are given in Table 9.

From Table 9, with highest adjusted R square of 85.7% for weld bead width (W) and 82% for weld bead height (H), it is evidence that the interaction models (Int.) do have a better fitting on the experimental data than the linear (Lin.) and curvilinear (Cur.) models. This is an improvement over the linear model that including only the main effect terms. And all the models are adequate since the adjusted R square for the developed equations show agreement of greater than 80%. Fig. 2 shows a plot of comparison between the calculated and measured bead geometry using three developed models (linear, curvilinear and interaction model) in which the line of best fit using the plotted points was calculated using the regression.

Table 9.
Analysis of variance tests for developed models

Bead geometry	Model	Adj. R Square	F value	P value	Adequate of model
W	Lin.	0.835	32.312	0.000	Adequate
	Cur.	0.841	33.816	0.000	Adequate
	Int.	0.857	31.871	0.000	Adequate
H	Lin.	0.809	27.183	0.000	Adequate
	Cur.	0.803	26.274	0.000	Adequate
	Int.	0.820	36.202	0.000	Adequate

a)



b)

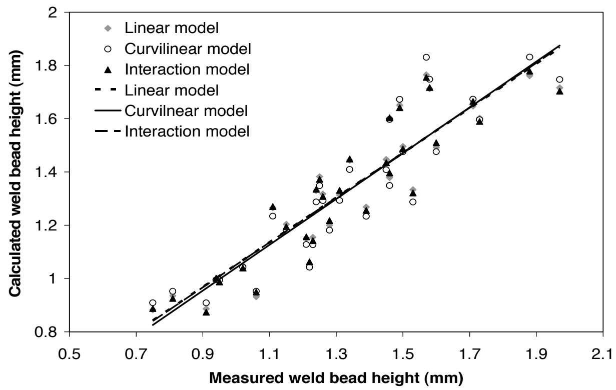


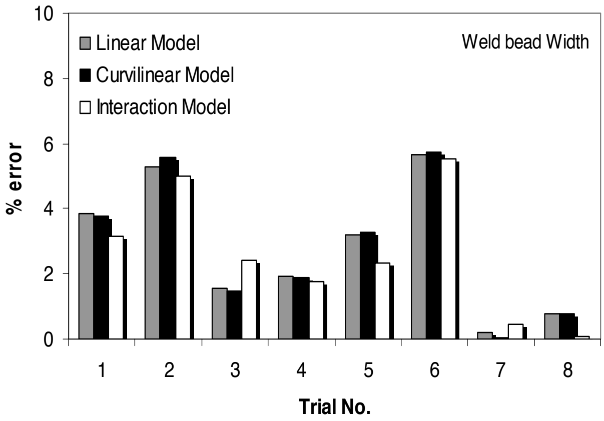
Fig. 2. Comparison of measured and calculated results for bead geometry; a) Weld bead width, b) Weld bead height

4. Results and discussion

In order to check the reliable model to predict and verify the developed models, the additional experiments were performed. The values of five process variables chosen for the additional experimental runs and the experimental results were shown in Table 10. Other experiment conditions were the same as the original experiment conditions. The percentage deviation was employed to judge the predictive power of all developed models. The results of this analysis for the bead geometry are presented in Fig.3.

This analysis indicates that the interaction produced better predicting on weld bead geometry than the linear and curvilinear models.

a)



b)

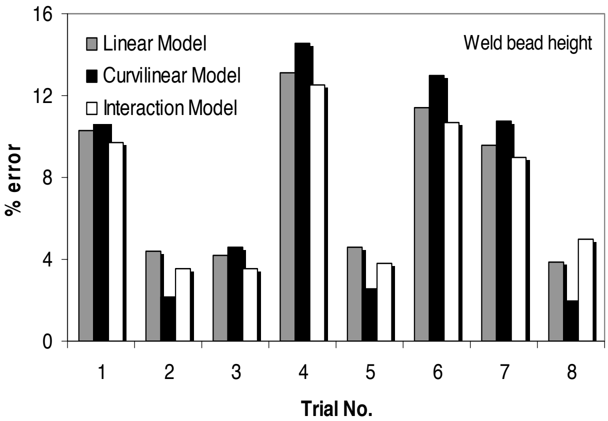
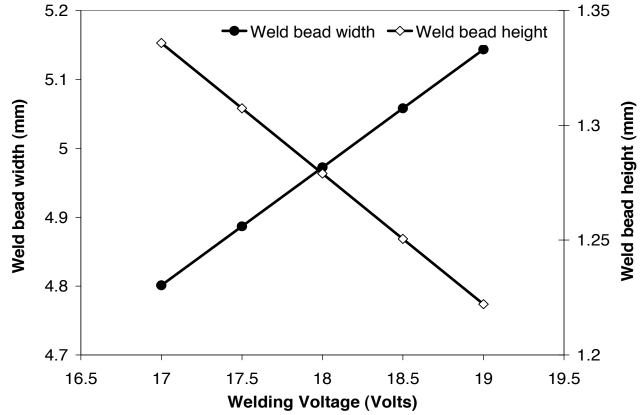


Fig. 3. Predictable accuracy of the developed models for additional experiments; a) Weld bead width, b) Weld bead height

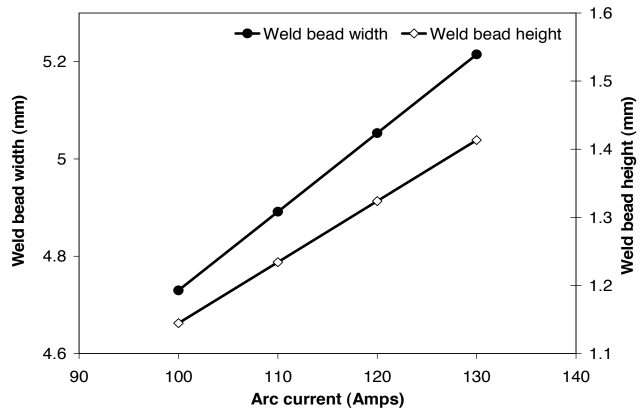
Table 10.
Process variables and experimental data of additional experiments

No.	V	I	S	C	A	W	H
1	17	110	4.6	15	65	5.07	1.63
2	17	110	4.8	18	55	4.49	1.25
3	17	120	4.6	18	55	5.12	1.51
4	17	120	4.8	15	65	4.98	1.58
5	19	110	4.6	18	55	5.06	1.31
6	19	110	4.8	15	65	5.37	1.32
7	19	120	4.6	15	65	5.39	1.59
8	19	120	4.8	18	65	5.3	1.23



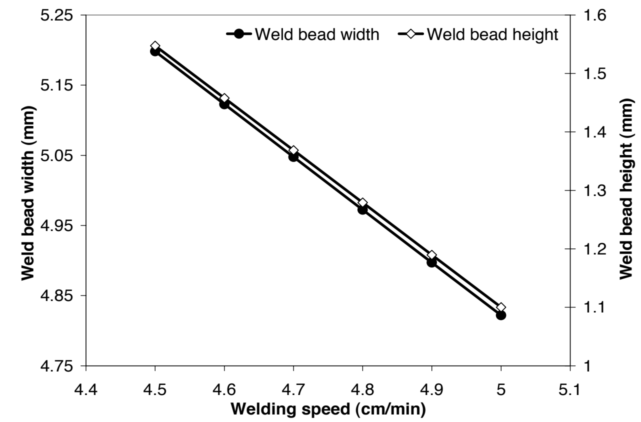
I = 115 Amps, S = 4.8 dm/min, C = 16 mm, A =60^o

Fig. 4. Effect of welding voltage on bead geometry



V = 18 Volts, S = 4.8 dm/min, C = 16 mm, A = 60^o

Fig. 5. Effect of arc current on bead geometry



V = 18 Volts, I = 115 Amps, C = 16 mm, A = 60^o

Fig. 6. Effect of welding speed on bead geometry

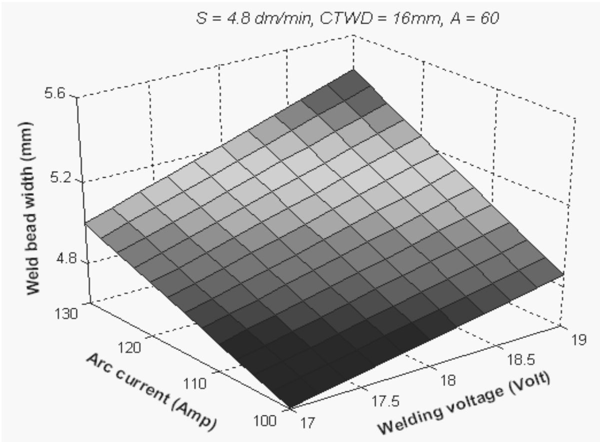


Fig. 7. Interaction effect of welding voltage and arc current on weld bead width

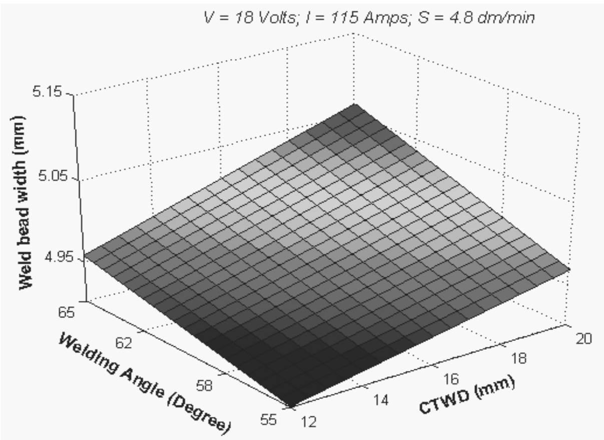


Fig. 8. Interaction effect of CTWD and welding angle on weld bead width

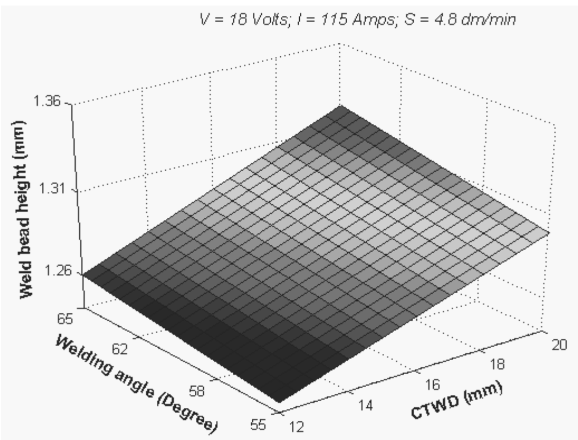


Fig. 9. Interaction effect of CTWD and welding angle on weld bead height

From the results obtained from the developed mathematical models based on experimental data and additional experiments for this study, it is evident that the fitting and the prediction capabilities of interaction models are reliable than the other ones.

Interaction models were employed to show graphically the main and interaction effects of process parameters on bead geometry within the range studied. Figs. 4, 5, and 6 show the main effects of welding voltage, arc current and welding speed, respectively on bead geometry. The increase in welding voltage was caused to increase the weld bead width but resulted in a decrease in weld bead height as indicated in Fig. 4. Also, the increase in arc current results in increase the bead width and bead height, while welding speed increases with decrease in the width and the height as indicated in Figs 5-6. As can be seen in Fig. 4-6, all the rates of change on bead geometry with the increase in welding voltage, arc current and welding speed are high, that mean the effects of these process parameters very significant.

The effects of welding voltage and arc current on weld bead width have been shown in Fig. 7. The process parameters such as welding speed at 4.8 dm/min, CTWD of 16mm, welding angle of 60^{o} are taken as constant. Because the positive effects of welding voltage (arc current), the weld bead width increases as welding voltage (arc current) increase for all values of arc current (welding voltage). As a result from surface plot, observed weld bead width becomes minimum (4.6 mm) when welding voltage is at 17 Volts and arc current is at 100 Amps. For the value of welding voltage (19 Volts), the bead width is maximum (5.43 mm) when the value of arc current is at 130 Amps.

The effects of CTWD and welding angle on weld bead geometry have been shown in Figs. 8-9. From these observed surface plots, the effect between CTWD and welding angle on bead geometry also is significant.

5. Conclusions

The full factorial design used in combination with the two levels with five parameters was employed to investigate effects of process parameters on bead geometry and develop three empirical models. The two-level factorial technique can be employed easily to develop the empirical models for prediction of bead geometry within the workable boundary. Welding voltage, arc current, welding speed and 2-way interaction CTWD$\times$welding angle have the large significant effects on bead geometry. With the experimental data of this study, the interaction models have a more reliable fitting and better predicting than that of linear and curvilinear models. Also, SPSS for Windows can be effectively used to perform the Design of Experiments (DOE) analysis steps and solve optimization problems in GMA welding process. The models developed are extended to many other parameters, which are not included in this research to establish a closed loop feedback control system to minimize possible errors from uncontrolled variations.

Acknowledgements

This paper was supported by the 2006 research funds from Mokpo National University.

References

[1] S. Datta, M. Sundar, A. Bandyopadhyay, P.K. Pal, S.C. Roy, G. Nandi, Statistical modeling for predicting bead volume of submerged arc butt welds, Australasian Welding Journal 51/2 (2006) 39-47.

[2] V. Gunaraj, N. Murugan, Application of response surface methodology for predicting weld bead quality in submerged arc welding of pipes, Journal of Materials Processing Technology 88/1-3 (1999) 266-275.

[3] V. Gunaraj, N. Murugan, Prediction and optimization of weld bead volume for the Submerged Arc Process - Part 1, Welding Journal 8 (2000) 286-294.

[4] V. Gunaraj, N. Murugan, Prediction and optimization of weld bead volume for the Submerged Arc Process - Part 2, Welding Journal 11 (2000) 331-338.

[5] A.A. Hopgood, Intelligent systems for engineers and scientists, CRC Press, Boca Raton London New York Washington, D.C., 2001.

[6] D. Kim, M. Kang, S. Rhee, Determination of optimal welding conditions with a controlled random search procedure, Welding Journal 8 (2005) 125-130.

[7] I.S. Kim, J.S. Son, C.E. Park, I.J. Kim, H.H. Kim, An investigation into an intelligent system for predicting bead geometry in GMA welding process, Journal of Materials Processing Technology 159/1 (2005) 113-118.

[8] J.I. Lee, K.W. Um, A prediction of welding process parameters by prediction of back-bead geometry, Journal of Materials Processing Technology 108/1 (2000) 106-113.

[9] P. Li, M.T.C. Fang, J. Lucas, Modelling of submerged arc welding bead using self-adaptive offset neural network, Journal of Materials Processing Technology 71 (1997) 288-298.

[10] J. Raveendra, R.S. Parmar, Mathematical models to predict weld bead geometry for flux cored arc welding, Metal Construction 19/2 (1987) 31-35.

[11] Y.S. Tang, H.L. Tsai, S.S. Yeh, Modelling, optimization and classification of weld quality in tungsten inert gas welding, Journal of Materials Processing Technology 39 (1999) 1427-1438.

[12] L.J. Yang, R.S. Chandel, M.J. Bibby, The effects of process variables on the weld deposit area of submerged arc welds, Welding Journal 72/1 (1993) 11-18.

[13] Image Analysis User's Manual, Rail, Macrail Automatrix Inc., 1990.

[14] SPSS for Windows. Release 12.0.1, 2003.