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Development of the intelligent algorithm to control on-line bead height for robotic welding process

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Analysis and modelling

ABSTRACT

Purpose: The demand to increase productivity and quality, the shortage of skilled labour and strict health and safety requirements finally led to the development of the robotic welding process to deal with many problems of the welded fabrication. Many techniques were developed to control process parameters to get the optimal bead geometry during welding process by minimizes their magnitude in the affected area.
Design/methodology/approach: The development of thermo mechanical mechanism in some techniques is not fully understood. To solve this problem, we have carried out the sequential experiment based on a Taguchi method and identified the various problems that result from the robotic GMA welding process.
Findings: To characterize the GMA welding process and establish guidelines for the most effective joint design. Also using multiple regression analysis with the help of a standard statistical package program, SPSS, on an IBM-compatible PC, a quadratic model has been developed for on-line control which studies the influence of process parameters on bead height and compares their influences on the bead height to see which one of process parameters is most affecting.
Originality/value: This model developed has been employed the prediction of optimal process parameters and assisted in the generation of process control algorithms.
Keywords: Robotic GMA welding; Empirical model; On-line control; Welding quality

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1. Introduction

Arc welding is generally accepted today as the preferred joining technique and commonly chosen for assembling most large metal. Apart from the utilized joining technology and in particular from the heat it permits to obtain effective joints with short process times and what is more it is easily developed through robots and automated systems [1]. As far as the process parameters are regarded, both geometrical and technological aspects have to be considered: both the former and the latter affect the material flow during the process and the generated heat flux. Several algorithms to control welding quality, productivity, micro-structure and weld properties in arc welding processes have been studied [2]. However, it is not an easy task to apply them for the various practical situations because not only the relationship between the welding parameters and the bead geometry is non-linear, but also they are usually dependent on the specific experimental results. Practically, it is important to know how to establish a mathematical model that can apply for the actual welding process and how to select the optimum welding condition under a certain constraint.

In recent years, the neural network has become a very powerful technique to develop a model to express interrelationship between the input and the output of complicated systems [3]. The neural network has learning and generalization capabilities so that the prediction of the correlation between the input as the examples and the expected output can be established systematically. After a certain amount of training process, the neural network can generate appropriate output in response to new input [4]. This capability guarantees the neural network to be a useful tool in many applications in current manufacturing industries covering the design phase through control, monitoring and scheduling to quality assurance [5].

Many researchers [6-14] have attempted to employ the neural network to apply for the various applications in the welding area. Cook [6] preliminarily worked at the development of intelligent welding control systems incorporating Artificial Neural Network (ANN). Juang et al. [7] explored the back-propagation and counter-propagation networks to associate the welding parameters with the features of the bead geometry, and concluded that the counter-propagation network has better learning ability than the back-propagation network for the Tungsten Inert Gas (TIG) welding process. Nagesh and Datta [8] applied the back-propagation neural network to predict the bead geometry in shielded metal-arc welding process. They claimed that the neural network might be employed a workable model to predict the bead geometry under a given set of welding conditions. Also, Li et al. [9] modelled the non-linear relationships between the five geometric variables and three welding parameters of Submerged Arc Welding (SAW) process using the Self-Adaptive Offset Network (SAON). Tarng et al. [10] studied relationships between welding parameters and the features of the bead geometry for TIG welding process. Jeng et al. [11] predicted the welding parameters in laser butt welding using the back-propagation and Learning Vector Quantization (LVQ) neural network. Kim et al. [12-13] have employed the back-propagation neural network to predict bead geometry for GMA welding process and shown that the design parameters of the neural network can be chosen from an error analysis, and the developed neural network model can predict the bead geometry with reasonably high accuracy.

This paper has been concentrated on the data analysis which was carried out by multiple regression analysis to develop the on-line empirical model. Multiple regression analysis was employed to investigate relationships between the welding parameters and bead height in the GMA welding process. Also the developed on-line empirical model was employed to predict the bead height. By using this method developed, the conventional empirical model's problem and solution have been searched.

2. Experimental details

In The GMA welding process, a very complex process which involves many scientific and engineering disciplines, has been employed to join any metal using many joint conrations, and in all welding positions [10].

In this study, the experimental materials were 200×70×12 mm steel SS400 plates with 60° groove. The chosen process parameters were arc voltage, welding speed and welding current with three levels.

The factors and their values could be seen in Table 1. The interaction effects between welding parameters are neglected. In this study, L27 orthogonal array was employed. The selection of the electrode wire should be based principally upon matching the mechanical properties and physical characteristics of the base metal. 1.2mm flux-cored wire diameters and 100% CO_2 shielding gas was employed in experiment.

The welding facility at the Welding and Intelligent Control Lab in Mokpo National University was chosen as the basis of the data collection and evaluation. In the process of the experiments the Daewoo ABB1500 robot manipulator with a GMA welding unit was employed in the experiment work. The welding facility was chosen for the data collection and evaluation. Equipment to measure the distributions of the weld surface temperature was included infrared thermometers, arc monitoring system and desktop computer. Three infrared thermometers were employed to detect temperature in the vicinity of the weld pool. Experimental test plates were located in the fixture jig by the robot controller and the required input weld conditions were fed into the particular weld steps. With welder and shield gas turned on, the robot was initialized and welding was executed. This continued until the Taguchi experimental design runs were completed.

Table 1.
Factors and their levels for experiment

Sample	Process process	Level 1	Level 2	Level3
V	Arc voltage (V)	26	28	30
S	Welding speed (cm/min)	8	10	12
C	Welding current (A)	240	260	280

To measure the bead height, the bead section 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_2O nital solution. The schematic diagrams of bead height employed were made using a metallurgical microscope interfaced with an image analysis system.

3. Results and discussion

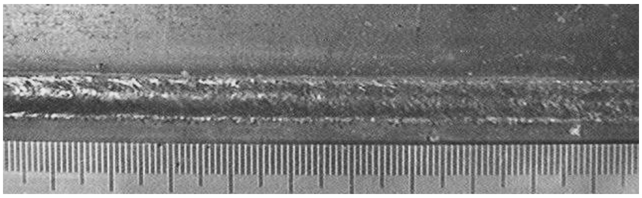
3.1. Analysis of experiment results

27 welded samples from SS400 mild steel adopting the butt welding were employed for this research because the workpiece offered a convenient reference plane for measurement of bead height, and the influences arising from joint preparation were removed. The chemical composition of weld material and the wire diameter were the same employed in calibration test. The typical experimental results of bead geometry according to change the welding conditions

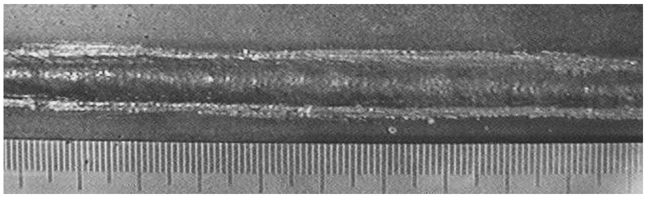
are shown in Figure 1. Also Figure 2 shows the experimental results of the measured bead geometry using 3D scanner.

The measured bead geometry has been transferred into bead height to compare the predicted bead geometry. The tests have been carried out with 250 samples in stable weld section for each experiment. The bead dimensions for test section were represented in Figure 3. The relationship between the welding parameters and bead height could be investigated and the welding parameters for the optimal bead height for the GMA welding could be determined.

a) Trial No. 6 (S = 12 mm/sec, V = 28 V, C = 240 A)



b) Trial No. 14 (S = 10 mm/sec, V = 28 V, C = 260 A)



c) Trial No. 25 (S = 8 mm/sec, V = 30 V, C = 280 A)

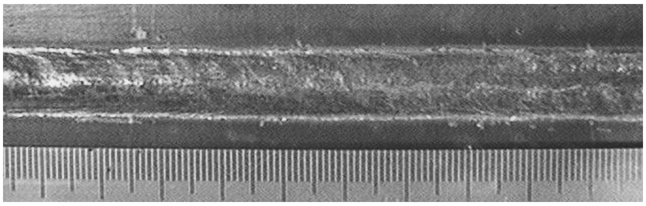
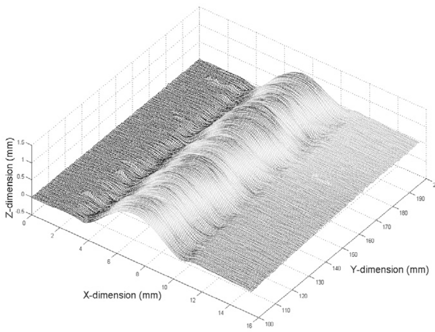
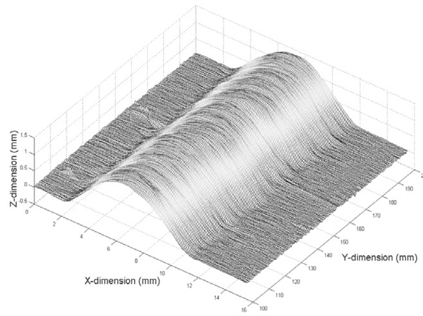


Fig. 1. The Typical bead geometry measured

a) Trial No. 6 (S = 12 mm/sec, V = 28 V, C = 240 A)



b) Trial No. 14 (S = 10 mm/sec, V = 28 V, C = 260 A)



c) Trial No. 25 (S = 8 mm/sec, V = 30 V, C = 280 A)

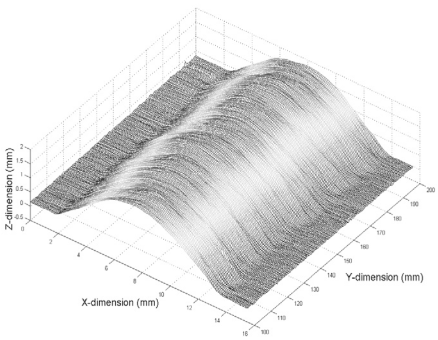


Fig. 2. The measured bead geometry using a 3D scanner in original experiment

a) Trial No. 6 (S = 12 mm/sec, V = 28 V, C = 240 A)

b) Trial No. 14 (S = 10 mm/sec, V = 28 V, C = 260 A)

c) Trial No. 25 (S = 8 mm/sec, V = 30 V, C = 280 A)

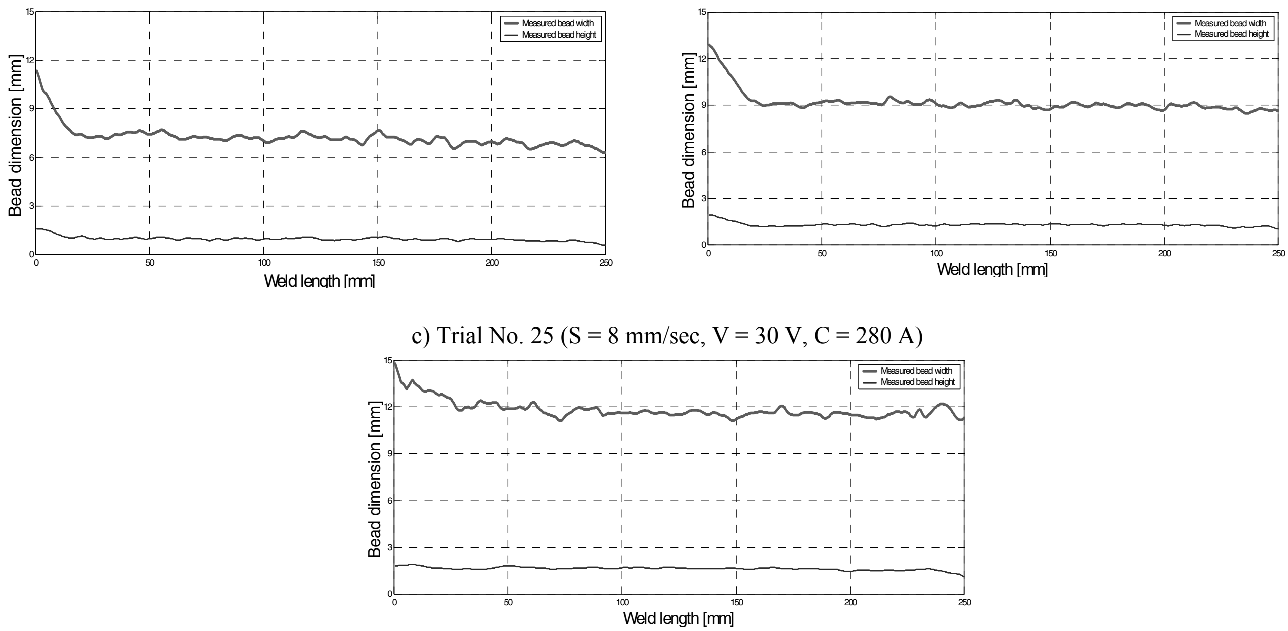


Fig. 3. The measured bead geometry

Table 2.
ANOVA results for bead height

Source	Sum of Squares (SS)	Degree of Freedom (DF)	Mean Square (MS)	F-value	P-value
Corrected model	108.892*	26	4.188	1451.309	0.000
Intercept	3062.868	1	3062.868	1061367	0.000
S	49.291	2	24.646	8540.393	0.000
V	5.001	2	2.501	866.576	0.000
C	52.163	2	26.082	9038.027	0.000
S×V	0.411	4	0.103	35.642	0.000
S×C	0.214	4	0.054	18.573	0.000
V×C	0.906	4	0.226	78.458	0.000
S×V×C	0.635	8	0.079	27.498	0.000
Error	4.796	1662	0.003	-	-
Total	3391.817	1689	-	-	-
Corrected Total	113.688	1688	-	-	-

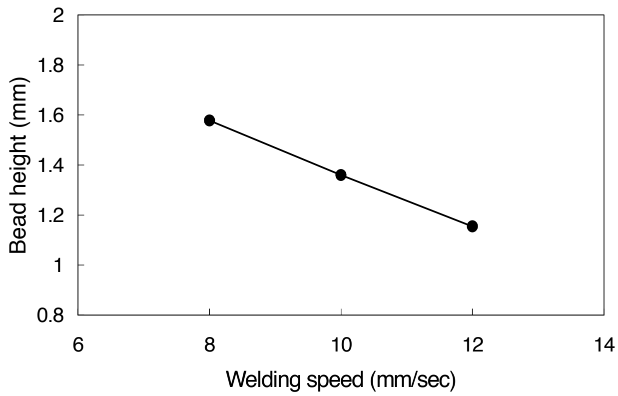
* R squared = 0.958 (adjust R squared = 0.957)

3.2. Analysis of variance for bead height

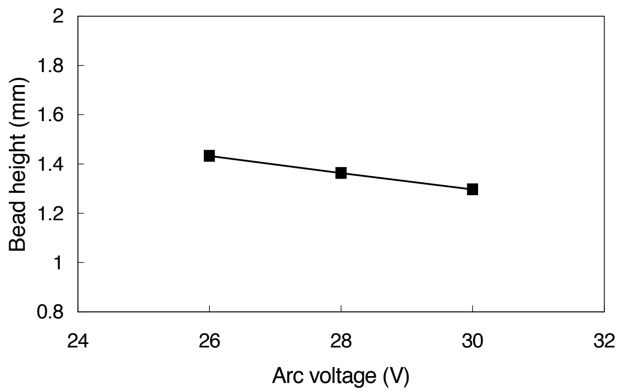
Table 2 represents the ANOVA results for bead height. As confirmed in previous section, it was also found that all main and interaction terms have the effect on bead height. Especially, welding speed and welding current have large mean square values. Figure 4 presents the effects of 3 main terms (welding speed, arc voltage and welding current) for average bead height. According to Figure 4, it can also be seen that the bead height increased with an increase in welding current, while decreased with increase in welding speed and arc voltage.

The effects of 2-way interaction terms on average bead height were shown in Figure 5. As shown in Figure 5, the variations of bead height were smaller than those of the bead height. So, it is difficult to find interrelationship between the 2-way interaction terms and bead height. Figure 5a represents the effect of welding speed on average bead height for three different arc voltages. The bead height increases as arc voltages increase and welding speeds decrease. The effect of arc voltage on average bead height for three different welding current is shown Figure 5b. Also Figure 5c represents the effect of welding current on average bead height for each welding speeds. It showed that the bead height increases with an increase welding current increase and with a decrease welding speeds.

a) Welding speed



b) Arc voltage



c) Welding current

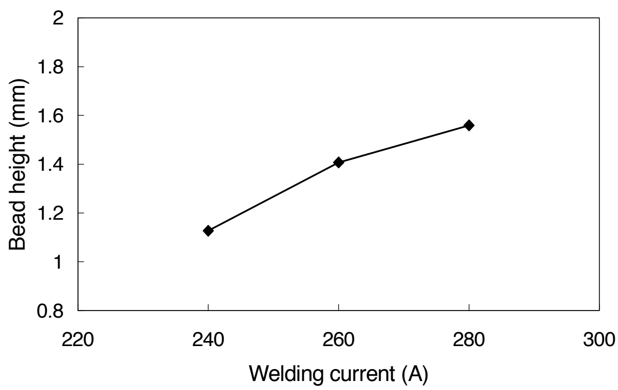
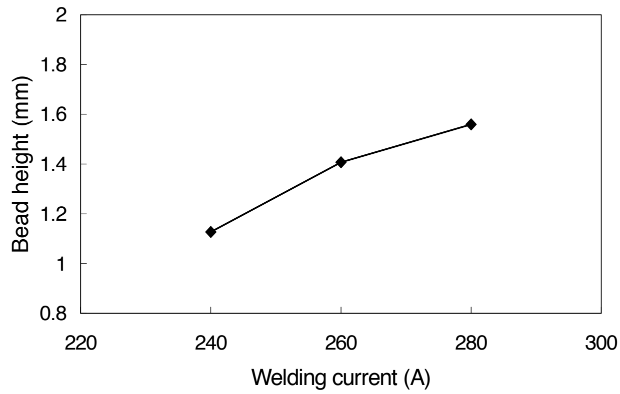
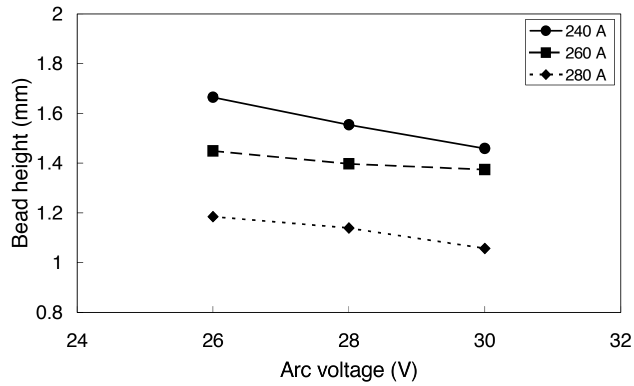


Fig. 4. The effect of welding parameter on average bead height

a) Welding speed × arc voltage



b) Arc voltage × welding current



c) Welding current × welding speed

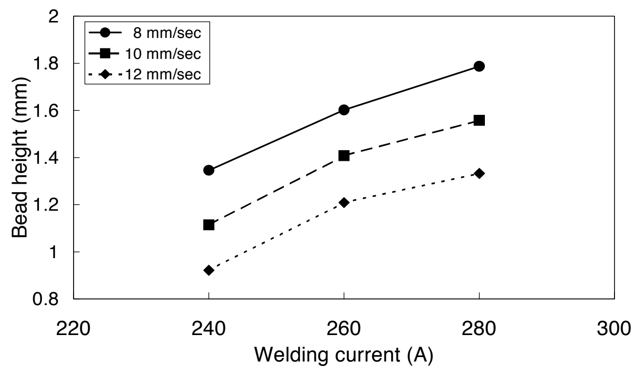


Fig. 5. The 2-way interaction effects of welding parameters on average bead height

3.3. On-line quadratic model for bead height

To develop the on-line quadratic model, the response bead height can be shown as bellows:

$$\begin{aligned} Y &= k_0 + k_1 S + k_2 V + k_3 C + k_4 T_1 + k_5 T_2 + k_6 T_3 \\ &+ k_{12} SV + k_{13} SC + k_{14} ST_1 + k_{15} ST_2 + k_{16} ST_3 \\ &+ k_{23} VC + k_{24} VT_1 + k_{25} VT_2 + k_{26} VT_3 + k_{34} CT_1 \\ &+ k_{35} CT_2 + k_{36} CT_3 + k_{45} T_1 T_2 + k_{46} T_1 T_3 + k_{56} T_2 T_3 \\ &+ k_{11} S^2 + k_{22} V^2 + k_{33} C^2 + k_{44} T_1^2 + k_{55} T_2^2 + k_{66} T_3^2 a \end{aligned} \tag{1}$$

The following two on-line quadratic models for bead height were developed and present as follow:

$$\begin{aligned} H_Q &= 9.341 - 0.265\, S + 0.748\, V + 0.044\, C \\ &- 0.030\, T_1 + 0.013\, T_2 - 0.006\, T_3 - 0.030\, SV \\ &+ 0.002\, SC + 3.70 \times 10^{-4} ST_1 + 2.810 \times 10^{-4} ST_2 \\ &+ 2.277 \times 10^{-4} ST - 1.9 \times 10^{-5} CT^{1} \\ &- 3.8 \times 10^{-5} CT_2 + 6.854 \times 10^{-5} CT_3 - 0.003\, S^2 \\ &- 0.007\, V^2 - 1.562 \times 10^{-4} C^3 + 8.089 \times 10^{-6} T_1^2 \\ &- 4.3 \times 10^{-7} T_2^2 - 3.8 \times 10^{-6} T_3^2 \end{aligned} \tag{2}$$

Figure 6 indicates comparison between the predicted and measured bead height using on-line quadratic model. It is shown that the bead height using on-line quadratic model is also good performance. Figure 7 shows the error of predicting results of bead height for on-line quadratic model. Table 3 represents performance of on-line quadratic models for predicting bead height. The values of PAM for the developed model to predict bead height are about 76.7442%.

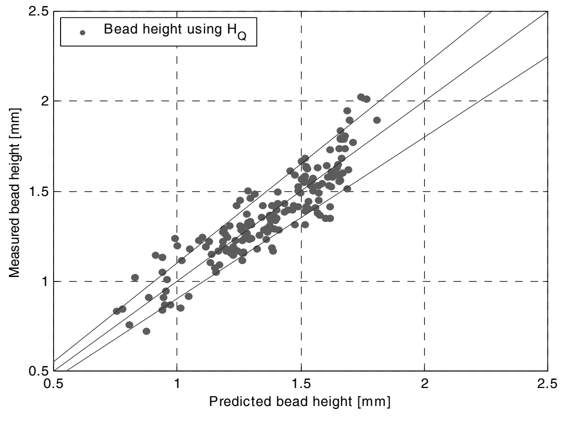


Fig. 6. Comparison between the predicted and measured bead height using on-line quadratic model

It can be concluded that procedure optimization for GMA welding process such as non-linear optimization in order to identify the welding parameter should be required Artificial Intelligence (AI) techniques such as neural network, fuzzy theory and so on. Therefore an artificial neural network is capable of modeling of non-linear relationship.

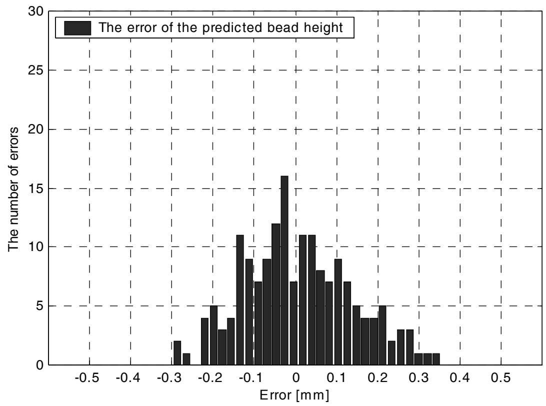


Fig. 7. The error of the predicted bead height using on-line quadratic model

Table 3.
Performance of on-line quadratic model for prediction of the bead height

Performance	PAM (%)	Standard deviation
H_Q	76.7442	0.1108

4. Conclusions

The on-line multiple regression models to predict optimal process parameters on the required weld height and to investigate the effects of process parameters on the bead height for the GMA welding process have been developed, and the following conclusions reached:

1. Welding voltage, arc current, and welding speed have significant effects on bead height. The bead height increased with an increase in welding current, while decreased with increase in welding speed and arc voltage. Not only the bead height increases as arc voltages increase and welding speeds decrease, but also the bead height increases with an increase welding current increase and with a decrease welding speeds.
2. Quadratic model for on-line control have been developed to study the interrelationship between process parameters and bead height for the robotic GMA welding process. Arc voltage shows no significant effect on the bead height. The comparison with values of coefficient of multiple correlations for quadratic equation presents no differences, which indicates that all equations are reasonably suitable.
3. The developed on-line empirical model are able to predict the optimal process parameters required to achieve desired bead height and weld criteria, help the development of automatic control system and expert system and establish guidelines and criteria for the most effective joint design. The predicted model of the bead height using quadratic model showed minimum 76.7442% in PAM, and the standard deviation has immensely dispersed in the measured bead height.

In this work, the developed formulae based on experimental results are valid for welding parameters and bead height. Therefore, these models are extended many other parameters which are not included in this research.

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