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A study on on-line mathematical model to control of bead width for arc welding process

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ABSTRACT

Purpose: Recently, not only robotic welders have replaced human welders in many welding applications, but also reasonable seam tracking systems are commercially available. However, fully adequate control systems have not been developed due to a lack of reliable sensors and mathematical models that correlate welding parameters to the bead geometry for the automated welding process.

Design/methodology/approach: In this paper, two on-line empirical models using multiple regression analysis are proposed in order to be applicable for the prediction of bead width. For development of the proposed models, an attempt has been made to apply for a several methods. For the more accurate prediction, the prediction variables are first used to the surface temperatures measured using infrared thermometers with the welding parameters (welding current, arc voltage) because the surface temperature are strongly related to the formation of the bead geometry. The developed models are applied to monitor and control the bead width as welding quality.

Findings: The developed two on-line empirical models are able to predict the optimal welding parameters required to achieve desired bead width and weld criteria, help the development of automatic control system and expert system and establish guidelines and criteria for the most effective joint design.

Research limitations/implications: This research was concentrated to develop on the on-line empirical models that can predict bead width in robotic GMA welding process. The developed empirical models can only be employed to control the bead width for butt welding.

Originality/value: It has been realized that with the use of the developed algorithms, the prediction of bead width becomes much simpler to even a novice user who has no prior knowledge of the robotic GMA welding process and optimization techniques.

Keywords: On-line empirical model; Optimization; Bead width; Robotic arc welding; Welding quality

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

Controlling the arc welding process requires a closed loop approach whereby sensed information is interpreted, and alteration is made to the process where necessary. Firstly, the system must receive the desired output parameters and then select the necessary parameters based on these output parameters, next it must initiate welding and finally monitor the welding outputs to determine the success of the weld. Subsequently, based on this process monitoring, the mathematical model must be able to take positive action for any corrections needed. Most conventional real-time, closed loop controlled welding systems attempt to control major output parameters such as bead width. Hunter et al. [1] not only employed logarithmic equations to model the GMA welding parameters, but also adapted capacitive distance transducers for gun positioning and ultrasonic sensing to monitor wire stick out. Richardson et al. [2] have been employed an optical sensor coaxially mounted with a GTA welding electrode to provide a pattern of reflected arc light for a computer algorithm to interpret joint width and location, and give successful joint tracking.

Other closed loop system has been developed by Smartt et al. [3] for real time control of reinforcement area and cooling rate. Doumanidis et al. [4-8] have attempted to derive simple dynamic models in their attempt to control bead width, bead penetration, reinforcement area, heat affected zone width and rate of cooling at the centre line of the weld. Mathematical based control systems are not suited to truly real-time adaptive control because of their inability to isolate the welding parameters, thereby resulting in excessive processing times. These systems are not capable of taking account of heuristic's and the relative effect of each welding parameter. Mathematical systems are also inflexible to changes in hardware due to their rigid control laws and consequently are unable to learn from successes and errors. However, it can only consider fuzzy logic or expert systems that are capable of a learning function [9-13].

Thus, a real-time bead penetration monitoring system is also achieved. Richardson [14] presented an on-line tracking optimization scheme for sensor guided robotic manipulators by associating sensor information, manipulator dynamics and a path generator model. Feedback linearization-decoupling permits the use of linear Single-Input Single-Output (SISO) prediction models for the dynamics of each robot joint. Scene interpretation of CCD-camera images generates spline fitted segments of future trajectory [15-20]. In the sensor vision field, the proposed optimization criteria minimize the error between state variables of the prediction model and the state variables of the spline trajectory generator. Experimental results on implementation of a CCD-camera guided hydraulic robot, and a welding robot demonstrated the practical relevance of the proposed approach [21-23].

This paper presents an on-line mathematical model for predicting bead width and for investigating the effects of various process parameters using three empirical models (on-line linear, on-line interaction and on-line quadratic models). Based on the experimental results, the on-line multiple regression models for predicting bead width are established. These two kinds of models are verified by data obtained from additional multi-pass butt welds, and compared. Finally predictive behaviors and advantages of each model are discussed.

2. Experimental procedure

In this study, the bead geometry, an important role in determining the optimal welding conditions, is employed to study the welding quality. Therefore in this study, Contact Tip to Work Distance (CTWD), gas flow rate, welding speed, arc current, welding voltage were chosen to investigate the effects of process parameters and develop the empirical models for predicting top-bead width as output parameter. Statistically designed experiments that are based upon factorial techniques, reduce costs and provide the required information about the main and interaction effects on the response factors [24-26]. The process parameters and their values employed in this study are given in Table 1. All other parameters except these were fixed.

The experimental data that included five process parameters on top-bead width at 2 levels were obtained by using a welding robot. The design matrix that has 32 experimental weld runs where each row corresponds to one experimental run with two replications [27]. In this study, the mean of these replications was considered output parameters to utilize the development of empirical models. The 150 x 200 x 4.5 mm SS400 materials and steel wire with a diameter of 1.2 mm were employed for the experiment. Data collection and evaluation has been carried out using the robot welding facility [28]. To measure the top-bead width as shown in Fig. 1, the specimen was cut transversely from the middle position using a wire-cutting machine. The selection of the electrode wire should be based principally upon matching the mechanical properties and physical characteristics of the base metal [29-31]. Secondary consideration should be given to items such as the equipment to be used, the weld size and existing electrode inventory. 1.2 mm diameter flux-cored wire diameters and 100% CO_2 shielding gas was employed in experiment.

Table 1.
Process parameters and values

Parameter	Symbol	Unit	Values
CTWD	T	mm	10, 12
Gas flow rate	G	l/min	10, 15
Welding speed	S	cm/min	18, 30
Arc current	I	Amp	150, 200
Welding voltage	V	Volt	20, 25

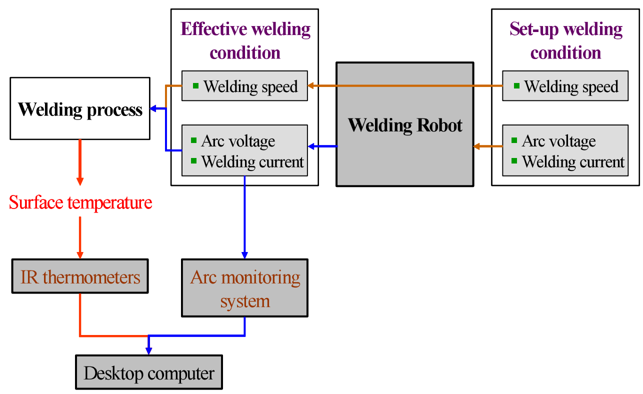

Fig. 1. Block diagram for experimental setup

3. Development of on-line empirical model

The results of the developed empirical on-line models were shown in good agreement. However, the development of formalized approach for procedure optimization should be included to establish combination of more welding parameters which would produce good weld quality. In this study, the response function redefined by using additional input parameter about surface temperature and represented as follows:

$$Y = f(S, V, C, T_1, T_2, T_3) \tag{1}$$

3.1. On-line linear model

The on-line linear equation of 6 independent parameters is expressed as below:

$$Y = k_0 + k_1 S + k_2 V + k_3 C + k_4 T_1 + k_5 T_2 + k_6 T_3 \tag{2}$$

The on-line linear models developed are given below:

$$\begin{aligned} W_L &= 7.282 - 0.767\,S + 0.206\,V + 0.026\,C \\ &\quad + 3.682 \times 10^{-4}\,T_1 + 1.0 \times 10^{-4}\,T_2 \\ &\quad - 9.007 \times 10^{-4}\,T_3 \end{aligned} \tag{3}$$

Fig. 2 shows comparison between the predicted and measured bead width using on-line linear model. In spite of adding 3 input parameters for temperature, the on-line linear model for bead width is similarly good performance as the on-line linear model. Fig. 3 represents the error of predicting results of bead width according to on-line linear model. To compare the precision of developed models, PAM has performed of the two models. Table 2 indicated performance of on-line linear models for predicting bead width. The PAM values for bead width are about 98.84%.

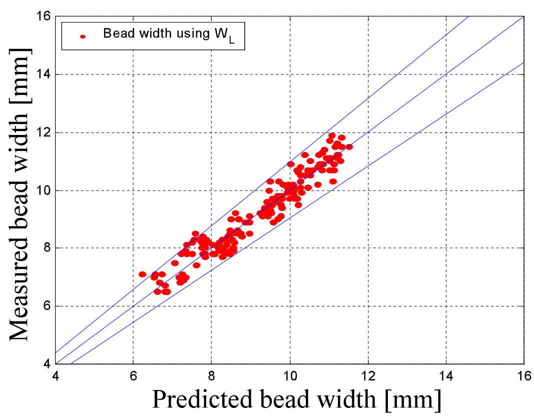

Fig. 2. Comparison between the predicted and measured bead width using on-line linear model

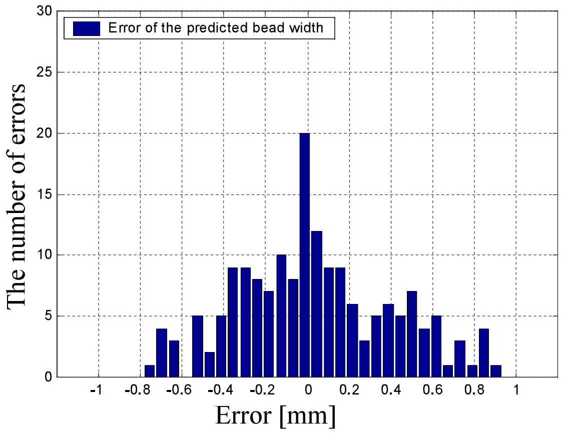

Fig. 3. The error of the predicted bead width using on-line linear model

Table 2.
Performance of on-line linear model for prediction of the bead geometry

Performance	Bead width (W_l)
PAM (%)	98.8372
Standard deviation	0.3728

3.2. On-line interaction model

To develop the on-line interaction model, all chosen welding parameters and interaction factors are given below:

$$\begin{aligned} Y = {} & k_0 + k_1 S + k_2 V + k_3 C + k_4 T_1 + k_5 T_2 \\ & + k_6 T_3 + k_{12} SV + k_{12} SC + k_{14} ST_1 \\ & + k_{15} ST_2 + k_{16} ST_3 + k_{23} VC + k_{24} VT_1 \\ & + k_{25} VT_2 + k_{26} VT_3 + k_{34} CT_1 + k_{35} CT_2 \\ & + k_{36} CT_3 + k_{45} T_1 T_2 + k_{46} T_1 T_3 + k_{56} T_2 T \\ & + k_{123} SVC + k_{124} SVT_1 + k_{125} SVT_2 \\ & + k_{126} SVT_3 + k_{134} SCT_1 + k_{135} SCT_2 \\ & + k_{136} SCT_3 + k_{145} ST_1 T_2 + k_{146} ST_1 T_3 \\ & + k_{156} ST_2 T_3 + k_{234} VCT_1 + k_{235} VCT_2 \\ & + k_{236} VCT_3 + k_{345} CT_1 T_2 + k_{346} CT_1 T_3 \\ & + k_{456} T_1 T_2 T + k_{346} CT_1 T_3 + k_{456} T_1 T_2 T \end{aligned} \tag{4}$$

The following two on-line interaction models for bead width were developed and presented as following:

$$\begin{aligned} W_l = {} & 40.639 - 1.469S + 0.735V + 0.051C \\ & - 0.006T_1 - 0.002T_2 - 0.031T_3 \\ & + 4.169 \times 10^{-4} SC + 3.391 \times 10^{-5} SVT_1 \\ & - 5.9 \times 10^{-5} SVT_2 - 1.8 \times 10^{-5} SVT_3 \\ & + 8.970 \times 10^{-7} ST_2 T_3 - 3.3 \times 10^{-7} VCT_1 \\ & - 1.8 \times 10^{-6} VCT_2 - 8.8 \times 10^{-8} VT_1 T_3 \\ & + 4.474 \times 10^{-7} VT_2 T_3 + 2.264 \times 10^{-8} CT_1 T_3 \\ & - 1.8 \times 10^{-9} T_1 T_2 T \end{aligned} \tag{5}$$

Comparison between the predicted and measured bead width using on-line interaction model indicates in Fig. 4. The on-line interaction model for bead width was shown good performance. Fig. 5 represents the error of predicting results of bead width by calculated from on-line interaction model. Table 3 represents performance of on-line interaction models for predicting bead width. As shown in Table 3, bead width was predicted very accurately more over 99% in PAM, but prediction of bead height was shown about 78% in PAM. Performance of on-line interaction model is a similar that of on-line interaction model.

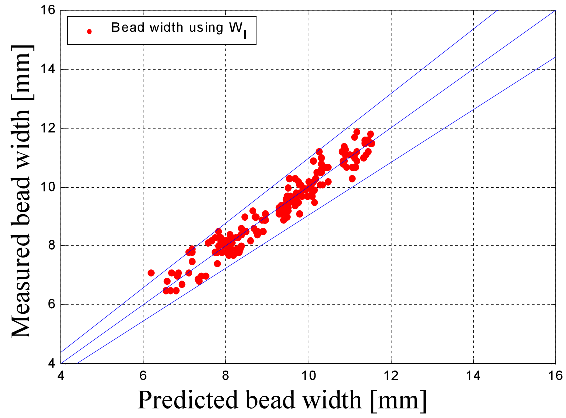

Fig. 4. Comparison between the predicted and measured bead width using on-line interaction model

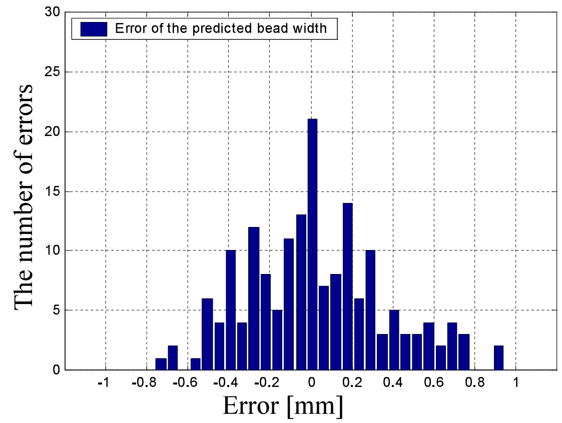

Fig. 5. The error of the predicted bead width using on-line interaction model

Table 3.
Performance of on-line interaction model for prediction of the bead geometry

Performance	Bead width (W_l)
PAM (%)	99.4186
Standard deviation	0.3372

3.3. On-line quadratic model

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

$$\begin{aligned} Y = {} & k_0 + k_1 S + k_2 V + k_3 C + k_4 T_1 + k_5 T_2 + k_6 T_3 \\ & + k_{12} SV + k_{13} SC + k_{14} ST_1 + k_{15} ST_2 + k_{16} ST_3 \\ & + k_{23} VC + k_{24} VT_1 + k_{25} VT_2 + k_{26} VT_3 + k_{34} CT_1 \\ & + k_{35} CT_2 + k_{36} CT_3 + k_{45} T_1 T_2 + k_{46} T_1 T_3 + k_{56} T_2 T_3 \\ & + k_{11} S^2 + k_{22} V^2 + k_{33} C^2 + k_{44} T_1^2 + k_{55} T_2^2 + k_{66} T_3^2 \end{aligned} \tag{6}$$

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

$$\begin{aligned} W_Q = {} & 38.513 - 2.131S + 1.734V + 0.135C \\ & - 0.050T_1 + 0.019T_2 - 0.037T_3 - 0.073SV \\ & + 0.001SC + 0.001ST_1 + 5.5\times10^{-4} ST_2 \\ & + 0.001ST_3 - 7.1\times10^{-6} CT_1 - 1.054\times10^{-4} CT_2 \\ & + 8.245\times10^{-5} CT_3 + 0.054S^2 - 0.014V^2 \\ & - 1.511\times10^{-4} C^2 + 1.227\times10^{-5} T_1^2 \\ & + 2.372\times10^{-6} T_2^2 + 2.244\times10^{-6} T_3^2 \end{aligned} \tag{7}$$

Fig. 6 shows comparison between the predicted and measured bead width using on-line quadratic model, and most predicted values distributed in dotted line. Fig. 7 presents the error of predicting results of bead width according to on-line quadratic model. Fig. 4 shows the error of predicting results of bead height for on-line quadratic model. Table 4 represents performance of on-line quadratic models for predicting bead width and bead height. The values of PAM for bead width and bead height model are about 99.42% and 76.74% respectively.

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.

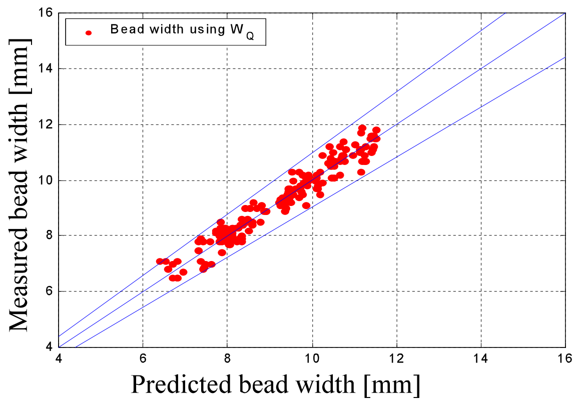

Fig. 6. Comparison between the predicted and measured bead width using on-line quadratic model

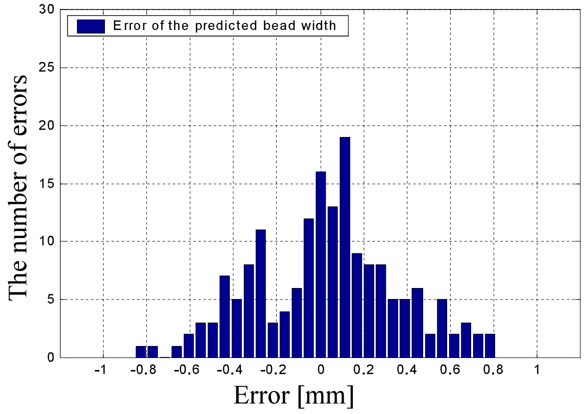

Fig. 7. The error of the predicted bead width using on-line quadratic model

Table 4.
Performance of on-line quadratic model for prediction of the bead geometry

Performance	Bead width (W_1)
PAM (%)	99.4186
Standard deviation	0.3313

4. Results and discussion

To select the most accurate model, additional experiments were carried out. The values of the three welding parameters were chosen for the additional experimental runs as shown in Table 5. Specially, arc voltage and welding current were changed during GMA welding process in order to survey the reflation of the developed models according to change the welding condition. The measured position of infrared thermometer was same as the original experiments.

Table 5.
Welding parameters and their values in additional experiment

Trial No.			1	2
Welding parameter	Welding speed(mm/sec)		9	11
	Section 1	Arc voltage(V)	27	27
		Welding Current(A)	250	250
	Section 2	Arc voltage(V)	27	29
		Welding Current(A)	270	250

Other experiment conditions have been fixed. The welding conditions including CTWD, gas flow rate, welding speed, arc current and welding voltage were employed as the input parameters. The output parameter is the bead width calculated by each model and the corresponding errors of prediction. From the results calculated from the developed models based on additional experiments for this study, it is evident from the three models developed that reasonable agreement between experimental and calculated top-bead width is shown even when the scatter about the calculated results using two empirical equations (linear and curvilinear) is considerable.

Based on the intelligent model that determine a given bead width and provide useful guidelines for systems which control top-bead width, a limited range of welding conditions, the effect of each process parameters and their significant interactions on top-bead width were computed and plotted. To compare the performance of on-line learning neural network model, comparison with the measured results of bead geometry has been made. In the on-line learning, the performance evaluation of neural network has been completed for the bead geometry excluded the bead height in trial No. 1, but in the on-line learning, the verification has been completed with the bead height as well as bead width because the neural network, which has been learned with the collected data for each bead geometry, should be evaluated.

a)

b)

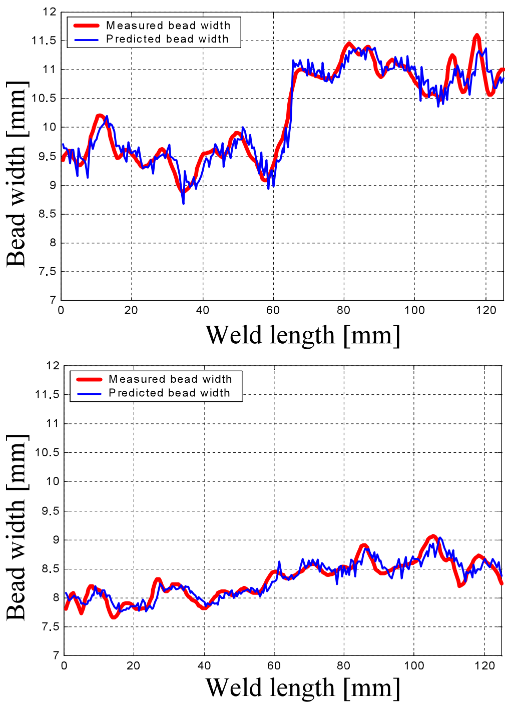

Fig. 8. Comparison of the measured and predicted bead width using on-line empirical model. Trial No. 1 (a), Trial No. 2 (b)

a)

b)

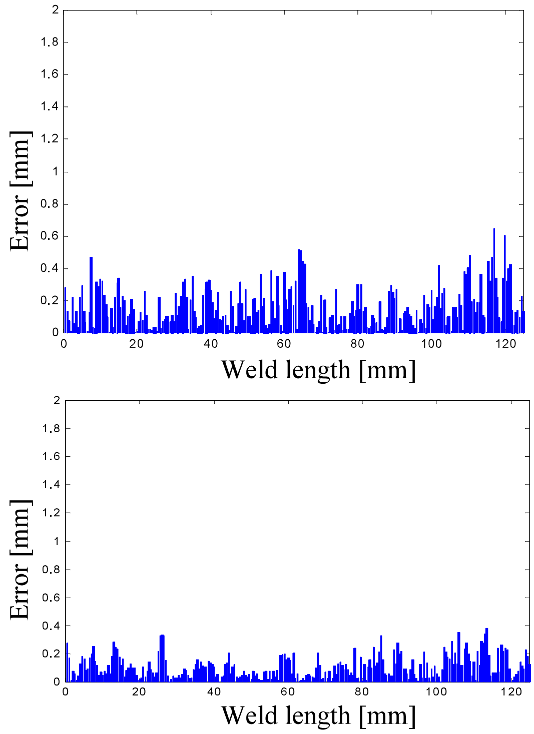

Fig. 8. The error of the predicted bead width using on-line empirical model. Trial No. 1 (a), Trial No. 2 (b)

Figure 8 shows the comparison of the measured and predicted bead width through the neural network using on-line learning method. As shown in Fig. 8, the values of predicted bead width using on-line learning neural network model is very closed to the values of the measured bead width. Fig. 8 shows the error of predicted bead width using on-line learning neural network model. Comparing to the on-line learning neural network, the error of the predicted bead width using on-line learning is concentrated immensely in lower direction. The performance of on-line learning neural network model for the bead height was similar to performance for the bead width. Therefore, it is verified that the performance of on-line learning is higher than conventional learning.

Table 6.
Performance of on-line empirical model for prediction of the bead width

		Trial No. 1	Trial No. 2
Bead width	PAM (%)	100	100
	Standard deviation	0.2057	0.1349
	Average error	0.1617	0.1064

For further verification, the comparison of the measured and predicted bead geometry using the on-line learning neural network model has been performed and represented in Table 6 with PAM, standard deviation and average error. The on-line learning neural network model has predicted very accurately. In the bead height in trial No. 2, on-line learning neural network didn't achieve 100% in PAM, but compared with on-line learning neural network model, on-line learning neural network model is improved significantly accuracy. In the comparison of standard deviation and average error, the predicted bead geometry showed the most concentrated distribution. Eventually, it was concluded that the on-line learning neural network model has a predictive ability that is superior to the other models.

5. Conclusions

The one-line empirical model to predict optimal welding parameters on the required weld geometry and to investigate the effects of welding parameters on the bead geometry for the GMA welding process has been developed.

Empirical equations (linear, interaction, quadratic model) for on-line controls can find the interrelationship between welding parameters and bead geometry for the robotic GMA welding process. Arc voltage shows no significant effect on the bead dimension. The comparison with values of coefficient of multiple correlations for linear, interaction and quadratic equations presents no differences, which indicates that all equations are reasonably suitable. The developed on-line empirical models are able to predict the optimal welding parameters required to achieve desired bead geometry (bead width and 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.

A rule-based expert system can be incorporated with the developed neural network system to integrate an optimized system for the robotic GMA welding process. It has been realized that with the use of the developed system, the prediction of bead geometry becomes much simpler to even a novice user who has no prior knowledge of the robotic GMA welding process and optimization techniques.

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Additional information

Selected issues related to this paper are planned to be presented at the 22nd Winter International Scientific Conference on Achievements in Mechanical and Materials Engineering Winter-AMME'2015 in the framework of the Bidisciplinary Occasional Scientific Session BOSS'2015 celebrating the 10th anniversary of the foundation of the Association of Computational Materials Science and Surface Engineering and the World Academy of Materials and Manufacturing Engineering and of the foundation of the Worldwide Journal of Achievements in Materials and Manufacturing Engineering.

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