Journal of
Mechanical
Science and
Technology

Journal of Mechanical Science and Technology 21 (2007) 1726~1731

A study on the prediction of bead geometry in the robotic welding system

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(Manuscript Received May 31, 2007; Revised August 30, 2007; Accepted September 30, 2007)

Abstract

The gas metal arc (GMA) welding is one of the most widely-used processes in metal joining process that involves the melting and solidification of the joined materials. 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 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, three empirical models (linear, interaction, quadratic model) have been developed for off-line control which studies the influence of welding parameters on bead width and compares their influences on the bead width to check which process parameter is most affecting. These models developed have been employed for the prediction of optimal welding parameters and assisted in the generation of process control algorithms.

Keywords: GMA welding; Empirical model; Off-line controls; Bead geometry

1. Introduction

GMA welding is generally accepted today as the preferred joining technique and commonly chosen for assembling most large metal structures such as automotive, aircraft and shipbuilding due to its joint strength, reliability, and low cost compared to other joint processes. The demand to increase productivity and quality, the shortage of skilled labor 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 [1]. 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

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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 for the development of intelligent welding control system 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 (bead height, bead width, penetration, fused and deposited areas) and three welding parameters (welding current, arc voltage and welding speed) 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 (the number of hidden layers and the number of nodes in a layer) 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 as well as off-line and on-line empirical models. Multiple regression analysis was employed to investigate relationships between the welding parameters and bead width in the GMA welding process. Also off-line and on-line empirical models were used to predict the bead width. By using these methods developed, the conventional empirical model's problem and solution have been searched.

2. Experimental details

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 configurations, 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 welding parameters were wire diameter, arc voltage, welding speed and welding current with two levels. The factors and their values could be seen in Table 1. The interaction effects between welding parameters are neglected. In this study, L16 ortho-gonal 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. 1.2 mm flux-cored wire diameters and 100 % CO_2 shielding gas was employed in experiments.

The welding facility at the welding and intelligent control laboratory 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 included infrared thermometers, arc monitoring system and desktop computer. Three infrared thermometers were employed to detect temperature in the vicinity of the weld pool. With the welder and argon shield gas

Table 1. Factors and their levels for experiment.

Sample	Process variables	Level 1	Level 2
A	Wire diameter (mm)	1.2	1.6
B	Arc voltage (V)	20	30
C	Welding speed (cm/min)	25	41
D	Welding current (A)	180	360

turned on, the robot was initialized and welding was then executed. This continued until the Taguchi experimental design runs were completed.

To measure the bead width, 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 width 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 obtained from the experiment results were employed for this research because the workpiece offered a convenient reference plane for measurement of bead geometry, and the influences arising from joint preparation were removed. The chemical composition of weld material and the wire diameter were the same as the one employed in calibration test. The experimental results of bead geometry according to the change of the welding parameters are shown in Fig. 1. Also, Fig. 2 shows the experimental results of the measured bead geometry using 3D scanner. The measured bead geometry has been transferred into bead dimension such bead width and bead height in order to compare the predicted bead geometry. The tests have been carried out with 250 samples in stable weld section for each experiment. The bead dimension and test section were represented in Fig. 3.

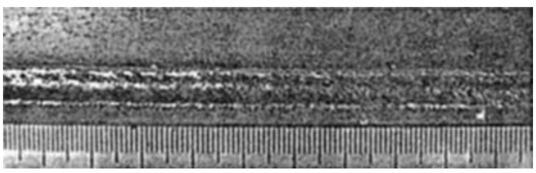


Fig. 1. Welding experiment results.

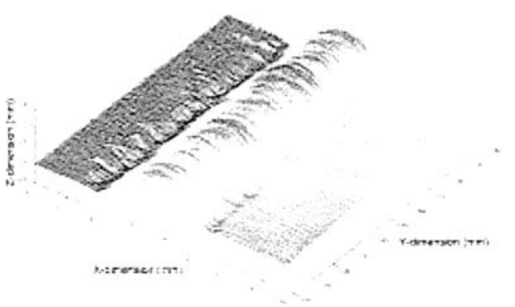


Fig. 2. The measured bead geometry using a 3D scanner in original experiment.

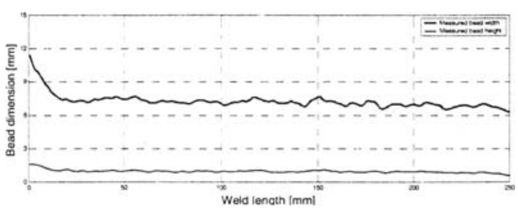


Fig. 3. The measured bead geometry.

3.2 Analysis of variance for bead width

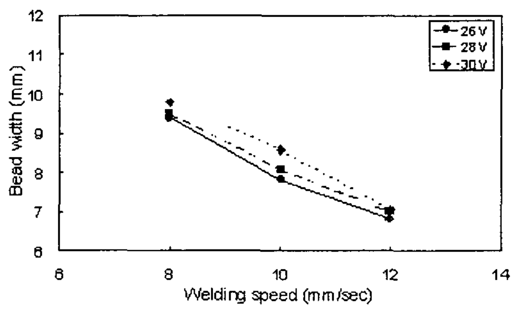
Multiple regression analysis is one of the most widely used methodologies for expressing the dependence of response parameters on several independent parameters. In this paper, this analysis has been applied, and three regression models for bead width are developed for investigating relationship between input parameters (welding speed, arc voltage and welding current) and the output parameters (bead width) in the GMA welding process.

Table 2. ANOVA results for bead width.

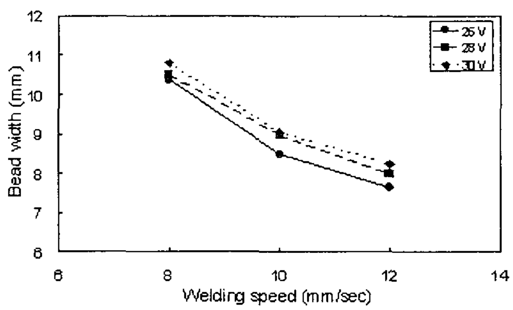
Source	Sum of Squares (SS)	Degree of Freedom (DF)	Mean Square (MS)	F-value	P-value
Corrected model	2951.134[a]	26	113.505	1958.152	0.000
Intercept	133582.466	1	133582.466	2304519	0.000
S	2195.046	2	1097.523	18934.090	0.000
V	65.737	2	32.8683	567.034	0.000
C	609.515	2	304.757	5257.569	0.000
S×V	4.822	4	1.205	20.796	0.000
S×C	37.352	4	9.338	161.097	0.000
V×C	0.962	4	0.240	4.147	0.0024
S×V×C	9.218	8	1.152	19.878	0.000
Error	96.339	1662	0.058	-	-
Total	145319.935	1689	-	-	-
Corrected Total	3047.473	1688	-	-	-

a. R squared = 0.968 (adjust R squared = 0.968)

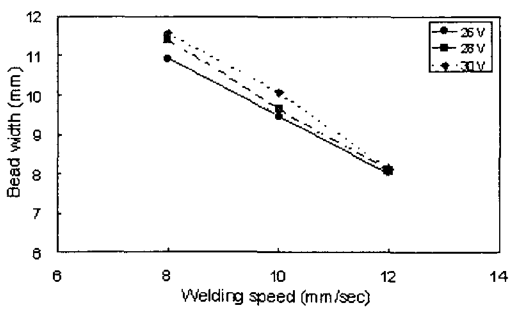
Analysis of variance (ANOVA) technique has been employed to detect significant factors in a multi-factor model. The effects of the welding parameters were quantified by this technique on each quality characteristic to verify the significance of each welding parameter on the optimized bead width. In this study, with a 33 full factorial design, the fitted empirical model contains 3 main effect terms, 3 two-way interaction terms and 1 three-way interaction term that can be founded. Using the output data obtained by the experiments, which were designed by Taguchi method, and the standard statistical techniques such as multiple regression analysis, three empirical equations for investigating the interrelationship between the three welding parameters, and bead width as welding quality was computed. This model was employed by a commercial standard statistical package program, SPSS, and the best-fit coefficients of the equation have also been calculated.



(a) 240A



(b) 260A



(c) 280A

Fig. 4. Three-way interaction effects of welding parameters on average bead width.

Table 2 represents the ANOVA results for bead width. P-value means a significant probability. Usually, even if P-value is smaller than 0.05, the factor is adjudicated significantly. As shown in Table 2, it was found that all of interaction terms have the effect on bead width. Especially, welding speed from the main welding parameters has a large mean square value which means the highest effect on bead width. Fig. 4 represents the effect of 3-way interaction terms on average bead width. According to three levels of welding currents, the average bead width decreases with an increase welding speed, while the effect of arc voltages for average bead width was not significant.

3.3 On-line quadratic model for bead width

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

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

The following on-line quadratic models for bead width was developed and presented as follow:

$$\begin{aligned} W_Q = {} & 38.513 - 2.131S + 1.734V + 0.135C - 0.050T_1 \\ & +0.019T_2 - 0.037T_3 - 0.073SV + 0.001SC \\ & +0.001ST_1 + 5.5 \times 10^{-4} ST_2 + 0.001ST_3 - 7.1 \\ & \times 10^{-6} CT_1 - 1.054 \times 10^{-4} CT_2 + 8.245 \times 10^{-5} CT_3 \\ & +0.054S^2 - 0.014V^2 - 1.511 \times 10^{-4} C^2 + 1.224 \\ & \times 10^{-5} T_1^2 + 2.372 \times 10^{-6} T_2^2 + 2.444 \times 10^{-6} T_3^2 \end{aligned} \quad (2)$$

Fig. 5 shows comparison between the predicted and measured bead widths using on-line quadratic model, and most predicted values distributed in dotted line. Fig. 6 presents the error of predicted results of bead width according to on-line quadratic model. It can be concluded that not only bead width using on-line quadratic model shows also good performance, but also procedure optimization for GMA welding pro-

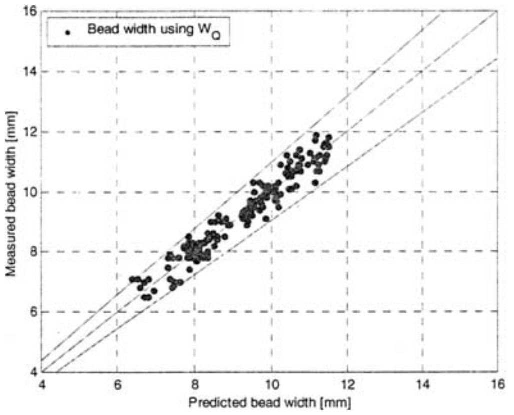


Fig. 5. Comparison between the predicted and measured bead width using on-line quadratic model.

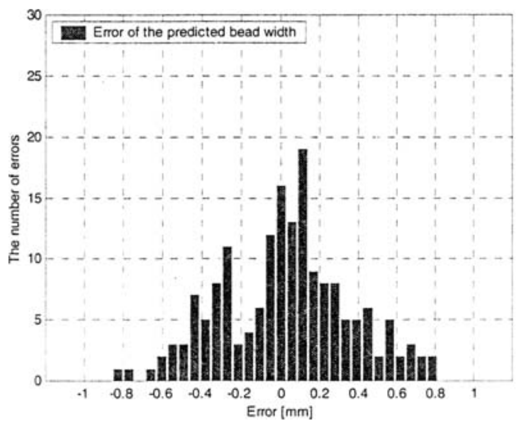


Fig. 6. The error of the predicted bead width using on-line quadratic model.

cess such as non-linear optimization in order to identify the welding parameter should require artificial intelligence (AI) techniques such as neural network, fuzzy theory and so on. Therefore, an artificial neural network is capable of modelling of non-linear relationship [14].

4. Conclusions

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

1. Empirical equations (linear, interaction, quadratic model) for off-line and on-line controls have been developed to study the interrelationship between welding parameters and bead width for the robotic GMA welding process. Arc voltage shows no significant effect on the bead width. 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.

2. The developed off-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.

In this work, the developed formulae based on experimental results are valid for determining welding parameters and bead width. Therefore, these models can be extended to include many other parameters which are not considered in this research.

Acknowledgement

This work was finically support by MOCIE through EIRC program.

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