Research Article
Robotics GMAW-weld Bead Geometry Modeling Using MATLAB Script Approach

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Abstract: This study is aimed at obtaining a relationship between the values of dependent and independent variables of robotic gas metal arc welding, using linear regression techniques. The welding parameters such as the arc current, stick out, arc voltage and welding speed are taken as independent variables and bead geometry namely bead width, bead penetration and bead reinforcement were dependent variables. In this study, the important factors on bead geometry are considered and the other parameters are held as constant. An extension of this model, namely multiple linear regressions, is used to represent the relationship between a dependent variable and several independent variables. Taguchi's L_{27}, 3 level 4 parameter orthogonal array design of experiments, twenty seven samples were analyzed and the bead geometry values of the weld bead have been measured. Then, the relationship between the welding parameters is modeled and expressed in multiple linear regression models by a script approach with MATLAB. Each model is checked for its adequacy by using ANOVA. The proposed model is compared with the experiment values and it has positive correlation with maximum of 3.67% error. The results were confirmed by further experiments.

Keywords: ANOVA, bead geometry, MATLAB, orthogonal array, robotic GMAW, Taguchi

INTRODUCTION

In the present scenario, all manufacturing sector, more than 85% of products require welding operations in their production line. The combination of the chosen input parameters jeopardizes the reliability of the welded components. But automation of welding is a complex process, difficult to monitor, parameterize and control effectively (Norberto *et al*., 2006). The traditional technique requires a lot of time to complete the task and also it will not guarantee the output quality. Even in robotic welding, the welded components quality purely depend the selection of input independent variables which is done by the programmer. In other words, still the ideal welding parameters combination requirement arises, which can be found only if scientific selection methodology is utilized.

Kim *et al*. (2003a to c) have been studied the interrelationship between robotic CO_2 arc welding parameters and bead penetration by developing mathematical models both linear as well as non linear multiple regression equations. Sensitivity analysis has been conducted to determine the effect of measurement errors on the uncertainty in estimated parameters. The fractional factorial techniques have been implemented to find the weld-bead geometry and shape relations of

FCAW process (Raveendra and Parmar, 1987). For the prediction of shape relationship and also the development of mathematical model, fractional factorial technique 2^{5-1} technique has been adopted (Gupta and Parmar, 1989). But Murugan and Parmar (1994) used a four-factor 5-levels factorial technique to predict the weld-bead. The linear regression equations are applied to compute the weld features from SAW process (Yang *et al*., 1993). Also the effect of process parameters on the bead shape in a narrow gap-GTAW process with magnetic arc oscillation using statistical experimental design was studied and modeled using linear-regression were proposed by Starling *et al*. (1995). Gunaraj and Murugan (1999a, b) has been developed the mathematical models using Response Surface Methodology (RSM) to study the direct and interaction effects of SAW parameters. These models were used to find the relationship between weld bead volume to its SAW parameters (Gunaraj and Murugan, 2000). Koleva (2001) and Manonmani *et al*. (2005) developed mathematical models to investigate the influence of Electron Beam Welding (EBW) parameters. Benyounis *et al*. (2005a, b) applied RSM to optimize the effect of laser welding parameters. Thamilarasi *et al*. (2014) predicted and also optimized the selected parameters of robotic GMAW using Taguchi techniques.

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Table 1: Input factor and their levels of the robotic GMAW process

Sl. No	Para meters	Units	Notation	Levels		
				1	2	3
1	Arc voltage	Volt	V	16.900	18	20.2
2	Travel speed	mm/min	S	0.175	0.225	0.3
3	Arc current	Ampere	I	160	190	220
4	Stick out	mm	h	3	5	7

Table 2: Chemical composition of base metal and electrode

Material	C	Mn	Si	S	P	Cu
IS 2062 BR	0.15	0.77	0.188	0.022	0.029	0.027
ER70S-6	0.06-0.15	1.40-1.85	0.800-1.15	0.035	0.025	0.500

Many Researchers have been contributing for the development of new welding processes and gain greater understanding of weld quality and mechanical properties (Weisman, 1976).

They have been realized the difficulties accompanied with theoretical estimation of input-output relationships of welding process, they have been tried to get those response through statistical analysis of the experimental data viz., mathematical model. Generally to solve the equations derived from multiple regression analysis, the computational methods apply matrix script approach. But the software gives only the final results, the users does not know what happened behind the scenes. For solving matrix problems, MATLAB is used. Thus, this paper focuses on expressing the multiple linear regression models using matrix notation and analyzing the model using a script approach with MATLAB for robotic Gas Metal Arc Welding (GMAW). Using Taguchi design of experiments L27 orthogonal array, the experimental data has been collected. Results of the above approaches have been compared and some important observations have been made.

Statement of the problem: The objective of the present investigation is to establish relationships between the process parameters (inputs) and responses (output) for 'bead-on-joint'-type GMAW process carried by robot, using multiple linear regression model by a script approach with MATLAB carried out on the data collected as per Taguchi design of experiments (DOE) L_{27} orthogonal array technique. Arc current, Arc Voltage, Travel Speed and stick out are chosen as process input parameters. Three levels are considered for each of the four input process parameters (Table 1), so that 27 combinations of input process parameters are to be considered for analysis.

METHODOLOGY

Experimental details: This section describes the experimental setup used in the present work and explains the method adopted for measurement of weld bead geometry. Experiments are conducted on the HR5 HW welding robot facility as shown in Fig. 1. Structural mild steel plates with dimensions of 150×100×10 mm has been used as base material.

Fig. 1: Experimental setup

Fig. 2: Sample work piece after etched

Copper coated mild steel wire with diameter of 0.8 mm manufactured as per ER70S-6 , IS: 6419-1971-S4 and DIN: SG2 DIN 8559 is employed as the welding consumables. The chemical composition of base material and electrode consumable is shown in Table 2. One hundred percent CO_2 is used as the shielding gas in all the experiments. Welding is performed by adopting a single pass bead on joint welding technique. To measure the bead geometry, the specimen was cut transversely from middle position. At each experimental level four specimens were prepared to minimize the noise factor and the mean value is taken for further calculation. To ensure the precision of the specimen it was etched with 3% HNO_3 and 97% CH_3OH Nital solution.

Each macro etched sample image is scanned by using a digital camera (Fig. 2) and then it is imported into CAD packages. Using CAD packages, the required critical parameters such as Bead Height (BH), Bead Width (BW), Bead Penetration (BP) have been measured. The measured dimensions are compared with the results obtained using a toolmakers' microscope to test the accuracy of measurement. The samples of experimental data were shown in Table 3.

MULTIPLE LEAST SQUARE REGRESSION ANALYSIS

The least square method is used to determine the co-efficient of the regression model, which is explained with the help of one dependent and 'k' independent variables, as shown below.

Table 3: Samples of experimental results

Sample No.	I	h	V	S	BW	BP	BH
S2	160	3	16.9	0.175	15.4600	0.738000	11.62
S4	190	3	20.2	0.225	19.3875	0.920750	12.65
S6	190	3	20.2	0.175	21.8525	1.451750	10.83
S9	220	3	18.0	0.175	23.1025	1.720375	10.63
S10	220	5	20.2	0.175	22.6575	1.862500	12.23
S11	220	5	20.2	0.225	19.0075	1.383750	9.50
S12	220	5	20.2	0.300	15.6500	1.002400	7.83
S13	220	7	16.9	0.225	17.6700	1.667500	10.62
S14	220	7	16.9	0.300	17.7425	1.056250	9.62
S15	220	7	16.9	0.175	19.8550	1.962500	11.98
S18	160	5	18.0	0.175	16.4275	0.950000	12.75
S19	160	7	20.2	0.175	16.9600	1.250000	11.10
S22	190	7	18.0	0.300	16.4000	0.618400	11.70
S23	190	7	18.0	0.225	18.3425	1.202500	10.85
S24	190	7	18.0	0.175	23.1175	1.906000	10.85
S25	190	5	16.9	0.175	22.0575	1.570000	10.01
S27	190	5	16.9	0.225	19.0100	1.062500	11.89

Consider a multiple linear regression model with 'k' predictor variables:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_k X_k + e \quad (1)$$

where, 'k' is number of predictor variables and X_1, X_2, X_3, ..., X_k, have 'n' levels. Then X_{ii} represents the ith level of the jth predictor variable X_i. Observations, Y_1, Y_2, Y_3, ..., Y_n recorded for each of these 'n' levels can be expressed in the following way:

$$y_1 = \beta_0 + \beta_1 X_{11} + \beta_2 X_{12} + \cdots + \beta_k X_{1k} + e_1$$
$$y_2 = \beta_0 + \beta_1 X_{21} + \beta_2 X_{22} + \cdots + \beta_k X_{2k} + e_2$$
$$\dots$$
$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + e_i$$
$$\dots$$
$$y_n = \beta_0 + \beta_1 X_{n1} + \beta_2 X_{n2} + \cdots + \beta_k X_{nk} + e_n \quad (2)$$

The system of 'n' equations shown previously can be represented in matrix notation as follows:

$$Y = X\beta + e \quad (3)$$

where,

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ y_n \end{bmatrix} \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1n} \\ 1 & x_{21} & x_{22} & \cdots & x_{2n} \\ \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & & \cdot \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \cdot \\ \cdot \\ \cdot \\ \beta_n \end{bmatrix} \quad \text{and} \quad e = \begin{bmatrix} e_1 \\ e_2 \\ \cdot \\ \cdot \\ \cdot \\ e_n \end{bmatrix}$$

The matrix X is referred to as the design matrix. It contains information about the levels of the predictor variables at which the observations are obtained. The vector β contains all the regression coefficients. To obtain the regression model, β should be known. β is

estimated using least square estimates. The following equation is used:

$$\hat{\beta} = (X'X)^{-1}X'y \quad (4)$$

where,
′ : The transpose of the matrix while
-1 : The matrix inverse

Knowing the estimates, $\hat{\beta}$ is the multiple linear regression model can now be estimated as:

$$\hat{Y} = X\hat{\beta} \quad (5)$$

The estimated regression model is also referred to as the fitted model. The observations, y_i, may be different from the fitted values $\hat{y}_i$ obtained from this model. The difference between these two values is the residual, e_i. The vector of residuals, e, is obtained as:

$$e = y - \hat{y}$$

The fitted model can also be written as follows, using:

$$\hat{\beta} = (X'X)^{-1}X'y:$$
$$\hat{y} = X\hat{\beta}$$
$$\hat{y} = X(X'X)^{-1}X'y$$
$$\hat{y} = Hy \quad (6)$$

where, $H = X(X'X)^{-1}X'$. The matrix, H, is referred to as the hat matrix. It transforms the vector of the observed response values, y, to the vector of the fitted values, $\hat{y}$. This method is used to determine the coefficients of linear regression equations represented in this present study. The same technique may be adopted in non linear regression forms too.

MATLAB APPROACH

There are several options in MATLAB to perform multiple linear regression analysis. One option is Generalized Linear Models in MATLAB. Another option is the Statistical Toolbox. MATLAB programs

can also be written with m-files. These files are text files created with either functions or script. A function requires an input or output argument. While the function method simplifies writing a program, using script better illustrates the process of obtaining the least squares estimator using matrix commands. In this study, the least squares estimators are found by writing the following MATLAB program in script form using matrix notation:

x1 = [1 160 3 16.9 0.225; 1 160 3 16.9 0.175; 1 160 3 16.9 0.3; 1 190 3 20.2 0.225; 1 190 3 20.2 0.3; 1 190 3 20.2 0.175; 1 220 3 18 0.3; 1 220 3 18 0.225; 1 220 3 18 0.175; 1 220 5 20.2 0.175; 1 220 5 20.2 0.225; 1 220 5 20.2 0.3; 1 220 7 16.9 0.225; 1 220 7 16.9 0.3; 1 220 7 16.9 0.175; 1 160 5 18 0.225; 1 160 5 18 0.3; 1 160 5 18 0.175; 1 160 7 20.2 0.175; 1 160 7 20.2 0.225; 1 160 7 20.2 0.3; 1 190 7 18 0.3; 1 190 7 18 0.225; 1 190 7 18 0.175; 1 190 5 16.9 0.175; 1 190 5 16.9 0.3; 1 190 5 16.9 0.225]

y = [11.9050; 15.4600; 11.8075; 19.3875; 12.5450; 21.8525; 14.6350; 15.4725; 23.1025; 22.6575; 9.0075; 15.6500; 17.6700; 17.7425; 19.8550; 15.9250; 13.0225; 16.4275; 16.9600; 13.9325; 10.0525; 16.4000; 18.3425; 23.1175; 22.0575; 13.9275; 19.0100]

A   = Transpose (X)
B   = (A*X)
K   = inv (B)
C   = ((K*A) *Y)
M   = X*C
E   = Y-M
MaxErr = Max (abs (Y-M))

The result of the above script gives the least squares estimators. For the other two responses namely bead penetration and bead height were calculated using the similar method and the estimators are tabulated in Table 4. The MATLAB command window screen shot is as shown in Fig. 3 and these data were tested using statistical technique ANOVA and the results are tabulated in Table 5.

Table 4: Co-efficient of the bead geometry

	Least square estimators for bead geometry		
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	Width (BW)	Penetration (BP)	Height (BH)
Intercept	12.2029	16.403	-1.059
Arc current	0.0746	-0.002	0.016
Stick out	0.2196	-0.173	0.129
Arc voltage	0.0436	-0.112	0.028
Travel speed	-48.5173	-9.287	-9.033

Table 5: Regression statistics

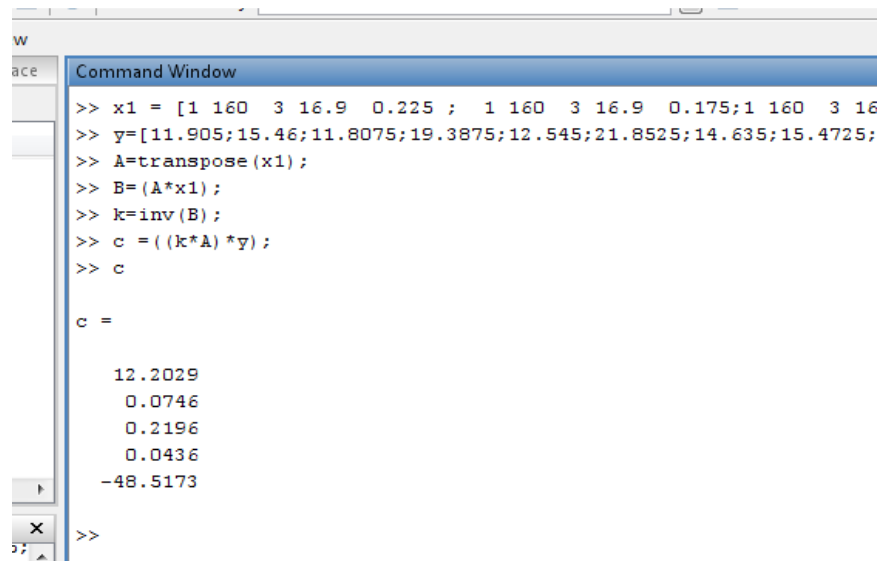|	Bead Width (BW)	Bead Height (BH)	Bead Penetration (BP)
Multiple R	0.95798	0.8828	0.879336
R square	0.91773	0.7794	0.755630
Adjusted R square	0.90277	0.7393	0.724835
Standard error	1.04725	0.3701	1.093655
Observations	27	27	27

Fig. 3: Screen shot of MATLAB results

From the script the results obtained from experimental data. The predicted equations are listed below:

$$BW = 12.2029 + 0.0746\ I + 0.2196\ h + 0.0436\ V - 48.517S \quad (7)$$

$$BH = -1.059 + 0.016\ I + 0.1296\ h + 0.028\ V - 9.033\ S \quad (8)$$

$$BP = 16.403 - 0.002\ I - 0.173\ h - 0.112\ V - 9.287\ S \quad (9)$$

These coefficient values can be used to determine the influence of the input variables with respect to the output variable which is estimated by the regression model. Using the coefficients in Eq. (7) to (9) and Table 4, the arc current, stick out and arc voltage appears to have a positive effect on the bead geometry, while the travel speed has negative effects on the bead geometry. This situation is consistent with the experimental results.

CONCLUSION

In this study, an alternative approach of combining MATLAB script and matrix algebra to analyze multiple linear regressions has been utilized. Using Design of Experiments concepts in matrix approach, the linear multiple regression techniques were applied to predict the weld bead geometry for IS: 2062 structural steel plates. The values of BP, BW and BH increase with the increase in arc current, whereas these values decrease with the increase in travel speed. Normally, the end user utilizes the power of windows approach in much statistical software without understanding the relationship between the algorithm and the results. This methodology gave a chance to the users to understand the theory behind the development of matrix approach and multiple linear regression models using the MATLAB script approach. This study offers one to observe what is going on inside the system during computations.

ACKNOWLEDGMENT

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