A New Approach for Predicting and Optimizing Weld Bead Geometry in GMAW

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***Abstract*—**Generally, the quality of a weld joint is directly influenced by the welding input parameter settings. In this study, the regression modeling is used in order to establish the relationships between input and output parameters for Gas Metal Arc Welding (GMAW) process. To gather the required data for modeling, actual tests were carried out based on the proposed Taguchi experimental matrix design. The process variables considered here include voltage (V); wire feed rate (F); torch Angle (A); welding speed (S) and nozzle-to-plate distance (D). The process output characteristics include weld bead height, width and penetration. To develop mathematical models, various regression functions have been fitted on the experimental data. The adequacies of the models are then evaluated using analysis of variance (ANOVA) technique. The best and most fitted model is then selected based on the ANOVA results and other statistical analysis. The ANOVA results recommend that the curvilinear model is the best fit in this case. In the next stage, the selected model is implanted into a Simulated Annealing (SA) optimization algorithm. This optimization procedure has been developed in order to determine the best set of process variables levels for any desired weld bead geometry characteristics. Computational results show very good compatibility with experimental data and demonstrate the effectiveness of the proposed modeling and optimization approach.

***Keywords*—**GMAW, Process parameters, Optimization, Regression modeling, SA algorithm

I. Introduction

WELDING is a fabrication or sculptural process that joins materials, usually metals or thermoplastics, by causing coalescence. These processes play an important role in metal fabrication industries. There are various welding techniques. The two most commonly used types of Gas Metal Arc Welding (GMAW) processes are tungsten inert gas (TIG) and metal inert gas (MIG/MAG). The distinction resides in the fact that the TIG process uses a no consumable electrode, while the MIG/MAG process utilizes a consumable electrode for joining. Generally, the quality of a weld joint is directly affected by the welding input parameters during the welding process. Therefore, welding can be considered as a multi-input multi-output process. Unfortunately, a common problem that has faced the manufacturer is the control of the process input parameters to obtain a good welded joint with the required bead geometry and weld quality with minimal detrimental residual stresses and distortion. Traditionally, it has been necessary to determine the weld input parameters for every new welded product to obtain a welded joint with the required specifications. To do so, requires a time-consuming trial and error development effort, with weld input parameters chosen by the skill of the engineer or machine operator. Then welds are examined to determine whether they meet the required specifications. Finally, the weld parameters may be determined to produce a joint which closely meets the requirements. Nevertheless, a pre-specified weld bead can often be produced with various parameters combinations. In other words, there is often a more ideal welding parameters combination, which can be used if it can only be determined.

Optimization of welding input parameters has always been an open research area. Christensen [1] derived no dimensional factors to relate bead dimensions with the operating parameters. Chandel [2] presented the theoretical predictions of the effect of current, electrode polarity, diameter, and electrode extension on the melting rate, bead height, bead width and weld penetration in submerged arc welding (SAW). Markelj and Tusek [3] mathematically modeled the current and voltage in TIG welding as quadratic polynomials of sheet thickness. The results were presented for algorithmic optimization in the case of T-joint with fillet weld. Kim [4] conducted a sensitivity analysis of a robotic GMAW (gas metal arc welding) process, to determine the effect of measurement errors on the uncertainty in estimated parameters. They employed non-linear multiple regression analysis for modeling the process and quantified the respective effects of process parameters on the weld bead geometric parameters. Kim [5] compared experimental data obtained for weld bead geometry with those obtained from empirical formulae in gas metal arc welding (GMAW).

The present study attempts to make use of experimental data to relate important process parameters to process output characteristics, through developing empirical regression models for various target parameters. In the next stage, the proposed model is implanted into a simulated annealing (SA) optimization procedure to identify a proper set of process parameters that can produce the weld bead geometry of GMAW welding. The data required for modeling are gathered using experimental tests. A welding sample used in this study is illustrated in Fig 1.

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Fig. 1 A sample welding test

II. Model Development

As mentioned above, the objective of the present study is to establish relationships between the process parameters (inputs) and process responses (outputs) in GMAW welding; using the statistical regression analysis carried out on the data collected as per Taguchi design of experiments (DOE). The most important process parameters in GMAW are the voltage (V); wire feed rate (F); torch Angle (A); welding speed (S) and the nozzle-to-plate distance (D). The process response characteristics considered are bead height (BH), bead width (BW), and penetration (BP). These geometrical characteristics are shown in Fig 2.

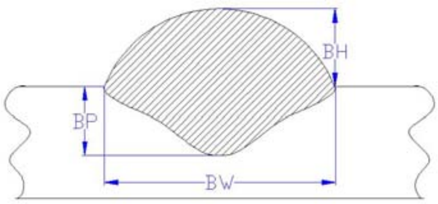

Fig. 2 Weld Bead Geometry Characteristics

The levels for each of the input parameters are given in Table I. Based on Taguchi L_{54} matrix a total of 54 combinations of input process parameters are to be considered experimental tests.

TABLE I
INPUT VARIABLES AND THEIR LEVELS OF THE GMAW PROCESS

No	Factor	Units	Symbol	Level -	Level 0	Level +
1	Welding Speed	cm/m	S	10	17	24
2	Arc Voltage	V	V	27	32	37
3	Wire Feed Rate	m/min	F	4	5.5	7
5	Torch Angle	degree	A	70	85	100
4	Nozzle-Plate Distance	cm	D	1	-	1.5

Various regression functions (linear, curvilinear, logarithmic, etc.) are fitted to the experimental data and the coefficients values are calculated using regression analysis.

The best model is the most fitted function to the experimental data. Such a model can accurately represent the actual GMAW process. Therefore in this research, the adequacies of various functions have been evaluated using analysis of variance (ANOVA) technique. The model adequacy checking includes test for significance of the regression model and test for significance on model coefficients [6]. Table II show the values of correlation factor (R^2) for each term of the three models.

TABLE II
CORRELATION FACTOR RESULTS FOR THE WBG

Model	BH	BW	BP
Linear	94.1%	94.7%	83.9%
Curvilinear	95.6%	98.3%	91.9%
Logarithmic	94.0%	97.0%	81.5%

Based on ANOVA, the values of R^2 in curvilinear model are over 95% for all weld bead characteristics. This illustrates that the model is statistically significant and provides an excellent representation of the actual process in terms of BH, BW and BP responses. The Stepwise elimination process removes the insignificant terms to adjust the fitted quadratic model. The final proposed curvilinear models are presented below:

$$BH = 4.08 - 0.00184SV - 0.000707AV + 0.00271AF + 0.646\,DD - 0.0535\,DS + 0.00144\,SS \quad (1)$$

$$BW = 2.07 + 0.0169\,VV - 0.0211\,SV - 0.183\,DV + 0.0172\,SS + 0.710\,DF - 0.0309\,FS \quad (2)$$

$$BP = -1.55 + 0.0834\,V + 0.00596\,FS - 0.257\,DD \quad (3)$$

For illustrative purposes, the distributions of real data around regression lines for curvilinear model are illustrated in Fig. 3 to 5. These figures demonstrate a good conformability of the proposed models to the real process.

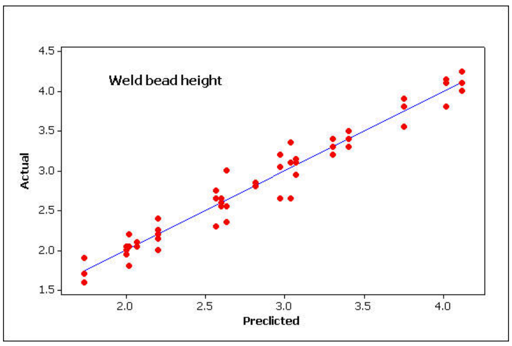

Fig. 3 Predicted values for BH vs. actual values

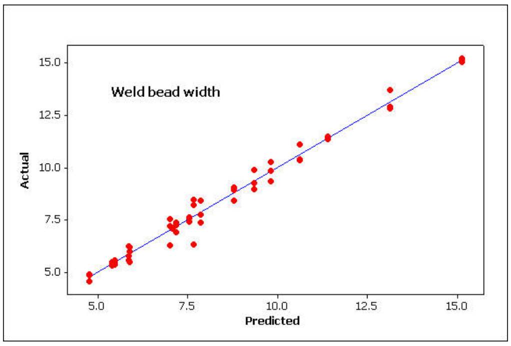

Fig. 4 Predicted values for BW vs. actual values

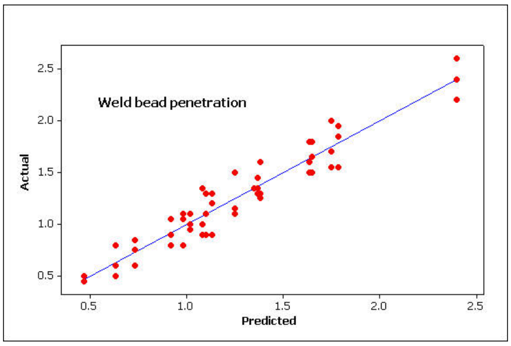

Fig. 5 Predicted values for BP vs. actual values

For illustrative purposes, the pairwise effects of two of the important process variables (welding speed and welding voltage) on the weld bead characteristics (height, width and penetration) are shown in Fig. 6 to 8 respectively.

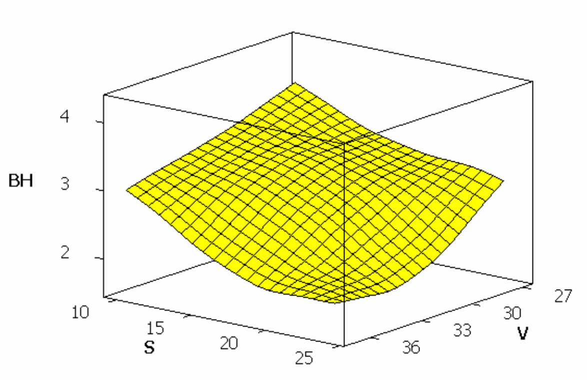

Fig. 6 The effects of welding speed and voltage on weld bead height

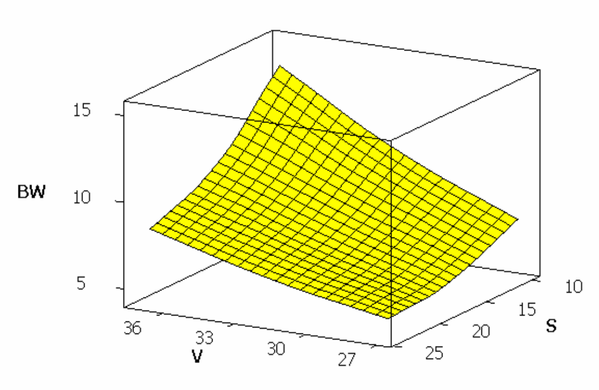

Fig. 6 The effects of welding speed and voltage on weld bead width

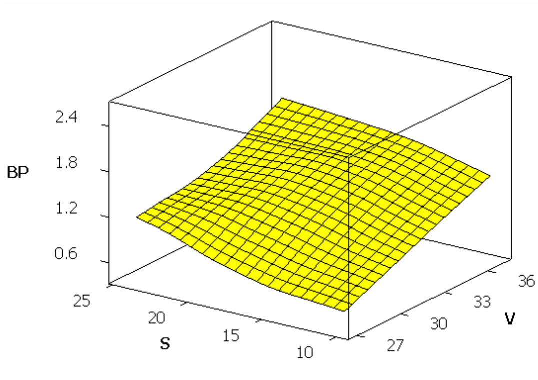

Fig. 8 The effects of welding speed and voltage on weld penetration

III. THE OPTIMIZATION PROCEDURE

In many practical situations, one needs to set the process parameters in such a way that a desired output is obtained (in this case WBG). The mathematical models provided above can be used to determine a set of process parameters values for a desired WBG characteristic specification.

Finding the optimal set of input parameters for a given WBG requires simultaneous solving of the model equations. This is a problem of combination explosion and hence evolutionary algorithms can be employed as the optimizing procedure. These techniques would make the combination converge to solutions that are globally optimal or nearly so.

Evolutionary algorithms are powerful optimization techniques widely used for solving combinatorial problems. As a promising approach, one of these algorithms called Simulated Annealing (SA) is implemented in this research.

Simulated Annealing is one of the novel algorithms initially proposed by Kirkpatrick [7]. SA is an approach to simulate the thermodynamic process of annealing (cooling a molten metal slowly to the solid state). It is an optimization technique that can theoretically converge to the global optimum solution, if the initial temperature is high enough and the cooling rate is infinitely slow. In this algorithm, an improving solution to the current objective function value is always accepted. However, to escape from local optima, a non-improving solution is also adopted with a certain probability; which is given by Boltzman function as follow:

$$e^{-\Delta c/T_0} \geq \left[ran(0,1)\right] \tag{4}$$

In our optimization process, we first define the objective function in the form of an error function given by:

$$E = \frac{(BH_d - BH)^2}{BH_d} + \frac{(BW_d - BW)^2}{BW_d} + \frac{(BP_d - BP)^2}{BP_d} \tag{5}$$

This function is used as the objective function and should be minimized in the optimization process. In the above formula, BH_d, BW_d and BP_d are the desired (target) values for GMAW weld bead geometry; which are usually pre-specified by welding standards. The terms without subscripts are those computed by the optimization process using the models given by equations 1 to 3. The objective is to set the process parameters at such levels that these values are achieved. In other words, we want to minimize the difference between the desired output and the output given by the SA algorithm. This is done by minimizing the error function given by equation (5). In this way, the process parameters are calculated in such way that the welding parameters approach their desired values.

IV. A Hypothesis Example

To illustrate the performance of the proposed model and the solution procedure, a set of numerical examples is presented. The error function given in (5) along with welding models 1 to 3 are embedded into SA algorithm. The objective are to determine the values of process parameters (S, V, F, A and D) in such a way that the process output responses for WBG converge towards their target values.

The algorithm was coded in MATLAB 7.0® software and executed on a Pentium 4 computer. The best set of algorithm parameters, found through several trial runs, is as follow: initial temperature (T_0) = 20; cooling rate (α) =0.97; and termination criteria = 500 iterations or objective function value (% error) less than 0.02.

A total of 5 example problems have been solve using the proposed solution procedure. The comparisons between predicted and desired values of process responses are shown in Table III. The process parameters values given in this table are those found by the algorithm. As illustrated, all the output parameters deviate by at most 2% from their desired values (most of them by less than 1%). These results prove that the proposed procedure can be efficiently used to determine optimal process parameters for any desired weld bead geometry output values in GMAW process

V. Conclusion

In this research a procedure was proposed to model and optimize weld bead geometry in GMAW process. Since, the relationships between bead geometry characteristics and welding output variables are complicated; a regression based method was employed to model the process. The experimental data for model development were gathered using the actual tests carried out by the authors. Along this line, using DOE approach and regression analysis, different mathematical models were developed to establish the relationships between welding input parameters and weld bead geometry outputs. The ANOVA results performed on different regression functions denote that the set of curvilinear models is the best representative for the actual GMAW process. The associated P-value for this model is lower than 0.05; i.e. $\alpha = 0.05$ or 95% confidence level. In this research, these models were employed as a part of optimization procedure for determining process parameters for any desired weld bead geometry. A Simulated Annealing technique was developed to minimize the error function consisting of desired and calculated weld bead geometry. By minimizing such a function, the process parameters can be determined so as the resultant bead geometry has the least deviation from its desired value. Computational results indicate that the proposed SA method can efficiently and accurately determine welding parameters so as a desired bead geometry specification is obtained.

TABLE III
A COM PARIOSON BETWEEN ACTUAL (TARGET) AND PREDICTED VALUES OBTAINED BY THE PREOPOSED SA ALGORITHM

No.	Process Parameters By SA					Predicted Value by SA (mm)			Target Value (mm)			Ave. Error %
	S	V	F	D	A	BH	BW	BP	BH_d	BW_d	BP_d	
1	10.0	37	7	1.0	70	3.15	15.15	15.15	3.20	15.20	1.70	**0.67**
2	18.5	32	7	1.5	70	3.19	7.44	7.44	3.30	7.38	1.35	**2.20**
3	16.5	37	6	1.0	97	2.20	11.33	11.33	2.20	11.36	1.85	**0.12**
4	17.0	29	4	1.3	92	2.65	5.42	5.42	2.65	5.40	0.80	**0.35**
5	10.0	27	6	1.5	83	4.09	7.38	7.38	4.10	7.40	0.45	**1.55**

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