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Modeling and optimization of the in submerged arc welding consuming a mixture of fresh flux and fused slag

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Abstract

In this paper, an attempt is made to determine input-output relationships in submerged arc welding consuming a mixture of fresh flux and fused slag using regression analysis. To develop mathematical models, various linear and curvilinear regression functions have been fitted to the experimental data and the best set of models is selected. Simulated Annealing (SA) is then used to optimally determine input parameters levels in order to obtain the desired set of outputs. Computational results demonstrate that the proposed method is quite effective in predicting and optimizing process parameters for any desired weld bead geometry.

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1. Introduction

Submerged arc welding is a versatile metal joining process in industry. It is a multi-variable, multi-objective metal fabrication process characterized by the use of granulated fusible flux which covers the molten weld pool during operation. This arrangement facilitates slower cooling rate, prevents atmospheric contamination into the weld pool and improves both mechanical properties and metallurgical characteristics of the weld bead as well as heat affected zone (HAZ). The acceptable quality characteristics of a weldment, in relation to the geometry of a weld bead and HAZ include deeper penetration, minimum reinforcement, minimum bead width and minimum HAZ width. Research related to slag reconsumption in the conventional SAW process has been carried out by Moi, S. C. et al. [1], and Pal, P. K. et al. [2]. The study introduced the concept of using slag-mix% as a process variable. The main effect of using slag-mix and interactive effects of process parameters (including slagmix%) on features of bead geometry and HAZ, in terms of bead height, depth of penetration, bead width and HAZ width has been evaluated through the analysis of variance (ANOVA) method. But their work did not provide the optimal factor combination to yield acceptable weldment and the maximum slag-mix% that can be used during SAW process without affecting bead geometry as well as HAZ dimension. Numerous research works exist on the modelling and optimization of process parameters in welding [3, 4]. Comprehensive surveys in this field can be found in literature [5].

In the present work, an attempt has been made to carry out linear as well as curvilinear regression analyses on the Submerged Arc Welding (SAW) data collected by Datta and Kumar [6] using an L16 Taguchi design. The text is organized as follows: Input-output variables of the process have been identified and their feasible ranges have been set. Both linear as well as curvilinear regression analyses carried out in the present work and the results are stated and discussed. Finally SA algorithm is used to optimize the SAW process.

2. problem statement

In order to achieve optimum welding performance, it is important to properly set the welding parameters. The selected input process parameters in this study and their levels of the SAW process are shown in Table 1 and the responses considered are like the following: bead width (BW), bead height (BH), bead penetration (BP) and heat affected zone (HAZ).

Table 1. Input factors and their levels of the SAW process

Parameter	Units	Notation	Factors levels			
Current	Ampere	(C)	*150*	*200*	*250*	*300*
Percent of slag-mix	-	(S)	*0*	*10*	*15*	*20*
Basisity index	-	(B)	*0.8*	*1*	*1.2*	*1.6*

The aim of the present investigation is to establish relations between the process parameters (inputs) and responses (outputs) for SAW process, using regression analysis, where each response would have a single regression equation relating it to the process parameters for the whole domain of the investigation. The performance of the different regression approaches in predicting the weld bead geometry from the process parameters are compared and SA algorithm is used to find the optimum input parameters in order to have the desired outputs. Four levels are considered for each of the three input process parameters and thus, 16 combinations of input process parameters are to be considered for the L16 Taguchi design.

3. The solution procedure – SA algorithm

With the advent of computer technology and computational capabilities in the last few decades, the applications of heuristic algorithms are widespread. These techniques are usually based on the physical or natural phenomena. In 1953, Metropolis proposed a procedure used to simulate the cooling of a solid for reaching a new energy state. The annealing process, used in metal working, involves heating the metal to a high temperature and then letting it gradually cools down to reach a minimum stable energy state. If the metal is cooled too fast, it won't reach the minimum energy state. Later Kirkpatrick and his colleagues [7] used this concept to develop a search algorithm called Simulated Annealing (SA). Among different heuristic algorithms, SA is one of the most powerful optimization methods that simulates the cooling process of a molten metal. The general stages of the SA algorithm are as follows:

1. Initialize the temperature parameter T 0 and the cooling schedule; r (0 < r < 1) and the termination criterion (e.g. number of iterations k = 1… K). Generate and evaluate an initial candidate solution (perhaps at random); call this the current solution, c.

2. Generate a new neighboring solution, m, and evaluate this new solution.

3. Accept this new solution as the current solution if:

   3-a) the objective value of new solution, f (m), is better than of the current solution, f (c).

   3-b) the value of acceptance probability function given by (exp (f (m) – f (c)) / T k) is greater than a uniformly generated random number “rand”; where 0 < rand < 1.

4. Check the termination criterion and update the temperature parameter (i.e., T k = r * T k-1) and return to Step 2.

The main advantages of SA are its flexibility, its fewer tuning parameters, and its ability to escape local optima and to approach global optimality.

4. Modeling

To develop the mathematical models, various linear and curvilinear regression functions have been fitted to the experimental data. The best set of models is then chosen based on two criteria, namely; correlation coefficient and Analysis of Variance (ANOVA) results, with 95% confidence level. The calculated correlation coefficient, P-value and F-value for regression functions are shown in Tables 2, 3 and 4, respectively.

Table 2. The calculated correlation coefficient for regression functions

objective function	BW	BH	BP	HAZ
First order	*89.7*	*89.1*	*90.0*	*94.8*
Second order	*93.0*	*96.5*	*95.7*	*97.8*

Table 3. The calculated P-value for regression functions

objective function	BW	BH	BP	HAZ
First order	*0.000*	*0.000*	*0.000*	*0.000*
Second order	*0.045*	*0.007*	*0.013*	*0.002*

Table 4. The calculated F-value for regression functions

objective function	BW	BH	BP	HAZ
First order	*16.51*	*15.42*	*17.00*	*35.67*
Second order	*4.28*	*9.12*	*7.16*	*14.93*

Based on these tables, since second order polynomial equations for all of the responses have great correlation coefficient and acceptable P and F value, second order polynomial equations will be used for optimization and third order is not needed. But first insignificant factors should be removed from equations using step backward elimination with 95 percent confidence level. Therefore, the modified regressions are as follows:

$$BW = 1.53 + 0.0526\ C - 0.00102\ CB + 0.191\ SB \quad (1)$$

$$BH = 4.63 + 0.00785\ C + 0.0152\ B - 4.60\ S + 2.02\ S^2 \quad (2)$$

$$BP = -\ 2.13 + 6.03\ S + 0.000022\ C^2 - 2.46\ S^2 \quad (3)$$

$$HAZ = -\ 4.58 + 0.0579\ C - 0.0477\ B - 0.000064\ C^2 + 1.23\ S^2 - 0.0111\ CS \quad (4)$$

Where, CB, CS ... are the interaction effects of the process parameters. Normal plot of residuals are shown in Figure 1.

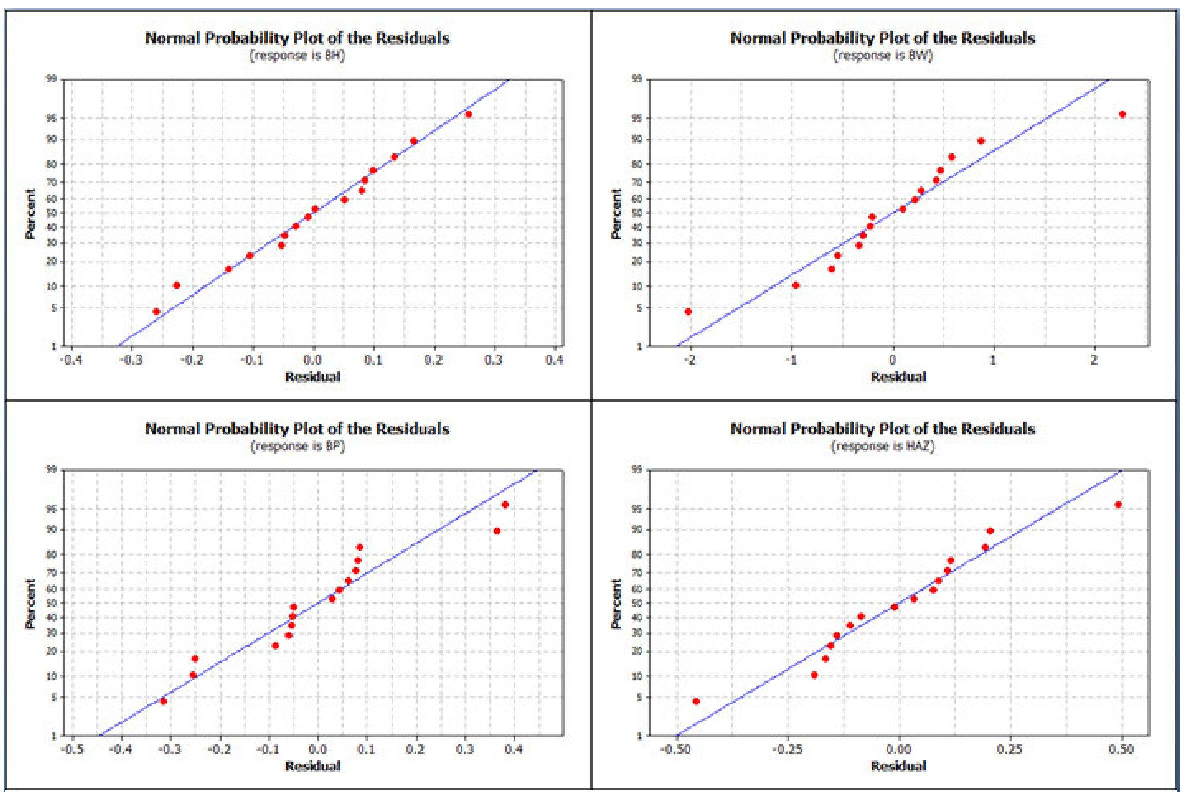

Figure 1. Normal plot of residuals for BW, BH, BP and HAZ.

5. Optimization

SA Algorithm is used to optimally determine input parameters levels in order to obtain any desired set of outputs. Usually, for high quality joint the BH, BW and WH (Width of HAZ) should be as low as possible while BP should be at the highest possible values. To achieve this, a multi-objective fitness function, based on mean square error, is defined as follows:

$$Fitness = \frac{(BH_d - BH)^2}{BH^2} + \frac{(BW_d - BW)^2}{BW^2} + \frac{(BP_d - BP)^2}{BP^2} + \frac{(WH_d - WH)^2}{WH^2} \quad (5)$$

In turn, BH_d, BW_d, BP_d, and WH_d are the desired values of the process output characteristics set by the operator. The algorithm along with its objective function has been coded in Matlab® software. In our computations, the relative importance (weights) of the output parameters are set to unity. In practices, these weights may be set at any relative values as required. SA parameters are as follows: initial temperature: 1000, cooling rate: 0.99, termination criterion: 1000 iterations. The convergence curve of the SA is shown in Figure 2.

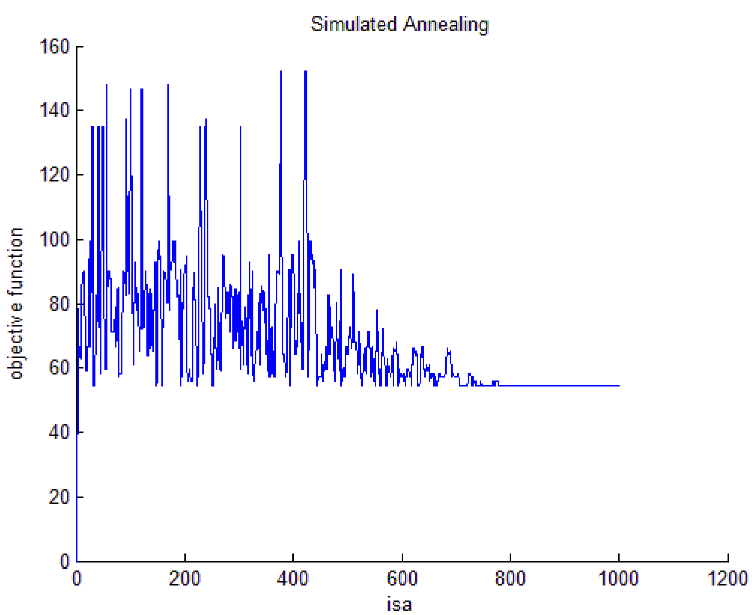

Figure 2: The convergence curve of the SA algorithm

The best input parameters to gain optimum results are as follows: C: 200, B: 1.2, S: 20. Since in all runs, which were started from random point, lead to one specific above mentioned answer, the answer is the global answer of the process.

6. Conclusions

Weld bead geometry is the most important quality measure in all types of welding techniques. To achieve a high quality weld, welding parameters should be set in such way that the desired bead geometry and HAZ is obtained. The relationships between bead geometry-HAZ and welding parameters are quite complicated involving many interactions. The main trust of this research was to establish the mathematical relationships between input and output parameters and to explore the possibility of using SA algorithm in predicting input parameters values in Submerged Arc Welding. 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-HAZ. The ANOVA results denote that the curvilinear models are the best representative for the actual SAW process. The direct use of these models is to calculate weld bead geometry for any given set of process parameters. In this research, these models were put to use as a part of prediction procedure for determining process parameters for any desired weld bead geometry. To achieve this, a SA technique was developed to minimize an error function consisting of desired and weld bead geometry-HAZ. 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 for a desired bead geometry specification.

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