Optimization of HAZ in TIG welding process using OA-Taguchi technique and simulated annealing algorithm

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Abstract

To tackle the problem of stainless steel parts welding, gas tungsten arc welding (GTAW) process also known as tungsten inert gas (TIG) welding, widely used for joining thin sheet metals due to its high quality joint (spatter free) has been introduced. In this study, the effects of welding process adjusting/input parameters on the joint quality of thin sheet metals (AISI304 austenite stainless steel sheets, extensively used for corrosive areas such as marine structures) have been investigated. To study the corrosion resistance and strength of the weldments, heat affected zone (HAZ) width has been considered as the process output characteristics. Conducting modeling procedure (regression modeling), orthogonal array (OA) Taguchi based design of experiments (DOE) technique has been used to design an experimental matrix to gather data needed for the procedure. Next, the proposed models (linear, curvilinear and logarithmic) has been verified employing analysis of variance (ANOVA) approach. Then, the proper and most fitted models have been selected. Furthermore, opted models have been used carrying out optimization of the process in such a way that HAZ width minimized using simulated annealing (SA) algorithm.

Keywords: GTAW process, orthogonal array (OA) Taguchi technique, Simulated annealing (SA) algorithm.

Introduction

Metallurgical changes such as solidification cracks and grain growth in the heat affected zone (HAZ) area often leads to poor mechanical properties [1, 2]. However, based on the excellent mechanical properties and proper resistance corrosion, austenitic stainless steels (such as AISI304/316) have been extensively used for marine structural materials. Generally, welding process is one of the processes widely used to fabricate stainless steel structures [3]. A non-consumable electrode and shielding inert gas like helium, argon or combination of both (to protect the molten weld pool and hot filler wire from atmospheric contaminants) has been used in gas tungsten arc welding (GTAW) process known as tungsten inert gas (TIG) welding extensively used for joining a number of metals such as stainless steel, magnesium and aluminum with 1-6 mm thickness [4]. Controlling of the welding input process parameters is a common problem for manufacturer to obtain a good welded joint with the required weld quality [5]. Conventionally, selection of process input parameters for every new weldments to obtain a joint with required specifications have been chosen by technicians/engineers based on time-consuming trial and error method. Then weldments have been examined to determine whether they meet the needed specifications or not [4]. Nowadays, application of different techniques such as design of experiment (DOE), evolutionary algorithms (SA, GA, PSO and etc.) and artificial neural networks (ANNs) are widely used to develop mathematical relationships between the process input parameters and output measures in order to determine the proper levels of input parameters that lead to the desired output characteristics [6].

On modeling and optimization of TIG welding process there is an extensive body of research. To the best of our knowledge there is no published study in which modeling and optimization of TIG welding process with proposed procedure has been considered. In this article mathematical models developed to establish the relations between multi-input, multi-output parameters of TIG welding process using different regression models (linear, curvilinear, modified curvilinear and logarithmic). The proposed model has five input variables and an output (heat affected zone (HAZ)). In the proposed approach optimization is carried out to determine optimal values of process parameters (to be set on the welding machine). These settings would results in minimum HAZ width. The proposed approach has been implemented on AISI304 stainless steel sheets, a widely used alloy in various industries including marine structures.

Experimental set up and equipment used

In this research, a semi-automatic welding machine ("Figure 1") has been employed to carry out the experiments. To conduct the pre-determined experiments based on design of experiments (DOE) approach, non-consuming Tungsten electrodes have been used. Furthermore, argon with 99.7% purity acted as welding shielding gas. Schematic illustration of TIG welding process has been shown in "Figure 1". Experiments were conducted on AISI304 stainless steel sheets with dimension of 100 mm×40 mm×5 mm.

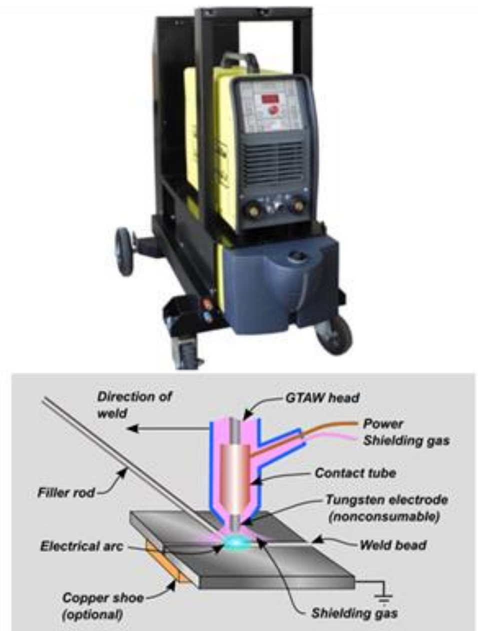

Figure 1. Schematic illustration of TIG welding process and the welding machine used

The variable limits were then evaluated by inspecting the weldments for a smooth appearance and good penetration without any visible defected to surface porosities and undercuts. The input variables and their corresponding levels based on the experimental tests are listed in Table 1. Other parameters with trivial effects (electrode diameter, electrode angle and etc.) have been considered at a fixed level based on the results of experimental preliminary tests.

Table 1. The process parameters and their corresponding levels.

Level	Welding current (I) (Ampere)	Base current (Ib) (Ampere)	Frequency (F) (Hz)	Welding Speed (S) (m/min)	Debi (D) (l/min)
Level 1	30	5	30	0.4350	5
Level 2	35	8	40	0.5075	7
Level 3	40	10	50	0.5365	-
Level 4	45	15	60	0.5800	-

Design of experiments (DOE) approach and experimental test results

The next step following process variables determination based on the experimental tests or reference studies, is determining the appropriate experimental design matrix for carrying out the experiments. Based on the input variables numbers and their levels, Taguchi's L_{32} design matrix has been selected. This experimental matrix (Table 2) consists of 32 sets of process input parameters, based on which the experiments have been performed. In DOE approach, the number of required experiments (and hence the experiment cost) increases as the number of parameters and/or their corresponding levels increase. Conducting experiments in random order results in increased accuracy, therefore, in this study tests were carried out in random orders. For measuring HAZ values from each sample, on each sample two transverse cross sections were made. Microstructural image processing (MIP) software has been used to determine samples HAZ width ("Figure 2").
Next, the cut faces were polished and etched smoothly using 10% Nital solution. Then, electro-polish and electro-etch machines have been used ("Figure 3").Then, an optical microscope with X10 magnification (OLYMPUS-530) has been used to take images ("Figure 3").

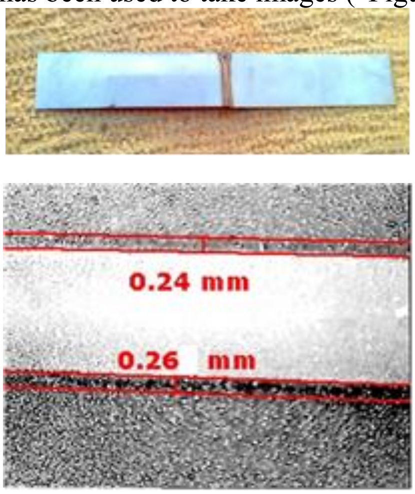

Figure. 2 The welded sample and evaluation of HAZ using microstructural image processing software

Figure 3. Electro-polish machine and optical microscope used

Table 2. The TIG welding process experimental conditions and their corresponding results.

No	I (Ampere)	I_b (Ampere)	F (Hz)	S (m/min)	D (l/min)	HAZ width (mm)
1	4	2	1	4	1	0.29
2	4	1	2	3	1	0.24
3	3	4	4	2	1	0.25
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
30	2	2	2	1	1	0.20
31	4	3	3	2	1	0.30
32	2	3	2	1	2	0.30

Regression modeling approach

To model the relation between independent process input variables and desired response/s different methods are used among which regression modeling is extensively used [5].The output for each test settings (required for modeling purpose) have been shown in last two columns of Table 2. Any of the above output is a function of process parameters which are formulated by linear, second order, modified second order and logarithmic functions; as stated in Equations 1 to 3 respectively [6, 7].

$$Y_1 = b_0 + b_1 C + b_2 F + b_3 D \qquad (1)$$

$$Y_2 = b_0 + b_1 C + b_2 F + b_3 D + b_{11} CC + b_{22} FF + b_{33} DD + b_{12} CF + b_{13} CD + b_{23} FD \qquad (2)$$

$$Y_3 = b_0 \times C^{b1} + F^{b2} + D^{b3} + CC^{b11} + FF^{b22} + DD^{b33} + CF^{b12} + CD^{b13} + FD^{b23} \qquad (3)$$

In Equations 1-3, b0, b1, b2 and b3 are the regression coefficients to be estimated. In this study, based on the UTS and HAZ data given in Table 2, the regression models are developed using MINITAB software.

The nature of initial data and the required accuracy dictate the proper model [8]. Models representing the relationship between process input parameters and output characteristics have been stated in equations 4 to 6.

Linear Model

$$HAZ = 0.260 + 0.0170\times D - 0.145\times S - 0.00298\times F + 0.00678\times Ib + 0.00182\times I \quad (4)$$

Logarithmic Model

$$HAZ = 0.986\times F^{(-0.456)} \times I_b^{(0.210)} \quad (5)$$

Second order/Curvilinear Model

$$HAZ = 3.98 - 0.207\times D + 4.51\,S - 0.0616\times F + 0.141\times Ib - 0.205\times I - 0.615\,D\times S + 0.00298\times D\times F + 0.0109\times D\times I + 0.0338\times S\times F - 0.157\times S\times Ib + 0.000422\times F\times Ib + 0.000869\times F\times I - 0.000129\times F\times F\ \ 0.00347\times Ib\times Ib + 0.00138\times I\times I \quad (6)$$

Analysis of variance (ANOVA) technique has been used to check the adequacies of the proposed models (Table 3) based on confidence limit of 95% [8]. Given the required confidence limit (Pr), the correlation factor (R2), the adjusted correlation factor (R2-adj) and predicted correlation factor (R2-pre) for these models, it is evidence that modified second order (second order model with elimination of unimportant factors) model is superior to linear and logarithmic models, thus, these models have been considered as the best representative of the authentic TIG welding process throughout in this paper.

Table 3. ANOVA results for the process characteristics.

Model	Variable	R^2	R^2 (adj)	R^2 (Pre)	F value	Pr>F
Linear	HAZ	49.4	43.9	42.18	9.1	<0.0001
logarithmic	HAZ	40.3	36.8	41.2	9.8	<0.0001
Second order	**HAZ**	**92.4**	**89.9**	**90.1**	**12.4**	**<0.0001**

The interaction effects of process parameters (frequency and pulse current) for HAZ have been shown in "Figure 4" As demonstrated, by increasing welding frequency, the HAZ decreases. Similarly by increasing pulse current, the HAZ at first increases then decreases.

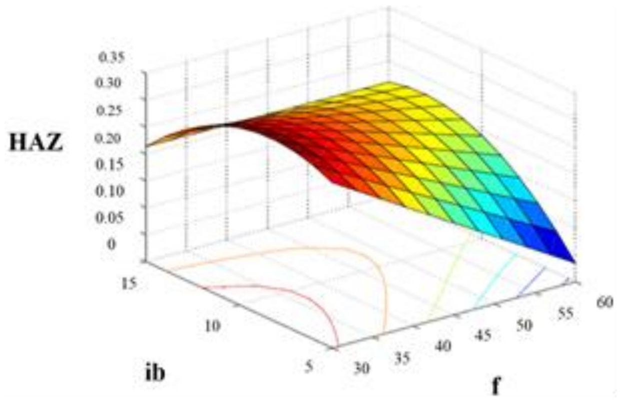

Figure 4. interaction of process parameters for HAZ

Simulated annealing algorithm

The SA algorithm procedure begins by generating a primary solution at random. At early stages, in the current solution a small random change is made, then the new solution objective function value is calculated and compared with that of current ones. A move is made towards the new solution if the new objective function either has better value or the probability function (Equation 10) implemented in SA has a higher value than a number which is been generated randomly between (0, 1] . The probability of accepting a new solution is given as Equation (7) [9]:

$$p=\begin{cases}1 & \text{if } \Delta<0\\ e^{-\Delta/t} & \text{if } \Delta\geq 0\end{cases} \qquad (7)$$

Where, T, is temperature parameter, on which the calculation of probability function relies, while the same role as the temperature in the physical annealing process is played. The rate of temperature reduction is also slow avoiding getting trapped at a local minimum point [5]. Equation (8) shows the method by which the temperature is reduced:

$$T_{i+1}=c\times T_i \qquad i=0,1,\ldots \quad \text{and} \quad 0.9\leq c<1 \qquad (8)$$

Based on the Equation (8) given, at the initial stages of SA algorithm most worsening moves may be accepted, nevertheless at the end only improving ones are likely to be accepted. This could help the procedure jump out of a local minimum trap. The algorithm may be terminated after a pre-determined iteration or a run time.

Performance improvement of other artificial intelligence methods and determining the optimal set of process parameters are some examples of SA algorithm diverse applications [9]. In this research, SA has been used twice (for single and multi-criteria optimization purpose).

Table 4 illustrates the results of optimization using SA algorithm and their corresponding confirmation tests for single objective optimization.

As shown in table 4 the predicted values for HAZ, are less than the desired values (approximately 0.07 mm) in TIG welding process. The results of optimization show the accuracy of the proposed method as the both objectives has been satisfied.

Table 4. Result of optimization.

Output	Process parameters					Predicted	experiment	Error (%)
	I	I_b	F	S	D			
HAZ	35	5	60	0.435	5	0.188	0.198	4

Conclusion

In this study, the problem of single and multi-criteria modeling and optimization of TIG welding process used for AISI304 stainless steel sheets has been addressed. First, experimental data gathered as per L_{32} Taguchi design of experiments (DOE) has been used to carry out the process of modeling of TIG welding process. Moreover, the MIP software has been used to measure the HAZ areas. Next, the models have been embedded to SA algorithm to determine the optimal set of process settings both for optimization. The result of optimization technique has shown using SA algorithm result in small errors (about 5%) which shows the proposed model can accurately simulate and optimized the actual TIG welding process.

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