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Modeling and optimization of ultimate tensile strength in TIG welding process using simulated annealing algorithm- A case study for Shirvan combined cycle power plant

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Abstract:

Nowadays, one of the most popular welding processes is Tungsten Inert Gas (TIG) due to its high quality and slag free joints. Joining thin sheet and pipe metals are one of the most important applications of this process. The effects of TIG welding process parameters on ultimate tensile strength (UTS) of thin pipes have been investigated. The material used for specimens was AISI 304 stainless steel pipes which is excessively used in oil and gas and power plant pipelines. Taguchi design of experiments (DOE) approach has been performed to design the experiment matrix and gathering required data for modeling and optimization. Different regression models have been used to establish the relationship between input and output parameters. Current (I), frequency (F), welding speed (S), gap (G) and debi (D) are the most important input parameters in TIG welding process considered in this paper. Ultimate tensile stress (UTS) has been selected as the quality characteristic to assess the process. The most fitted model was selected using analysis of variance (ANOVA). The UTS model was then maximized using simulated annealing (SA) algorithm. The performance of the proposed optimization method has been proved through experimental test.

Key words:

TIG welding, ultimate tensile stress (UTS), Optimization, Taguchi method, Simulated Annealing (SA) algorithm.

1. Introduction

Austenitic stainless steels have been extensively used in piping structural materials as power plants, valve bodies, and vessel internals [1, 2]. Welding process is one of the most extensively used processes to fabricate stainless steel parts [3]. Gas tungsten arc welding (GTAW), also known as tungsten inert gas (TIG) welding is an arc welding process that uses a non-consumable electrode. The molten weld pool and red hot filler wire are protected from atmospheric contamination by an inert shielding gas (argon or helium or their combination). Joining a number of metals such as steel, magnesium and aluminum of thickness (1-6 mm) can be carried out using this process [4]. Mechanical and metallurgical properties of the weldments are affected by process parameters [4, 5]. Nowadays, design of experiment (DOE) approach used to develop mathematical relationships between the welding process input parameters and the output characteristics of the weld joint in order to determine the optimized welding input parameters that lead to the desired weld quality [6]. Taguchi method has been applied to obtain maximum depth of penetration (DOP) on mild steel through optimization of the process parameters namely; current, voltage and welding speed by Sapkal and Teslang [7]. For developing experiential relationships, incorporating pulsed current parameters and weld pool geometry (front height, back height, front width and back width), Box–Behnken design of experiments was used by Balasubramanian [8]. Yan et al [3] investigated the microstructure and mechanical properties of AISI304 stainless steel joined by TIG welding, laser welding and laser-TIG hybrid welding. Highest tensile strength has been achieved through the joints made by laser welding. Moreover, the results revealed that the smallest dendrite size, while the joints made by TIG welding had lowest tensile strength, biggest dendrite size. Based the results the laser welding and hybrid welding are suitable for welding AISI304 stainless steel parts due to their high welding speed and excellent mechanical properties. Berretta [9] had studied the pulsed Nd:YAG laser welding of AISI 304–AISI 420 stainless steels. The tensile strength of ferritic/austenitic laser-welded components has been optimized by Anawa [10].

An extensive body of research exist on modeling and optimization of TIG welding process. However, to the best of our knowledge, there is no study in which modeling and optimization of UTS has been carried out using Taguchi approach and simulated annealing algorithm. Therefore, in this article mathematical models developed to establish the relations between input and output parameters of TIG welding process. The proposed model has five inputs namely: Current (I), frequency (F), welding speed (S), gap (G) and debi (D), and ultimate tensile stress (UTS) specification has been taken into account. In the proposed approach, optimization is carried out to determine optimal values of process parameters (to be set on the welding machine). The proposed approach has been implemented on AISI304 stainless steel sheets, a widely used alloy in various industries including petrochemical and oil and power plant pipelines.

2. Experimental procedures

A DIGITIG 250 AC/DC welding machine with a 250 ampere capacity, and high value of pulse frequency (up to 500 Hz) conventional DCEN TIG welder has been employed to carry out the experiments (Fig. 1). The tungsten electrode and argon with 99.7% purity as welding shield gas was used for experiments. Experiments were carried out on AISI304 stain less steel pipes with dimension of Φ 20 mm×40 mm×5 mm.

Fig 1. Pipeline considered for study and welding machine used and

2-1- Process input parameters

Current (I), frequency (F), welding speed (S), gap (G) and debi (D) are the most prominent parameters in TIG welding process [1-3]. Ultimate tensile stress (UTS) is the most important characteristic of the process. Welding references and several preliminary tests were carried out and have been used to determine the practical working ranges of each input variable [11, 12]. According to the preliminary test results, the input variables and their corresponding levels are listed in Table 1. Other input parameters with minor effects (electrode diameter, electrode angle and etc.) have been considered at a fixed level.

Table 1. TIG welding process input variables and their feasible levels

Level	Welding current (I) *(Ampere)*	Base current (I_b) *(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	-

2-2- Design of experiments

Taguchi is one of the effective techniques that can dramatically reduce the number of experiments required to gather necessary data [13, 14]. Based on the number of input variables and their specified levels, in this study Taguchi's L_{32} has been selected to provide a well-balance design for test runs in order to gain the data needed for modeling purpose. It consists of 32 sets of process parameters (Table 2), based of which the experiments have been performed. Table 1 lists the ranges of process parameters and their corresponding levels. As shown, Debi is considered at two levels, while all other process variables have four levels. In DOE, the number of required experiments (and hence the experiment cost) rises as the number of parameters and/or their corresponding levels increase. That is why it is recommended that the parameters with less likely pronounced effects on the process outputs be evaluated at fewer levels. In addition, the limitations of test equipment may also dictate a certain number of levels for some of the process parameters [13-15].

2-3- Experimental results

Tests were carried out in random orders to increase accuracy. In the next step, UTSs were measured and reported (Table 2).

Table 2. The TIG welding process experimental conditions and their corresponding results based on Taguchi method

No.	I *(Ampere)*	I_b *(Ampere)*	F *(Hz)*	S *(m/min)*	D *(l/min)*	UTS (Mpa)
1	4	2	1	4	1	4296
2	4	1	2	3	1	4871
3	3	4	4	2	1	5246
4	3	2	1	3	1	3825
5	1	1	3	3	2	1567
6	2	4	3	4	1	5189
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.	.	.	.	.	.	.
27	4	4	4	1	1	4734
28	1	4	1	1	2	4948
29	4	1	4	1	2	5621
30	2	2	2	1	1	5517
31	4	3	3	2	1	5603
32	2	3	2	1	2	5418

3. Regression modeling of TIG welding process

Regression modeling is a statistical way for estimating the relationships among variables. [16- 18]. The last column of Table 2 is the outputs for each test setting. These data can be used to develop mathematical models. These relations can be described by the equation of $y = f(x_1, x_2, x_3, x_4)$. Any of the above output is a function of process parameters which are expressed by linear, logarithmic and second order functions; as stated in Equations 1 to 3 respectively [8].

$$Y_1 = b_0 + b_1X_1 + b_2 X_2 + b_3 X_3 \tag{1}$$

$$Y_2 = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_{11} X_1 X_1 + b_{22} X_2 X_2 + b_{33} X_3 X_3 + b_{12} X_1 X_2 + b_{13} X_1 X_3 + b_{23} X_2 X_3 \tag{2}$$

$$Y_3 = b_0 \times X_1^{\,b1} + X_2^{\,b2} + X_3^{b3} + X_1 X_1^{b11} + X_2 X_2^{b22} + X_3 X_3^{b33} + X_1 X_2^{b12} + X_1 X_3^{b13} + X_2X_3^{b23} \tag{3}$$

Where, regression coefficients are shown with b_0, b_1, b_2 and b_3 and are to be estimated. X_i are the process output characteristics (I, I_b, F, S and D). In this study, based on the UTSs data given in Table 2, the regression models are developed using MINITAB software. Based on the nature of initial data and the required accuracy models are chosen [17]. Models representing the relationship between process parameters and output characteristics can be stated in Equations 4 to 6.

4-1- Linear Model

$$UTS = 491 - 11.8\times D - 1200\times S - 1.41\, F + 14.8\times I_B + 14.9\times I \tag{4}$$

4-2- Logarithmic Model

$$UTS = 0.019 \times s^{-2.17} \times I_b^{\,0.460} \tag{5}$$

4-3- Second Order Model

$$UTS = 329 + 219\times D - 88.1\times I_b - 2.87\times D\times F - 11.0\times D\times I_b + 49.9\times S\times F + 311\times S\times I_b + 305\times S\times I - 0.900\times F\times I - 1.21\times I_b\times I - 18500 \times S\times S + 0.329\times F\times F + 2.72\times I_b\times I_b - 1.13\times I\times I \tag{6}$$

Analysis of variance (ANOVA) technique within the confidence limit of 95% has been used to check the adequacies of proposed models (Table 3) [19-21]. Given the required confidence limit (Pr), the correlation factor (R^2), the adjusted correlation factor (R^2-adj) and predicted correlation factor (R^2-pre) for these models, it is evidence that second order model is superior to linear and logarithmic models, thus, these models are considered as the best representative of the authentic TIG welding process throughout in this paper.

Table 3. ANOVA results for the TIG welding process charactristics

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**

Fig 2, exhibits the interaction effect of process parameters (frequency and welding current) for UTS. As illustrated by increasing welding current, UTS increases. Similarly by increasing welding frequency, the UTS increases.

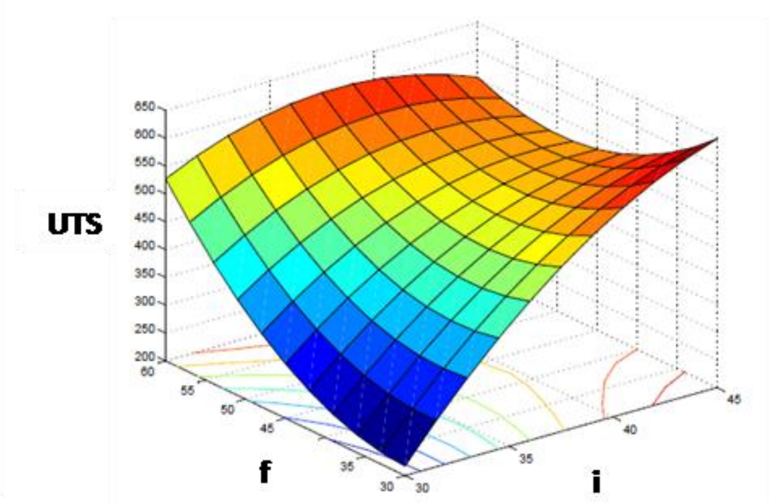

Fig. 2 interaction of process parameters for UTS

4. Simulated annealing algorithm

Annealing is a physical process in metallurgy where metals are slowly cooled down from a high temperature to make them reach a state of low energy. A metal is first heated up to a temperature below its melting point. At this temperature, all particles of the metal are in intense random motion. Then, the temperature slowly cooled down. Therefore, all particles of the metal rearrange themselves and tend toward a low energy state. As the metal is cooled down appropriately slowly, lower and lower energy states are obtained until the lowest state of energy is reached. Likewise, in TIG welding process an energy function is created which is minimized. The lowest energy level gives the optimized value of TIG welding process parameters. In recent years, the SA algorithm has been developed as a practical tool for complex optimization problems [21, 22].

In a standard SA algorithm, the procedure is begins by generating an initial random solution. At initial stages, a small random change is made. Then the value of the objective function for the new solution (E_1) is calculated and compared with the current solution's objective function value (E_0). If the value is better or if the probability function implemented in SA algorithm (P_r) has a higher value than a randomly generated number between 0 and 1, a move is made to the new solution. Equation (7) shows the probability of accepting a new solution [22]:

$$P_r = \exp\left(-\frac{\Delta E}{T_i}\right) \quad (7)$$

The calculation of this probability depends on parameter, T, which is referred to as temperature parameter, since it plays a similar role as the temperature in the annealing process. The rate of reduction should be slow to avoid getting trapped at a local minimum point [13]. In our problem to reduce the temperature the Equation (8) has been used:

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

Where, T_{i+1} is the current temperature, T_i is the former temperature and λ is the cooling rate. Therefore, at the start of SA, most worsening moves may be accepted, but at the end only improving ones are likely to be allowed. This can help the procedure jump out of a local minimum and avoid trapping in them. After a certain volume fraction for the structure has been reached or after a pre-determined run time or iterations the algorithm may be terminated. Flowchart of SA algorithm for TIG welding process optimization is shown in Fig.3.

SA algorithm has varied applications including improving the performance of other artificial intelligence techniques and determining the optimal set of process parameters [13, 23]. In this research, SA has been used twice. First it is employed for single objective optimization, then for multi-criteria optimization.

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

Table 4. Optimization results for the TIG welding process

Output	Process parameters					Predicted	experiment	Error (%)
	I	Ib	F	S	D			
UTS	45	15	30	0.435	5	598	587	2

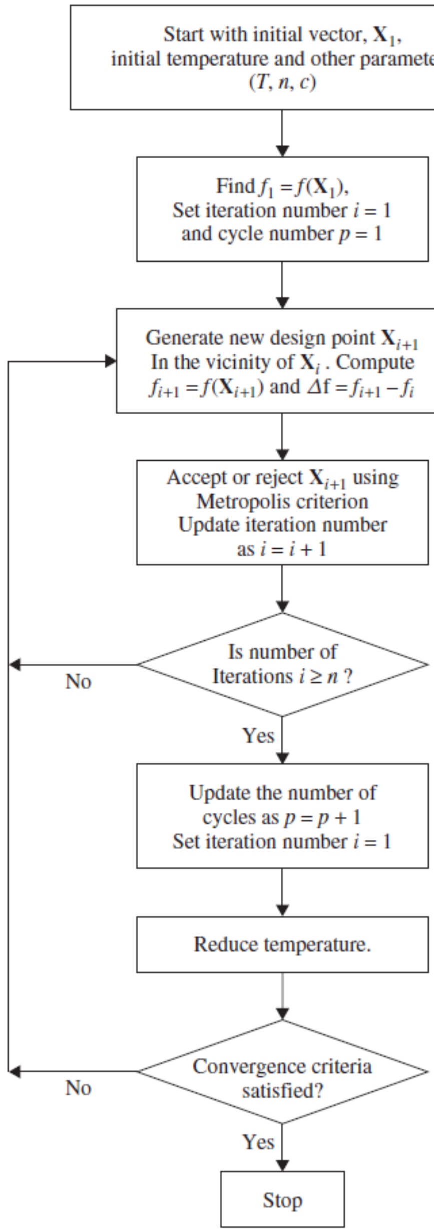

Fig. 3 Flowchart of SA algorithm used for the TIG welding process optimization

Table 4 indicate that both welding and base current should be at their highest and other parameters at their lowest permissible ranges, resulting in maximum possible UTS.

5. Conclusion

The quality of final product in TIG welding process is considerably affected by the selection of process parameters levels. In contrast, the conflicting nature of various quality measures, necessitate simultaneous selection of their optimal values. In this study the problem of modeling and optimization of TIG welding process for AISI304 stainless has been addressed. First, TIG welding modeling has been carried out using experimental data gathered as per L_{32} Taguchi design of experiments (DOE). Then, UTSs have been measured. Five process input variables take into account to predict the output response using regression modeling. Next, the selected model has been embedded to SA algorithm to determine the optimal set of process settings both for single and multi-criteria optimization. The multi-criteria optimization procedure involves finding a certain combination of welding parameters so as optimize UTS. These further illustrate that optimization results are consistent with the inherent characteristics of TIG welding process. The result of optimization technique has shown using SA algorithm result in minor errors (2%) which shows the proposed model can accurately simulate the actual TIG welding process.

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