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Research Paper

Simultaneously Modeling and Optimization of Heat Affected Zone and Tensile Strength in GTAW Process Using Simulated Annealing Algorithm

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ABSTRACT

In the present study, a technique has been addressed in order to model and optimize gas tungsten arc welding (GTAW) process which is one of the mostly used welding processes based on the high quality fabrication acquired. The effects of GTAW process variables on the joint quality of AISI304 stainless steel thin sheets (0.5 mm) have been investigated. The required data for modeling and optimization purposes has been gathered using Taguchi design of experiments (DOE) technique. Next, based on the acquired data, the modeling procedure has been performed using regression functions for two outputs; namely, heat affected zone (HAZ) width and ultimate tensile stress (UTS). Then, analysis of variance (ANOVA) has been performed in order to select the most fitted proposed models for single-objective and multi-criteria optimization of the process in such a way that UTS is maximized and HAZ width minimized using simulated annealing (SA) algorithm. Frequency, welding speed, base current and welding current are the most influential variables affecting the UTS at 22%, 21%, 20% and 17% respectively. Similarly, base current, welding current, frequency and welding speed affect the HAZ at 28%, 20%, 16%, and 15% respectively. Based on the results considering the lowest values for current results in the smallest amount of HAZ. By the same token in order to acquire the largest amount of UTSs the highest values of current must be considered. Setting welding and base current, frequency, speed, and debi at 42 and 5 apms, 46 Hz, 0.4495 m/min, and 5 lit/min respectively resulted the optimized HAZ and UTS simultaneously. The proper performance of the proposed optimization method has been proved through comparison between computational results and experimental data with less than 6% error.

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1. Introduction

Due to excellent corrosion resistance and mechanical properties, austenitic stainless steels have been extensively used as reactor coolant piping in nuclear structural materials, valve bodies, and vessel internals. Nevertheless, the metallurgical changes such as micro-segregation, precipitation of secondary phases, presence of porosities, solidification cracking, grain growth in the heat affected zone (HAZ) and loss of materials by vaporization welding often leads to low mechanical properties [1,2]. Usually, one of the most extensively used processes to fabricate stainless steel parts is welding process among which gas tungsten arc welding (GTAW) is the most extensively used one [3]. GTAW is a multi-objective and multi-factor metal fabrication process using of which joining of a number of common metals such as steel, magnesium and aluminum in almost all positions can be carried out [4]. Weld bead geometry, mechanical and metallurgical properties of the weldments are affected by selecting the proper process variables [4, 5]. Conventionally, expert operators or engineers choose parameters based on trial and error method which is time consuming for every new welded product to obtain a welded joint with the required specifications. Then welds are examined to determine whether they meet the specification or not [4]. Nowadays, different modeling procedures such as regression modeling, artificial neural network are widely used to develop mathematical relationships between the welding process input variables and the output characteristics of the weld joint in order to determine the optimized welding input variables that lead to the desired weld quality [6]. Sapkal and Teslang [7] applied Taguchi method to obtain maximum depth of penetration (DOP) on mild steel through optimization of the process variables (current, voltage and welding speed). 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 fabricated by GTAW, laser welding and laser-GTAW hybrid welding. The results revealed that the joints made by laser welding had highest tensile strength and smallest dendrite size, while the joints made by GTAW had the lowest tensile strength and the biggest dendrite size. The results showed that the laser welding and hybrid welding are suitable for welding of AISI304 stainless steel parts due to their high welding speed and excellent mechanical properties. Berretta et al. [9] 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]. Multiple linear regression procedure has been used to develop mathematical models for weld bead shape parameters of GTAW process. Also by using the same experimental data, an attempt has been made to model the process using artificial neural network. Then, for optimization procedure genetic algorithmic (GA) coupled with artificial neural network has been employed [11].

Modeling and optimization of GTAW process has been considered in different studies. However, to the best of our knowledge, there is no study in which modeling and optimization of both microstructure and mechanical properties are considered as single and multi-criteria optimization. Therefore, in this study mathematical models developed to establish the relations between multi-input, multi-output parameters of GTAW process. The proposed approach has been implemented on AISI304 stainless steel sheets, a widely used alloy in various industries including petrochemical and oil pipelines.

2. Experimental procedures

In this study, A DIGITIG 250 AC/DC (GAAM-Co, Iran) semi-automatic welding machine with a 250 ampere capacity, and high value of pulse frequency (up to 500 Hz) conventional DCEN GTAW welder has been employed to carry out the experiments. 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 sheets with dimension of 100 mm×40 mm×0.5 mm.

2.1. Process input variables and their corresponding levels

In this study current (I), frequency (F), welding speed (S), and shielding gas debi (D) have been considered as the process input variables. Similarly, heat affected zone (HAZ) and ultimate tensile stress (UTS) have been selected as the process output characteristics. Welding references have been studied and several preliminary tests based on the screening method have been carried out to determine the practical working ranges of each process input variable and their corresponding levels [12]. The input variables limits were then evaluated by inspecting the weldment for a good penetration without any visible defects such as surface porosities and undercut and smooth appearance. According to the preliminary test results, the input variables and their corresponding levels are listed in Table 1. Other input variables with trivial effects (electrode diameter, electrode angle and etc.) have been considered at an optimum and fixed level.

Table 1. GTAW 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	-

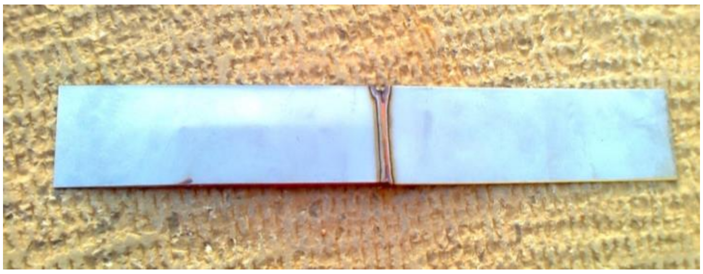
2.2. Design of experiments

When, the process input variables, their feasible ranges and proper levels have been selected, the next step is to select an appropriate experimental design matrix for conducting the experiments required for modeling and optimization purposes. orthogonal array Taguchi (OR-Taguchi) technique is one of the most effective methods that can dramatically reduce the number of experiments required for data gathering [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 acquire the needed data for modeling and optimization. This matrix consists of 32 sets of process parameters (Table 2), based of which the experiments have been conducted. The main purpose of fractional DOE techniques, including Taguchi method, is to obtain as much information as possible from a limited number of experiments. In many DOE patterns, having the same number of levels for each variable is necessary. Taguchi is one of the few that allows for uneven levels. 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

To increase the accuracy of the experiments the tests have been carried out in a random orders. After welding, two types of characteristics have been taken from each sample. For measuring HAZs and UTSs, on each samples two transverse cross sections were made. Next, the cut faces were smoothly polished and etched using 10% Nital solution to clearly show heat affected zones using electro-polish and electro-etch machines [4].

Then, images were taken using an optical microscope with X10 magnification (OLYMPUS-530). These images were subsequently processed by microstructural image processing (MIP) software (Fig. 1), to determine samples HAZs. For each sample the average of two measurements are reported. In the next step, UTSs were measured and reported (Table 2).



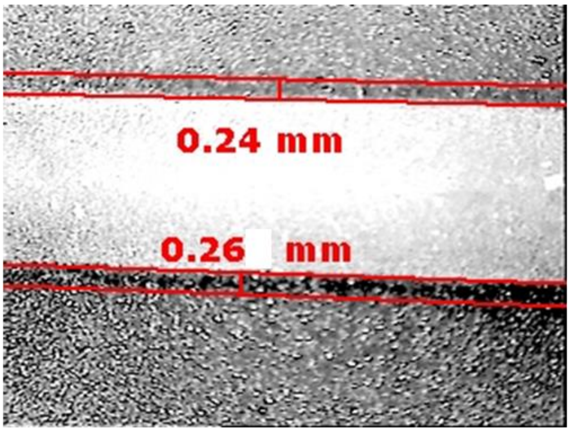


Fig. 1. The welded specimen and evaluation of HAZ width using microstructural image processing software

Table 2. The GTAW 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)	HAZ width (mm)	UTS (N)
1	4	2	1	4	1	0.29	4296
2	4	1	2	3	1	0.24	4871
3	3	4	4	2	1	0.25	5246
4	3	2	1	3	1	0.31	3825
5	1	1	3	3	2	0.18	1567
6	2	4	3	4	1	0.31	5189
7	4	2	3	2	2	0.51	4963
8	1	2	4	4	2	0.20	601
9	3	1	4	2	2	0.30	5780
10	2	1	3	4	2	0.19	862
11	2	1	1	2	1	0.26	5604
12	2	2	4	3	2	0.26	4481
13	1	3	2	2	2	0.20	1020
14	3	4	2	4	2	0.35	5298
15	4	3	1	4	2	0.15	539
16	2	4	1	2	2	0.20	5001
17	3	3	3	1	1	0.31	539
18	3	2	3	1	2	0.29	5716
19	1	3	4	4	1	0.38	2254
20	3	1	2	4	1	0.28	2038
21	2	3	4	3	1	0.21	5636
22	3	3	1	3	2	0.42	5800
23	1	1	1	1	1	0.32	4310
24	4	4	2	3	2	0.40	5792
25	1	4	3	3	1	0.37	5484
26	1	2	2	2	1	0.23	1847
27	4	4	4	1	1	0.22	4734
28	1	4	1	1	2	0.38	4948
29	4	1	4	1	2	0.29	5621
30	2	2	2	1	1	0.20	5517
31	4	3	3	2	1	0.30	5803
32	2	3	2	1	2	0.30	5418

3. Regression modeling of GTAW process

In order to establish the relations between process variables and output characteristics different procedures have been proposed among which regression modeling is the most extensively used one [16- 18]. The last two columns of Table 2 are 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 variables which are expressed by linear, logarithmic and second order functions; as stated in Equations 1 to 3 respectively [8].

The proposed model has five process input variables namely: current (I), frequency (F), welding speed (S), and debi (D), and two output characteristics (heat affected zone (HAZ) width and ultimate tensile stress (UTS)). In the proposed approach, single and multi-criteria optimization is carried out to determine optimal values of process variables in such a way that results in minimum HAZ and desired UTS.

$$Y_1 = b_0 + b_1X_1 + b_2 X_2 + b_3 X_3 \quad (1)$$

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

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

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 input variables (I, I_b, F, S and D). In this study, based on the UTSs and HAZs 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 9.

4-1. Linear Model

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

$$UTS = 491 - 11.8\times D - 1200\times S - 1.41 F + 14.8\times I_B + 14.9\times I \quad (5)$$

4.2. Logarithmic Model

$$HAZ = 0.986 \times F^{-0.456} \times I_b^{0.210} \quad (6)$$

$$UTS = 0.019 \times s^{-2.17} \times I_b^{0.460} \quad (7)$$

4-2. Second Order Model

$$HAZ = 3.98 - 0.207\times D + 4.51 S - 0.0616 F + 0.141 I_b - 0.205 I - 0.615 D\times S + 0.00298 D\times F + 0.0109 D\times I + 0.0338 S\times F - 0.157\times S\times I_b + 0.000422\times F\times I_b + 0.000869\times F\times I - 0.000129\times F\times F - 0.00347\times I_b\times I_b + 0.00138\times I\times I \quad (8)$$

$$UTS = 329 + 219\times D - 88.1\times I_b - 2.87\times D\times F - 11.0\times D\times I_b + 49.9\times S\times F + 311\times S\times I_b + 305\times S\times I - 0.900\times F\times I - 1.21\times I_b\times I - 18500\times S\times S + 0.329\times F\times F + 2.72\times I_b\times I_b - 1.13\times I\times I \quad (9)$$

Analysis of variance (ANOVA) technique with the confidence limit of 95% has been used to check the adequacy of the 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 GTAW process throughout this paper.

Table 3. ANOVA results for the GTAW 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**
Linear	UTS	51.5	46.3	45.9	9.9	<0.0001
logarithmic	UTS	49.0	43.5	41.3	8.97	<0.0001
Second order	**UTS**	**95.4**	**91.7**	**90.6**	**25.7**	**<0.0001**

In order to confirm the adequacy of the proposed models, some experimental which have not been within the proposed design matrix have been conducted. Based on the results of confirmation tests (Table 4), the proposed model is quite efficient in modeling of the process.

Table 4. confirmation of the proposed models

I(Ampere)	Ib(Ampere)	F(Hz)	S(m/min)	D(l/min)	HAZ width (mm)	UTS (N)	Predicted	Error (%)
35	5	60	0.435	5	0.153	-	0.163	6.5
30	15	45	0.435	5	-	620	580	6.4

Fig. 2, demonstrates the interaction effect of process variables (frequency and pulse current) for HAZ. As illustrated, by increasing welding frequency, the HAZ decreases. Similarly by increasing pulse current, the HAZ increases then decreases. By the same token, Fig 3, exhibits the interaction effect of process variable (frequency and welding current) for UTS. As illustrated by increasing welding current, UTS increases. Similarly by increasing welding frequency, the UTS increases.

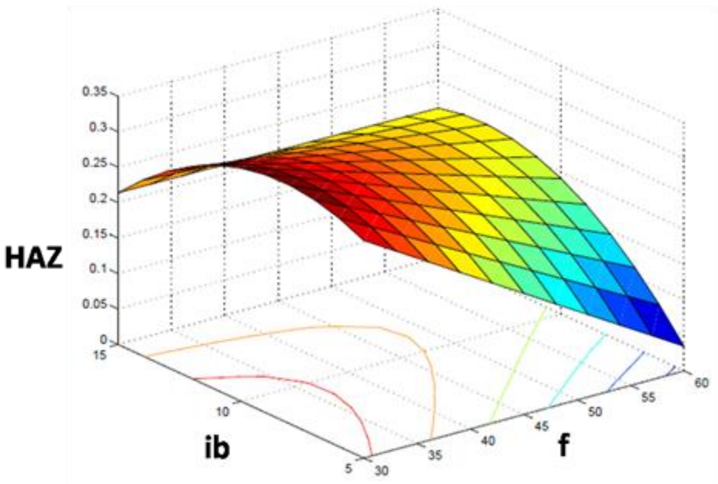


Fig. 2. interaction of process parameters for HAZ

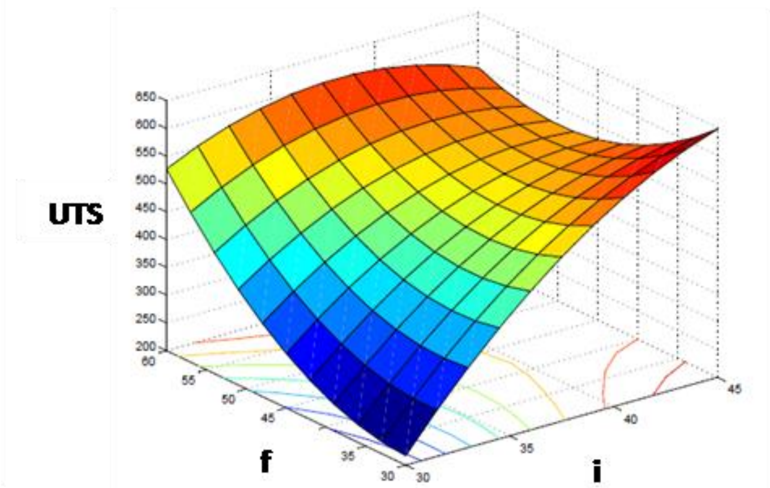
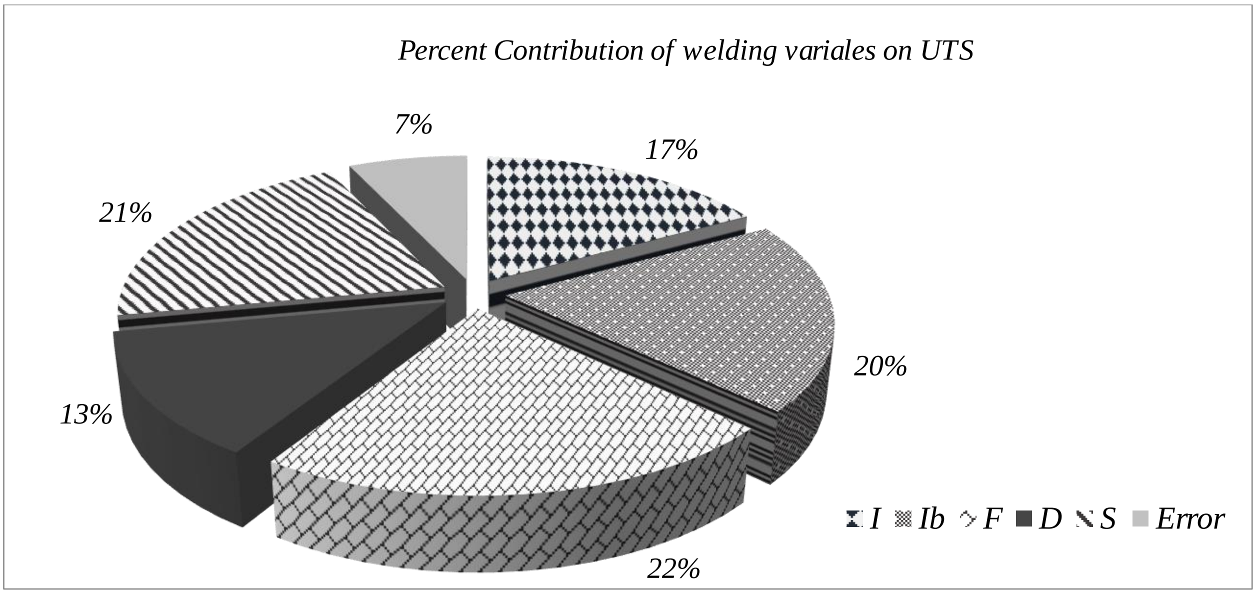


Fig. 3. interaction of process parameters for UTS

ANOVA results may provide the percent contributions of each process variable [17]. The percent contributions of the GTAW process variables on the process parameters are shown in Fig. 4.

$$P_i\ (\%) = \frac{SS_i - (DOF_i \times MS_{error})}{Total\ Sum\ of\ \ Squre} \tag{10}$$

In the above formula, P_i is Contribution percentage, SS_i is sum of square, DOF_i is degree of freedom of ithfactor, and MS_{error} is mean sum of square of error [17].



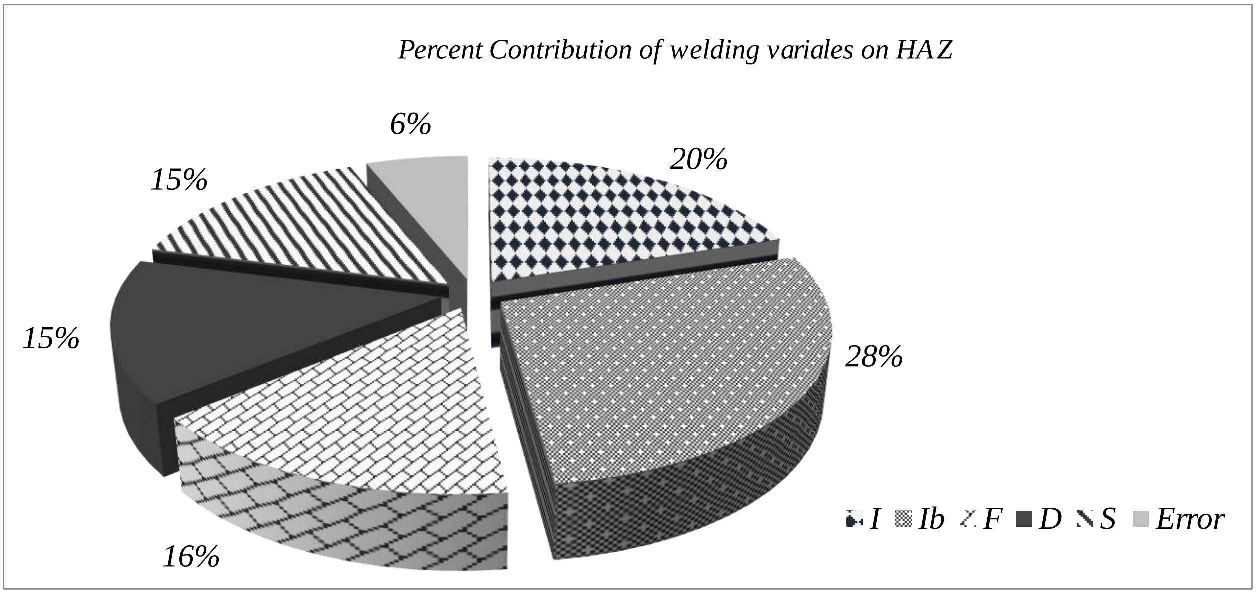


Fig 4. Percent contributions of welding parameters on HAZ and UTS

4. Simulated annealing algorithm

To interpolate between the process input variables intervals to select the most appropriate values of process input parameters reaching the desired output characteristics, different procedures have been introduced among which heuristic algorithms have been extensively employed for different optimization problems. All heuristic algorithms are reminiscent of biological or physical processes. In this regard, SA algorithm is reminiscent of annealing in heat treatment process [21, 22]. In annealing process, metals are heated up to a specific and pre-determined temperature (near the melting point), at which all metal particles are in random motion. Then, all metal particles rearranged by cooling down slowly toward the lowest energy state. As the cooling process is conducted appropriately slowly, lower and lower energy states are achieved until the lowest energy state is reached. Similarly, in A-TIG welding process the lowest energy level gives the optimized value for variables based on an energy function is created and minimized. The mechanism of SA algorithm is defined as follows [23]:

Defining an acceptable answer space and generating an initial random solution in this space. Next, the new solution’s objective function (C_1) is computed and compared with the current ones (C_0). A move to a new solution is made either the new solution has better value or the value of SA probability function (Equation (11)) is higher than a randomly generated number between 0 and 1 [22]:

$$P_r = \exp(-\frac{\Delta E}{T_i}) \quad (11)$$

Where, temperature parameter is shown by T_k, which acts as the temperature in the physical annealing process does [21]. Equation (12), is used as a temperature reduction rate to cool down the pre-determined temperature at each iteration.

$$T_{i+1} = \lambda \times T_i \qquad i = 0,1,\ldots \text{ and } 0.9 \le \lambda < 1 \tag{12}$$

Where, the current and former temperatures are shown by T_{k+1} and T_k respectively. The cooling rate also presented by parameter α. Consequently, at the first iterations of SA due to higher temperature, most of the not improving (or even worsening) moves may be accepted. Nonetheless, as the algorithm proceeds and temperature is reduced only improving moves are likely to be accepted. This strategy could help the algorithm avoid being trapped in local minimum and jump out of it. After a specific number of iterations, a number of iterations in which no development is detected, and a pre-determined run time, the algorithm may be dismissed. The SA algorithm strategy flowchart is depicts in Fig. 5. Simulated annealing algorithm has varied applications including improving the performance of other artificial intelligence techniques and determining the optimal set of process parameters [13, 23].

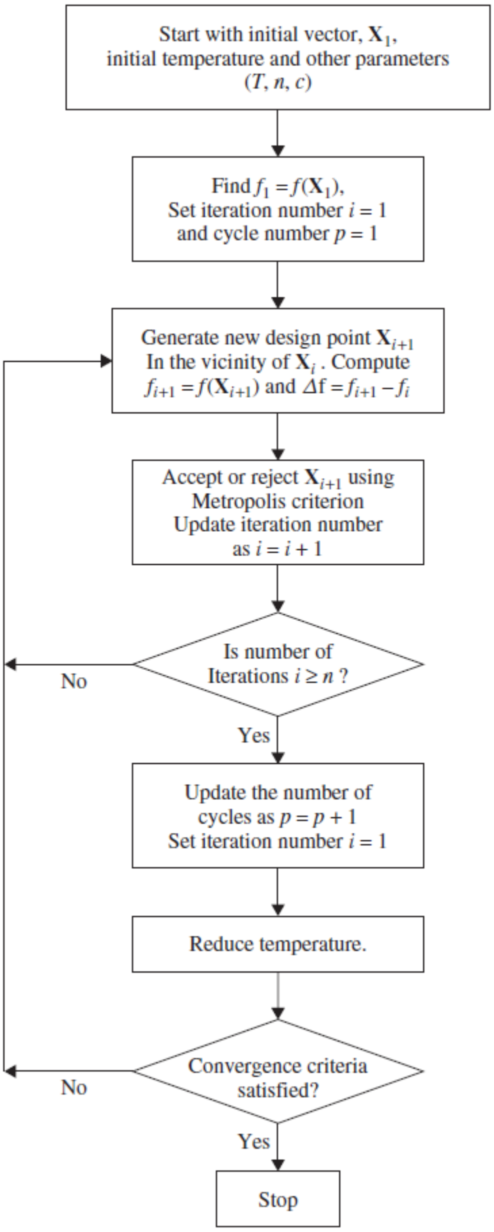


Fig. 5. Flowchart of SA algorithm used for the GTAW process optimization

5. Results and discussion

In this research, modeling and optimization of GTAW process has been addressed. The data required for modeling and optimization purposes has been acquired using Taguchi technique. Regression analysis has been employed to establish a relation between process input and output variables. In order to opt the most fitted and appropriate model ANOVA has been used. Then, simulated annealing algorithm has been employed to optimize the process in such a way that the desired UTS and HAZ achieved. SA has been used twice. First it is employed for single objective optimization, then for multi-criteria optimization.

Table 5 illustrates the results of optimization using SA and their corresponding confirmation tests for single objective optimization.

Table 5. single objective optimization results for the GTAW process

Output	Process parameters					Predicted	experiment	Error (%)
	I	Ib	F	S	D			
UTS	45	15	30	0.435	5	595	578	3
HAZ	35	5	60	0.435	5	0.188	0.198	4

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. Likewise, for achieving the lowest HAZ, welding current, frequency, debi and base current should be approximately set at their lower ranges.

The quality of final product in GTAW process is significantly affected by the choice of process variable levels. On the other hand, simultaneous selection of process parameters optimal values due to the interactions of these parameters is required. Therefore, several conflicting goals such as increasing product quality and reducing production time could be simultaneously achieved using multi-criteria optimization of processes parameters. In this section the effects of GTAW process variables settings on the two important output characteristics (HAZ and UTS) have been investigated simultaneously (Equation (13)).

$$\text{Minimaize f}(x) = \frac{HAZ^2}{0.285} + \frac{(\text{UTS} - 577)^2}{438} \qquad (13)$$

Table 6 shows the results of multi-criteria optimization of GTAW process and their corresponding confirmation test.

Table 6. multi-criteria optimization results for the GTAW process

Process parameters					Predicted		experiment		Error (%)	
I	Ib	F	S	D	UTS	HAZ	UTS	HAZ	UTS	HAZ
42	5	46	0.4495	5	577	0.021	602	0.020	4	5

6. Conclusion

The quality of final product in GTAW process is considerably affected by the selection of process variables values. In contrast, the conflicting nature of various quality measures, necessitate simultaneous selection of their optimal values. In this study the problem of single and multi-criteria modeling and optimization of GTAW process for AISI304 stainless has been addressed. First, GTAW modeling has been carried out using experimental data gathered as per L_{32} Taguchi design of experiments (DOE). Then, UTSs have been measured. Moreover, the MIP software has been used for measurement of HAZs. Five process input variables take into account to simultaneously predict two outputs responses using regression modeling. In order to evaluate the adequacy of the proposed models some experiments out of the matrix have been conducted based on which the adequacy of the proposed models have been proved. The errors which have been reported for the confirmation experiments were less than 7%. Next, the models have been embedded into 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 variables in such a way to optimize HAZ and UTS simultaneously. Frequency, welding speed, base current and welding current are the most influential variables affecting the UTS at 22%, 21%, 20% and 17% respectively. Similarly, base current, welding current, frequency and welding speed affect the HAZ at 28%, 20%, 16%, and 15% respectively. Based on the results considering the lowest values for currents, results in the smallest amount of HAZ. By the same token in order to acquire the largest amount of UTSs the highest values of currents must be considered. Setting welding and base current at 42 and 5 apm, frequency at 46 Hz, speed at 0.4495 m/min, and debi at 5 lit/min resulted the optimized HAZ and UTS simultaneously. These further illustrated that optimization results are consistent with the inherent characteristics of GTAW process. The result of optimization technique has shown the proposed model can accurately simulate the actual GTAW process (with less than 6% error).

Reference

[1] H.T. Lee, S.L. Jeng, "Characteristics of dissimilar welding of alloy 690 to 304L stainless steel", Sci Technol Weld Joining, Vol. 6, 2001, pp. 225–34.

[2] H. Jamshidi Aval, A. Farzadi, S. Serajzadeh, A.H. Kokabi, "Theoretical and experimental study of microstructures and weld pool geometry during GTAWof 304 stainless steel", Int J Adv Manuf Technol, Vol. 5, 2008, pp.1663-1676.

[3]. J. Yan, M. Gao, X. Zeng, "Study on microstructure and mechanical properties of 304 stainless steel joints by TIG, laser and laser-TIG hybrid welding", Optics and Lasers in Engineering, Vol. 48, 2010, pp.512–517.

[4]. A. K. Srirangan, S. Paulraj, "Multi-response optimization of process parameters for TIG welding of Incoloy 800HT by Taguchi grey relational analysis", Engineering Science and Technology, an International Journal, Vol. 4, 2015, pp. 54-67.

[5] F. Kolahan, M. Heidari, "A new approach for predicting and optimizing weld bead geometry in GMAW", Int. J. Aerosp. Mech. Eng. Vol. 5, 2011, pp.138–142.

[6] M. Azadi Moghaddam, R. Golmazerji, F. Kolahan, "Multi-variable measurements and optimization of GMAW parameters for API-X42 steel alloy using a hybrid BPNN-PSO approach", Measurement, Vol. 6, 2016, pp. 123-136.

[7] S.V. Sapakal, M.T. Telsang, "Parametric optimization of MIG welding using Taguchi design method", Int. J. Adv. Eng. Res. Study, Vol. 1, 2012, pp. 28–37.

[8] M. Balasubramanian, "Prediction of optimum weld pool geometry of PCTIG welded titanium alloy using statistical design", Eng. Sci. Technol. Int. J. Vol. 5, 2015, pp. 106-120.

[9] R. B. Jose, R. Wagner, M. N. David, A. J. Alves, V. J. Dias, "Pulsed Nd:YAG laser welding of AISI 304 to AISI 420 stainless steels". Opt Laser Eng, Vol. 12, 2007, pp. 45-60.

[10] E.M. Anawa, A.G. Olabi, "Optimization of tensile strength of ferritic/austenitic laser-welded components", Opt Laser Eng, Vol. 3, 2008, pp. 571–577.

[11]. D.S. Nagesh, G.L. Datta, "Genetic algorithm for optimization of welding variables for height to width ratio and application of ANN for prediction of bead geometry for TIG welding process", Applied Soft Computing, Vol. 10, 2010, pp. 897–907.

[12] "Guidelines for Gas Tungsten Arc Welding (GTAW)", Miller Electric Mfg. Co., from 'www.MillerWelds.com', 2008.

[13] F. Kolahan, R. Golmezerji, , M. Azadi Moghaddam, "Multi Objective Optimization of Turning Process using Grey Relational Analysis and Simulated Annealing Algorithm", Applied Mechanics and Materials, Vol. 4, 2012, pp. 2926-2932.

[14] M. Azadi Moghaddam, R. Golmazerji, F. Kolahan, "Multi-variable measurements and optimization of GMAW parameters for API-X42 steel alloy using a hybrid BPNN-PSO approach", Measurement, Vol. 12, 2016,pp. 132- 143.

[15] F. Kolahan, M. Azadi Moghaddam, "The use of Taguchi method with grey relational analysis to optimize the EDM process parameters with multiple quality characteristics", Scientia Iranica B, Vol. 22, 2015, pp. 530-538

[16]. B. Senthilkumar, T. Kannan, "Effect of flux cored arc welding process parameters on bead geometry in super duplex stainless steel claddings", Measurement. Vol. 62, 2015, pp. 127-136.

[17] S.S. Chong, A.R.A. Aziz, S.W. Harun, H. Arof, S. Shamshirband, "Application of Multiple Linear Regression, Central Composite Design, and ANFIS models in Dye concentration Measurement and Prediction Using Plastic Optical Fiber Sensor", Measurement, Vol. 10, 2015, pp. 16-29.

[18] D. Jaimon, S. Quadros, A. Khan, A. J. Antony, "Modelling of Suddenly Expanded Flow Process in Supersonic Mach Regime using Design of Experiments and Response Surface Methodology", JCAMECH, Vol. 49, 2018, pp. 149-160.

[19] S. Ghorbanhosseini, F. Fereshteh-saniee, "Multi-objective optimization of geometrical parameters for constrained groove pressing of aluminium sheet using a neural network and the genetic algorithm", JCAMECH, Vol. 50, 2019, pp. 275-281

[20] M. Vishwakarma, V,V.K. Parashar, "Regression Analysis and Optimization of Material Removal Rate on Electric Discharge Machine for EN-19 Alloy Steel", International Journal of Scientific and Research Publications, Vol. 2, 2012, pp. 167-175.

[21] D. Vishnu, R.I. Asal, T. Patel, B. Alok, "Optimization of Process Parameters of EDM Using ANOVA Method", International Journal of Engineering Research and Applications, Vol. 3, 2013, pp. 1119-1125.

[22] S. Kirkpatrick, C.D. Gelatt, M.P. Vecchi, "Optimization by simulated annealing. American Association for the Advancement of Science", Vol. 220, 1983, pp. 671–680.

[23] M.H.M.A. Jahromi, R. Tavakkoli-Moghaddam, A. Makui, A. Shamsi, "Solving an one-dimensional cutting stock problem by simulated annealing and tabu search", Journal of Industrial Engineering International, Vol. 8, 2012, pp. 1-8.