Optimization of TIG welding process using response surface methodology and simulated annealing algorithm

Ali Sirjani[1], Farhad Kolahan[2]

[1] *M.Sc. Student, Ferdowsi University of Mashhad, Department of Mechanical Engineering, Mashhad, Iran*
[2] *Associate Professor, Ferdowsi University of Mashhad, Department of Mechanical Engineering, Mashhad, Iran*

ABSTRACT

This study addresses a modeling and optimization procedure in tungsten inert gas (TIG) welding of AL5052 alloy. Experimental required data for modeling and optimization purposes gathered using central composite design (CCD). Welding current (I), frequency (F), welding speed (S) and gap (G) are the most important parameters in TIG welding process. The weld bead geometry (WBG) and heat affected zone (HAZ) considered as the most important quality measures of the welding process. Image processing technique is used to take accurate measurements of WBGs and HAZs. In order to determine the relationship between input and output parameters based on regression models, the response surface methodology (RSM) has been used. The significance of the process parameters on the quality characteristics of the process was also evaluated quantitatively using the analysis of variance (ANOVA) method. Next, simulated annealing (SA) algorithm has been used to optimize HAZ and WBG separately (single-objective optimization) and simultaneously (multi-objective optimization). The results based on the analysis of RSM has also been compared with the optimized results using SA algorithm. Verification tests demonstrate that the proposed RSM-SA approach is quite efficient in single and multi-criteria modeling and optimization of TIG welding process.

Keywords: *Tungsten inert gas (TIG) welding process; Central composite design (CCD); Multi-criteria Optimization; analysis of variance (ANOVA); Simulated annealing (SA) algorithm.*

1. *INTRODUCTION*

Nowadays, Tungsten inert gas (TIG) welding process is generally used for welding of Al–Mg alloys. [1]. TIG welding uses a non-consumable electrode and shielded by an inert gas like argon or helium to protect the molten weld pool and filler wire from atmospheric contaminants [2].

In welding processes, the quality of the weldment is usually determined by such process quality measures as weld bead geometry (WBG) and heat affected zone (HAZ) [2]. WBG is a significant factor as it strongly affects the mechanical properties of the weldment [1, 2]. Another key quality indicator of the joint is HAZ that determines the metallurgical and microstructural changes of the weldment due to the heat generated during welding process [3].

Various factors influence the size of HAZ and the shape of weld bead in TIG welding process. An important group consists the process parameters to be set on the welding machine; namely, welding current (I), frequency (F), welding speed (S) and gap (G) [2]. Therefore, to achieve full penetrated weld with desired WBG and minimum HAZ, process parameters selection must be carefully considered. Conventionally, expert operators or engineers choose parameters based on trial-and-error method which was time consuming for every new welded product to obtain a welded joint with the required specifications. Then joint parts are examined to determine whether they meet the specification or not [1]. The inherent nonlinearity of TIG welding process and various interactions between its input parameters, have motivated the researchers to employ different modeling techniques and heuristic algorithms [1-3]. To gather experimental data needed for modeling, design of experiments (DOE) technique has been employed in many studies [3- 5].

*There exist an **extensive** body of research on modeling and optimization of welding processes. However, to the best of our knowledge, there is no study in which WBG and HAZ considered, modeled and optimized as single and multi-criteria problem using RSM and SA algorithm. Therefore, in this article a new approach based on response surface methodology (RSM) and simulated annealing (SA) algorithm has been developed to* *establish the relations between multi-input, multi-output parameters of TIG welding process and optimize them in order to achieve a desired WBG with minimum HAZ. Both of these features are important quality measures in TIG welding process. Furthermore, comparison of RSM and SA results, illustrated that application of SA is quite efficient in optimization of the process. The proposed approach has been implemented on AL5052 alloy sheets).*

2. Experimental procedure

2 .1. Material and Equipment

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) 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

AL5052 is a high-strength, non-heat-treatable Al alloy which has very good corrosion resistance to seawater and marine and industrial atmosphere. It also has very good weld ability and good cold formability. It is a medium to high strength alloy with a strength slightly higher than 5251 and a medium to high fatigue strength which is widely used in boiler making, containers, welded tubes, pressure vessels and etc. [6].

2 .2. Process input variables and their levels

The most prominent parameters in TIG welding process include Welding current (I), frequency (F), welding speed (S) and gap (G) [1-3]. Likewise, process quality measures include front height to front width ratio (Fr), back height to back width ratio (Br), and heat affected zone (HAZ) (Fig. 1). To determine the practicable working ranges of each input variable, several preliminary tests were conducted. The variable limits were then evaluated by inspecting the weldment for a smooth appearance and good penetration without any visible defects such as surface porosities and undercut. According to the preliminary test results, the input variables and their corresponding levels are listed in Table 1. Other parameters with trivial effects (electrode diameter, polarity, electrode angle and etc.) have been considered at a fixed level based on the results of preliminary tests.

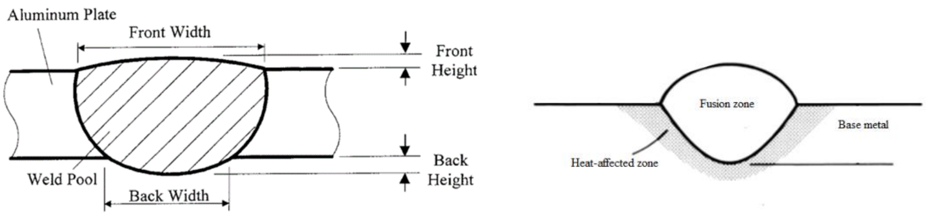

Fig. 1. Schematic illustration of weld bead geometry and heat affected zone area for TIG welding process

Table 1 TIG welding process input variables and their levels

Level	*Welding Speed (S)* (cm/min)	*Welding current (I)* (Ampere)	*Frequency (V)* (Hz)	Gap (G) (mm)
Level 1	*240*	*110*	*85*	*2.5*
Level 2	*300*	*120*	*100*	*3*
Level 3	*360*	*130*	*115*	*3.5*

2 .3. Response surface methodology

Response surface methodology (RSM) is an experiential modeling approach using polynomials as local approximations to the exact input/output relationship. This experiential method is often suitable for process development in an industrial setting [7]. Once the process variables and their feasible ranges are selected, the next step is to select an appropriate design matrix for carrying out the experiments. Design of experiments (DOE) approach facilitates the identification of the influence of individual parameters, establishing the relationships between process parameters and output responses, and finally determining the optimum levels [8]. The essential data for building the response models are generally collected by an experimental design. The most common of the many classes of RSM designs is the central composite design (CCD).

Central composite design (CCD) is a suitable statistical-based experimental design tool which has been extensively used to identify and optimize the performance of complex systems [9]. In this study CCD, L_{27} has been selected to provide a well-balance design for test runs. It consists of 27 sets of process parameters, based of which the experiments have been performed. To increase accuracy, tests were carried out in random orders.

After welding, three types of characteristics have been taken from each sample. For measuring HAZs and WBGs, two transverse cross sections were made on each sample. Next, the cut faces were smoothly polished and etched using 10% Nital solution to clearly show bead geometry specifications and heat affected zones.

Then, images were taken using an optical microscope with X10 magnification (OLYMPUS-530). These images were subsequently processed by Microstructural Image Processing (MIP) software, developed at Metallurgy Lab of Ferdowsi University of Mashhad, to determine samples HAZs and WBGs. For each sample the average of two measurements are reported.

Fig. 2 illustrates results for weld bead geometry and heat affected zone area using MIP software.

The TIG welding process parameters settings along with their corresponding outputs are reported in Table2. In this table, besides the test numbers, the first four columns represent parameters settings used to perform experiments and the last three columns are the measured process outputs.

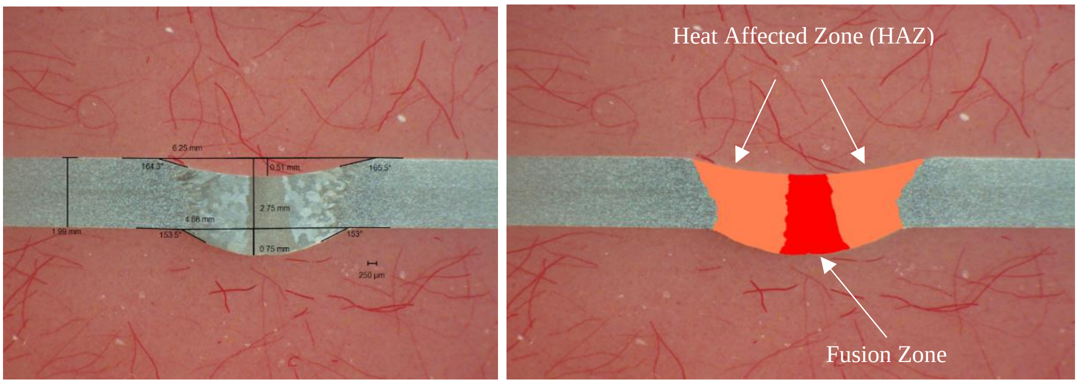

Fig. 2. Evaluation of WBG and HAZ using microstructural image processing software

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

No.	I (Ampere)	S (cm/min)	V (Hz)	G (mm)	Fr	Br	HAZ area (mm2)
1	110	240	85	2.5	0.1496	0.0779	7.430
2	130	240	85	2.5	0.1758	0.1458	13.087
3	110	240	115	2.5	0.1384	0.0511	6.350
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
25	120	300	100	3	0.1407	0.0832	8.585
26	120	300	100	3	0.1536	0.0816	7.633
27	120	300	100	3	0.1740	0.0944	8.001

3. Regression modeling of the process

3.1. Single objective modeling

RSM method is the procedure of finding a quantitative form of the relationship between desired response(s) and independent input variables using statistical and mathematical techniques [7-9].

The last three columns of Table 3 are the output for each test setting. These data can be used to develop mathematical models. Any of the above output is a function of process parameters which are expressed by linear and second order functions; as stated in Equations 1 to 2 respectively.

$$Y_1 = b_0 + b_1C + b_2F + b_3D \tag{1}$$

$$Y_2 = b_0 + b_1C + b_2F + b_3D + b_{11}CC + b_{22}FF + b_{33}DD + b_{12}CF + b_{13}CD + b_{23}FD \tag{2}$$

In the above formula b_0, b_1, b_2 and b_3 are the regression coefficients to be estimated. In this study, based on the Fr, Br and HAZ data given in Table 3, the regression models are developed using MINITAB software.

The choice of the model depends on the nature of initial data and the required accuracy [10]. Models representing the relationship between process parameters and output characteristics can be stated in equations 3 to 8.

4-1. Linear Model

$$Fr = 0.086776 + 0.043871I - 0.00245F - 0.03151S + 0.00434G \quad (3)$$

$$Br = 0.13965 + 0.038I - 0.00987F - 0.03036S + 0.00351G \quad (4)$$

$$HAZ = 8.2614 + 2.286I - 0.3501F - 1.968S - 0.2877G \quad (5)$$

4-2. Second order Model

$$\begin{aligned} Fr = {} & 0.0864 + 0.0416I - 0.000198F - 0.03376S + 0.00208G \\ & + 0.0125I^2 + 0.0081F^2 - 0.0222S^2 + 0.0043G^2 - 0.00432IF \\ & + 0.0059IS + 0.0047IG - 0.00217FS - 0.00444SG \end{aligned} \quad (6)$$

$$\begin{aligned} Br = {} & 0.15526 + 0.02546I - 0.0248F - 0.0429S + 0.0061G \\ & + 0.0105I^2 + 0.01228F^2 - 0.0382S^2 + 0.0069G^2 + 0.0221IF \\ & + 0.03388IS + 0.00516FS - 0.0053SG \end{aligned} \quad (7)$$

$$\begin{aligned} HAZ = {} & 8.0745 + 2.398I - 0.6549F - 1.5865S - 0.279G \\ & + 1.1875I^2 + 0.4083F^2 + 0.1266S^2 - 1.8671G^2 - 0.9584IS \\ & + 0.4354IG - 0.4132FS \end{aligned} \quad (8)$$

Adequacies of models were checked by analysis of variance (ANOVA) technique within the confidence limit of 95% [10]. Results are shown in Table 3. 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 models, thus, these models are considered as the best representative of the authentic TIG welding process throughout 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	Fr	93.65	86.4	78.18	81.08	<0.0001
Second order	Fr	99.32	**98.58**	**96.64**	**134.64**	<0.0001
Linear	Br	69.36	63.79	49.66	12.45	<0.0001
Second order	Br	98.15	**96.13**	**93.40**	**48.64**	<0.0001
Linear	HAZ	83.89	80.96	71.12	28.64	<0.0001
Second order	HAZ	98.64	**97.40**	**94.55**	**79.19**	<0.0001

Fig. 3, demonstrates the interaction effect of process parameters for Fr. For instance, a) illustrates the effect of welding speed and welding current on Fr. As illustrated, by increasing welding speed, the Fr increases. Similarly, by increasing welding current, the Fr increases.

Fig 6, exhibits the interaction effect of process parameters for Br. As illustrated by a), shows the effect of welding speed and welding current on Br. By increasing welding speed, the Br increases, similarly by increasing welding current, the Br increases.

By the same token, Fig. 7, shown the interaction effect of process parameters for HAZ. As illustrated by a), manifests the effect of welding speed and welding current on HAZ. By increasing welding speed, the HAZ decreases, similarly by increasing welding current, the HAZ increases.

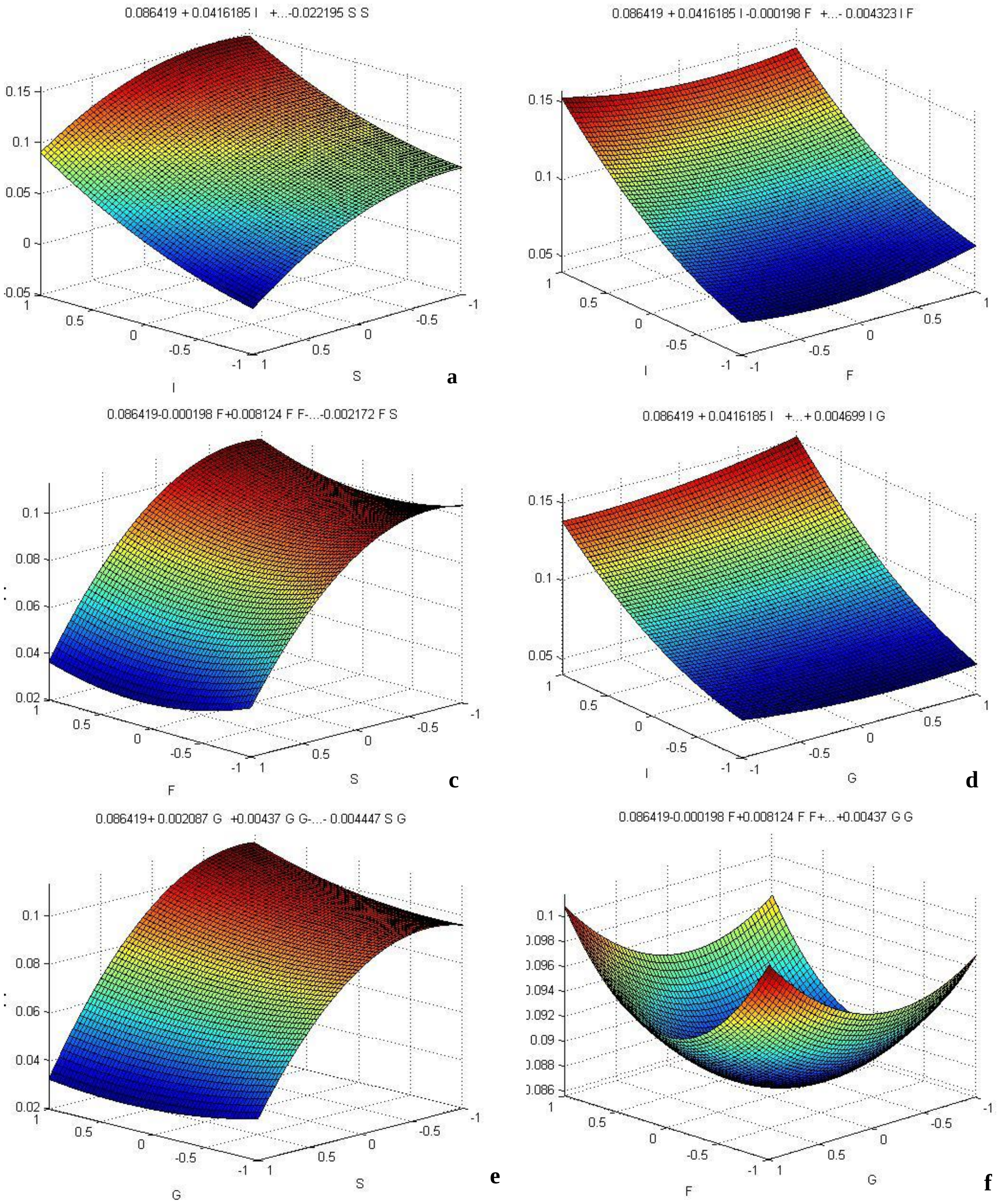

Fig. 3. interaction of process parameters for Fr

3.2. Multi-criteria modeling

The quality of final product in TIG welding process is significantly affected by the choice of process parameters levels. On the other hand, the interactions of these parameters call for simultaneous selection of *their optimal values. Therefore, multi-criteria optimization of processes parameters could be used to achieve several conflicting goals such as increasing product quality and reducing production time simultaneously. In this section the effects of TIG welding process parameters settings on the three important output characteristics have been investigated simultaneously. First, using Equation 9, the process measures have been normalized [11].*

$$z_{ij} = \frac{(y_{ij} - t_j)^2}{\hat{y}_j} \tag{9}$$

Where, i is the number of experiments, j is the number of process output measured, y is the output measured and $\hat{y}$ is the mean of the measured output. Then, the outputs have been weighted using the following formula according to the importance of process output taking in to account [11].

$$c_i = \sum_{j=1}^{k} z_{ij} w_j \tag{10}$$

Where Z is the process output and W is the weight for each output taking in to account. In this study for Br the 0.5 weight considered according to the importance of that. Based on the knowledge that HAZ has the important role for resistance in corrosive environments, for HAZ, 0.3 and for Fr, 0.2 weight considered.

Model representing the relationship between process parameters and weighted output characteristic can be seen in equation 11.

$$\begin{aligned} C = {} & 0.27019 + 0.29764A - 0.03729F - 0.24059S + 0.03551G + 0.37195A^2 \\ & + 0.32409S^2 - 0.22934G^2 - 0.10222AF - 0.47004AS - 0.04257SG \end{aligned} \tag{11}$$

The result of ANOVA for the weighted model has been shown in Table 4. As shown the weighted model is quite accurate in multi criteria modeling of TIG welding process.

Table 4 Result of ANOVA For weighted model

Machining parameters	*Degree of freedom (DoF)*	*Sum of square (SS_j)*	*F- value*	*P- value*
Model	*10*	*7.49726*	*57.55*	*0*
Residual Error	*13*	*0.16936*	*-*	*-*
Total	*23*	*-*	*-*	*-*
$R^2 = 97.8$	$R^2_{pred} = 91.84$	$R^2_{adj} = 96.1$		

4. TIG welding process optimization using simulated annealing algorithm

Simulated annealing (SA) algorithm is an optimization process whose operation is reminiscent of the physical annealing of crystalline compounds such as metals and metallic alloys [10]. In condensed matter physics, annealing is a physical process that is used to reconstruct the crystal structure of a solid with a low energy state. A solid in a state bath is first heated up to a temperature above the melting point of the solid. At this temperature, all particles of the solid are in violent random motion. The temperature of the heat bath is then slowly cooled down. All particles of the solid rearrange themselves and tend toward a low energy state. As the cooling of the particle is carried out sufficiently slowly, lower and lower energy states are obtained until the lowest energy state is reached. Similarly, in TIG welding process an energy function is created which is minimized. While minimizing efforts are made to avoid local minima and to achieve global minima. The lowest energy level gives the optimized value of TIG welding process parameters. In recent years, the simulated annealing algorithm has emerged as a leading tool for large-scale combinational optimization problems.

A standard SA procedure begins by generating an initial solution at random. At initial stages, a small random change is made in the current solution. Then the objective function value of new solution is calculated and compared with that of current solution. A move is made to the new solution if it has better value or if the probability function implemented in SA has a higher value than a randomly generated number. The probability of accepting a new solution is given as follows [11]:

$$p = \begin{cases} 1 & \text{if } \Delta < 0 \\ e^{-\Delta/t} & \text{if } \Delta \geq 0 \end{cases} \tag{12}$$

The calculation of this probability relies on a temperature parameter, T, which is referred to as temperature, since it plays a similar role as the temperature in the physical annealing process. To avoid getting trapped at a local minimum point, the rate of reduction should be slow [11]. In our problem the following method to reduce the temperature has been used:

$$T_{i+1} = cT_i \qquad i = 0,1,\ldots \quad \text{and} \quad 0.9 \leq c < 1 \tag{13}$$

Thus, 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. The algorithm may be terminated after a certain volume fraction for the structure has been reached or after a pre-specified run time.

Simulated annealing algorithm has diverse applications including improving the performance of other artificial intelligence techniques and determining the optimal set of process parameters [11]. In this research, SA has been used twice. First it is employed for single objective optimization, then for multi-criteria optimization.

Table 5 illustrates the result of optimization using RSM and SA and their corresponding confirmation tests. As shown, error has been reduced using SA algorithm in comparison with RSM.

Table 5 Result of single objective optimization

Output	*Method*	*Process parameters*				*Predicted*	*experiment*	*Error (%)*
		I	*F*	*V*	*G*			
Fr	*SA*	*111*	*103*	*282*	*3.1*	*0.073*	*0.080*	*8*
	RSM	*111*	*103*	*282*	*2.9*	*0.070*	*0.082*	*14*
Br	*SA*	*121*	*108*	*346*	*2.7*	*0.104*	*0.110*	*5.5*
	RSM	*120*	*108*	*344*	*3.1*	*0.107*	*0.121*	*11.5*
HAZ	*SA*	*119*	*108*	*342*	*2.7*	*5.999*	*5.540*	*8*
	RSM	*118*	*110*	*338*	*3.2*	*6.335*	*7.100*	*10*

The result of multi-criteria optimization and confirmation tests has been demonstrated in Table 6. As shown, using SA algorithm result in reduced error.

Table 6 Result of multi-criteria optimization

Optimization Method	Process				output	Predicted Value	Experimental Value	T
	I	F	S	G				
SA	119	115	330	2.7	Fr	0.075	0.080	6
					Br	0.117	0.130	11.8
					HAZ	6.230	6.788	8
RSM	118	113	330	3.2	Fr	0.0687	0.0750	10
					Br	0.1186	0.1140	15
					HAZ	6.1600	6.864	10

5. Conclusion

The quality of final product in TIG welding process is considerably affected by the selection of process parameters levels. In contrast, the interactions of these parameters and the conflicting nature of various quality measures, necessitate simultaneous selection of their optimal values. In this study the problem of multi-criteria modeling and optimization of TIG welding process for AL5052 alloy sheets has been addressed. First, TIG welding modeling has been carried out using experimental data gathered as per L27 central composite design (CCD) matrix. Moreover, the MIP software has been used for measurement of heat affected zone area and *weld bead geometry (Fr and Br). The proposed regression models simultaneously take into account four process input variables to predict three outputs responses. Next, the models have 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 HAZ and WBG simultaneously. These further illustrate that optimization results are consistent with the inherent characteristics of TIG welding process. It is noted that in this research weight of Br, HAZ and Fr were given 0.5, 0.3 and 0.2 respectively. Based on the relative importance of the HAZ and WBG, any other combinations of these two objectives may also be achieved. The result of optimization technique has shown using SA algorithm result in smaller errors for both single and multi-criteria optimization which shows the proposed model can accurately simulate the actual TIG welding process.*

REFERENCES

[1] *Kumar, A., Sundarrajan, S. (2009). Optimization of pulsed TIG welding process parameters on mechanical properties of AA 5456 Aluminum alloy weldments, Materials and Design. 30 1288–1297.*

[2] *Kumar, A., Paulraj, S.S. (2015). Multi-response optimization of process parameters for TIG welding of Incoloy 800HT by Taguchi grey relational analysis, Engineering Science and Technology, an International Journal, 25 112-122.*

[3] *Cunha, T.V., Voigt, A. L., Bohórquez, C.E. (2016). Comparison of microstructure and mechanical properties of TIG and laser welding joints of a new Al–Zn–Mg–Cu alloy, Journal of Materials Processing Technology. 231 449–455.*

[4] *Dutta, P., Pratihar, D.K. (2007). Modeling of TIG welding process using conventional regression analysis and neural network-based approaches, Journal of Materials Processing Technology. 184 (3), 56–68.*

[5] *Nagesh, D.S., Datta, G.L. (2010). 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, 10 (3), 897–907.*

[6] *Ghelichi, R., MacDonald, D., Bagherifard, S., Jahed, H., Guagliano, M., Jodoin, B. (2012). Microstructure and fatigue behavior of cold spray coated Al5052, Acta Materialia, 60, 6555–6561.*

[7] *Correia, D. S., Gonçalves, C.V., Cunha, S.S., Ferraresi, V.A. (2005). Comparison between genetic algorithms and response surface methodology in GMAW welding optimization, Journal of Materials Processing Technology. 160, 70–76.*

[8] *Senthilkumar, B., Kannan, T., (2015). Effect of flux cored arc welding process parameters on bead geometry in super duplex stainless steel claddings. Measurement. 62, 127-136.*

[9] *Chong, S.S., Aziz, A.R.A., Harun, S.W., Arof, H., Shamshirband, S. (2015). Application of Multiple Linear Regression, Central Composite Design, and ANFIS models in Dye concentration Measurement and Prediction Using Plastic Optical Fiber Sensor, Measurement. 10, doi: http://dx.doi.org/10.1016/j.measurement. 2015.06.019.*

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

[11] *Kolahan, F., and Azadi Moghaddam M (2015). The use of Taguchi method with grey relational analysis to optimize the EDM process parameters with multiple quality characteristics. Scientia Iranica B 22(2), 530-538.*

Gelatt, K.J., Vecchi, D.D. Optimization by simulated annealing, Science, (1983), 671–680.