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ORIGINAL ARTICLE

Optimization of weld bead geometry in GTAW of CP titanium using imperialist competitive algorithm

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Abstract This paper aims to use a novel optimization algorithm called imperialist competitive algorithm (ICA) in order to optimize the weld bead geometry in the gas tungsten arc welding process. This algorithm offers some advantages such as simplicity, accuracy, and time saving. Experiments were conducted in order to collect welding data and obtain a relationship for the bead geometry as a function of welding current, arc voltage, welding speed, and arc length. Furthermore, a regression equation for depth of penetration and bead width was obtained using the least squares method, and the equations were optimized using ICA. Ultimately, the value of the input variables to obtain minimum bead width and maximum depth of penetration was calculated using ICA. Computational results indicate that the proposed algorithm is quite effective and powerful in optimizing the cost function.

Keywords Gas tungsten arc welding · Imperialist competitive algorithm · Weld bead geometry · Optimization

1 Introduction

Gas tungsten arc welding (GTAW) is a process that melts and joins metals by heating them with an arc established between a non-consumable tungsten electrode and the metals that the weld pool is protected from air contamination by a stream of a shielding gas [1]. Since the GTAW process is a very clean welding process, it can be used to weld reactive metals, such as titanium, zirconium, aluminum, and magnesium. In the GTAW process, different input welding parameters greatly affect the weld bead geometry which is one of the weld quality characteristics. The quality of a welded product is evaluated by different parameters like weld bead geometry, deposition rate, and hardness [2]. In order to obtain a good welded joint with the required bead geometry and weld quality with minimal detrimental residual stresses and distortion, the input variables should be selected in appropriate combination, but proper selection of these variables needs to have adequate information about the effects of different input variables on weld bead characteristic. Design and execution of the experiment are useful for obtaining the required information about the welding input variable main effects and their interaction effects on the response parameter. As such, several researches have been conducted to study how welding parameters affected weld bead characteristics. Mir Sadat et al. [3] studied the effects of the input variables on the weld bead characteristics for the GTAW process and reported that an increase in the welding current led to an increase in the bead width. Also, an increase in the welding current results in an increase in the depth of penetration up to the maximum point, and from this point onward, penetration decreased gradually. In the automated welding process, welding control variables must be adjusted on the welding system using mathematical equations in order to achieve the desired quality characteristics. Parikshit et al. [4] utilized the regression analysis technique and neural network for modeling and predicting weld bead geometrical features of the GTAW process. Sudhakaran et al. [5] studied the effects of control variables on the bead geometry in the GTAW of stainless steel plates and proposed a mathematical model based on regression analysis to predict weld bead dimensions and reported that the regression method can be effectively used to predict the bead dimensions in GTAW. Also, it was found that out of the four process parameters selected for investigation, welding current and shielding gas

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flow rate have a positive effect on the depth to width ratio (DWR), whereas welding speed and welding gun angle have a negative effect on the depth to width ratio. The mathematical model not only helps us in better understanding of the welding process but also helps us in optimizing the weld bead response for obtaining a high quality welded joint at a relatively low cost with higher productivity. Nagesh and Datta [6] developed a mathematical model based on a multiple linear regression technique for the weld bead shape parameters of the tungsten inert gas (TIG) welding process. Also, by using the same experimental data, an attempt has been made to predict the bead shape parameters using back-propagation neural network, and finally, the genetic algorithmic (GA) approach has been applied to optimize the process parameters to achieve the desired bead geometry. Tarng et al. [7] used a neural network to construct the relationships between welding process parameters and weld pool geometry in TIG welding, and the developed network has been optimized by optimization algorithm called simulated annealing (SA) for searching the process parameters with optimal weld pool geometry.

Increasing the quality and productivity of the GTAW process is the main goal of most researchers. In the GTAW process like any other arc welding process, welding engineers often face the problem of selecting appropriate and optimum combinations of input welding variables in order to achieve the optimum weld bead quality. In this work, the effect of four input variables namely welding current, arc voltage, welding speed, and arc length on the weld bead geometry of CP Titanium Grade 2 plates was studied. The choice of CP Titanium was mainly because it is used widely in various industries such as aerospace, marine, chemical plants, oil and gas extraction, medical, and sports due to its inherent advantages. For efficient welding, it is essential to optimize the welding parameters by selecting proper inputs in order to reach the required bead geometry as a characteristic of quality. This paper focuses on the execution of the experiment in order to build the mathematical model by the multiple regression technique and subsequently using the same for the case of imperialist competitive algorithm for optimizing the bead geometry in the GTAW process.

2 Imperialist competitive algorithm

The optimization problem can be easily described as to find an argument x whose relevant cost $f(x)$ is optimum, and it has been extensively used in many different situations such as industrial planning, resource allocation, scheduling, pattern recognition, and so on. Different methods have been proposed to solve the optimization problem. Evolutionary algorithms, such as genetic algorithm, particle swarm optimization, taboo search, ant colony optimization, bees algorithm, and simulated annealing, are a set of algorithms that are introduced and suggested in the past decades for solving optimization problems in different science and engineering fields. Imperialist competitive algorithm (ICA) is an algorithm introduced for the first time in 2007 by Atashpaz-Gargari and Lucas [9] and used for optimizing inspired by the imperialistic competition and has a considerable relevance to several engineering applications [10, 11]. Like other evolutionary ones, the proposed algorithm starts with an initial population. Population individuals called country are of two types: colonies and imperialists that all together form some empires. Imperialistic competition among these empires forms the basis of the proposed evolutionary algorithm. During this competition, weak empires collapse, and powerful ones take possession of their colonies. Imperialistic competition hopefully converges to a state in which there exists only one empire and its colonies are in the same position and have the same cost as the imperialist [9]. Using this algorithm, one can find the optimum condition of the most functions. In this connection, the proposed model-based on regression analysis is then embedded into the ICA to optimize the objective function. The goal of optimization algorithms is to find an optimal solution in terms of the variables of the problem (optimization variables). We form an array of variable values to be optimized. In genetic algorithm terminology, this array is called "chromosome," but here the term "country" is used for this array. In an N_{var} -dimensional optimization problem, a country is a $1\times N_{\mathrm{var}}$ array. This array is defined by:

$$country = \left[p_1, p_2, p_3, \ldots, p_{N_{\mathrm{var}}}\right] \quad (1)$$

The variable values in the country are represented as floating point numbers. The cost of a country is found by evaluating the cost function f at the variables $\left(p_1, p_2, p_3, \ldots, p_{N_{\mathrm{var}}}\right)$ [9]. Then

$$cost = f(country) = f\left(p_1, p_2, p_3, \ldots, p_{N_{\mathrm{var}}}\right) \quad (2)$$

The flowchart of the ICA algorithm is shown in Fig. 1. To start the optimization algorithm, we generate the initial population of size N_{pop}. We select N_{imp} of the most powerful countries to form the empires. The remaining N_{col} of the population will be the colonies, each of which belongs to an empire. Then, we have two types of countries: imperialist and colony. To form the initial empires, we divide the colonies among imperialists based on their power. That is, the initial number of colonies of an empire should be directly proportionate to its power. To divide the colonies among imperialists proportionally, we define the normalized cost of an imperialist by $C_n = c_n - \max\{c_i\}$, where c_n is the cost of nth imperialist and C_n is its normalized cost. Having the normalized cost of all

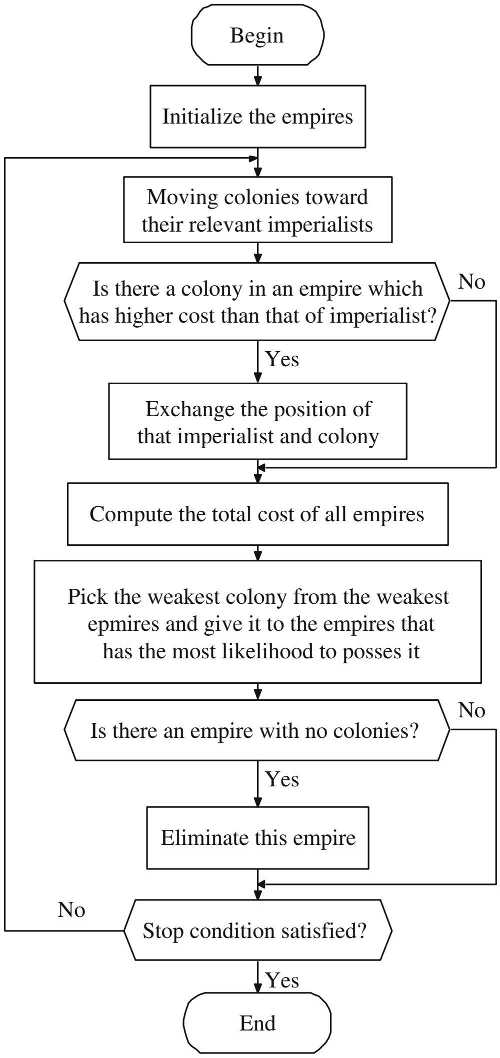

Fig. 1 The procedure of the proposed algorithm [9]

imperialists, the normalized power of each imperialist is defined by [9]

$$p_n = \left| C_n / \sum_{i=1}^{N_{imp}} C_i \right| \tag{3}$$

From another point of view, the normalized power of an imperialist is the portion of colonies that should be possessed by that imperialist. Then, the initial number of colonies of an empire will be

$$N.C._n = round\{p_n . N_{col}\} \tag{4}$$

where $N.C._n$ is the initial number of colonies of the nth empire, and N_{col} is the number of all colonies. To divide the colonies, for each imperialist, we randomly choose $N.C._n$ of the colonies and give them to it. These colonies along with the imperialist will form the nth empire. A schematic representation of the initial population of each empire can be observed in Fig. 2. As shown in this figure, bigger (powerful) empires have more number of colonies, while smaller (weaker) ones have less [9]. As mentioned, imperialist countries started to improve their colonies. We have modeled this fact by moving all the colonies toward the imperialist. This movement is shown in Fig. 3, where the colony moves toward the imperialist by x units. The new position of the colony is shown in a darker color. The direction of the movement is the vector from the colony toward the imperialist. In this figure, x is a random variable with uniform or any proper profile [9]. Then, for x we have

$$x \sim U(0, \beta \times d) \tag{5}$$

where β is a number greater than 1, and d is the distance between the colony and the imperialist. A $\beta>1$ causes the colonies to get closer to the imperialist state from both sides.

To search different points around the imperialist, we added a random amount of deviation to the direction of movement. Figure 4 shows the new direction. In this figure, θ is a random number with uniform or any proper profile. Then,

$$\theta \sim U(-\gamma, \gamma) \tag{6}$$

where γ is a parameter that adjusts the deviation from the original direction. Nevertheless, the values of β and γ are arbitrary; in most of our implementation, a value of about 2 for β and about $\pi/4$ (Rad) for γ have resulted in good convergence of countries to the global minimum.

3 Tools and techniques

3.1 Experimental procedure

In this study, welding current (I), arc voltage (V), welding speed (S), and arc length (L) were considered

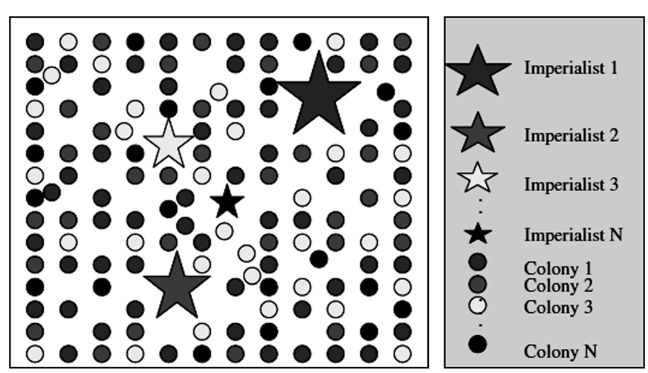

Fig. 2 Generating the initial empires: the more colonies an imperialist possesses, the bigger its relevant *shaded star* mark [9]

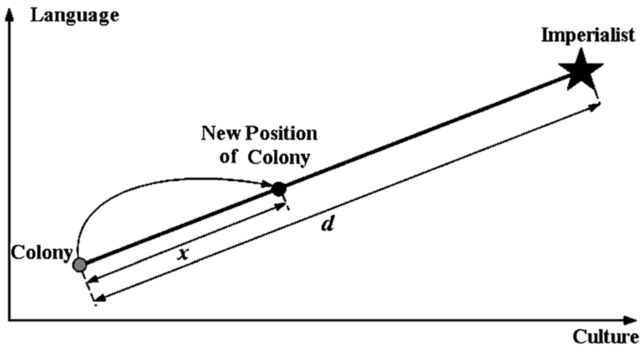

Fig. 3 Moving colonies toward their relevant imperialists [9]

as input variables. Test pieces of size 100 mm×30 mm×4 mm were cut from CP Titanium Grade 2 plates, and surfaces were cleaned before welding operation. The chemical composition of the base metal is shown in Table 1. Twenty-four experiments were conducted by a semiautomatic ESAB DTA300 machine using direct current straight polarity (DCEN), and the butt weld technique was adopted for welding the specimens. After welding operation, the specimens were cut perpendicular to the welding direction by the cutting machine in order to measure the weld bead geometry. The cut surfaces were grinded manually and cleaned to remove the possible grease; depth of penetration and bead width were measured by means of an optical microscope. In the present study, TIG welding experiments are carried out by varying the arc length in a range of 3–5 mm, the arc voltage in a range of 13.7–17.2 V, the welding current in a range of 160–220 Amps, and the welding speed in a range of 150–250 mm/min. The shielding gas is pure argon, and the flow rate of the shielding gas is 20 l per minute. The input variables and experimental outputs are shown in Table 2.

Different regions including weld metal, heat-affected zone (HAZ), and base metal of sample 10 are shown in Fig. 5. Figure 6a, b illustrates the back and front sides

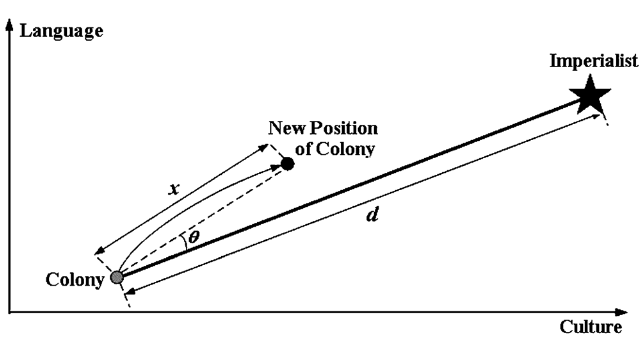

Fig. 4 Moving colonies toward their relevant imperialist in a randomly deviated direction [9]

Table 1 Chemical composition of base metal

Elements	H	C	N	O	Fe	AL	V	Si
%W	–	–	–	–	0.05	0.27	0.04	0.04

of the weld bead of sample 14, respectively. Moreover, non-fusion line and fusion zone of the sample are shown in Fig. 6c.

3.2 Mathematical model

Regression analysis is one of the most widely used statistical techniques in almost every field of application [8]. The objective of this section is, therefore, establishing relationships between the process parameters (inputs) and process response (output) in the GTAW process using the statistical regression analysis. Statistical techniques are used for mathematical modeling and analysis

Table 2 The input variables and experimental outputs

No.	V	L	S	I	Pen	Width
1	13.7	3	150	160	2	10.9
2	13.7	3	200	160	1.9	9.3
3	13.7	3	250	160	1.4	7.25
4	14.2	3	150	180	2.4	11.5
5	14.2	3	200	180	2.3	10.35
6	14.2	3	250	180	1.7	8.5
7	15.3	3	150	200	3.8	14.25
8	15.3	3	200	200	2.9	11.7
9	15.3	3	250	200	2.1	9.5
10	15.7	3	150	220	4.7	15.3
11	15.7	3	200	220	3.6	12.9
12	15.7	5	250	220	2.1	11.1
13	14.6	5	150	160	2.3	11.2
14	14.6	5	200	160	1.6	9
15	14.6	5	250	160	0.9	6.7
16	15.2	5	150	180	3.2	12.8
17	15.2	5	200	180	1.7	10
18	15.2	5	250	180	1.4	8.25
19	16.3	5	150	200	4.3	14.4
20	16.3	5	200	200	2.2	11
21	16.3	5	250	200	1.5	8.8
22	17.2	5	150	220	4.4	15.4
23	17.2	5	200	220	2.9	12.8
24	17.2	5	250	220	1.9	10.5

Fig. 5 Different regions of sample 10 including weld metal, HAZ, and base metal

of problems in which a desired response is influenced by several input variables. These techniques are a sequential process that is performed in the following manner: First, a series of experiments are performed as per designed matrix; subsequently, responses are measured, and after that a mathematical model of the response surface based on experimental data is developed. The goal of this method is to find an approximating function for predicting future response. The second-order response function for the k quantitative factor is given as:

$$Y = f(X_1, \ldots, X_k, X_{11}, \ldots, X_{kk}, X_{12}, \ldots, X_{k-1}X_k)$$

where $X_1, X_2, \ldots, X_k$ are the independent input variables, and Y is the response.

Based on the performed experiment, the relationship between the investigated four input variables and the responses can be obtained by a regression equation. The least square method was used to determine the coefficients of the regression model. The statistical software, Minitab 14, was used to calculate the values of these coefficients for response functions. The final models for weld bead features were reduced to the following equations.

The coded forms of the regression equation for the responses were found to be as follows:

$$P = -9.91 - 3.99\ V - 0.473\ L - 2.77\ S - 0.547\ VS + 0.107\ SI - 0.386\ V^2$$

$$R\text{–}Sq = 94.0\% \quad R\text{–}Sq(\text{adj}) = 91.9\%$$

$$W = -4.28 - 5.55\ V - 4.08\ S + 0.160\ VL - 0.395\ VS - 0.777\ V^2$$

$$R\text{–}Sq = 94.0\% \quad R\text{–}Sq(adj) = 92.4\%$$

where P and W are the depth of penetration and bead width, respectively, and V, I, S, and L are the input variables.

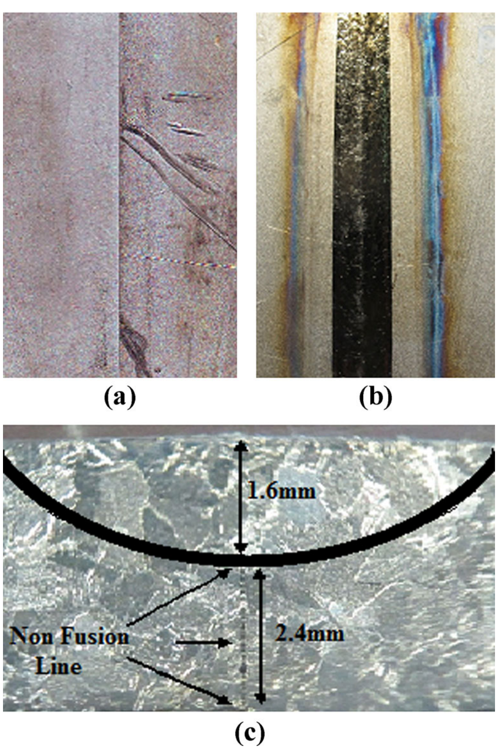

Fig. 6 **a** Back side of weldment, **b** front side of weldment, and **c** cross section of weld metal

3.3 Optimization of the process

Basically, the higher the depth to width ratio in the GTAW process, the better is the welding performance. Thus, the objective of optimization in this research work is to maximize the depth to width ratio. It should be noticed that since ICA minimizes the cost function basically, the equation of depth to width ratio has been multiplied by minus. The models are developed in the MATLAB platform, which is highly reliable, and the regression equation was embedded into the ICA, and it was optimized. The optimum algorithmic parameters used in the ICA model are brought in Table 3.

Table 3 Optimum algorithmic parameters setting for ICA

Number of total countries	80
Number of initial imperialist countries	8
Number of epochs (decades)	15
Revolution rate	0.3
Assimilation coefficient	2
Assimilation angle	0.5
Cost function	−(depth to width ratio)

Table 4 The optimal input variables for optimum solution

Variable	*V* (V)	*L* (mm)	*S* (mm/min)	*I* (Amp)
Coded value	−3.914	−3.500	−3.500	−5.000
Decoded value	17.2	3	150	160

The optimum levels of input variables in coded and un-coded form to achieve an optimal solution are shown in Table 4. Results show that to achieve the maximum depth to width ratio, the traveling speed, arc length, and welding current should be set at a lower level, and arc voltage should be set at a high level.

Moreover, the concerned problem is optimized by the so-called optimization algorithm namely genetic algorithm (GA) in order to evaluate the obtained results from ICA. The optimum algorithmic parameters used in the GA model are brought in Table 5.

Best fitness, mean fitness, fitness function, and generation in GA are equivalent to minimum cost, mean cost, cost function, and decades in ICA, respectively. These equivalent terminologies help us to compare the results of two aforementioned algorithms accurately.

4 Results and discussion

In this research work, the experiments were carried out to collect welding data using a semiautomatic ESAB DTA300 machine. Mathematical relationships (objective functions) for depth of penetration and bead width in terms of input variables using the statistical regression analysis were developed and the R^2 of both developed models was obtained, which is equal to 94.0 %. The R^2 indicates how well the proposed model fits the given data that the results show a good consistency of the proposed models with experimental data. Figure 7 shows the minimum and mean cost of all imperialists for minimization of cost function versus epochs (decades). From

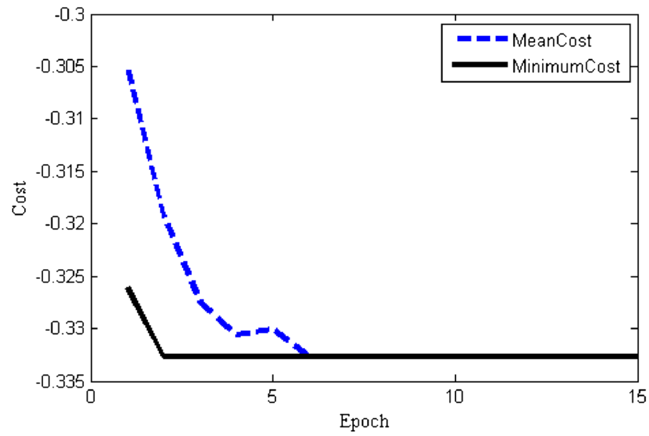

Fig. 7 Mean and minimum cost of all imperialists versus epochs for maximum DWR

the figure, it is evident that the minimal cost function is obtained at the sixth epoch. Figure 8 shows the best fitness and mean fitness of objective function during the optimization process using GA. The depth to width ratio is gradually increasing up to the sixth epoch, and it is constant for further epochs. The best calculated DWR due to maximization by ICA and GA are 0.333 and 0.331, respectively.

Moreover, confirmation experiments were performed for both GA and ICA. The percentage errors related to penetration and width are found to be equal to 3.15 and 6.64 %, respectively, for GA, and 2.9 and 4.35 %, respectively, for ICA.

Also, Figs. 7 and 8 indicate that ICA converges to the global optimum solution at a faster rate in comparison with GA. Thus, it can be concluded that the optimization process by ICA especially for complicated function is less time consuming than the optimization process by GA.

Table 5 Algorithmic parameters setting for GA

Population size	20
Elite count	2
Number of generations	50
Cross-over fraction	0.8
Migration fraction	0.2
Fitness function	−(depth to width ratio)

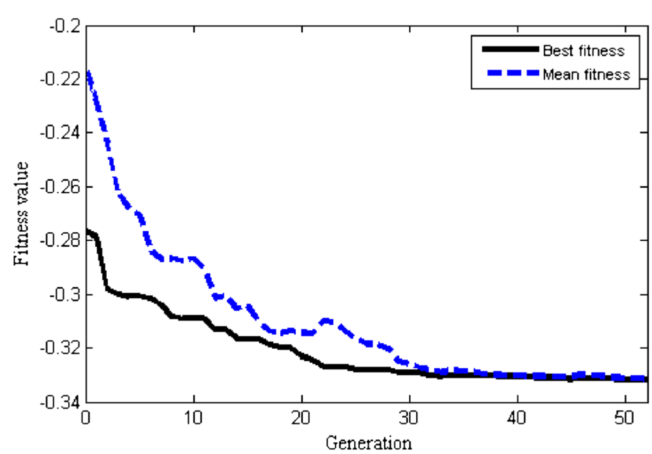

Fig. 8 Mean and best fitness versus generation

5 Conclusions

In this paper, experiments were carried out for generating data, and butt weld runs were performed. A correlation was developed using regression analysis to gain a relationship between optimization parameters and an output variable. The adequacy of the proposed model was tested, and results show good conformability of the developed model to the real process. Evolutionary computing techniques such as genetic algorithm (GA) and imperialist competitive algorithm (ICA) are performed to optimize the parameters of GTAW for optimal weld performance. From the obtained results by the proposed ICA and GA, it can be concluded that the ICA model gives optimal results than the GA model. In addition, it is observed that the proposed algorithm is quite effective and powerful in optimizing the cost function, and it converges to the global optimum solution at a faster rate in comparison with GA.

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