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# The application of imperialist competitive algorithm for optimization of deposition rate in submerged arc welding process using $TiO_2$ nano particle †

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**Abstract**

We used a novel optimization algorithm based on the imperialist competitive algorithm (ICA) to optimize the deposition rate in the submerged arc welding (SAW) process. This algorithm offers some advantages such as simplicity, accuracy and time saving. Experiments were conducted based on a five factor, five level rotatable central composite design (RCCD) to collect welding data for deposition rate as a function of welding current, arc voltage, contact tip to plate distance, welding speed and thickness of $TiO_2$ nanoparticles coated on the plates of mild steel. Furthermore, regression equation for deposition rate was obtained using least squares method. The regression equation as the cost function was optimized using ICA. Ultimately, the levels of input variables to achieve maximum deposition rate were obtained using ICA. Computational results indicate that the proposed algorithm is quite effective and powerful in optimizing the cost function.

*Keywords*: Imperialist competitive algorithm; Optimization; Submerged arc welding; Design of experiments

## 1. Introduction

The desire to increase productivity through continuous improvement of quality of weldments provides an ongoing incentive for process, equipment, and consumable development. One such development is the application of $TiO_2$ nanoparticles in the submerged arc welding (SAW) process. One weld productivity index as affected by input welding parameters in the SAW process is the weld deposition rate, which is defined as the rate that weld metal can be deposited by a given welding wire. In hard-facing processes, the weld deposition rate plays an important role in determining the productivity of weldments. This paper reports the optimization of deposition rate as affected by the combined effect of $TiO_2$ nanoparticles and input welding parameters such as the arc voltage, welding current, welding speed, and contact tip to plate distance in the SAW process using imperialist competitive algorithm (ICA) which has not been reported so far.

The idea was to introduce the $TiO_2$ nanoparticles directly into the weld puddle, which was not possible to accomplish due to its size and cost. Therefore, we decided to disperse the nanoparticles in ethanol and then apply the obtained paste on the low-carbon steel plates in different thicknesses as per the design matrix before the actual welding operation. To collect the experimental data to be used for modeling the process, 32 welding runs were performed by using a five-level five-factor rotatable central composite design of experiments.

In this research work input variables were changed in five levels to extend the searching domain in order to increase the chance of finding the best solutions and optimization performed by novel algorithm, the imperialist competitive algorithm (ICA). To validate the output of the proposed algorithm in actual welding conditions, confirmation tests were carried out.

## 2. Review of literature

It is generally well established that nanotechnology is the research field which will lead to the next generation of breakthroughs in the science and engineering sectors. Macwan et al. [1] defined nanomaterials as particles having diameters ranging from 1 to 100 nm. Chen et al. [2] reported that small size and large surface and volume effects of nanoparticles offer unique mechanical, electrical, magnetic, optical, and physiochemical properties which make them suitable candidates for different applications in defense, electronic, aerospace, and chemical industries.

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A search of science direct [3] from 2000 to the present confirmed that although many investigations have been reported on the effect of different input parameters on weld bead penetration in arc welding processes [4], few have been conducted on the application of $TiO_2$ nanoparticles in arc welding processes [5-8]. Fattahi et al. [7] reported the improvement of impact toughness of the AWS E6010 weld metal with addition of $TiO_2$ nanoparticles to the electrode coating. Pal and Maity [8] investigated the effect of nanosized $TiO_2$ particles on mechanical properties of the AWS E11018M-type electrode and concluded that the charpy impact property was improved due to variation of Ti content of the weld deposit. Aghakhani et al. [5] investigated the effect of $TiO_2$ nanoparticles on the weld bead width in submerged arc welding process and concluded that addition of $TiO_2$ nanoparticles initially increased the bead width and decreased it subsequently. Aghakhani et al. [6] reported that weld bead penetration was affected by the addition of $TiO_2$ nanoparticles to the weld pool.

To achieve the required weld bead, the input variables should be selected in appropriate combination, and 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 experiment is useful for obtaining the required information about the welding input variable main effects and their interaction effects on the response parameter. Many efforts have been made to study how welding parameters affected weld bead characteristics. Gunaraj and Murugan [9] utilized response surface methodology (RSM) in submerged arc welding of pipes for generating welding data and subsequently developed a mathematical model to predict process responses. In the automatic SAW process, input welding variables must be adjusted on the welding system using mathematical equations to achieve the desired quality characteristics. The mathematical model not only helps us in better understanding of the welding process, but also in optimizing the weld bead response for obtaining a high quality welded joint. In addition, several studies have been conducted on optimization of the SAW process. Patnaik et al. [10] utilized genetic algorithm (GA) for parameter optimization of SAW in the hard-facing process using weighting method. The relationship between control factors and performance outputs is established by means of nonlinear regression analysis. Tarng et al. [11] utilized the grey-based Taguchi methods for optimization of SAW process parameters in hardfacing and obtained optimum values of input variables to achieve maximum deposition rate and other weld bead characteristics.

## 3. Submerged arc welding

SAW is an arc welding process widely used in heavy fabrication industries, especially in semiautomatic or automatic form for fabrication of water and petrochemical pipelines, gas cylinders, ship building and repair, and resurfacing (hardfacing) applications in the mining, mineral processing, and power industries due to its high weld quality, reliability, deep penetration, high deposition rate, and a smooth bead [12, 13]. It is a process that melts and joins metals by heating them with an arc established between a consumable wire electrode and the metals, with the arc being shielded by a molten slag and granular flux [12]. The weld pool is protected from air contamination by continuous stream of a flux that is supplied from a hopper traveling with the torch.

## 4. 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. The imperialist competitive algorithm (ICA) is an algorithm introduced for the first time by Atashpaz-Gargari and Lucas [14] and used for optimizing inspired by imperialistic competition and has a considerable relevance to several engineering applications. Like other evolutionary ones, the proposed algorithm starts with an initial population. Population individuals called "country" are in 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 [14]. Using this algorithm, one can find the optimum condition of 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. We form an array of variable values to be optimized that is called "country". In an $N_{Var}$-dimensional optimization problem, a country is a $1 \times N_{Var}$ array. This array is defined by:

$$country = [p_1, p_2, p_3, ..., p_{N_{\mathrm{var}}}] . \tag{1}$$

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 $(p_1, p_2, p_3, ..., p_{N_{\mathrm{var}}})$ [14]. Then

$$cost = f(country) = f(p_1, p_2, p_3, ..., p_{N_{\mathrm{var}}}) . \tag{2}$$

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

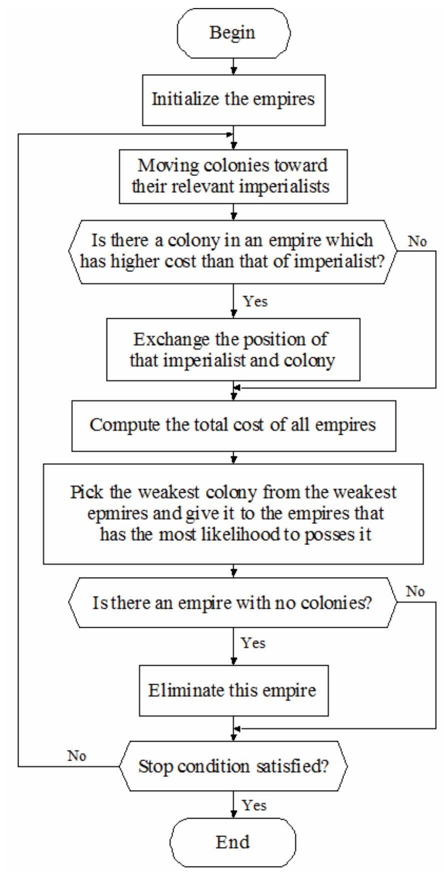


Fig. 1. The procedure of the proposed algorithm [14].

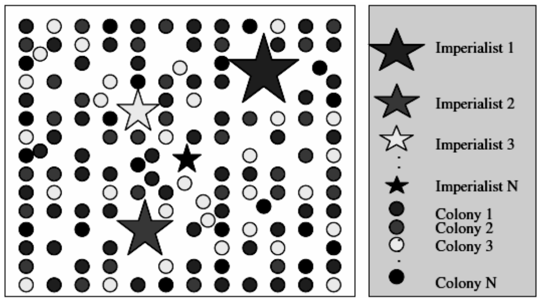


Fig. 2. Generating the initial empires: the more colonies an imperialist possess, the bigger its relevant ★ mark [14].

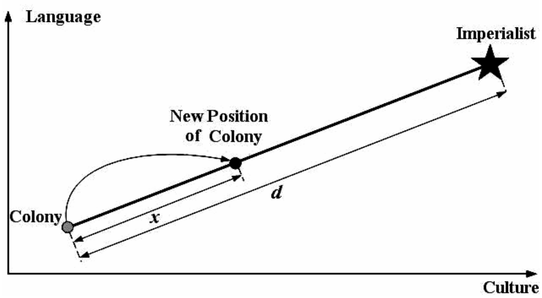


Fig. 3. Moving colonies toward their relevant imperialists [14].

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 imperialists, the normalized power of each imperialist is defined by [14]:

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

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 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, bigger (powerful) empires have a greater number of colonies, while smaller (weaker) ones have fewer [14]. 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 colony is shown in a darker color. The direction of the movement is the vector from colony toward imperialist. In this figure x is a random variable with uniform or any proper profile [14]. 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 colony and imperialist. A,β > 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. Fig. 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 π/4 (Rad) for γ have resulted in good convergence

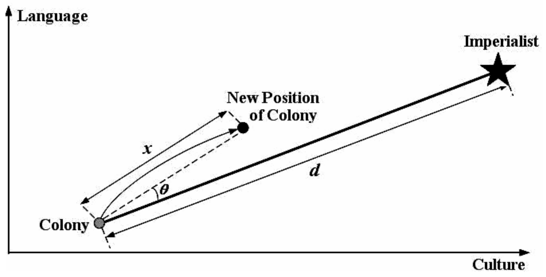


Fig. 4. Moving colonies toward their relevant Imperialist in a randomly deviated direction [14].

of countries to the global minimum.

## 5. Genetic algorithm

Genetic algorithms have their philosophical basis in Darwin's natural evolution process theory of survival. These algorithms encode a possible solution to a specific problem on a simple chromosome string such as a data structure and apply specified operators to these structures to preserve important information, and to produce a new population to generate strings, which have a higher function value. The basic operations which affect the binary string's makeup in natural evolution are a selection, a crossover of genetic information between reproducing parents and a mutation of genetic information.

The GA works according to selection rules as defined by the laws of evolutionary genetics. The model seeks the ''fittest'' model to the observed values. In the deposition rate value of the welded joint estimation, it is the model whose parameters, when input to the source (i.e., welding current, arc voltage, travel speed, contact tip to plate distance, thickness of $TiO_2$ nano-particle), produce an estimation of the reinforcement area, which is best matched with those measured in the experiments. The fitness function, f(x), takes the following form: f(x) = - Deposition rate. Inside the experimental space, the GA chose, randomly, the initial welding setup, i.e., the parameter values of the first experiment. After it was done, its response characteristics were measured and fed into the GAs. Then, based on the previous information, the algorithm chose another setup, which was done and its data again fed into the algorithm. The process continued until the optimum was found and the objective function reached its minimum, which is equal with reached the deposition rate into its maximum.

## 6. Tools and techniques

### *6.1 Response surface methodology*

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for modeling and analysis of problems in which a desired response is influenced by several input variables [15]. The RSM is a sequential process performed in the following manner [9]. 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. Finally, the main effects of input variables and their interactions are presented through two- and three-dimensional plots. The goal of RSM is to find an approximating function to predict a future response [9]. The main effect and second-order effects will generally capture the essence of the response function since third-order and higher effects are usually unimportant. The second-order response function for k quantitative factor is given as [16]:

$$Y = f(X_1,...,X_k,X_{11},...,X_{kk},X_{12},...,X_{k-1}X_k) \tag{7}$$

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

### *6.2 Central composite rotatable design (CCRD)*

The first requirement for RSM involves the design of experiments to achieve adequate and reliable measurement of the response of interest. The experimental design techniques commonly used for process analysis and modeling are the full factorial, partial factorial and central composite rotatable designs. A full factorial design requires at least three levels per variable to estimate the coefficients of the quadratic terms in the response model [17]. A partial factorial design requires fewer experiments than the full factorial design. However, the former is particularly useful if certain variables are already known to show no interaction. An effective alternative to factorial design is central composite rotatable design (CCRD), developed by Box and Wilson [17] and improved upon by Box and Hunter [18]. CCRD gives almost as much information as a three-level factorial, requires many fewer tests than the full factorial design and has been shown to be sufficient to describe the majority of steady-state process responses. Hence we decided to use CCRD to design the experiments. When the response data are obtained from the test work, a regression analysis is carried out to determine the coefficients of the response model ($\beta_0$,$\beta_1$, $\beta_2$, …, $\beta_k$), their standard errors and significance [19]. the response model is

$$\begin{aligned} Y = \beta_0 + \beta_1 X_1 + ... + \beta_k X_k + \beta_{11} X_1^2 + ... + \\ \beta_{kk} X_k^2 + \beta_{12} X_1 X_2 + ... + \beta_{k-1,k} X_{k-1} X_k \end{aligned} \tag{8}$$

where $\beta_0$ is the constant coefficient, $\beta_k$ is the linear effect of the kth factor coefficients, $\beta_{kk}$ represents the quadratic effect of the kth factor and $\beta_{k-1}$,k represents the interaction effect, between (k-1)th and kth factors under consideration, and Y is response.

### *6.3 Experimental procedure*

Experiments are performed today in many manufacturing organizations to increase our understanding and knowledge of various manufacturing processes [20]. In this study experi-

Table 1. The input variables and their range.

| | Coding | | | | | |
|---|---|---|---|---|---|---|
| Variable | -2 | -1 | 0 | +1 | +2 | Units |
| I | 500 | 550 | 600 | 650 | 700 | Amp |
| V | 24 | 26 | 28 | 30 | 32 | Volts |
| C | 30 | 32.5 | 35 | 37.5 | 40 | mm |
| S | 300 | 350 | 400 | 450 | 500 | mm/min |
| F | 0 | 0.25 | 0.5 | 0.75 | 1 | mm |

Table 2. Chemical composition of base metal.

| | Cr | P | S | Si |
|---|---|---|---|---|
| % W | 0.031 | 0.007 | 0.01 | 0.024 |
| | Ti | Mn | C | Fe |
| % W | 0.002 | 0.417 | 0.113 | Balance |

ments were performed based on rotatable central composite design (RCCD) having five factors and five levels each. The welding current (I), arc voltage (V), welding speed (S), contact tip to plate distance (C), and thickness of $TiO_2$ nano particles (F) were considered as input variables. The input variables and their levels are given in Table 1.

Test pieces of size 150 mm ×50 mm ×15 mm were cut from steel plates; surfaces were cleaned and coated with layers of $TiO_2$ nano powder before welding operation. The coated nano powder (AEROXIDE $TiO_2$ P 25) is a highly dispersed titanium dioxide manufactured according to the AEROSIL process, obtained from the Degussa AG, Germany. Titanium Dioxide P 25 has an average primary particle size of about 21 nm and a specific surface of about 50 $m^2/g$. The chemical composition of the base metal is shown in Table 2.

The experiments were performed by automatic SAW machine using direct current reverse polarity (DCRP), and the bead-on-plate technique was adopted for welding the specimens. We conducted 32 experiments. The specimens were cut perpendicular to welding direction by BUEHLER cutting machine to measure the output of the process. The cut surfaces were grained with 240, 320, 400 and 600 numbered grinding paper and etched with 2% nital solution. The deposition rate is the rate that weld metal can be deposited by a given electrode or welding wire. Deposition rate is defined as below:

$$Deposition\ Rate = \rho A_R V \qquad (9)$$

where $\rho$ = 7833 $Kg/m^3$, AR and V denote the density of filler wire, reinforcement area and welding speed respectively.

Finally, the area of reinforcement was measured by means of an Olympus optical microscope and deposition rate was calculated.

### *6.4 Mathematical model*

The objective of this section is to establish relationships between the process parameters (inputs) and process responses (outputs) in SAW process using regression analysis. Based on the response surface method, the relationship between the investigated five input variables and the response can be obtained by regression equation. The least-square method was used to determine the coefficients of the regression model. The statistical software, MINITAB, was used to calculate the values of this coefficient for response function. The regression coefficients of the final model and their P-values (probability of error) used to determine the significant variables are given in Table 3. Therefore, the final model with the variables was reduced to the following equation:

Table 3. Model regression coefficients and their P-values.

| Predictor | Coef. | SE Coef. | T | P |
|---|---|---|---|---|
| Constant | 8.248 | 0.164 | 50.26 | 0.000 |
| V | -0.143 | 0.095 | -1.50 | 0.150 |
| I | 1.435 | 0.095 | 15.15 | 0.000 |
| C | 0.497 | 0.095 | 5.24 | 0.000 |
| F | 0.523 | 0.095 | 5.52 | 0.000 |
| VS | 0.210 | 0.116 | 1.81 | 0.087 |
| VN | 0.186 | 0.116 | 1.61 | 0.126 |
| IS | 0.424 | 0.116 | 3.65 | 0.002 |
| SN | 0.231 | 0.116 | 1.99 | 0.062 |
| NF | 0.393 | 0.116 | 3.38 | 0.003 |
| VV | 0.227 | 0.085 | 2.66 | 0.016 |
| II | 0.268 | 0.085 | 3.14 | 0.006 |
| SS | 0.092 | 0.085 | 1.07 | 0.297 |
| NN | 0.100 | 0.085 | 1.18 | 0.255 |

Table 4. Analysis of variance.

| Source of variance | Degree of freedom (d.f.) | Sum of square (SS) | Mean of square (MS) | F | P |
|---|---|---|---|---|---|
| Regression | 13 | 74.2864 | 5.7143 | 26.53 | 0.00 |
| Residual error | 18 | 3.8772 | 0.2154 | | |
| Lack of fit | 12 | 3.3339 | 0.2778 | 3.07 | 0.089 |
| Pure error | 6 | 0.5432 | 0.0905 | | |
| Total | 31 | 78.1635 | | | |

$$\begin{aligned} DR &= 8.25 - 0.143\,V + 1.44\,I + 0.497\,C + 0.523\,F \\ &\quad - 0.210\,VS + 0.186\,VC + 0.424\,IS - 0.231\,SC + \\ &\quad 0.393\,CF - 0.227\,V^2 + 0.268\,I^2 + 0.0917\,S^2 + 0.100\,C^2 \end{aligned} \qquad (10)$$

where DR is deposition rate and V, I, S, C and F are the input variables. The adequacy of the models was tested using analysis of variance (ANOVA). Table 4 is the ANOVA data for the deposition rate.

Table 3 shows the influence of various process parameters and their interactions on response numerically. Analysis was

Table 5. 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 | -(Deposition rate) |

Table 6. The optimal input variables for optimum solution.

| Variable | I (Amp) | V (Volt) | C (mm) | S (mm/min) | F (mm) |
|---|---|---|---|---|---|
| Coded value | 2.00 | -0.4207 | 2.00 | 2.00 | 2.00 |
| Decoded value | 700 | 27 | 400 | 500 | 1 |

Table 7. 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 | -(deposition rate) |

undertaken at a desired level of confidence 95%. The last column of Table 3 shows whether each factor has significant effect on response or not. Since the P-value of arc current, contact tip to plate distance and thickness of nano particles is less than 0.05, therefore these parameters significantly influence the deposition rate.

### *6.5 Optimization of the process*

As mentioned, the weld deposition rate plays an important role in determining the productivity of weldments in hard-facing processes. Thus, the objective of optimization in this research work is to maximize the deposition rate. Note that since ICA minimizes the cost function basically, the equation of deposition rate 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 optimized. The optimum algorithmic parameters used in the ICA model are brought in Table 5.

The optimum levels of input variables in coded and uncoded form to achieve optimal solution are shown in Table 6. Results show that to achieve the maximum DR the traveling speed, welding current, contact tip to plate distance and thickness of $TiO_2$ should be set at high level. Moreover, the problem is optimized by the so-called optimization algorithm, namely genetic algorithm (GA) to evaluate the obtained results from ICA. The optimum algorithmic parameters used in the GA model are brought in Table 7.

Table 8. Comparison of experimental output and optimum values of the weld deposition rate.

| S. No. | ICA | GA | Experimental output |
|---|---|---|---|
| 1 | 17.39 | 17.29 | 17.30 |
| 2 | | | 17.38 |
| 3 | | | 17.36 |
| Average | | | 17.35333 |
| % Error | 0.210849 | 0.3663 | |

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.

## 7. Validation of the optimization results

To test the accuracy of the algorithm outputs in actual welding conditions, confirmation tests were carried out by assigning output values of the algorithm to input parameters of validation welding operation. Three experiments were performed, and their deposition rate was obtained. The percentage of error will provide the deviation of optimum values from the actual measured values. From Table 8, the average error of ICA and GA is 0.21 and 0.36, respectively.

## 8. Results and discussion

Our experiments were based on central composite design and RSM using automatic SAW machine as per design matrix. From Table 1 it can be seen that five input variables all were changed in five levels. A mathematical relationship (objective function) for DR in terms of input variables using statistical regression analysis was developed and the R-squared of developed model obtained and equal to 95%. The R-square indicates how well the proposed model fits given data that the results show a good consistency of proposed model with experimental data. Fig. 5 shows the minimum and mean cost of all imperialists for minimization of cost function versus epochs (decades). From the figure it is evident that the minimal cost function is obtained at the 7st epoch. The DR is gradually increasing up to the 7st epoch, then the DR is constant for further epochs. Fig. 6 shows the best fitness and mean fitness of the objective function during optimization process using GA. The best calculated deposition rate due to maximization by ICA and GA is 17.39 Kg/hr and 17.29 Kg/hr, respectively. The performance of the proposed ICA and GA algorithms to optimize parameters of SAW was compared and results show that ICA model gives more optimal results than the GA model.

Also Figs. 5 and 6 indicate that ICA converges to the global optimum solution at a faster rate in comparison with GA. Thus, the optimization process by ICA, especially for complicated functions, is less time consuming than optimization by GA.

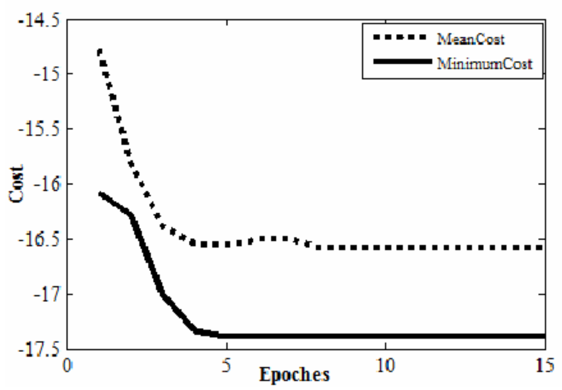


Fig. 5. Mean and minimum cost versus epochs.

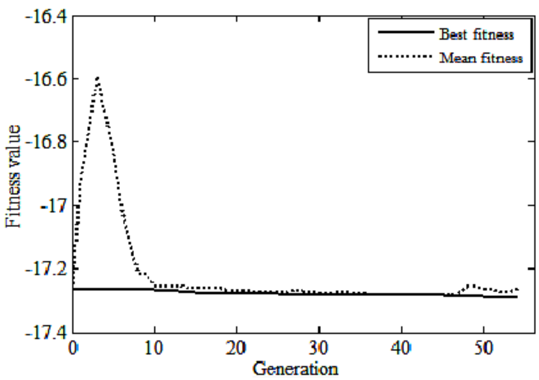


Fig. 6. Mean and best fitness versus generation.

## 9. Conclusion

Experiments were carried out using automatic SAW machine based on rotatable central composite design for generating data and bead-on-plate 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 proposed model was tested and results show good conformability of the developed model to the real process. Evolutionary computing techniques, genetic algorithm (GA) and imperialist competitive algorithm (ICA), were performed to optimize the parameters of SAW, for optimal weld performance. According to the optimization results, all of the input variables except arc voltage should be set at high level to achieve maximum deposition rate. From the obtained results by proposed ICA and GA, it can be concluded that the ICA model gives more optimal results than the GA model. In addition, 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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