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Multi-Objective Optimization of Welding Parameters in GMAW for Stainless Steel and Low Carbon Steel Using Hybrid RSM-TOPSIS-GA-SA Approach

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Abstract— ***Most of the failures are arisen on the welded elements due to the setting of inappropriate welding parameters. The forte of welded joints in GMAW depends on numerous input process parameters such as welding current, welding voltage, gas flow rate, torch angle, electrode feed rate etc. Wrong selection of these process parameters will lead to bad quality welds. So there is a need to control the process parameters to obtain good quality welded joints. For getting the better values of these parameters, it needs to conduct experiments by varying the input process parameters that are affecting the strength of the welded joints. Present study deals with multi objective optimization of Gas Metal Arc Welding GMAW) parameters used for welding disparate metals i.e. AISI 1018 and SS 202. Welding current, time and voltage has been used as input parameters. Experiments have been planned as per Response Surface Method. Multi-response optimization has been carried out using TOPSIS method (Technique for order of preference by similarity to ideal solution).The developed predictive model is used to formulate the objective function for genetic algorithm and simulated annealing which was used to search for an optimal setting for better metal deposition rate(MDR), ultimate tensile strength(UTS) and hardness of the welded joint.***
Keywords*— *GMAW, RSM, TOPSIS, Genetic Algorithm, Simulated Annealing, MDR, UTS

I. INTRODUCTION

Welding is a fabrication process that junctures metals or thermoplastics, by causing amalgamation. This is frequently done by melting the work pieces and adding a filler material to form a weld pool that cools to become a strong joint, with pressure sometimes used in combination with heat, or by itself, to produce the weld. Several different energy sources can be used for welding, with a gas flame, an electric arc, a laser, an electron beam, friction, and ultrasound. GMAW process is a kind of arc welding in which the metal electrode is melted, then dripping and solidifying to form welds on the material to be jointed [1]. GMAW is applicable to thicker plate materials such as stainless steel, aluminum alloy, steel etc. In the MIG welding process, a gas shield is typically used to protect the arc and the weld from atmospheric contamination, an electric potential is established between the electrode and the work piece that essentials to be welded, such electric potential will cause the current to flow and therefore a thermal energy will be generated in the partially ionized inert gas [2]. The circuit diagram of GMAW is illustrated in figure 1.

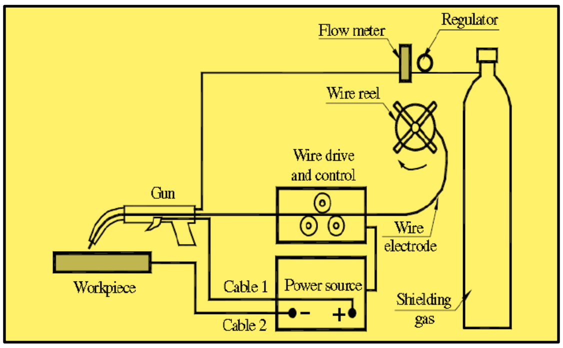

Fig. 1GMAW Setup Layout

Numerous Inert gases are used in MIG welding, like Argon, CO2, Argon and CO2 mixtures, argon mixtures with oxygen or helium mixtures. GMAW is the most common industrial welding process, chosen for its versatility, speed and the relative ease of adapting the process to robotic automation. Design of Experiment (DOE) and statistical techniques are generally used for the optimization of process parameters [3]. In the present study the welding process parameters of GMAW can be optimized to maximize the Metal deposition rate, Ultimate Tensile Strengthand hardness of the welded joint. A combination of statistical and heuristic optimization approach has been done for obtaining an optimal welding parameters.

II. MATERIAL USED AND EXPERIMENTAL SETUP

Stainless steel (SS 202 grade) and low carbon steel (AISI 1018) with 70 mm × 50 mm × 5 mm size was used as work-piece material. The composition of the work-piece material is shown in Table 1.

TABLE I
MATERIAL COMPOSITION OF STAINLESS STEEL AND LOW CARBON STEEL

Element	**Concentration (% by weight)**	
	SS 202	**AISI 1018**
Iron	68	99.8
Manganese	10	0.6
Carbon	0.15	0.2
Phosphorous	0.06	0.04
Sulphur	0.03	0.05
Chromium	19	-
Nickel	6	-
Silicon	1	-
Nitrogen	025	-

The experimental studies were performed MIGMATIC 250 (ESAB INDIA)gas metal arc welding machine. This machine can be used to weld thin sheets and allows high speed welding without compromising quality. Diverse settings of welding current, time and voltage are used in the experiments.

TABLE III
INPUT VARIABLES WITH LEVELS VALUE

Factors	**Symbol**	**Level 1**	**Level 2**	**Level 3**
Welding current (amp)	A	50	80	110
Welding Time (sec)	B	86	116	146
Welding Voltage (volt)	C	18	24	30

Fig. 2 GMAW of SS 202 and AISI 1018

III. EXPERIMENTAL DESIGN WITH RESPONSE SURFACE METHOD

Response surface method is a collection of mathematical and statistical techniques that are cooperative for modelling and analysis of problems in which response is influenced by several input variables, and the main objective is to find the correlation between the response and the variables inspected. Response surface method has many advantages and has effectively been applied to study and optimize the processes. It offers enormous information from a small number of experiments. In addition, it is possible to detect the interaction effect of the independent parameters on the response. The model easily clarifies the effect for binary combination of the independent process parameters. Furthermore, the empirical model that related the response to the independent variables is used to obtain information. RSM has been widely used in analyzing various processes, designing the experiment, building models, evaluating the effects of several factors and searching for optimum conditions to give desirable responses and reduce the number of experiments. The experimental values are analyzed, and the mathematical model is then developed that illustrates the relationship between the process variable and response. The following second-order model explains the behaviour of the system:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i,j=1, i\neq j}^{k} \beta_{ij} X_i X_j + \in \quad \text{(i)}$$

where Y is the corresponding response, X_i is the input variables and X_{ii} and X_iX_j are the squares and interaction terms, respectively, of these input variables. The unknown regression coefficients are β_0, β_i, β_{ij} and β_{ii}, and the error in the model is depicted as ϵ [4].

A. *TOPSIS Method*

TOPSIS Method (Technique for order of preference by similarity to ideal solution) is used for estimating the substitutions before the multiple attribute decision making; based on fact that chosen substitute should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution. Positive ideal solution defines the best performance values established by any substitute for each attribute whereas negative ideal solution can be demarcated as worst performance values [5]. Following are steps involved in TOPSIS:

Step 1: Formation of decision Matrix:

$$D = \begin{array}{c} A_1 \\ A_2 \\ \cdot \\ A_i \\ \cdot \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & \cdot & x_{1j} & x_{1n} \\ x_{21} & x_{22} & \cdot & x_{2j} & x_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{i1} & x_{i2} & \cdot & x_{1j} & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{m1} & x_{m2} & \cdot & x_{mj} & x_{mn} \end{bmatrix} \quad \text{(ii)}$$

Here, A_i (i=1,2, ..., m) represents the possible alternatives; x_j(j=1,2, ..., n) represents the attributes relating to alternative performance, j=1,2, ..., n and x_{ij} is the performance of A_i with respect to attribute x_j

Step 2: Normalization of matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \text{(iii)}$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute x_j.

Step 3: Weighted Decision matrix:

$$V = \lfloor v_{ij} \rfloor V = w_j r_{ij} \quad \text{(iv)}$$

$$D = \begin{bmatrix} y_{11} & y_{12} & \cdot & y_{1j} & y_{1n} \\ y_{21} & y_{22} & \cdot & y_{2j} & y_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ y_{i1} & y_{i2} & \cdot & y_{1j} & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ y_{m1} & y_{m2} & \cdot & y_{mj} & y_{mn} \end{bmatrix} \quad \text{(v)}$$

Here, $\sum_{j=1}^{n} w_j = 1$

Step 4: Determine the positive ideal and negative ideal solutions:

a) The positive ideal solution:

$$A^{+} = \{(\max_i y_{ij} \ |j \in J), (\min_i y_{ij} \ |j \in J|i = 1,2, \dots, m)\} = \{y_1^{+}, y_2^{+}, \dots \dots .. y_j^{+}, \dots \dots \dots y_n^{+}\} \quad \text{(vi)}$$

$$A^{+} = \{(\min_i y_{ij} \ |j \in J), (\max_i y_{ij} \ |j \in J|i = 1,2, \dots, m)\} = \{y_1^{-}, y_2^{-}, \dots \dots .. y_j^{-}, \dots \dots \dots y_n^{-}\} \quad \text{(vii)}$$

Here,

$J = \{j = 1,2, \dots \dots .., n|j\}$: Associated with the beneficial attributes

$J' = \{j = 1,2, \dots \dots .., n|j\}$: Associated with non-beneficial attributes

Step 5: Determine the distance measures. The separation of each alternative from the ideal solution is given by n-dimensional Euclidean distance from the following equations:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^{+})^2 \ i = 1,2, \dots \dots \dots, m} \quad \text{(viii)}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^{-})^2 \ i = 1,2, \dots \dots \dots, m} \quad \text{(ix)}$$

Step 6: Calculate the Overall performance coefficient closest to the ideal solution:

$$C_i^{+} = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}, i = 1,2, \dots \dots \dots, m; 0 \leq C_i^{+} \leq 1 \quad \text{(ix)}$$

B. Genetic Algorithm

Genetic Algorithm depends on the natural advancement process which is utilized to develop answers for complex streamlining issues. A potential answer for an issue might be spoken to by an arrangement of parameters known as genes. These genes are joined together to shape a string which is alluded to as a chromosome. The arrangement of parameters spoken to by a specific chromosome is called as genotype. This genotype contains the data required to develop a creature called the phenotype. A wellness work is practically equivalent to the target work in a streamlining issue. The fitnessfunction restores a solitary numerical fitness which is corresponding to the utility or the capacity of the individual which that chromosome represents. Two parents are chosen and their chromosomes are recombined, ordinarily utilizing the components of crossover and mutation. Crossover is more critical for quickly investigating a pursuit space. Transformation gives just a little measure of arbitrary pursuit[6].

1) Algorithm of GA approach

1. Generate random population of chromosomes.
2. Evaluate the fitness of each chromosome in the population.
3. If the end condition is satisfied, stop and return the best solution in current population.
4. Create a new population by repeating the following steps until the new population is complete. Select two parent chromosomes of the population according to their fitness. With a crossover probability, cross over the parents to form a new offspring. If no crossover was performed, the offspring is an exact copy of parents. With a mutation probability, mutate new offspring at each locus (position in the chromosome).
5. Use new generated population for a further run of the algorithm.
6. Go to step no. 2.

C. Simulated Annealing

Simulated Annealing is a probabilistic method which imitates the process of annealing (slow cooling of molten metal) in order to achieve minimum unguent value in a minimization problem. The cooling phenomenon is conceded out by governing a temperature like parameter presented with the concept of the Boltzmann probability distribution. Conferring to this dispersal a system in thermal equilibrium at temperature T has its energy probabilistically disseminated as per Equation (x).

$$P(E) = exp(-\Delta E/kT) \tag{x}$$

Where the exponential term is Boltzmann coefficient and k is the Boltzmann constant. According to equation (vi), a system at high temperature has a nearly unvarying probability of being in any energy state, but at low temperatures, it has an inferior probability of being in a higher energy state. This controls the convergence of the algorithm to the global minimum [7].

IV. RESULTS AND DISCUSSION

Samples are prepared by using RSM experimental design which is shown in fig 3. The samples are then tested for ultimate tensile strength using universal testing machine and for hardness using hardness testing machine.

Fig. 3 Welded specimen of SS 202 and AISI 1018

TABLE IIIII
RSM BASED BOX-BEHNKEN DESIGN FOR EXPERIMENTAL RUNS AND RESULTS

Run No.	A	B	C	MDR (g/sec)	UTS (MPa)	Hardness (RHN)
1	50	86	24	0.0842	141	150.1
2	110	86	24	0.07857	146	142.2
3	50	146	24	0.06153	147	143.6
4	110	146	24	0.07368	155	151.7
5	50	116	18	0.0838	140	160.3
6	110	116	18	0.09589	148	143.5
7	50	116	30	0.15714	136	149.1
8	110	116	30	0.08667	139	142.7
9	80	86	18	0.08134	141	151.2
10	80	146	18	0.09899	135	150.9
11	80	86	30	0.09664	132	144.4
12	80	146	30	0.08429	146	146.8
13	80	116	24	0.09447	153	148.1
14	80	116	24	0.10264	139	146.3
15	80	116	24	0.12167	147	149.5

A. Optimization using TOPSIS method

In TOPSIS, the output responses have been normalized into a single dimensionless scale in between 0 to 1. These normalized data have been tabulated in Table IV. Here, each response parameters have been supposed to equally important so they have been assigned equal priority weight. Table V presents the weighted normalized decision matrix. Positive ideal solution and negative ideal solution are expressed in order to evaluate separation distance which is furnished in Table VI. Finally, overall performance index (OPI) has been computed by TOPSIS has been shown in. main effect plot for evaluating optimal setting has been shown in Figure 8.

TABLE IVV
NORMALIZED OUTPUT RESPONSES

Sl. No.	MDR	UTS	Hardness
1	0.226649	0.254338	0.261692
2	0.211494	0.263357	0.247919
3	0.165626	0.265161	0.250360
4	0.198331	0.279592	0.264482
5	0.225572	0.252534	0.279475
6	0.258116	0.266965	0.250185
7	0.422988	0.245319	0.259949
8	0.233297	0.250731	0.248790
9	0.218950	0.254338	0.263610
10	0.266460	0.243515	0.263087
11	0.260135	0.238104	0.251754
12	0.226891	0.263357	0.255939
13	0.254293	0.275984	0.258205
14	0.276276	0.250731	0.255067
15	0.327501	0.265161	0.260646

TABLE V
WEIGHTED OUTPUT RESPONSES

Sl. No.	MDR	UTS	Hardness
1	0.07479	0.08393	0.08898
2	0.06979	0.08691	0.08429
3	0.05466	0.08750	0.08512
4	0.06545	0.09227	0.08992
5	0.07444	0.08334	0.09502
6	0.08518	0.08810	0.08506
7	0.13959	0.08096	0.08838
8	0.07699	0.08274	0.08459
9	0.07225	0.08393	0.08963
10	0.08793	0.08036	0.08945
11	0.08584	0.07857	0.08560
12	0.07487	0.08691	0.08702
13	0.08392	0.09107	0.08779
14	0.09117	0.08274	0.08672
15	0.10808	0.08750	0.08862

TABLE VI
POSITIVE IDEAL AND NEGATIVE IDEAL SOLUTION

	MDR	UTS	Hardness
Positive ideal solution	0.13959	0.09227	0.27948
Negative ideal solution	0.05466	0.07857	0.24792

TABLE VII
CALCULATED DISTANCE MEASURE AND OVERALL PERFORMANCE COEFFICIENT

Sl. No.	S+	S-	C+
1	0.2195	0.1525	0.4099
2	0.2315	0.1483	0.3904
3	0.2249	0.1450	0.3919
4	0.2121	0.1419	0.4009
5	0.2168	0.1360	0.3854
6	0.2060	0.1330	0.3923
7	0.2053	0.1389	0.7925
8	0.0954	0.1343	0.5846
9	0.2973	0.1363	0.3143
10	0.1677	0.1370	0.4496
11	0.0474	0.1274	0.7289
12	0.0883	0.1221	0.5803
13	0.2162	0.1342	0.3831
14	0.2135	0.1321	0.3823
15	0.2109	0.1303	0.3820

Based on this study, one can select a combination of the levels that provide the larger average response. In Fig. 4, the combination of A_1 B_2 and C_3 shows the largest value of the Mean effect plot for the factors A, B and C respectively. Therefore, $A_2B_2C_3$ i.e. welding current 80amp, welding time116sec and welding voltage of 30V is the optimal parameter combination.

Table VII gives the results of the analysis of variance (ANOVA) for the Metal Deposition Rate, Ultimate Tensile Strength and hardness of welded jointusing the calculated values from the Overall performance coefficient of Table VII. According to Table VIII, factor C, the welding voltage with 14.51% of contribution, is the most significant controlled parameters for the GMAW followed by factor B, the welding time with 2.14% and factor A, the welding current with 0.0% of contribution if the maximization of Metal Deposition Rate, Ultimate Tensile Strength and hardness of welded joint simultaneously considered.

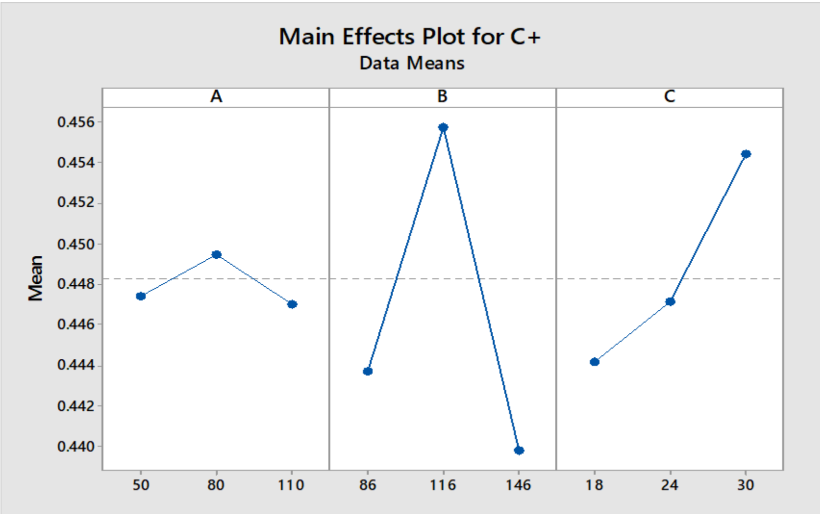

Fig. 4Main effect plot with factors and their levels

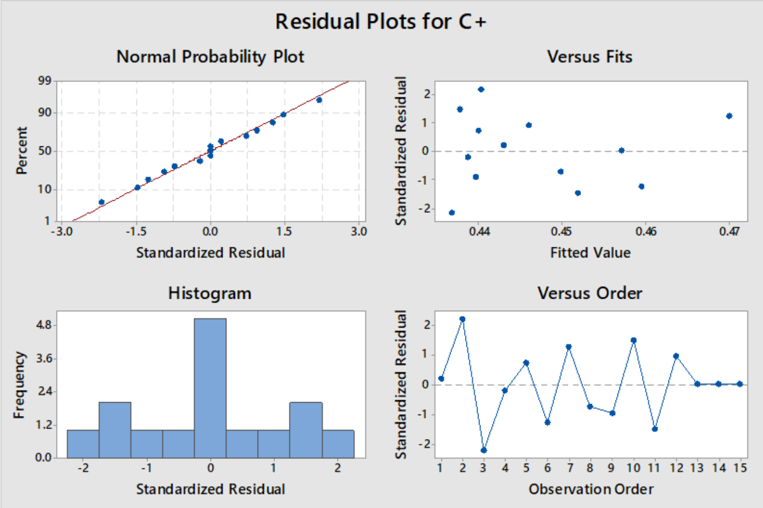

Fig. 5Residual Plots for overall performance index (OPI)

TABLE VIII
ANOVA RESULT FOR OVERALL PERFORMANCE COEFFICIENT

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% Contribution
Model	9	0.001427	0.000159	41.07	0.000	98.62
Linear	3	0.000241	0.000080	20.81	0.003	16.66
A	1	0.000000	0.000000	0.06	0.812	0.00
B	1	0.000031	0.000031	7.96	0.037	2.14
C	1	0.000210	0.000210	54.41	0.001	14.51
Square	3	0.000780	0.000260	67.34	0.000	53.90
A*A	1	0.000038	0.000038	9.91	0.025	2.63
B*B	1	0.000745	0.000745	193.05	0.000	51.49
C*C	1	0.000003	0.000003	0.84	0.400	0.21
2-Way Interaction	3	0.000406	0.000135	35.06	0.001	28.06
A*B	1	0.000006	0.000006	1.45	0.283	0.41
A*C	1	0.000397	0.000397	102.74	0.000	27.44
B*C	1	0.000004	0.000004	1.01	0.362	0.28
Error	5	0.000019	0.000004			1.31
Lack-of-Fit	3	0.000019	0.000006			1.31
Pure Error	2	0.000000	0.000000			
Total	14	0.001447				

S = 0.0019651, R-sq = 98.67%, R-sq(adj)= 96.26%, R-sq(pred) = 78.65%

B. Optimization using Genetic Algorithm and Simulated Annealing

The selection of optimum parameters has always been a difficult task in designing. In practice, the designing parameters are generally selected on the basis of human judgment, experience and referring the available catalogues and handbooks which leads to non-optimal parameters. The optimum parameters can be achieved efficiently by using an appropriate optimization method. Therefore, the designing parameters are defined in the standard optimal format and solved using genetic algorithm and simulated annealing. The minimization problem formulated in the standard mathematical format is as below:

Maximize

$$0.1151+0.001742a+0.003624b+0.00466c-0.000004a^2-0.000016b^2+0.000026c^2+0.000001ab-0.000055ac-0.000005bc \quad \ldots(xi)$$

Subjected to constraints:

$50 \leq a \leq 110$

$86 \leq b \leq 146$

$18 \leq c \leq 30$

A genetic algorithm and simulated annealing was used to solve the above objective function. For GA, a population size of 200 and initial population range covering the entire range of values for a and b *has* been used to avoid getting local minimum. The cross over rate used was 0.8 and mutation function was *uniform*. The scaling function and selection function were rank and *uniform* respectively. The optimum parameters obtained by the GA are shown in Figure 8. The optimal solution was obtained after 76 generations.

For SA, maximum iterations and time limit has been set to infinite. Boltzmann annealing has been chosen as annealing function. The Initial temperature of the body has been set to 100. The optimal solution was obtained after 1500 generations.The optimum parameters obtained by the SA are shown in Figure 8

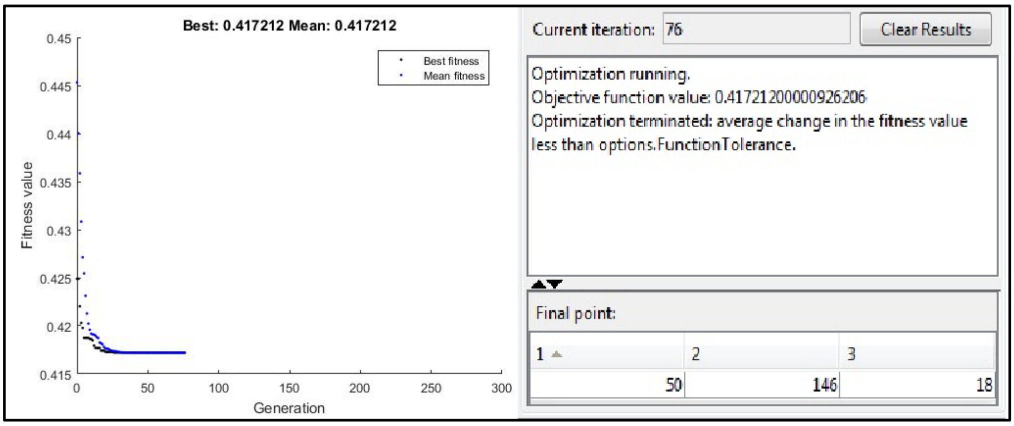

Fig. 6variations of the best fitness value with generations and the optimum parameters using GA

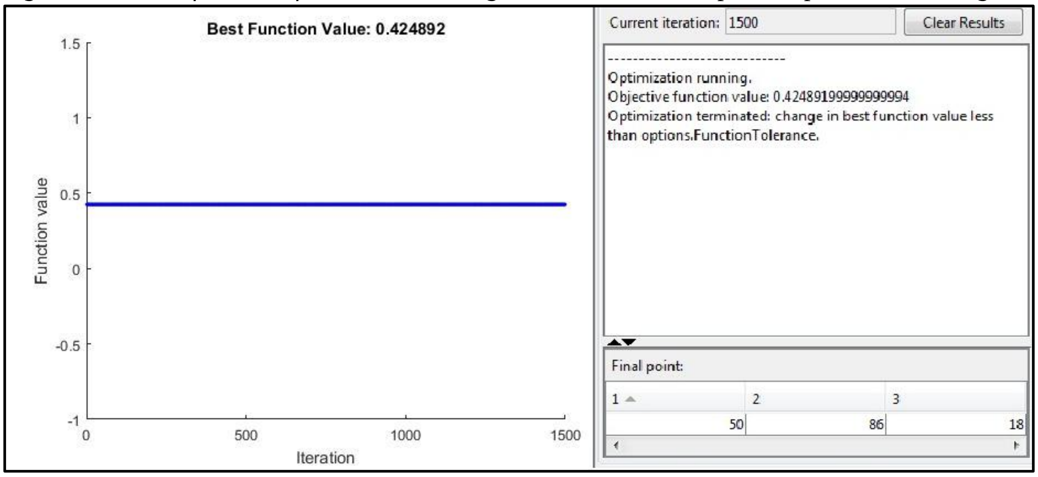

Fig. 7variations of best fitness value with generations and the optimum parameters using SA

TABLE IX
OPTIMAL CUT PARAMETERS USING THREE OPTIMIZATION METHODS

Algorithm	A	B	C
TOPSIS	80amp	116sec	30V
Genetic Algorithm	50amp	146sec	18V
Simulated Annealing	50amp	86sec	18V

V. CONCLUSIONS

The effects of welding current, time and voltage are experimentally studied during welding of SS 202 and AISI 1018 using GMAW process. The TOPSIS method based on the RSM response table was used to optimize the GMAW process parameters for welding stainless steel and low carbon steel. Based on the results of the present study, it was found that Metal deposition rate, UTS and hardness increases when the welding voltage leads to increase.From ANOVA, the percentage of contribution to the WEDM process, in sequence is found out to be the welding voltage, welding time and welding current. Hence, the welding voltage is the most important controlled factor for the GMAW operation when maximization of the MDR, UTS and hardness are concurrently considered.

It has been shown that the GA and SA approach can be used as an effective and alternative approach for costly and time consuming experimental studies and can contribute to economic optimization of machining parameters. Both Heuristic approach gives similar result and better result than statistical optimization technique when employed for predicting optimum factor setting. More reliable prediction of unit process will enable industry to develop more optimal values during selection of welding parameters for GMAW.

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