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Genetic Approach to optimize bead dilution in Submerged Arc welding process

Edwin Raja Dhas J (Correspondence author)
Faculty of Automobile Engineering, NICHE
Kumaracoil - 629180, INDIA
E-mail: edwinrajadhas@rediffmail.com

Satheesh M
Faculty of Mechanical Engineering,
Bahrain Trainning Institute, Ministry of Education, Bahrain.
E-mail: satheeshudaya@gmail.com

Abstract: Welding is one of the chief metal joining processes in fabricating industries. This paper concerns with the development of genetic algorithm model to optimize the quality of submerged arc welding process parameters of mild steels. In order to develop the proposed model data are collected using Taguchi's design. Weld parameters are current, arc voltage, welding speed and electrode stickout with dilution as response. Signal-to-Noise ratio is computed based on performance characteristics of observed output. Significant contributions of the parameters are estimated using Analysis of Variance. Response surface equations are generated and the objective function is formed to minimize bead dilution. The developed Genetic Algorithm models determine the optimal weld-bead dilution and recommend the necessary process parameters for the same. Results are compared and reported. This scheme can be used in decision-making to select process parameters for a welding operator. The proposed and developed method has good competency enhancing robotization.

Keywords: Process Parameters, Parameter optimization, Taguchi method, Genetic Algorithm.

1. Introduction

Submerged arc welding is a multi-objective, multi-factor metal joining technique. Quality of weld depends on mechanical properties of bead geometry, which in turn are controlled by the process parameters [1]. Especially the welding parameters are closely related to the geometry of the weld, a relationship which is very complicated. Weld dilution is a significant parameter to evaluate the quality of the weld joint. Many problems are faced by the weld operator to control the process parameters to obtain a good weld joint with the required bead geometry, minimal detrimental residual stresses and distortion. Hence these parameters should be selected in a judicious manner to reach the desired target by the area of application of the weldment. Traditionally, it is necessary to determine the weld input parameters for every new weld product to obtain a weld joint with the required specifications. To do so, weld input parameters should be chosen by the skill of the engineer or machine operator which is a time-consuming trial and error development effort. In order to overcome this problem, various optimization methods have emerged to define the desired output variables. Mathematical models have evolved to predict weld bead geometry [2] and melting rates of SAW process [3]. Curvilinear equations [4], linear regression equations [5], response surface methodology [6], multiple regression analysis [7], sensitivity analysis [8] and Taguchi method [9] have been used to model SAW process parameters. Design of experiments [10], fractional factorial technique [11], fuzzy desirability method [12], entropy measurement [13] and principal component analysis [14] has been employed for optimizing SAW process parameters.

Taguchi method [15, 16] utilizes the orthogonal array to study a large number of variables with a small number of experiments [17, 18]. It recommends the use of the loss function to measure the performance characteristic deviating from the desired value. The value of the loss function is further transformed into a S/N ratio. The performance characteristic in the analysis of the S/N ratio are the lower the better, the higher the better, and the nominal-the-better.
S/N ratio ηij for the ith performance characteristic in the jth experiment is expressed in equation1.

$$\eta_{ij} = -10\log(L_{ij}) \quad (1)$$

Loss function L_{ij} for the higher-the-better performance characteristic is expressed in equation 2.

$$L_{ij} = \frac{1}{n}\sum_{k-1}^{n} \frac{1}{y_{ijk}^2} \quad (2)$$

L_{ij} - loss function of the ith process response in the jth experiment, k- number of tests

y_{ijk} - experimental value of the ith performance characteristic in the jth experiment at the kth tests.

For lower-the-better performance characteristic, L_{ij} is expressed in equation 3.

$$L_{ij} = \frac{1}{n}\sum_{k-1}^{n} y_{ijk}^2 \quad (3)$$

Mathematical models find limitation in application due to difficulties in modeling, time consuming and are cumbersome. Due to the inefficiency and inadequacy of the mathematical models to explain the nonlinearities between the input and output parameters of manufacturing process, different intelligent systems such as Artificial Neural Network (ANN) [19] and fuzzy logic systems [20, 21] have emerged. Although these techniques have several advantages with conventional regression models, neural network modeling needs extensive time, lot of samples and cost to train the network. Also optimization using regression modeling, Taguchi methods, and neural network could be effective only when the process was set near the optimal conditions or at a stable operating range [22]. To overcome the above problems non conventional techniques such as Genetic Algorithm (GA) [23], Particle Swarm optimization [24] etc have been used to find out the optimal solution.

Genetic Algorithm [25] is effective tool in finding near-optimal conditions. It does not need derivatives of objective functions, but needs only the values of objective to optimize. GA is applied to optimize different welding process [26-30].This paper explores the application of response surface modeling with GA to find optimal set of welding process variables that produce the desired weld dilution in submerged arc weld of mild steel. The proposed GA model to optimize weld parameters for bead dilution undergoes three stages of development. They are (a) data collection (b) development of response surface model (c) optimization using GA. Results obtained are compared and presented.

2. Data Collection

Experiments are proposed using Taguchi's design of experiments and performed through L27 orthogonal array by varying the initial parameters as in Table 1. Experiments are conducted on CU-BUILT DC electrode positive Submerged Arc welding machine as in Fig.1 at Precision Storage Vessels Ltd, Kanyakumari, India. Test pieces (250mm×200mm×8 mm) are cut from mild steel plate and its surfaces are ground to remove oxide scale and dirt before cladding. Copper coated electrode wire of diameter 2.5 mm) and flux of grain size 0.2-1.2 mm was used for welding. The flux was baked for 2 hours at 523 K before use. The operating ranges of the parameters are chosen from American Welding Society handbook [31]. The experimental setup consists of a travelling carriage with a table for supporting the specimens. The nozzle was held stationary in a frame mounted above the work table, and it is provided with an attachment for up and down movement to adjust nozzle-to-plate distance.

Table 1 Process parameters and their levels chosen for experiments

No	Process parameters	Level 1	Level 2	Level 3
1	Welding current (I), amperes	275	325	400
2	Arc voltage (V), volts	28	32	36
3	Welding speed (S), cm/min	16	19	22
4	Electrode stickout (E), mm	25	30	35

Figure 1 Photograph of the experimental setup

While performing experimentation, the following precautionary measures are taken:

1. To reduce error due to experimental set up, each experiment was repeated three times in each of the trial conditions.
2. The order and replication of experiment was randomized to avoid bias, if any, in the results.
3. Each set of experiments was performed at room temperature in a narrow temperature range (32±2o C).

Non Destructive test like Visual inspection and liquid penetrant inspection are done on the weld samples. Visual inspection relies upon the detection of surface imperfections using eye. Liquid penetrant inspection reveals surface flaws by the "bleed-out" of a penetrating medium against a contrasting background. This was done by applying penetrant to the pre-cleaned surface and flaw of the item being inspected. The penetrant was applied to the surface and allowed to remain on the surface for a prescribed time (dwell time); the penetrant liquid will be drawn into any surface opening by capillary action. Following removal of excess penetrant an application of a developer reverses the capillary action and draws penetrant from the flaw. The resultant indications revealed the presence of the flaw so that it can be visually inspected and evaluated as depicted in Figure 2. Three samples are transversely cut from each perfectly selected welded joint. The samples from each weld joint has the fusion zone, the heat affected zone and the base metal. The samples are prepared in accordance with ASTM E3 standard metallographic technique. The sample preparation included sectioning, grinding and polishing as well as etching.

Weld samples of size 10mm (width) are cut from the centre of the weld specimen. The transverse face of the samples were polished using mesh size of 245, 425 and 515 (grade 1/0, 2/0, and 3/0) Sianor B 1600 sandpaper. The specimens are further polished using aluminum oxide initially and then by utilizing diamond paste and velvet cloth in a polishing machine. The polished specimens after cleaning with alcohol are macro-etched using 2%Nital (98% nitric acid + 2% alcohol) solution to view the geometry of the weld bead. Each macro-etched sample image is scanned [32] using an Epson Scan jet (2400 X 4800 DPI resolutions using 1:1 scale). With the help of a digital planimeter, the areas of the parent metal melted and the metal forming the reinforcement are measured. Percentage of dilution is calculated as D = [AP / (AP+ AR)] x 100 as in Figure 3. The experimental design and observed values from the specimens are given in Table 2.

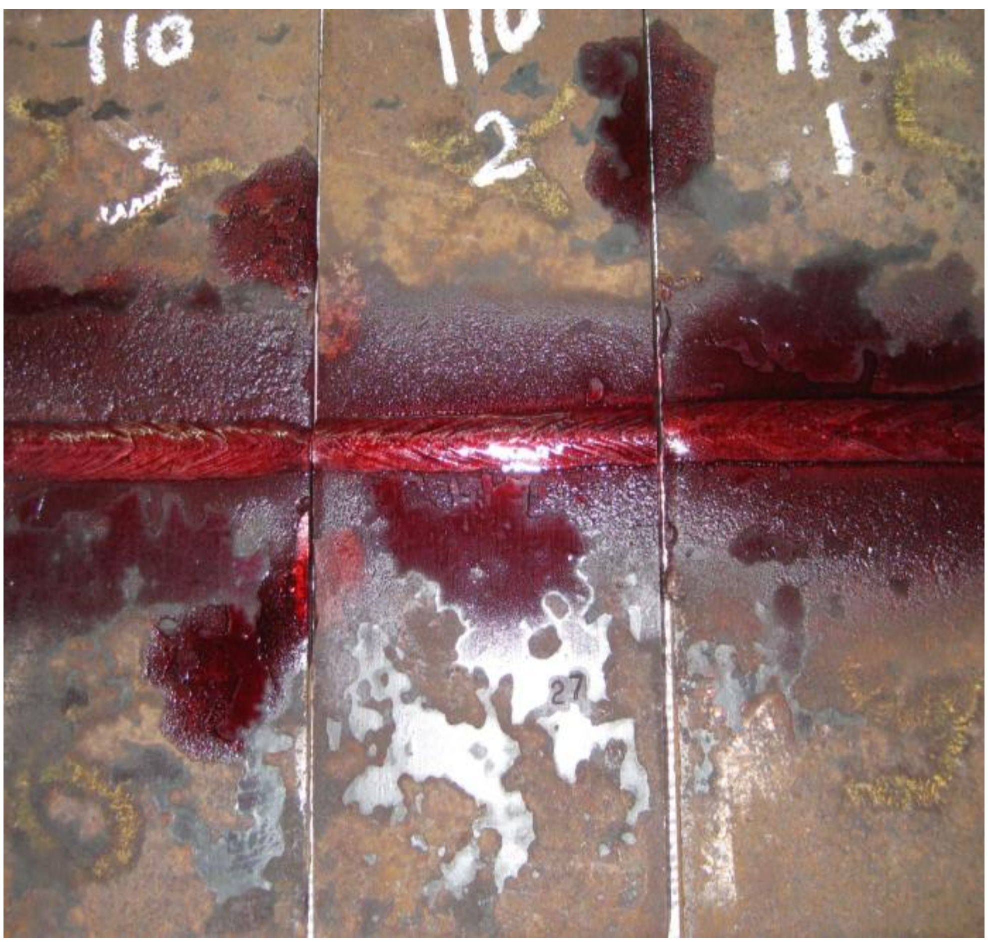

Figure 2 Photograph of liquid penetrant inspection

Table 2 Experimental design and their performance evaluation

Ex. run	Process variables				Dilution D (%)	S/N ratio
	I (Amps)	V (Volts)	S (cm/min)	E (mm)		
1	275	28	16	25	15.73	-23.9346
2	275	28	19	30	17.9	-25.0571
3	275	28	22	35	19.6	-25.8451
4	275	32	16	30	18.12	-25.1632
5	275	32	19	35	20.1	-26.0639
6	275	32	22	25	17.53	-24.8756
7	275	36	16	35	19.34	-25.7291
8	275	36	19	25	16.37	-24.2810
9	275	36	22	30	19.2	-25.6660
10	325	28	16	30	18.8	-25.4832
11	325	28	19	35	21.2	-26.5267
12	325	28	22	25	19.02	-25.5842
13	325	32	16	35	21.14	-26.5021
14	325	32	19	25	18.3	-25.2490
15	325	32	22	30	20.96	-26.4278
16	325	36	16	25	17.41	-24.8160
17	325	36	19	30	19.71	-25.8937
18	325	36	22	35	22.4	-27.0050
19	400	28	16	35	23.1	-27.2722
20	400	28	19	25	19.24	-25.6841
21	400	28	22	30	23.2	-27.3098
22	400	32	16	25	18.19	-25.1967
23	400	32	19	30	21.4	-26.6083
24	400	32	22	35	21.57	-26.6770
25	400	36	16	30	23.37	-27.3732
26	400	36	19	35	21.87	-26.7970
27	400	36	22	25	22.6	-27.0822

3. Development of Response Surface Models

In order to quantitatively evaluate the effect of process variables on dilution a response surface model is performed using Minitab statistical software. Response function of the weld quality parameters is expressed in equation 4.

$$Y = f(X_1, X_2, X_3, X_4)$$
(4)

Where Y is the response, Percentage of dilution (D), X1 is the welding current (I), X2 is the arc voltage (V), X3 is the welding speed (S) and X4 is the electrode stickout (E).

R2 value for dilution is tabulated in Table 3 and the desired full quadratic equation is shown in Eqn. 5. The normal probability plot of the residual for dilution is shown in Figure 3. The validities of the regression model are further tested by scatter diagram in Figure 4.

$$D = -31.6079 + 0.0272 * X_1 - 0.6801 * X_2 - 0.9079 * X_3 + 3.6838 * X_4 + 0.0085 * X_2^2 + 0.0377 * X_3^2 - 0.0302 * X_4^2 + 0.0008 * X_1 * X_2 - 0.0001 * X_1 * X_3 - 0.001 * X_1 * X_4 + 0.025 * X_2 * X_3 - 0.0196 * X_2 * X_4 - 0.0348 * X_3 * X_4 \quad (5)$$

Table 3 R2 - Value of Response surface model

Response surface regression	R2 Value for
Linear	82.6%
Linear+ Square	86.16%
Linear+ Interaction	88.60%
Full quadratic	92.14%

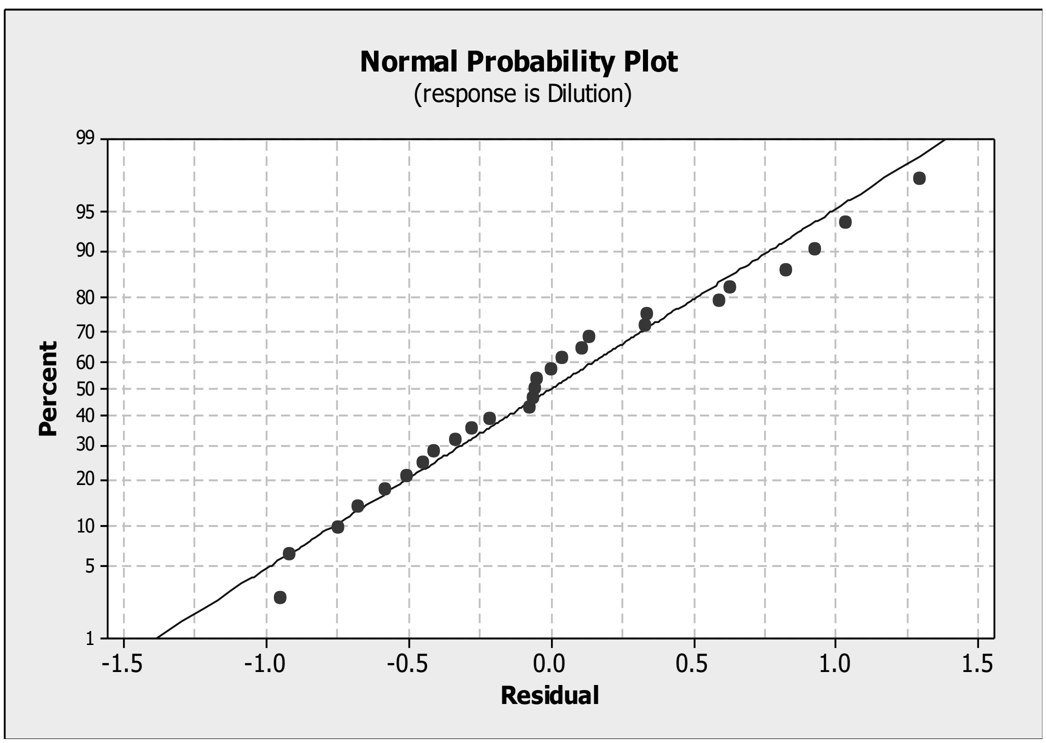

Figure 3 Normal Probability plot of dilution model

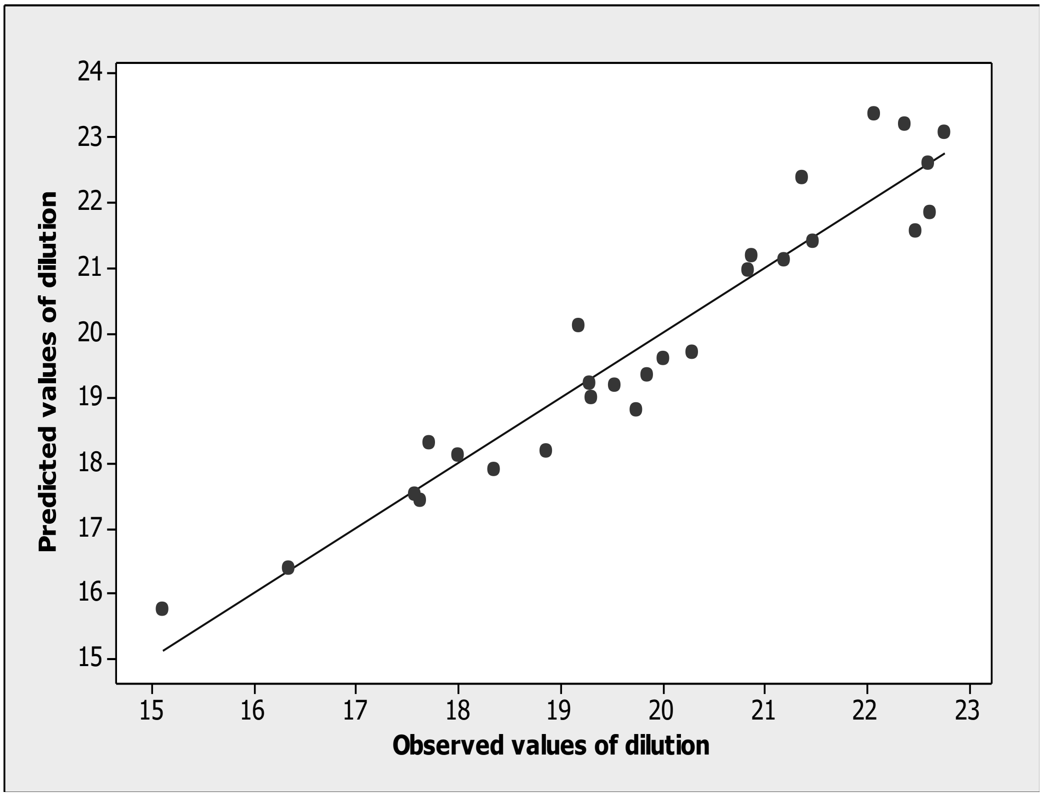

Figure 4 Scatter diagram for the dilution model

Solutions from analytical/iterative methods such as Newton method, Bisection method, etc may converge to a stationary point and there is no guarantee that the solution converges to a global optimum. But genetic algorithm utilizes a population of solutions initially distributed over the whole function space and quickly identifies the sub domain in which the global minimum function is located, by maintaining the constant exploration of the search space. Hence it is possible to reach accurately and reliably the global optimum solution in a short computation time. The proposed and developed optimization procedure for SAW using genetic algorithm is shown in Figure 5.

In this work, a possible solution is formed by variables of the welding current, arc voltage, welding speed, and electrode stickout. An objective function has been formulated by establishing a linear relationship between four input parameters and dilution using regression analysis as shown in equation 5.

Minimize D   by equation 5

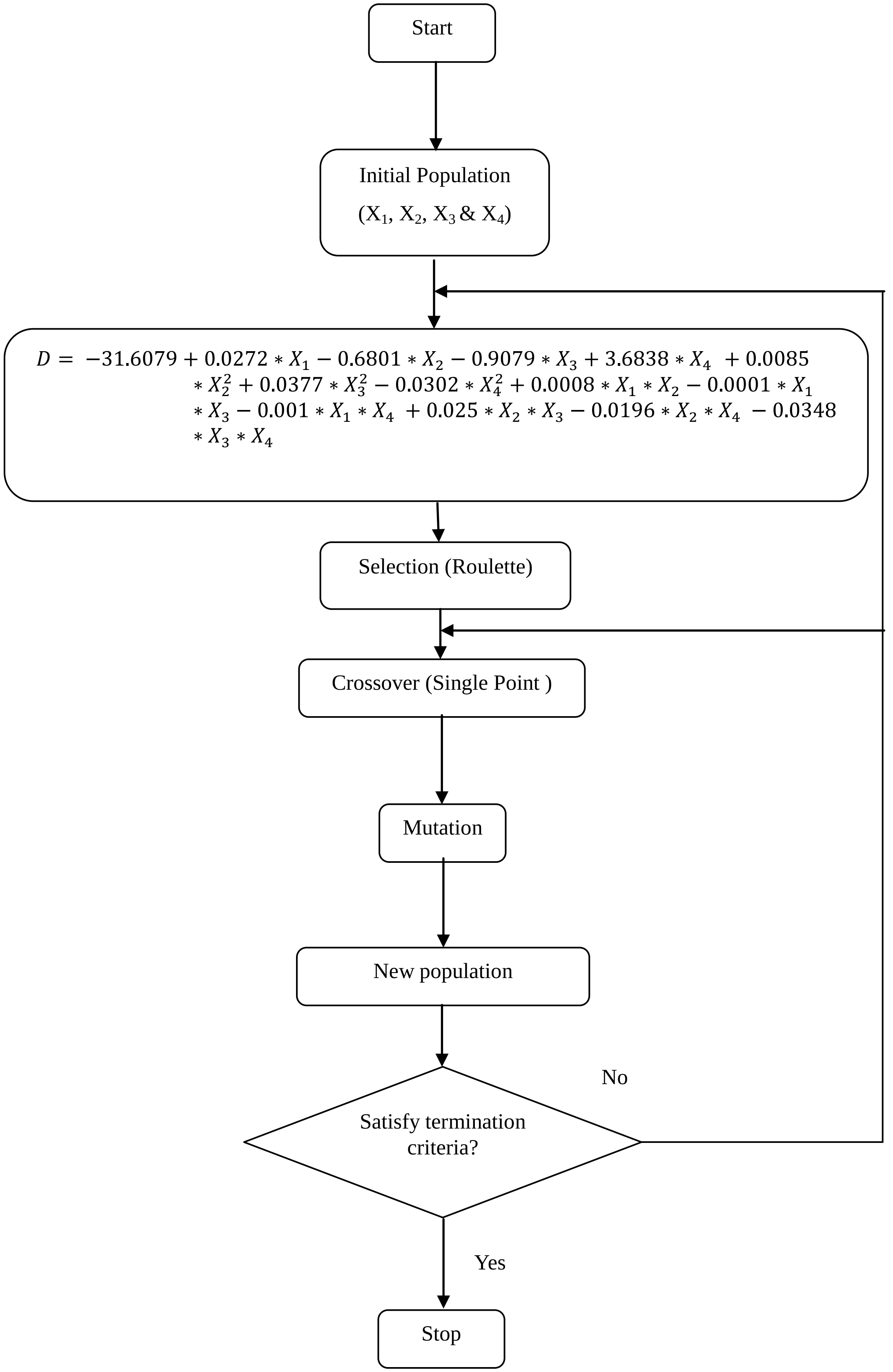

Figure 5 Procedure of GA to optimize SAW process parameters.

The survival of each individual in a GA is evaluated by the fitness function. The steps used in optimization by GA are:

1. Determine the objective function ie minimization of dilution
2. Identify the parameters which affect the objective function.
3. Construct an analytical/experimental model of the system to express the objective function as the function of a system.
4. Formulate an objective function shown in equation 5.
5. Formulate the constraints for the objective function as :

275 < = Welding current < = 400

28 < = Arc voltage < = 36

16 < = Welding speed < = 22

25 < = Electrode stickout < = 35

The objective function is taken from equation 5 to minimize dilution using arc voltage, welding current, welding speed and electrode stickout as SAW process parameters. Initial population is the possible number of solutions of the optimization problem, and each possible solution is called an individual. It is assumed that the near optimum point is within the following experimental region, defined by the GA search ranges as given in Table 1. Initial population is created using the welding process parameters and random solutions are obtained for dilution. Fitness function values of each individual are computed for the current populations using the objective function. Genetic operators (reproduction, crossover and mutation) are employed to produce the next generation of the new population. Parameters for GA computations are displayed in Table 4. Mutation rate is 1% and crossover rate is 80 %, whereas the other 20% are added to the next generation without crossover. The final value of the objective function is constant for last 15 generations shows that it is the best value for the problem.

Table 4 Parameters for GA computations

Population size	40
Number of generations allowed	350
Mutation rate	1 %
Crossover rate	80 %
Type of crossover	Single point
Type of selection	Roulette wheel

4. Results and Discussion

Experiments are conducted in SAW machine using Taguchi's principles. The response dilution is calculated for every experiment and recorded. Effect of weld parameters on dilution is analyzed.

4.1 Effect of process variables on dilution

S/N ratio is computed to analyze the performance characteristics of the weld parameters. Lower the better characteristic is used to achieve dilution. The S/N ratio is calculated using equations 1 and 3 and presented in Table 2. The mean of the S/N ratio of each level of the welding process parameters is summarized in Table 5 for dilution. The corresponding response graph in Figure 6 shows the quality characteristics of individual parameters. It is observed that the optimal parameter combination for the dilution is when welding current is 275 amperes, arc voltage is 28 volts, welding speed is 16 cm/min and electrode stickout is 25 mm.

Table 5 Response table for S/N ratio

S/N ratio		Control factors			
		I	V	S	E
Dilution	Level 1	-25.1791	-25.8550	-25.7182	-25.1893
	Level 2	-25.9430	-25.8626	-25.7956	-26.1091
	Level 3	-26.6667	-26.0715	-26.2740	-26.4909
	Max-min	1.4876	0.2165	0.5558	1.3016
	Rank	1	4	3	2

Effects of welding current, arc voltage, welding speed and electrode stickout on dilution are depicted in Figure 7. Results indicate the percentage dilution increases with the increase of welding current and electrode stickout. This may be due to the decrease in the melting rate of electrode and diffusing energy of the arc as it strikes on the base metal when electrode stickout increases. It is evident that the dilution initially decreases with the increase in arc voltage but increases with the further increase of arc voltage. This may be due to the increase in heat input with the increase in arc voltage. Dilution increases with increase in welding speed. This matches with the finding of Cornu [33]. It is stated that the dilution of the base metal in the weld pool increases with the increase in the welding speed since the weight of the deposited metal per unit length decreases while the cross section of the bead decreases very little.

From Figures 8 and 9, it is clear that dilution increases with increase in welding current for all values of welding speed. But this increasing trend of percentage of dilution with the increase in welding current decreases gradually with the decrease in welding speed. These effects occur because both welding current and welding speed have a positive effect on percentage dilution. There is very weak interaction between all the other process parameters in affecting the dilution since their responses at different levels of process parameters for a given level of parameter value are almost parallel.

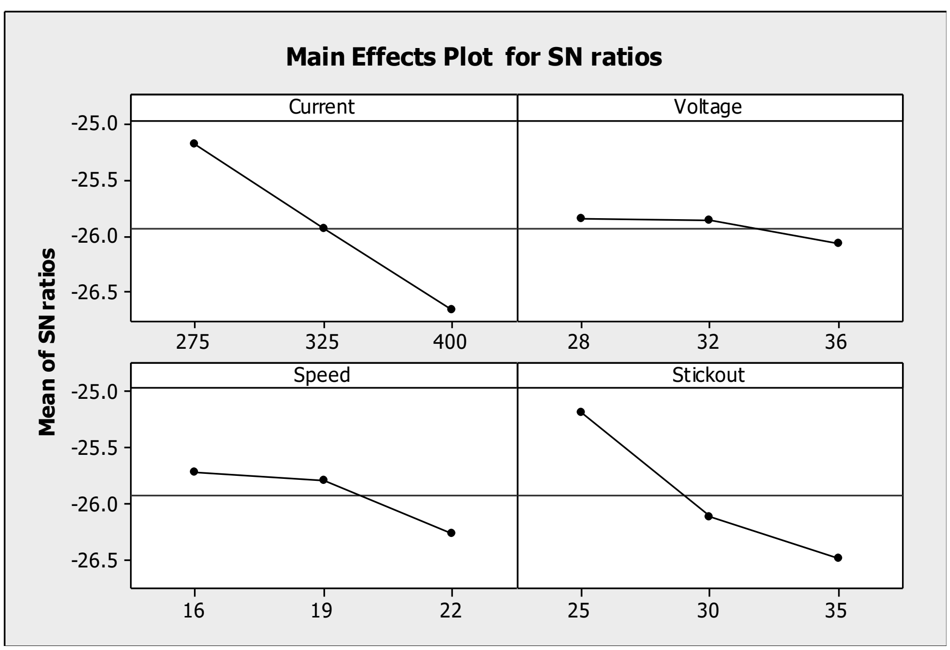

Figure 6 Effects plot for S/N ratio on weld parameters

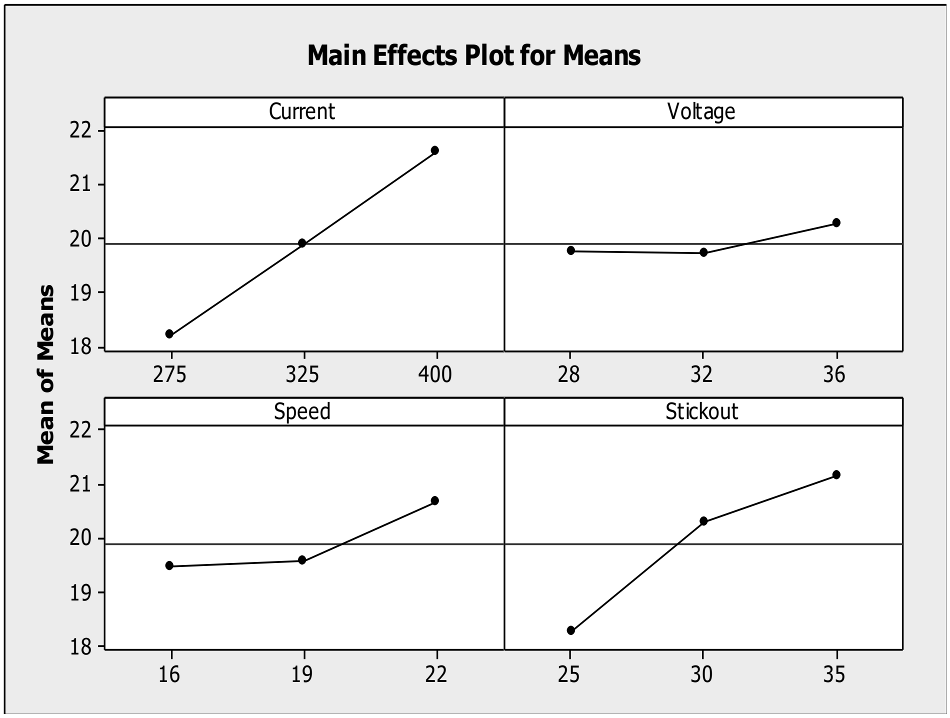

Figure 7 Effects of Process Parameters on dilution

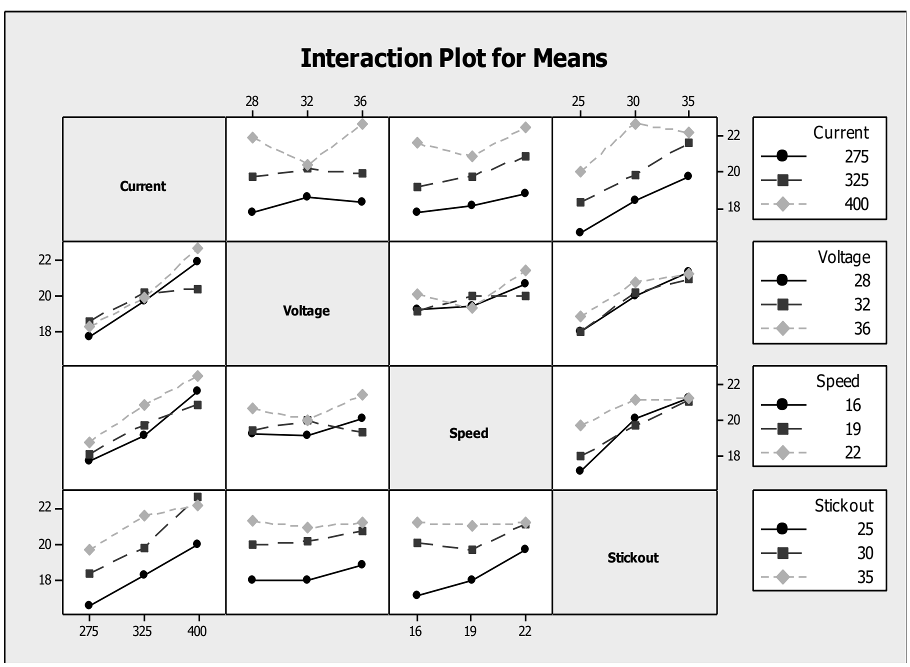

Figure 8 Effects of Process Parameters Interactions on dilution (Raw Data)

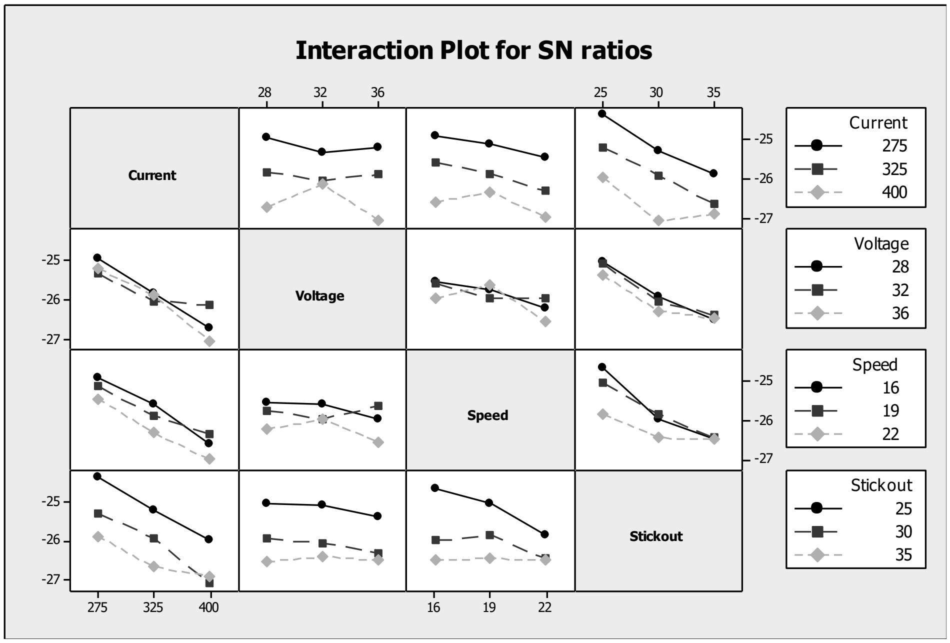

Figure 9 Effects of Process Parameters Interactions on dilution (S/N Data)

4.2. Analysis of Variance

Analysis of Variance and F-test are used to find out the significant process parameters. Result from ANOVA in Table 6 shows that welding current is the most significant control factor followed by electrode stickout affecting weld dilution. The percentage contribution of each control factor to the total variance is welding current 44.35%, electrode stickout 33.37 %, welding speed 6.89 % and arc voltage 1.41%. Here, arc voltage and welding speed is an insignificant factor in influencing the quality.

Table 6 Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% of contribution	Rank
I	2	52.196	52.196	26.098	28.85	0.000	44.35	1
V	2	1.663	1.663	0.832	0.92	0.417	1.41	4
S	2	8.110	8.110	4.055	4.48	0.026	6.89	3
E	2	39.438	39.438	19.719	21.80	0.000	33.37	2
Error	18	16.284	16.284	0.905	-	-	-	-
Total	26	117.691	-	-	-	-	-	-

4.3. Checking the adequacy of the model developed

The adequacies of the model developed were tested using ANOVA and the results are presented in Table 7. From the analysis, the calculated F ratios are higher than the tabulated value at 95% confidence level. Hence the developed model is adequate. Determination of coefficient of R^2 and adjusted R^2 values from Table 3 indicates the developed regression model is quite adequate. The normal probability plot of the residuals for bead dilution is shown in Figure 3. It points that the residuals generally fall on a straight line implying that the errors are distributed normally and they have no obvious pattern and unusual structure. From this it is evident that the proposed model is well adequate. From the scatter diagram in Figure 4 it is evident that the observed values and predicted values of the responses are scattered close to 45◦ line, indicating an almost perfect fit of the developed empirical models.

Table 7 ANOVA for the developed model (dilution)

Sum of		Degrees of freedom		Mean-square		F-ratio	P	R^2 (%)	Adjusted R^2 (%)
Regression	Residual	Regression	Residual	Regression	Residual				
108.45	9.235	14	12	7.74	0.769	10.0	0.00	92.14	83.6
Tabulated values of F:F0.05(14, 12) = 2.63									

4.4. Results from the developed GA model

An attempt is made using genetic algorithm to determine the minimum values of bead dilution by varying the input process parameters, that is, I, V, S and E within their respective ranges. Since the performance of GA depends on its parameters chosen, a detailed study was made to determine the optimal GA-parameters. Convergence of GA model for optimal bead dilution is shown in Fig. 10. The optimal values for welding current, arc voltage, welding speed and electrode stickout are shown in Fig. 11. The near optimal value of bead dilution is 13.85 mm for welding current 285.588 amperes, arc voltage 30.098 volts, welding speed, 17.358 cm/min and electrode extension 25.238 mm.The developed GA model is validated by conducting experiment. Experiment is performed using welding current 285 amperes, arc voltage 30 volts, welding speed, 17cm/min and electrode extension 25 mm. Bead dilution obtained is 14.72 which is nearer to the value obtained.

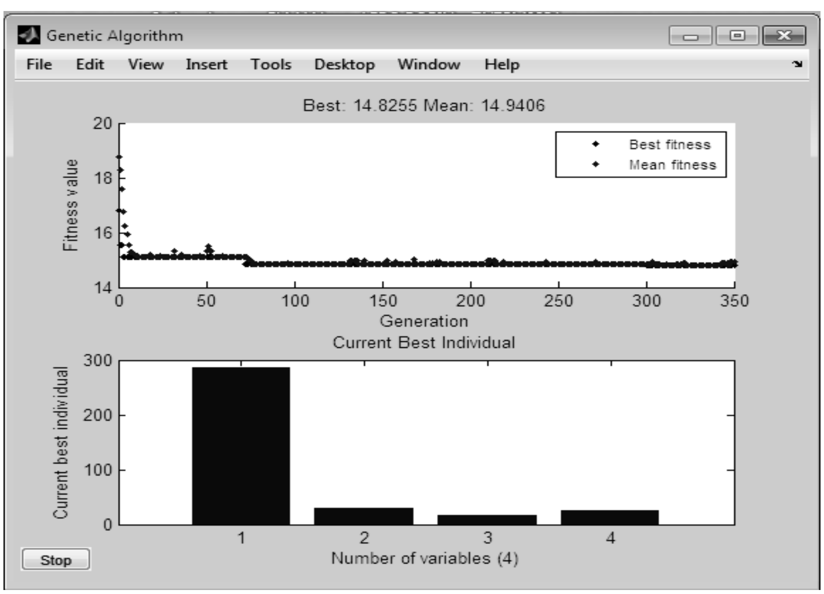

Figure 10 Convergence of developed GA model for optimal bead dilution

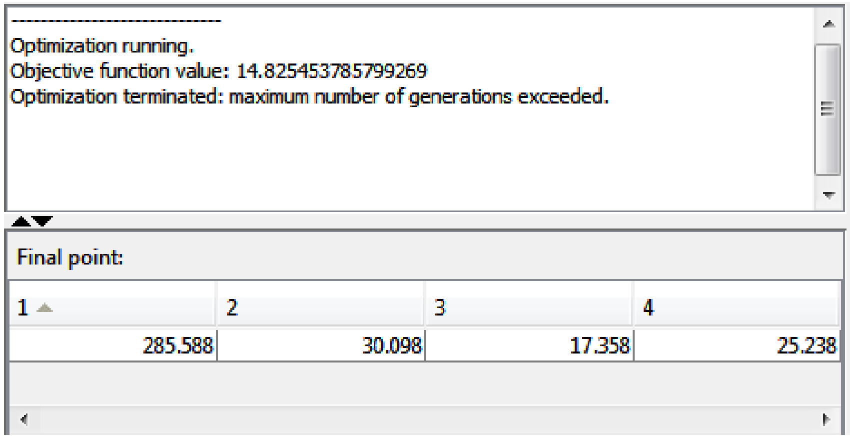

Figure 11 Results obtained from GA model for optimal bead dilution

5. Conclusions

Evolutionary powerful technique GA was being attempted to develop model that optimize the weld parameters. Application of Taguchi method is used to optimize the quality (Dilution) of submerged arc welding process parameters mild steels has been reported in this work. By analyzing the response table and response graph S/N ratio, the optimal parameters are obtained. Percentage of contribution of each process variables were analyzed using ANOVA. Response surface equations are generated using experimental data and the objective function is formed to minimize bead dilution using GA. The closer agreement of the experimental and theoretical values confirms the effective approach of this method towards welding process. Hence the solutions from this method can be useful for academicians, industrial experts and researchers who are willing to search for an optimal solution of welding condition.

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