An evolutionary approach to parameter optimisation of submerged arc welding in the hardfacing process

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Abstract: The Submerged Arc Welding (SAW) process finds wide industrial application due to its easy applicability, high current density and ability to deposit a large amount of weld metal using more than one wire at the same time. It is highly emphasised in manufacturing especially because of its ability to restore worn parts. SAW is characterised by a large number of process parameters influencing the performance outputs such as deposition rate, dilution and hardness, which subsequently affect weld quality. An exhaustive literature survey indicates that five control factors, *viz.*, arc current, arc voltage, welding speed, electrode stick-out and preheat temperature, predominantly influence weld quality. In relation to this, an attempt has been made in this study to analyse the effect of process parameters on outputs of welding using the Taguchi method. The relationship between control factors and performance outputs is established by means of nonlinear regression analysis, resulting in a valid mathematical model. Finally, Genetic Algorithm (GA), a popular evolutionary approach, is employed to optimise the welding process with multiple objectives.

Keywords: Submerged Arc Welding; SAW; Taguchi method; hardfacing; optimisation; Genetic Algorithm; GA.

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1 Introduction

Surface engineering is an economical method for the production of materials, tools and machine parts with required surface properties, particularly resistance to wear and corrosion (Kahraman and Gulenc, 2002; Iordanova *et al.*, 2001). Hardening is a method of surface treatment for improving the surface properties of metals, whereas hardfacing is concerned with the deposition of a welding metal having excellent resistance to wear and oxidation onto the surface of a low-strength metal. In hardfacing, Submerged Arc Welding (SAW) is preferred over other methods because of its inherent qualities such as ease of control of process variables, high quality, deep penetration, smooth finish, capability to weld thicker sections and prevention of atmospheric contamination of the weld pool (Hould Croft, 1989). SAW is basically an arc-welding process in which the arc is concealed by a blanket of granular and fusible flux. Therefore, physical properties of flux are important considerations in SAW for improving welding properties. The source of heat for SAW is obtained from the arc generated between a bare solid metal (or cored) in the form of a consumable wire or strip electrode and the workpiece. The arc is maintained in a cavity of molten flux or slag that refines the weld metal and protects it from atmospheric contamination. Alloy ingredients in flux attempt to enhance the mechanical properties and crack resistance of the weld deposit (Ogborn, 1993; Sacks, 1981; Richard, 1995). Since hardfacing involves the deposition of metals on the surface of a metallic workpiece employing a welding method such as SAW and finds widespread application in the steel, mining and petroleum industries, the process of hardfacing should be aimed at achieving a strong bond between the deposit and base metal with a high deposition rate (Murugan *et al.*, 1993). Therefore, it is of utmost importance to select SAW process parameters properly in order to improve weld quality in hardfacing (Murugan *et al.*, 1993; Tsai *et al.*, 1996).

In this study, the process parameters affecting weld quality in SAW have been identified and their effects on performance measures have been analysed using an inexpensive and easy-to-operate experimental strategy based on Taguchi's parameter design. Further, an attempt has been made to analyse the impact of more than one parameter on welding in the hardfacing process because the resultant performance output is the combined effect of the impacts of several interacting parameters in actual practice. The experimental strategy has been adapted from the methodology outlined for successful parametric appraisal in other applications, such as the Wire Electrical Discharge Machining (WEDM) process, drilling of metal matrix composites, and erosion behaviour of metal matrix composites such as aluminium reinforced with red mud (Mahapatra and Patnaik, 2006a–e; Mahapatra and Patnaik, 2007). The Taguchi method helps to determine the significant process parameters and their interactions and leads to the development of valid predictive equations through nonlinear regression. Next, the process parameters need to be optimised for obtaining the best weld quality that simultaneously satisfies more than one performance measure of conflicting nature. Therefore, it is vital to select an optimisation algorithm suitable in multiobjective environments and that possesses characteristics such as ease of representation and computational efficiency. Hence, Genetic Algorithm (GA), a popular evolutionary approach, is employed to optimise SAW process parameters with multiple objectives. Evolutionary algorithms, *e.g.*, GAs, are search methods that take their inspiration from natural selection and survival of the fittest in the biological world. They differ from traditional optimisation techniques in that they involve a search from a 'population' of solutions, not from a single point. At each iteration, a competitive selection is involved to weed out poor solutions so as to reach a global solution in an effective manner.

2 Design of experiment based on the Taguchi method

The chemical composition of the base metal and the electrode (stainless steel substrate material flux cored) of 40 mm diameter is shown in Table 1. The electrode was connected to the positive terminal of a Lincoln DC-1500 power source with an NA-3A controller. The flux was baked for two hours at 250°C before use.

Table 1 Chemical composition of base metal and electrode

Material	*Chemical composition (mass %)*							
	C	*Ci*	*Mn*	*S*	*P*	*Ni*	*Cr*	*Cu*
1 Mild steel base metal	0.13	0.20	0.80	0.014	0.02	–	0.03	0.02
2 Stainless steel electrode	0.44	0.40	1.65	0.01	0.017	0.09	15.2	–

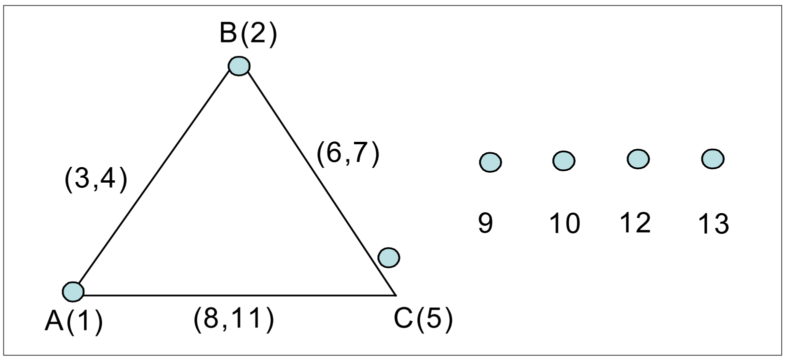
The base metal was preheated using an oxyacetylene gas torch with a heating nozzle. The temperature was measured with a precision temperature-measuring device. Each experiment consisted of depositing materials of length 100 mm in a pass on a plate. On each plate, four passes of metal deposition were used. Four layers of plates completed an experimental run. The input and fixed parameters used in the present investigation, as identified through an exhaustive literature review, experience and a preliminary study of the SAW process, are shown in Table 2. In this experiment, a martensitic stainless steel hardfacing layer was deposited by the SAW process on 39mm ×120mm mild steel plates.

Table 2 Welding process parameters

Control factor	*Level*			*Units*
	I	*II*	*III*	
A: Arc current	400	450	500	A
B: Arc voltage	26	28	30	V
C: Welding speed	30	35	40	cm/sec
D: Electrode stick-out	19	22	25	mm
E: Preheat temperature	180	200	215	°C

The most important performance measures in the SAW process are deposition rate (kg/hr), dilution (%) and hardness. The deposition rate was calculated simply by multiplying the cross-sectional area of the weld deposit above the surface of the base metal by the welding speed and the density of the stainless steel electrode. The dilution was measured by the ratio of the area of the fused base metal to the total area of the weld and is generally expressed in percentages. Hardness was measured by Rockwell C hardness measurements on the surface of the weld deposit in the longitudinal direction for each weld deposit. Welding performance in the SAW process is mainly expressed as higher values of deposition rate, hardness and small dilution. Both the deposition rate and hardness are the-higher-the-better performance characteristics while dilution is a the-lower-the-better performance characteristic. For the experimental plan, the Taguchi method of three-level experiments was chosen with careful understanding to select levels for each factor. Table 2 indicates the factors to be studied and their preferred levels that can be controlled through the experimental process. Assignment of factors to various columns was made in accordance with the linear graph shown in Figure 1 for an L_{27} (3^{13}) orthogonal array (Peace, 1993; Phadke, 1989).

Figure 1 Standard linear graph for L_{27} array



The details of the orthogonal array are shown in Table 3. The chosen experimental design had 27 rows corresponding to the number of experiments with 13 columns at three levels, as shown in Table 3. The plan required 27 experimental runs (array rows), in which the first column was assigned to the arc current (A), the second column to the arc voltage (B), the fifth column to welding speed (C), the ninth column to electrode stick-out (D), the third and fourth columns were assigned to $(A \times B)_1$ and $(A \times B)_2$ respectively to estimate the interaction between arc current (A) and arc voltage (B), the sixth and seventh columns to $(B \times C)_1$ and $(B \times C)_2$ respectively to estimate the interaction between arc voltage (B) and welding speed (C), and the eighth and eleventh columns to $(A \times C)_1$ and $(A \times C)_2$ respectively to estimate the interaction between arc current (A) and welding speed (C). Two replications under each combination of factors were used and performance output was calculated as the average of the two values. The experimental observations were further transformed into a signal-to-noise (S/N) ratio.

Table 3 Orthogonal array for L_{27} (3^{13}) Taguchi design

$L_{27}(3^{13})$	*1* A	*2* B	*3* $(A \times B)_1$	*4* $(A \times B)_2$	*5* C	*6* $(B \times C)_1$	*7* $(B \times C)_2$	*8* $(A \times C)_1$	*9* D	*10* E	*11* $(A \times C)_2$	*12*	*13*
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

There are several S/N ratios available depending on the type of performance characteristic. The characteristics that higher value represents better performance, such as deposition rate and hardness, 'higher is better (HB)' characteristics were used. Inversely, the characteristic that lower value represents better performance, such as dilution, 'lower is better (LB)' characteristic was used. The loss function (L) for the objectives of HB and LB is defined as follows:

$$L_{HB} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{D_e^2} \tag{1}$$

$$L_{LB} = \frac{1}{n}\sum_{i=1}^{n} D_i^2 \tag{2}$$

$$L_{HB} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{H_r^2} \tag{3}$$

where De, Di and Hr represent the response for deposition rate, dilution and hardness respectively and 'n' denotes the number of experiments.

The signal-to-noise (S/N) ratio can be expressed as the logarithmic transformation of the loss function, as shown in Equations (4), (5) and (6) for deposition rate, dilution and hardness respectively.

$$\text{S/N ratio for De} = -10 \log_{10} (L_{HB}) \tag{4}$$

$$\text{S/N ratio for Di} = -10 \log_{10} (L_{LB}) \tag{5}$$

$$\text{S/N ratio for Hr} = -10 \log_{10} (L_{HB}). \tag{6}$$

3 Results and discussion

The experimental results are tabulated in Table 4. The overall mean for the S/N ratio of deposition (De), dilution (Di) and hardness (Hr) is found to be 17.49 dB, –23.48 dB and 34.59 dB respectively. Analysis of experimental data was carried out using the popular software known as MINITAB 14. The effects of the five control factors on performance measures De, Di and Hr are shown graphically in Figures 2, 3 and 4 respectively.

Before any attempt is made to use this simple model as a predictor of the measures of performance, the possible interactions between factors must be considered. Factorial design incorporates a simple means of testing for the presence of the interaction effects. The S/N ratio response tables for performance measures De, Di and Hr are depicted in Tables 5, 6 and 7 respectively.

An interesting phenomenon can be observed from Table 5 – that factors B and C do not show any significant effect individually in comparison to factor A for improving De, but their interaction with factor A and with each other is quite significant. The interaction graphs between factors A × B, B × C and A × C on De are shown in Figures 5, 6 and 7 respectively. Therefore, careful analysis of the response table (Table 5) and Figures 2, 5, 6 and 7 leads to the conclusion that the maximum value of De can be achieved if control factors are set at levels A_2, B_2, C_3, D_3 and E_2.

Table 4 Experimental design using L_{27} orthogonal array

Expt. no.	*A*	*B*	*C*	*D*	*E*	*Deposition rate (kg/hr)*	*S/N ratio (dB)*	*Dilution (%)*	*S/N ratio (dB)*	*Hardness*	*S/N ratio (dB)*
1	1	1	1	1	1	6.43617	16.1725	14.7091	–23.3517	54.6398	34.7502
2	1	1	2	2	2	7.57006	17.5820	17.4148	–24.8184	52.6253	34.4239
3	1	1	3	3	3	7.68809	17.7164	14.1346	–23.0057	53.6109	34.5851
4	1	2	1	2	2	6.45267	16.1948	14.6212	–23.2997	53.6820	34.5966
5	1	2	2	3	3	7.59972	17.6159	14.3976	–23.1658	53.6135	34.5855
6	1	2	3	1	1	7.31733	17.2871	15.0770	–23.5663	53.7907	34.6141
7	1	3	1	3	3	7.50052	17.5018	16.5567	–24.3795	55.6627	34.9113
8	1	3	2	1	1	6.19187	15.8364	15.2104	–23.6428	53.8302	34.6205
9	1	3	3	2	2	7.37206	17.3518	15.0218	–23.5344	54.7651	34.7701
10	2	1	1	2	3	7.64975	17.6729	12.3707	–21.8479	53.5591	34.5767
11	2	1	2	3	1	7.75433	17.7909	14.0712	–22.9666	53.5486	34.5750
12	2	1	3	1	2	7.52439	17.5294	14.7814	–23.3943	54.7179	34.7626
13	2	2	1	3	1	7.66269	17.6876	14.2783	–23.0935	53.6014	34.5835
14	2	2	2	1	2	8.41631	18.5024	18.0129	–25.1117	53.7244	34.6034
15	2	2	3	2	3	7.55431	17.5639	14.7577	–23.3804	53.7060	34.6005
16	2	3	1	1	2	8.29845	18.3799	15.1569	–23.6122	55.7750	34.9288
17	2	3	2	2	3	7.45003	17.4432	14.8977	–23.4624	53.7448	34.6067
18	2	3	3	3	1	7.59885	17.6150	14.7010	–23.3470	52.6819	34.4332
19	3	1	1	3	2	7.81555	17.8592	14.0360	–22.9449	53.4862	34.5648
20	3	1	2	1	3	7.60607	17.6232	14.7126	–23.3538	54.6546	34.7525
21	3	1	3	2	1	7.71972	17.7520	14.4558	–23.2008	53.6369	34.5893
22	3	2	1	1	3	7.49269	17.4928	14.9038	–23.4659	54.7107	34.7614
23	3	2	2	2	1	7.63453	17.6556	14.6942	–23.3429	53.6417	34.5900
24	3	2	3	3	2	7.74304	17.7782	14.4318	–23.1864	53.6269	34.5876
25	3	3	1	2	1	7.53890	17.5462	16.8429	–24.5284	53.6904	34.5979
26	3	3	2	3	2	7.66124	17.6860	14.5733	–23.2712	54.6627	34.7538
27	3	3	3	1	3	7.41333	17.4003	15.2557	–23.6686	53.7902	34.6141

Figure 2 Effect of control factors on De

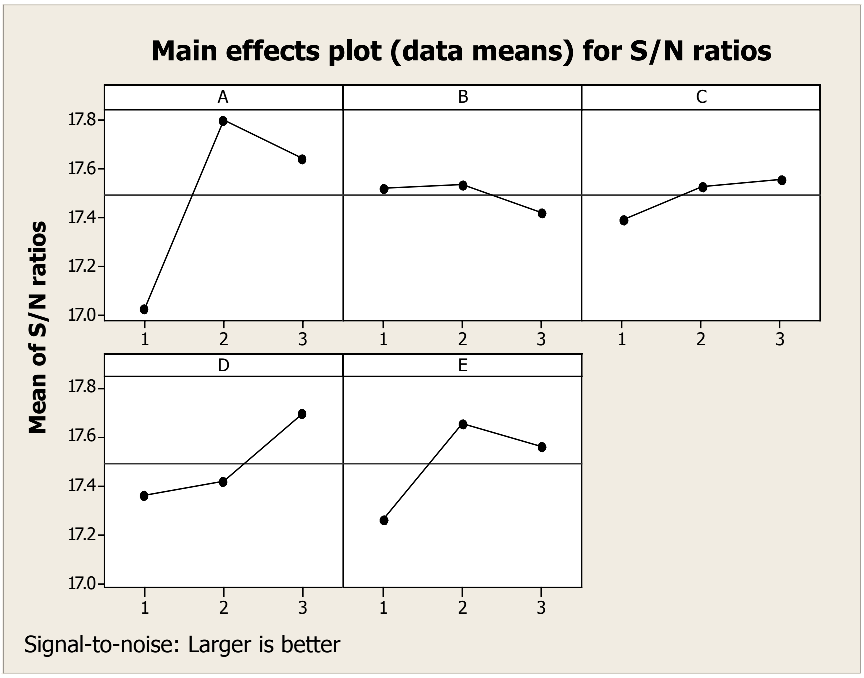


Figure 3 Effect of control factors on Di

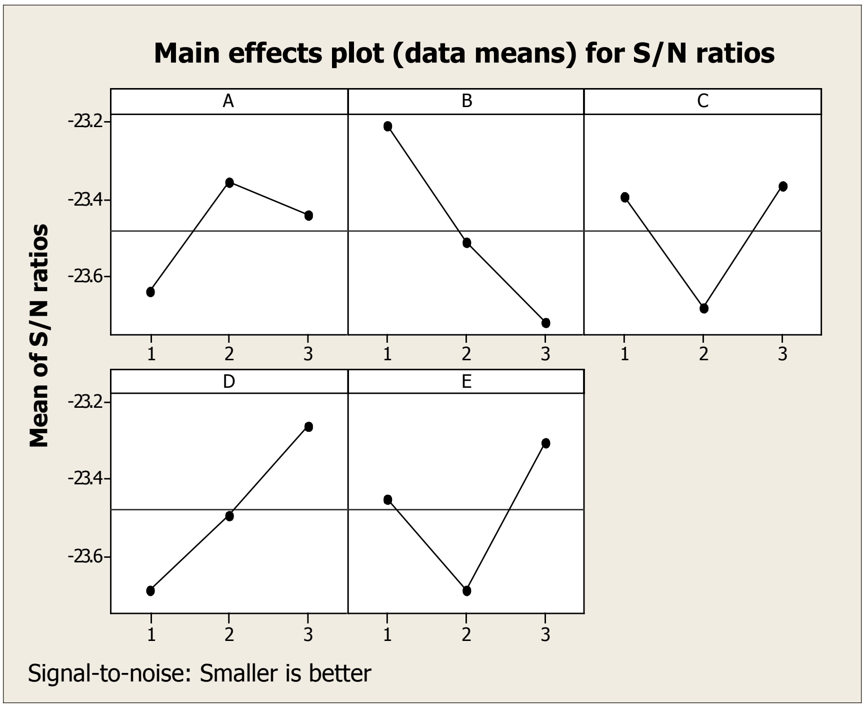


Figure 4 Effect of control factors on Hr

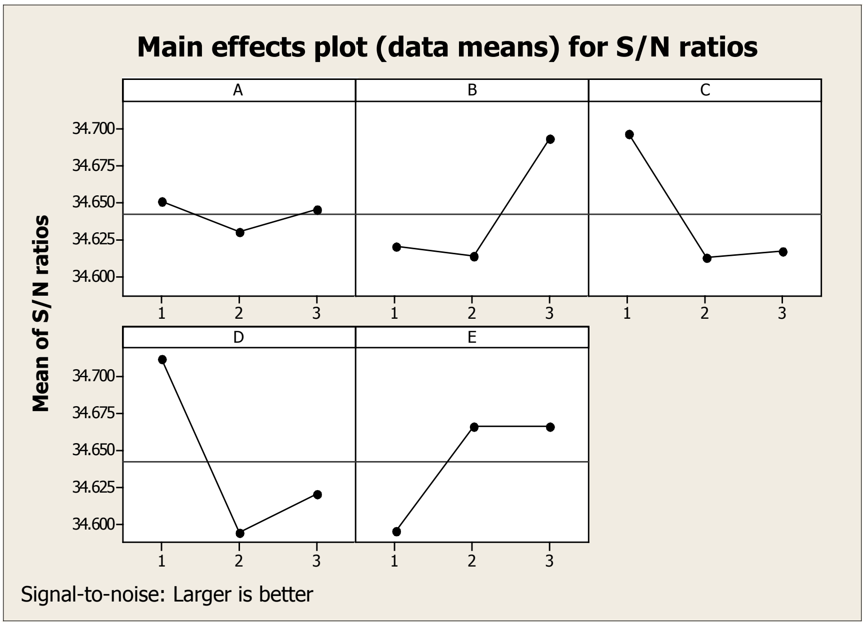


Table 5 S/N ratio response table for De

Level	*A*	*B*	*(A × B)₁*	*(A × B)₂*	*C*	*(B × C)₁*	*(B × C)₂*	*(A × C)₁*	*(A × C)₂*	*D*	*E*
1	17.03	17.52	17.39	17.28	17.39	17.26	17.36	17.26	17.53	17.54	17.42
2	17.80	17.53	17.53	17.52	17.40	17.42	17.42	17.65	17.55	17.67	17.68
3	17.64	17.42	17.55	17.67	17.67	17.80	17.69	17.56	17.39	17.26	17.38
Delta	0.77	0.11	0.17	0.38	0.28	0.54	0.34	0.39	0.16	0.41	0.30
Rank	1	11	9	5	8	2	6	4	10	3	7

Table 6 S/N ratio response table for Di

Level	*A*	*B*	*(A × B)₁*	*(A × B)₂*	*C*	*(B × C)₁*	*(B × C)₂*	*(A × C)₁*	*(A × C)₂*	*D*	*E*
1	–23.64	–23.21	–23.39	–23.46	–23.63	–23.18	–23.69	–23.45	–23.33	–23.37	–23.45
2	–23.36	–23.51	–23.68	–23.36	–23.63	–23.51	–23.49	–23.69	–23.63	–23.75	–23.67
3	–23.44	–23.72	–23.36	–23.62	–23.18	–23.75	–23.26	–23.30	–23.48	–23.32	–23.32
Delta	0.28	0.51	0.32	0.26	0.45	0.57	0.42	0.38	0.30	0.44	0.35
Rank	10	2	8	11	3	1	5	6	9	4	7

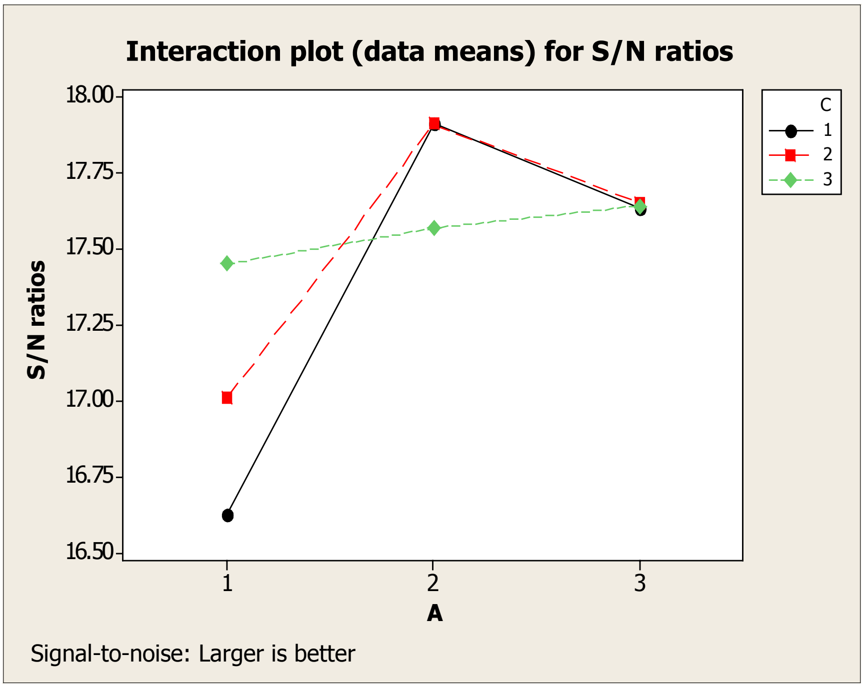
Table 7 S/N ratio response table for Hr

Level	*A*	*B*	*(A × B)₁*	*(A × B)₂*	*C*	*(B × C)₁*	*(B × C)₂*	*(A × C)₁*	*(A × C)₂*	*D*	*E*
1	34.60	34.58	34.59	34.59	34.60	34.59	34.61	34.60	34.60	34.59	34.60
2	34.60	34.60	34.59	34.60	34.60	34.60	34.60	34.60	34.60	34.60	34.60
3	34.59	34.60	34.60	34.60	34.60	34.60	34.58	34.60	34.60	34.60	34.60
Delta	0.01	0.02	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00
Rank	4	2	3	7	10	6	1	9	11	5	8

Figure 5 Interaction graph between A × B for De

Figure 6 Interaction graph between B × C for De

Figure 7 Interaction graph between A × C for De



Similar reasoning can be applied to the analysis of performance measure D_i. The interaction graphs for A × B, B × C, and A × C on Di are shown in Figures 8, 9 and 10 respectively. It is observed from the response table (Table 6) that factors A, D and E have the least contribution to the minimisation of Di. However, interaction between factors A and B, B and C, and A and C cannot be neglected. Therefore, the recommended settings for minimisation of Di are at levels A_2, B_1, C_2, D_3 and E_3 with due consideration given to interaction effects.

As far as maximisation of hardness is concerned, factor B is the most important factor among all the factors, whereas factor C has the least impact as shown in the response table (Table 7). However, the interaction of factors A × B, B × C and A × C as shown in the interaction graphs of Figures 11, 12 and 13 respectively cannot be neglected. Although the effects of factors A, C and D seem to be less significant, factors A and B show a significant effect from the interaction point of view. Of course, factors B and C show a more significant effect compared to any other interaction. Hence, the optimal factor combination for maximisation of hardness can be given as A_1, B_3, C_1, D_1 and E_3.

Analysis of Variance (ANOVA) of the experimental data for the responses for deposition rate, dilution and hardness was carried out to check the statistical significance of the conclusions already drawn based on a simple analysis of means. The ANOVA tables (Tables 8, 9 and 10) show the influence of various process parameters and their interactions on responses. Analysis was undertaken at a level of significance of 5%.

Figure 8 Interaction graph between A × B for Di

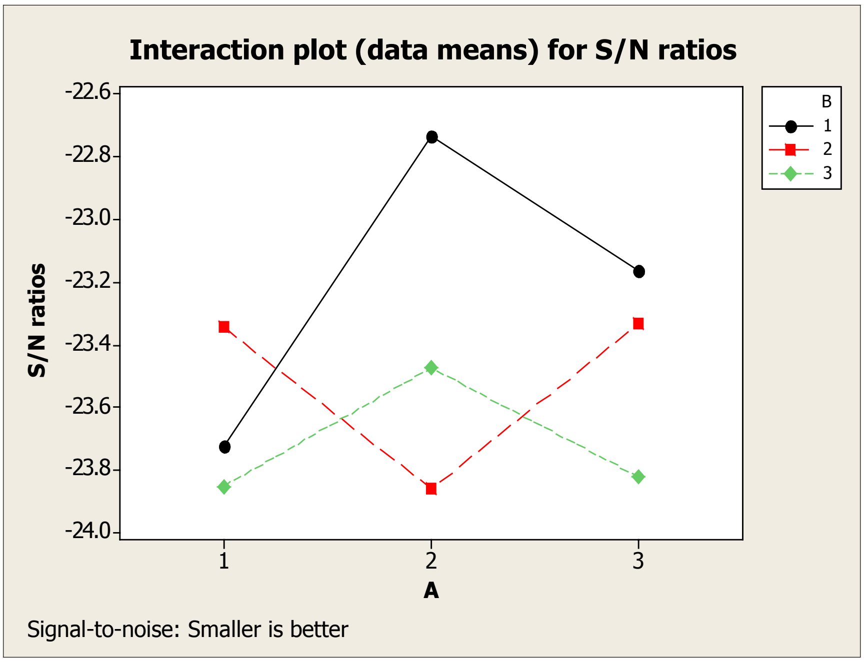


Figure 9 Interaction graph between B × C for Di

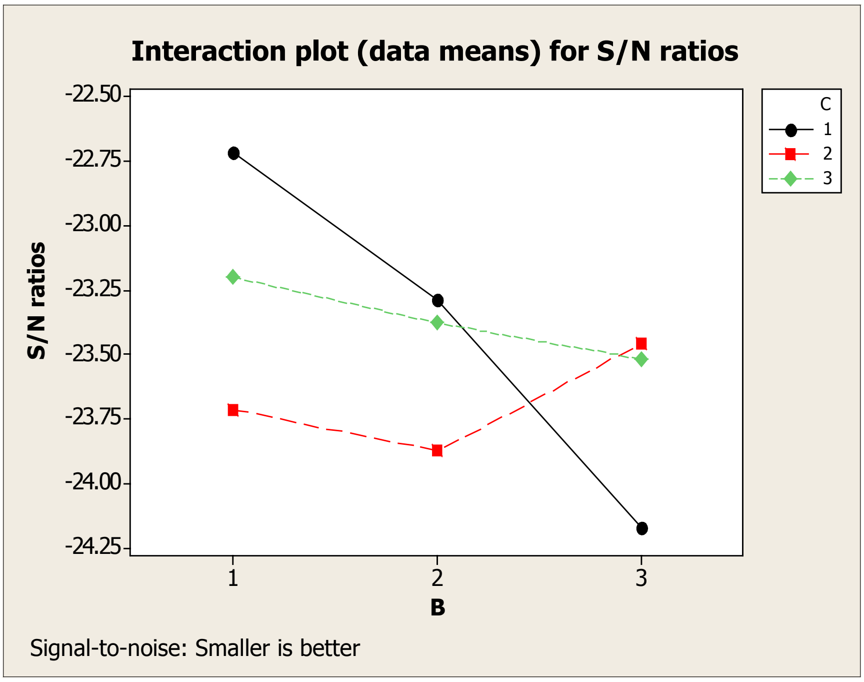


Figure 10 Interaction graph between A × C for Di

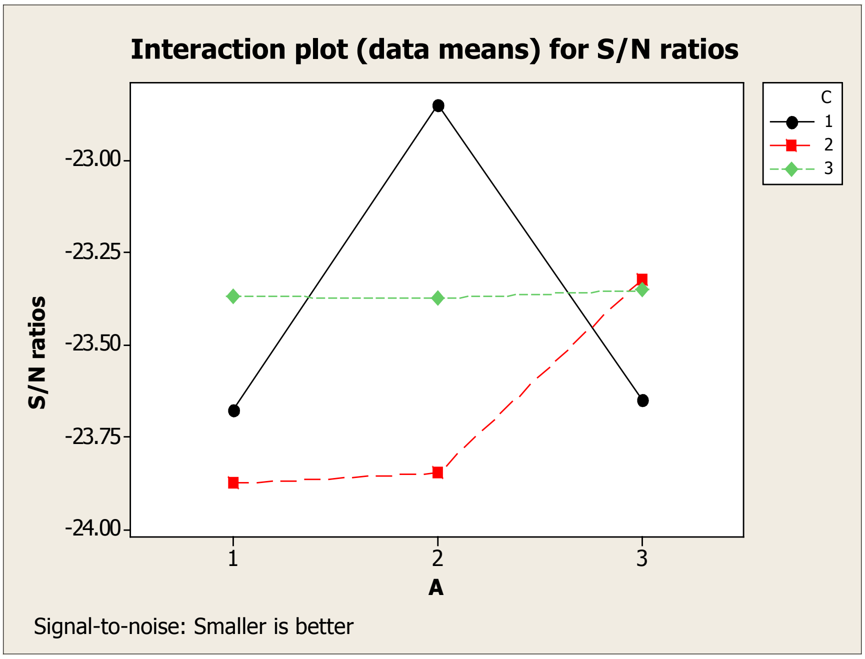


Figure 11 Interaction graph between A × B for Hr

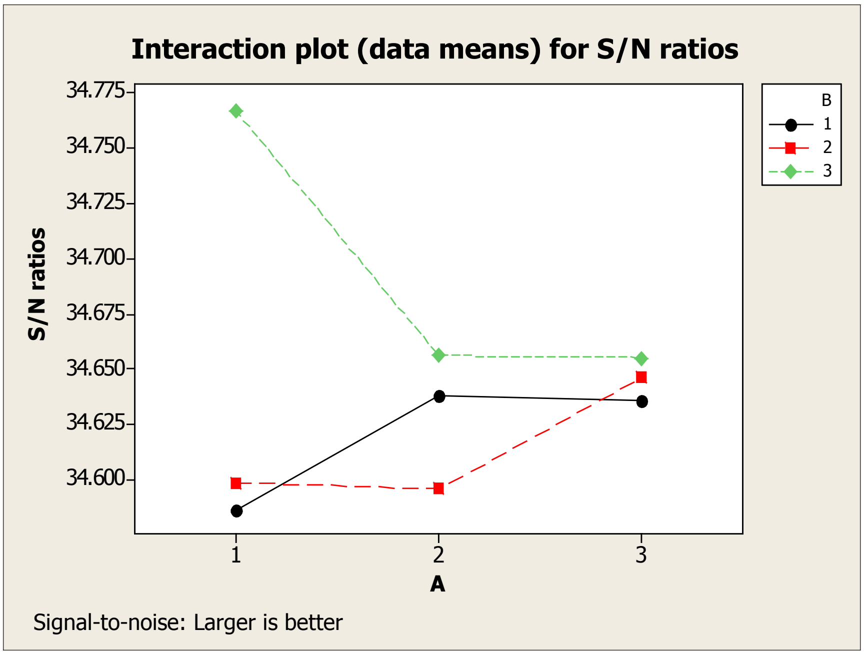


Figure 12 Interaction graph between B × C for Hr

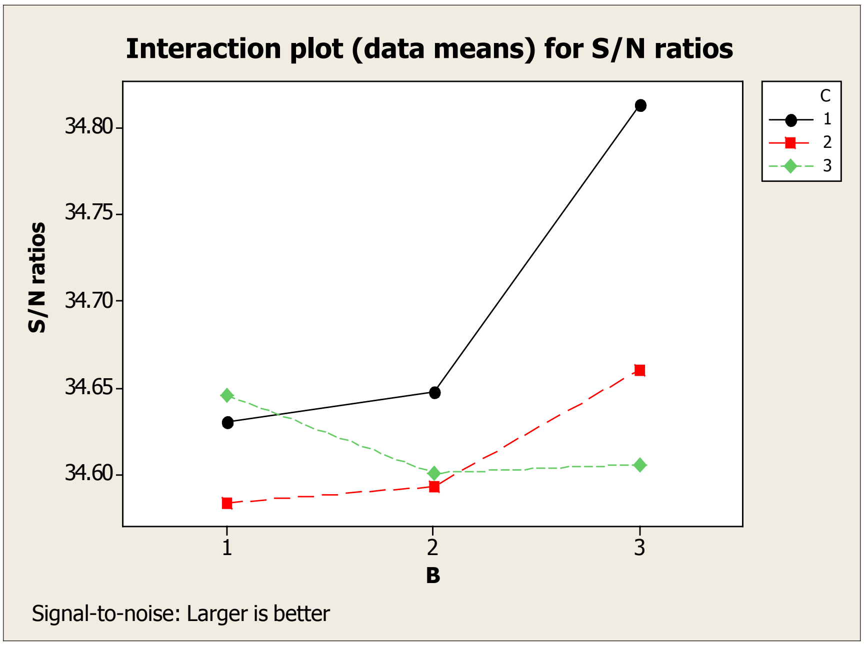
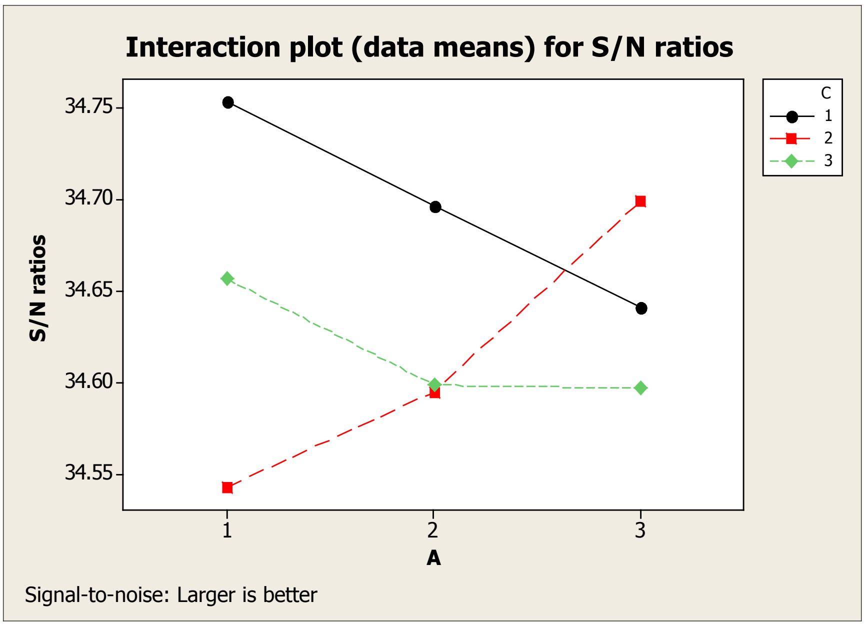


Figure 13 Interaction graph between A × C for Hr



From the last column of Table 8, it can be concluded that arc current (0.087), arc voltage (0.044) and electrode stick-out (0.000) have great influence on deposition rate. While interactions of arc current and arc voltage (0.016) and arc voltage and welding speed (0.079) cause a significance contribution to deposition rate, the factor welding speed (0.631) and the interaction between arc current and welding speed (0.130) show less significance.

Table 8 ANOVA table for deposition rate (De)

Source	*Degrees of Freedom (DF)*	*Sum of Squares (SS)*	*Mean Square (MS)*	*F-statistic (F)*	*Probability (P)*
A	2	0.124509	0.062254	319.36	0.087
B	2	0.168015	0.084007	357.73	0.044
C	2	0.000392	0.000196	0.67	0.631
D	2	0.301428	0.150714	506.14	0.000
E	2	0.000747	0.000374	1.25	0.378
A*B	4	0.000871	0.000218	0.73	0.016
B*C	4	0.001260	0.000315	1.06	0.079
A*C	4	0.001100	0.000275	0.92	0.130
Error	4	0.001191	0.000298		
Total	26	0.599512			

Table 9 indicates that arc voltage (0.000), welding speed (0.011) and electrode stick-out (0.000) largely influence dilution. The interactions between arc voltage and welding speed (0.083) show significant contribution, whereas the interaction between arc current and arc voltage (0.811) and that between arc current and welding speed (0.573), along with the factor arc current (0.753), have less significant effects on dilution.

Table 9 ANOVA table for dilution (Di)

Source	*Degrees of Freedom (DF)*	*Sum of Squares (SS)*	*Mean Square (MS)*	*F-statistic (F)*	*Probability (P)*
A	2	0.00312	0.00156	20.40	0.753
B	2	1.14396	0.57198	381.49	0.000
C	2	0.07261	0.03631	21.86	0.011
D	2	1.76725	0.88363	234.90	0.000
E	2	0.00025	0.00013	0.34	0.728
A*B	4	0.00057	0.00014	0.38	0.811
B*C	4	0.00691	0.00173	4.66	0.083
A*C	4	0.00122	0.00030	0.82	0.573
Error	4	0.00148	0.00037		
Total	26	2.99739			

Similarly, it is obvious from Table 10 that arc voltage (0.000), arc current (0.003) and electrode stick-out (0.202) have great influence on hardness. The interactions between arc current and arc voltage (0.024) and arc voltage and wire speed (0.050) show significant contribution to hardness, whereas the factor wire speed (0.506) and the interaction between arc current and wire speed (0.501) have less contribution to the response *i.e.*, hardness (Hr).

Table 10 ANOVA table for hardness (Hr)

Source	*Degrees of Freedom (DF)*	*Sum of Squares (SS)*	*Mean Square (MS)*	*F-statistic (F)*	*Probability (P)*
A	2	0.0799	0.0400	0.13	0.003
B	2	1.3872	0.6936	5.90	0.000
C	2	1.5862	0.7931	2.03	0.506
D	2	2.6599	1.3300	2.25	0.202
E	2	1.1837	0.5918	1.00	0.414
A*B	4	1.2668	0.3167	0.54	0.024
B*C	4	1.5702	0.3925	0.66	0.050
A*C	4	2.3628	0.5907	1.00	0.501
Error	4	2.3664	2.3664	0.5916	
Total	26	14.4630			

4 Confirmation experiment

The optimal contribution of welding process parameters has been determined for three responses commonly used for hardfacing through SAW in the previous section. However, any design of experiment strategy emphasises conducting a confirmation experiment. Therefore, new combinations of welding process parameters are used for verification or confirmation experiments and necessary predictive equations are developed. The estimated S/N ratio for deposition rate can be calculated with the help of the following prediction equation:

$$\begin{aligned}\hat{\eta}_1 &= \bar{T} + (\bar{A}_1 - \bar{T}) + (\bar{B}_2 - \bar{T}) + [(\bar{A}_1\bar{B}_2 - \bar{T}) - (\bar{A}_1 - \bar{T}) - (\bar{B}_2 - \bar{T})] + (\bar{C}_2 - \bar{T}) \\ &+ [(\bar{B}_2\bar{C}_2 - \bar{T}) - (\bar{B}_2 - \bar{T}) - (\bar{C}_2 - \bar{T})] + [(\bar{A}_1\bar{C}_2 - \bar{T}) - (\bar{A}_1 - \bar{T}) - (\bar{C}_2 - \bar{T})] \\ &+ (\bar{D}_1 - \bar{T}) + (\bar{E}_3 - \bar{T})\end{aligned} \tag{7}$$

$\hat{\eta}_1$ = predicted average

$\bar{T}$ = overall experimental average

$\bar{A}_1$, $\bar{B}_2$, $\bar{C}_2$, $\bar{D}_1$ and $\bar{E}_3$ = mean response for factors and interactions at designated levels.

By combining like terms, the equation is reduced to:

$$\hat{\eta}_1 = \bar{A}_1\bar{B}_2 + \bar{B}_2\bar{C}_2 + \bar{A}_1\bar{C}_2 + \bar{A}_1 - \bar{B}_2 - \bar{C}_2 + \bar{D}_1 + \bar{E}_3 - \bar{T}. \quad (8)$$

A new combination of factor levels A_1, B_2, C_2, D_1 and E_3 is used to predict deposition rate through the prediction equation, and it is found to be $\bar{\eta}_1 = 17.3097\ dB$.

Similarly, a prediction equation is developed for estimating the S/N ratio of dilution, given in Equation (9):

$$\begin{aligned}\hat{\eta}_2 = {} & \bar{T} + (\bar{A}_3 - \bar{T}) + (\bar{B}_3 - \bar{T}) + [(\bar{A}_3\bar{B}_3 - \bar{T}) - (\bar{A}_3 - \bar{T}) - (\bar{B}_3 - \bar{T})] + (\bar{C}_2 - \bar{T}) \\ & + [(\bar{B}_3\bar{C}_2 - \bar{T}) - (\bar{B}_3 - \bar{T}) - (\bar{C}_2 - \bar{T})] + [(\bar{A}_3\bar{C}_2 - \bar{T}) - (\bar{A}_3 - \bar{T}) - (\bar{C}_2 - \bar{T})] \\ & + (\bar{D}_1 - \bar{T}) + (\bar{E}_2 - \bar{T})\end{aligned} \quad (9)$$

$\hat{\eta}_2$ = predicted average

$\bar{T}$ = overall experimental average

$\bar{A}_3$, $\bar{B}_3$, $\bar{C}_2$, $\bar{D}_1$ and $\bar{E}_2$ = mean response for factors and interactions at designated levels.

Again, by combining like terms, the equation is reduced to:

$$\hat{\eta}_2 = \bar{A}_3\bar{B}_3 + \bar{B}_3\bar{C}_2 + \bar{A}_3\bar{C}_2 - \bar{A}_3 - \bar{B}_3 - \bar{C}_2 + \bar{D}_1 + \bar{E}_2 - \bar{T}. \quad (10)$$

A new experimental set-up with factor levels at A_3, B_3, C_2, D_1 and E_2 is considered to predict the S/N ratio for dilution, which is found to be $\hat{\eta}_2 = -23.6576\ dB$.

Similarly, a prediction equation is developed for estimating the S/N ratio of hardness, given in Equation (11):

$$\begin{aligned}\hat{\eta}_3 = {} & \bar{T} + (\bar{A}_2 - \bar{T}) + (\bar{B}_1 - \bar{T}) + [(\bar{A}_2\bar{B}_1 - \bar{T}) - (\bar{A}_2 - \bar{T}) - (\bar{B}_1 - \bar{T})] + (\bar{C}_2 - \bar{T}) \\ & + [(\bar{B}_1\bar{C}_2 - \bar{T}) - (\bar{B}_1 - \bar{T}) - (\bar{C}_2 - \bar{T})] + [(\bar{A}_2\bar{C}_2 - \bar{T}) - (\bar{A}_2 - \bar{T}) - (\bar{C}_2 - \bar{T})] \\ & + (\bar{D}_3 - \bar{T}) + (\bar{E}_1 - \bar{T})\end{aligned} \quad (11)$$

$\hat{\eta}_3$ = predicted average

$\bar{T}$ = overall experimental average

$\bar{A}_2$, $\bar{B}_1$, $\bar{C}_2$, $\bar{D}_3$ and $\bar{E}_1$ = mean response for factors and interactions at designated levels.

Again, by combining like terms, the equation is reduced to:

$$\hat{\eta}_3 = \bar{A}_2\bar{B}_1 + \bar{B}_1\bar{C}_2 + \bar{A}_2\bar{C}_2 - \bar{A}_2 - \bar{B}_1 - \bar{C}_2 + \bar{D}_3 + \bar{E}_1 - \bar{T}. \quad (12)$$

A new experimental set-up with factor levels at $\bar{A}_2$, $\bar{B}_1$, $\bar{C}_2$, $\bar{D}_3$ and $\bar{E}_1$ is considered to predict the S/N ratio for hardness, which is found to be $\hat{\eta}_3 = 34.5271\ dB$.

For each performance characteristic, new experiments with different combinations of factors and their levels were conducted and compared with the result obtained from the predictive equations as shown in Table 11. The resulting model seems to be capable of predicting De, Di and Hr to a reasonable accuracy. Errors of 1.38% for the S/N ratio of

De, 2.917% for the S/N ratio of Di and 0.25% for the S/N ratio of Hr are observed. However, the errors can be further reduced if the numbers of measurements are increased. This validates the development of the mathematical model for predicting the measures of performance based on knowledge of the input parameters.

Table 11 Results of confirmation experiments

	Confirmation experiment for De		*Confirmation experiment for Di*		*Confirmation experiment for Hr*	
	Prediction	*Experimental*	*Prediction*	*Experimental*	*Prediction*	*Experimental*
Level	$A_1B_2C_2D_1E_3$	$A_1B_2C_2D_1E_3$	$A_3B_3C_2D_1E_2$	$A_3B_3C_2D_1E_2$	$A_2B_1C_2D_3E_2$	$A_2B_1C_2D_3E_1$
S/N ratio	17.30	17.54	–23.6576	–24.3479	34.5270	34.6140

5 Multiobjective optimisation of SAW parameters

Multivariate regression analysis can quantitatively determine the relationship between the responses with welding process parameters. The mathematical model in the following form is suggested to establish the relation between various responses with SAW parameters:

$$Y = K_0 + K_1{*}A + K_2{*}B + K_3{*}C + K_4{*}D + K_5{*}E + K_6{*}A{*}B + K_7{*}B{*}C + K_8{*}A{*}C \tag{13}$$

where Y is the performance output term and K_i (i = 0, 1, 2, 3……..8) denotes model constants. The constants are obtained through a nonlinear regression analysis method with the help of MINITAB 14 software. The calculated coefficients are substituted in Equation (13) to develop the following relations:

$$De = 1.001 - 0.07A - 0.3B - 0.042C + 0.126D + 0.008E + 0.152AB + 0.023BC + 0.028AC \tag{14}$$

$$r^2 = 0.99$$

$$Di = 0.731 + 0.029A + 0.160B - 0.064C - 0.137D - 0.002E - 0.042AB + 0.094BC + 0.003AC \tag{15}$$

$$r^2 = 0.98$$

$$Hr = 0.929 + 0.002A + 0.049B + 0.037C - 0.010D - 0.001E - 0.004AB - 0.033BC - 0.002AC \tag{16}$$

$$r^2 = 0.99.$$

The validity of mathematical models and correctness of the calculated constant are established as high correlation coefficients (r^2) to the tune of above 0.9 in all cases. It is interesting to note that optimal settings of parameters for De, Di and Hr are quite different and pose difficulty in achieving the goals of meeting all the objectives simultaneously. Therefore, developed mathematical models can be used for the optimisation of SAW parameters.

The performance measures have different objectives – maximisation of deposition rate, minimisation of dilution and maximisation of hardness – and all are to be achieved simultaneously. The multiobjective optimisation techniques quantitatively determine the values of welding process parameters to achieve optimal deposition rate, dilution and hardness at the same time. GA, an efficient evolutionary approach, is used for multiobjective optimisation (Holland, 1975). A weighting method is normally adopted when optimisation of the process with multiperformance characteristics is sought so that a single objective function can be used conveniently. Since De, Di and Hr are the three different objects, the function corresponding to every performance characteristic is normalised first in order to overcome the effect of large differences in their numerical values. Then, a weighting method is used on the normalised performance characteristics to obtain a single objective function.

The resultant weighted objective function to be maximised is given as:

$$\text{Maximise } Z = (w_1 \times f_1 + w_2 \times 1/f_2 + w_3 \times f_3)\,(1 - K.C) \tag{17}$$

where:

f_1 = normalised function for D_e

f_2 = normalised function for D_i

f_3 = normalised function for H_r

C = violation coefficient

K = a penalty parameter; the value is usually 10.

Subjected to constraints:

$$A_{min} \leq A \leq A_{max} \tag{18}$$

$$B_{min} \leq B \leq B_{max} \tag{19}$$

$$C_{min} \leq C \leq C_{max} \tag{20}$$

$$D_{min} \leq D \leq D_{max} \tag{21}$$

$$E_{min} \leq E \leq E_{max} \tag{22}$$

where w_1, w_2 and w_3 denote the weighting factors for normalised De, Di and Hr functions. The minimum and maximum in Equations (18) to (22) indicate the lowest and highest welding process parameter settings respectively (Table 2). The weighting factors are selected in such a manner that their sum is equal to 1. A higher weighting factor for an objective indicates more emphasis on it. Four cases of optimisation schemes have been suggested by varying weighting factors. The flowchart for the algorithm is shown in Figure 14 and implemented in Visual C^{++}.

The population size, probability of crossover and mutation are set at 50, 55%, and 5% respectively in all cases. The number of generations varies from case to case. Table 12 shows the optimum conditions of the machining parameters for multiperformance outputs with different combinations of the weighting factors. It is observed that case 4 gives optimal performance characteristics that maximise the deposition rate and hardness and minimise the dilution simultaneously under equal importance of weighting factors ($w_1 = 0.25$, $w_2 = 0.25$) for deposition rate and dilution and with a higher weighting factor for hardness ($w_3 = 0.50$).

Figure 14 Flowchart for genetic algorithm

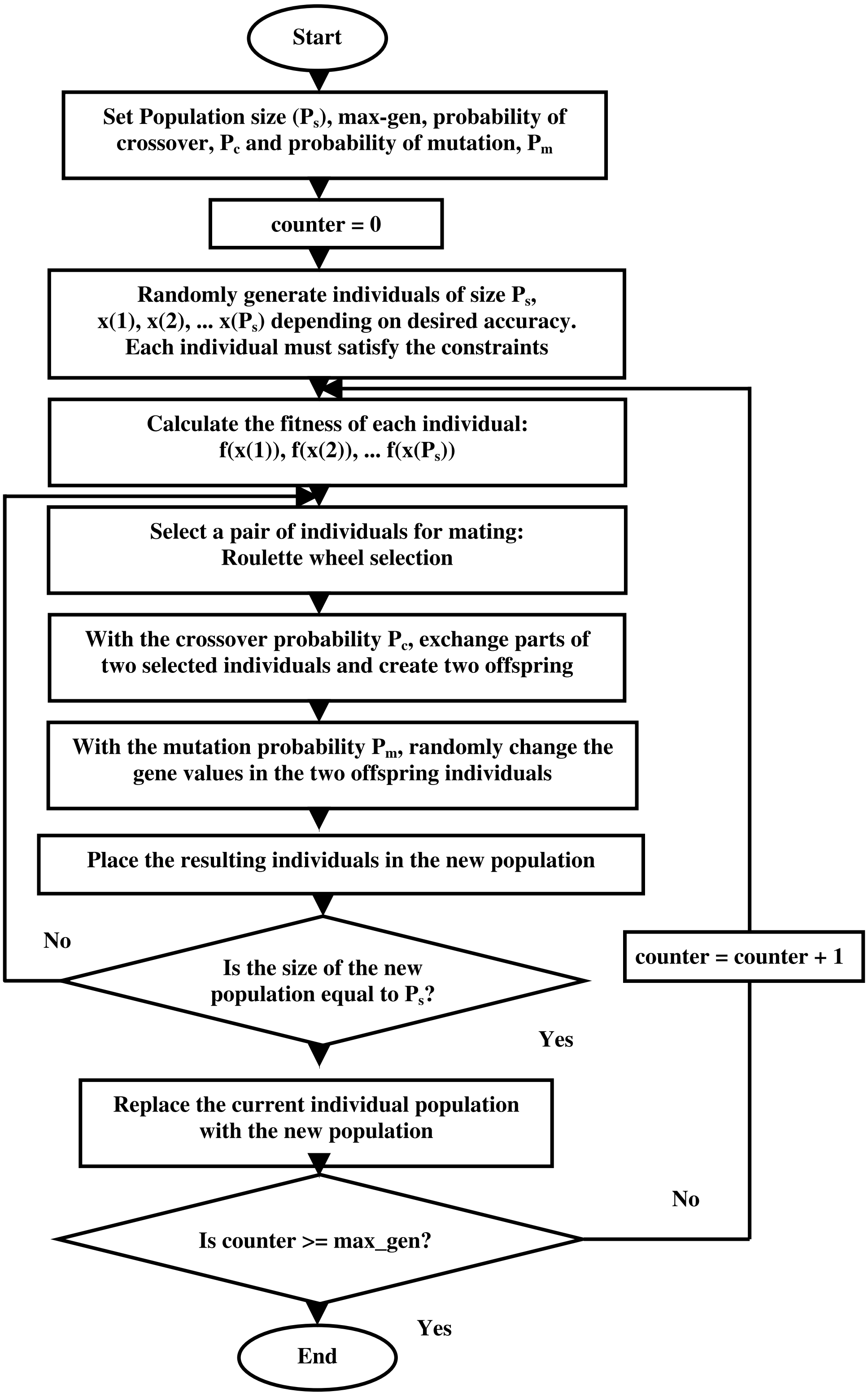


Table 12 Optimum welding performance for multiperformance with different weighting factors

Control factors and performance characteristics	*Optimum welding performance*			
	Case 1 (w_1 = 0.33, w_2 = 0.33 and w_3 = 0.33)	*Case 2 (w_1 = 0.50, w_2 = 0.25 and w_3 = 0.25)*	*Case 3 (w_1 = 0.25, w_2 = 0.50 and w_3 = 0.25)*	*Case 4 (w_1 = 0.25, w_2 = 0.25 and w_3 = 0.50)*
A: Arc current	412.5	487	487.5	487
B: Arc voltage	26.16	26.10	26.31	26.1
C: Welding speed	30.84	36.68	31.24	36.88
D: Electrode stick-out	24.83	24.98	24.85	24.98
E: Preheat temperature	197.163	202.32	212.42	206.19
De (kg/hr)	7.5590	7.6820	7.6700	7.6831
Di (%)	13.378	13.385	13.386	13.385
Hr	53.80	53.83	53.78	53.83

6 Conclusion

In this work, an attempt was made to determine important welding process parameters for the three performance characteristics deposition rate, dilution and hardness in the SAW process. Factors such as arc current, arc voltage and welding speed and their interactions play a significant role in the SAW process in hardfacing. Taguchi's experimental design strategy was applied to obtain optimum welding-process-parameter combinations for each of the performance criteria – maximisation of deposition rate, minimisation of dilution and maximisation of hardness. Interestingly, the optimal levels of the factors for all the three objectives happened to be different. The analysis was further supplemented by a more rigorous statistical analysis known as ANOVA. Identified factors and their interactions were validated through a set of confirmation experiments. Mathematical models obtained through the nonlinear regression method were proposed to determine deposition rate, dilution and hardness. The optimum search for welding process parameter values for the objective of maximisation of deposition rate and hardness and minimisation of dilution was formulated as a multiobjective, multivariable, nonlinear optimisation problem. It was demonstrated that a multiobjective optimisation problem can be effectively tackled using GA. It was observed that the performance characteristics of the SAW process, such as deposition rate, dilution and hardness, are improved together by using the method proposed in this study.

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