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Genetic algorithm for optimization of welding variables for height to width ratio and application of ANN for prediction of bead geometry for TIG welding process

D.S. Nagesh[a,*], G.L. Datta[b]

[a] Department of Mechanical Engineering, Delhi College of Engineering, Delhi 110042, India
[b] IIT Kharagpur, India

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ABSTRACT

This paper explains an integrated method with a new approach using experimental design matrix of experimental designs technique on the experimental data available from conventional experimentation, application of neural network for predicting the weld bead geometric descriptors and use of genetic algorithm for optimization of process parameters. The properties of the welded joints are affected by a large number of welding parameters. Modeling of weld bead shape is important for predicting the quality of welds. In an attempt to model the welding process for predicting the bead shape parameters (also known as bead geometry parameters) of welded joints, modeling and optimization of bead shape parameters in tungsten inert gas (TIG) welding process has been tried in the present work. Multiple linear regression technique has been used to develop mathematical models for weld bead shape parameters of TIG welding process, considering the effects of main variables as well as two factor interactions. Also by using the same experimental data, an attempt has been made to predict the bead shape parameters using back-propagation neural network. To optimize the process parameters for the desired front height to front width ratio and back height to back width ratio, genetic algorithmic approach has been applied.

1. Introduction

Tungsten inert gas welding is an arc welding process wherein coalescence is produced by heating the job with an electric arc established between a tungsten electrode and the base metal. No flux is used but the arc and the molten metal are shielded by an inert gas, which may be argon, helium, hydrogen, nitrogen or mixtures of some of these gases.

Weld bead geometric parameters have a large influence on the quality of the product. It is obvious then that studies on the effects of various welding process parameters on the formation of bead, depth of penetration and bead geometry have attracted the attention of many researchers [1–3] to carry out further investigations. Mathematical modeling of processes using the principle of design of experiments has proved to be an efficient procedure for understanding the behavior of a process by conducting minimum number of experiments [4–6]. This has led to saving of cost and time. Recent developments in the evolution of artificial neural networks have been found to be useful in solving many engineering problems. In different fields of engineering, back-propagation neural network has proved to be one of the best algorithms for predictive type of work [7–16]. Genetic algorithms are attracting the attention of many researchers when it comes to optimization of process parameters. These algorithms encode a potential solution to a specific problem on a simple chromosome like data structure and apply recombination operators to these structures so as to preserve critical information [17–22]. In a broader usage of the term, a genetic algorithm is any population-based model that uses selection and recombination operators to generate new sample points in a search space.

In the present work a two level fractional factorial design technique has been used on the experimental data with the objective of modeling the TIG welding process. For this purpose in the present analysis, we have studied the effects of welding speed (S), wire speed (WS), cleaning percentage (CP), welding current (C) and arc gap (G) which are the TIG welding variables, on weld bead shape parameters comprising of front height (FH), front width (FW), back height (BH) and back width (BW). In this work the approach was to construct the experimental design matrix on the experimental data available from conventional experimentation for developing regression equations for estimating the bead shape parameters. Using two level, five factor fraction factorial design, only 16 tri-

* Corresponding author. Tel.: +91 9213728762.
E-mail address: nageshds@yahoo.com (D.S. Nagesh).

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Table 1
Experimental database of Juang et al.

Number	Input					Output			
	Speed ($cm\,min^{-1}$)	Wire speed ($cm\,min^{-1}$)	Cleaning (%)	Gap (mm)	Current (V)	Front height (mm)	Front width (mm)	Back height (mm)	Back width (mm)
1	24	1.5	30	2.4	80	−0.149	6.09	0.672	5.664
2	24	1.5	30	3.2	80	0.027	6.411	0.412	5.197
3	24	1.5	70	2.4	80	−0.179	7.432	0.593	7.058
4	24	1.5	70	3.2	80	−0.306	7.287	0.63	6.895
5	24	2.5	30	2.4	80	0.155	6.676	0.743	5.96
6	24	2.5	30	3.2	80	0.099	6.824	0.803	5.732
7	24	2.5	70	2.4	80	−0.129	7.009	0.878	6.989
8	24	2.5	70	3.2	80	−0.077	7.46	0.82	7.809
9	24	1.5	30	2.4	95	−0.017	8.664	0.437	8.75
10	24	1.5	30	3.2	95	−0.25	8.782	0.593	9.993
11	24	1.5	70	2.4	95	−0.553	9.757	0.852	9.993
12	24	1.5	70	3.2	95	−0.42	10.374	0.736	10.687
13	24	2.5	30	2.4	95	−0.345	9.783	0.965	10.237
14	24	2.5	30	3.2	95	−0.043	8.803	0.654	9.076
15	24	2.5	70	2.4	95	−0.134	9.75	0.798	9.465
16	24	2.5	70	3.2	95	−0.168	10.348	0.708	10.193
17	24	1.5	30	2.4	110	−0.599	11.348	0.805	11.679
18	24	1.5	30	3.2	110	−0.745	11.491	1.1	11.848
19	24	1.5	70	2.4	110	−0.254	11.237	0.47	12
20	24	1.5	70	3.2	110	−0.683	12.946	0.945	13.921
21	24	2.5	30	2.4	110	−0.232	9.338	0.866	10.611
22	24	2.5	30	3.2	110	−0.557	12.348	1.139	12.403
23	24	2.5	70	2.4	110	−0.623	11.767	1.128	12.86
24	24	2.5	70	3.2	110	−0.617	12.533	1.084	13.346
25	35	1.5	30	2.4	80	0.123	5.355	0.245	4.104
26	35	1.5	30	3.2	80	0.108	5.173	0.34	3.418
27	35	1.5	70	2.4	80	−0.044	5.833	0.51	4.875
28	35	1.5	70	3.2	80	−0.09	5.831	0.502	5.082
29	35	2.5	30	2.4	80	0.251	5.656	0.557	4.37
30	35	2.5	30	3.2	80	0.23	5.562	0.593	3.948
31	35	2.5	70	2.4	80	0.18	5.711	0.45	5.085
32	35	2.5	70	3.2	80	0.12	5.85	0.626	4.989
33	35	1.5	30	2.4	95	−0.213	6.348	0.458	5.874
34	35	1.5	30	3.2	95	−0.19	6.992	0.447	6.74
35	35	1.5	70	2.4	95	−0.152	7.163	0.464	6.994
36	35	1.5	70	3.2	95	−0.213	7.25	0.504	7.019
37	35	2.5	30	2.4	95	−0.164	7.288	0.715	6.724
38	35	2.5	30	3.2	95	−0.113	6.966	0.746	6.433
39	35	2.5	70	2.4	95	−0.107	7.055	0.696	7.24
40	35	2.5	70	3.2	95	−0.018	7.549	0.591	7.166
41	35	1.5	30	2.4	110	−0.575	8.337	0.766	8.763
42	35	1.5	30	3.2	110	−0.267	8.605	0.506	8.58
43	35	1.5	70	2.4	110	−0.385	9.109	0.672	9.652
44	35	1.5	70	3.2	110	−0.564	9.67	0.743	9.952
45	35	2.5	30	2.4	110	−0.556	8.756	1.011	8.853
46	35	2.5	30	3.2	110	−0.188	9.442	0.666	9.614
47	35	2.5	70	2.4	110	−0.309	9.015	0.784	9.041
48	35	2.5	70	3.2	110	−0.318	9.297	0.785	9.47
49	46	1.5	30	2.4	80	0.357	4.982	0.001	2.255
50	46	1.5	30	3.2	80	0.168	4.898	0.277	2.998
51	46	1.5	70	2.4	80	0.088	5.02	0.281	3.302
52	46	1.5	70	3.2	80	0.09	4.423	0.42	3.172
53	46	2.5	30	2.4	80	0.39	4.78	0.062	1.33
54	46	2.5	30	3.2	80	0.487	4.992	0.139	1.6
55	46	2.5	70	2.4	80	0.38	5.231	0.397	2.817
56	46	2.5	70	3.2	80	0.394	5.337	0.378	3.041
57	46	1.5	30	2.4	95	−0.321	5.847	0.44	5.332
58	46	1.5	30	3.2	95	−0.152	5.704	0.386	5.35
59	46	1.5	70	2.4	95	−0.155	5.967	0.445	5.415
60	46	1.5	70	3.2	95	−0.09	5.892	0.399	5.319
61	46	2.5	30	2.4	95	−0.236	5.984	0.696	5.531
62	46	2.5	30	3.2	95	0.067	6.03	0.575	5.636
63	46	2.5	70	2.4	95	−0.075	5.562	0.816	4.835
64	46	2.5	70	3.2	95	0.138	6.546	0.575	6.285
65	46	1.5	30	2.4	110	−0.217	6.092	0.359	6.419
66	46	1.5	30	3.2	110	−0.339	7.335	0.619	7.52
67	46	1.5	70	2.4	110	−0.249	7.719	0.492	7.706
68	46	1.5	70	3.2	110	−0.396	7.633	0.458	7.601
69	46	2.5	30	2.4	110	−0.01	6.396	0.536	6.197
70	46	2.5	30	3.2	110	0.074	6.863	0.484	6.072
71	46	2.5	70	2.4	110	−0.201	7.052	0.658	7.48
72	46	2.5	70	3.2	110	−0.358	7.759	0.798	7.917

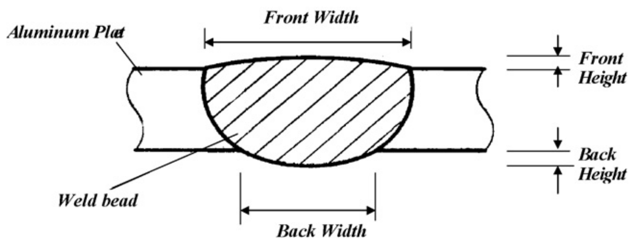

Fig. 1. Weld bead shape parameters.

als are needed for complete analysis. In this new approach these 16 trials are selected from already performed detailed conventional experimental data available from a published work [10] based on 2^{5-1} fraction factorial design of experiments design matrix.

2. Details of experiments on TIG welding process

To study the effects of welding process variables (WPVs) on the weld bead shape parameters of TIG welding process, the experimental data are taken from the experimental database of Juang et al. [10] shown in Table 1. The base material used for the experiments was pure 1100 aluminum with a plate thickness of 1.6 mm. AWSA5-10 wire compatible with the base metal was used, as filler metal and shielding gas was argon.

The weld bead shape parameters are expressed as front height, front width, back height and back width as shown in Fig. 1. A study on the relationship between weld bead shape parameters and welding conditions has been made to obtain a good welded joint. In TIG welding, the WPVs constitute welding speed, wire speed, cleaning percentage, welding current and arc gap. Cleaning percentage means the amount of time that the electrode is positive versus the mount of time that the electrode is negative. When the electrode has the positive polarity, the aluminum oxide layer is broken by the electrons, they go from the aluminum to the electrode. The cleaning percentage can be set on the welding power source.

3. Fractional factorial D.O.E. technique and analysis of variable effects

It is a common practice to develop regression equations using either conventional detailed experimental data or by using experimental data obtained with the help of design of experiments technique. In the present work, for developing the regression equations and for modeling and optimizing the process parameters of TIG welding process, experimental data were selected from published experimental data. The selection of data is based on design matrix of 2^{n-1} fractional factorial design of experiments. From the conventional experimental database of Juang et al. [10] shown in Table 1, the required number of experimental data were selected. In this method 'n' means the number of WPVs. In the present study 'n' is 5 and 2^{n-1} can be represented by 2^{5-1}. For determining the 5 main variable effects and 10 two-factor interaction effects only 16 trials are needed. To evaluate the individual and interaction effects, the welding conditions were set as shown in Table 2. The five main effects, each at lower and higher levels used for the study, are shown in Table 3. As per the design of experiments convention, the low level of a variable is designated by −1 and high level by +1. The standardized variables are denoted by $X1$, $X2$, $X3$, $X4$ and $X5$. The uncoded and coded design matrices constructed for the experiment are shown in Table 4. The experimental data are based on the design matrix and the response values are recorded on a data sheet for analysis. The variables affected by the standardized variables are denoted by FH, FW, BH and BW. The resulting response table is shown in Table 5.

Table 2
Electrode, shielding gas and base metal.

Experimental condition	Description
Welding wire	Solid wire AWSA5-10
Shielding gas	Argon
Base metal	Pure 1100 aluminum (1.6 mm thickness)

Table 3
Experimental variable levels and response factors.

Experimental variables		Low level (−1)	High level (+1)
S	Welding speed (cm/min)	24	46
WS	Wire speed (cm/min)	1.5	2.5
CP	Cleaning percentage (%)	30	70
C	Current (A)	80	110
G	Arc gap (mm)	2.4	3.2
Experimental response factors			
FH	Front height (mm)		
FW	Front width (mm)		
BH	Back height (mm)		
BW	Back width (mm)		

Table 4
Welding conditions and standardized variables for trials 1–16.

Trial no.	Welding conditions					Standardized variables														
	S	WS	CP	*C*	*G*	*X*1	*X*2	*X*3	*X*4	*X*5	*X*12	*X*13	*X*14	*X*15	*X*23	*X*24	*X*25	*X*34	*X*35	*X*45
1	24	1.5	30	80	3.2	−1	−1	−1	−1	1	1	1	1	−1	1	1	−1	1	−1	−1
2	46	1.5	30	80	2.4	1	−1	−1	−1	−1	−1	−1	−1	−1	1	1	1	1	1	1
3	24	2.5	30	80	2.4	−1	1	−1	−1	−1	−1	1	1	1	−1	−1	−1	1	1	1
4	46	2.5	30	80	3.2	1	1	−1	−1	1	1	−1	−1	1	−1	−1	1	1	−1	−1
5	24	1.5	70	80	2.4	−1	−1	1	−1	−1	1	−1	1	1	−1	1	1	−1	−1	1
6	46	1.5	70	80	3.2	1	−1	1	−1	1	−1	1	−1	1	−1	1	−1	−1	1	−1
7	24	2.5	70	80	3.2	−1	1	1	−1	1	−1	−1	1	−1	1	−1	1	−1	1	−1
8	46	2.5	70	80	2.4	1	1	1	−1	−1	1	1	−1	−1	1	−1	−1	−1	−1	1
9	24	1.5	30	110	2.4	−1	−1	−1	1	−1	1	1	−1	1	1	−1	1	−1	1	−1
10	46	1.5	30	110	3.2	1	−1	−1	1	1	−1	−1	1	1	1	−1	−1	−1	−1	1
11	24	2.5	30	110	3.2	−1	1	−1	1	1	−1	1	−1	−1	−1	1	1	−1	−1	1
12	46	2.5	30	110	2.4	1	1	−1	1	−1	1	−1	1	−1	−1	1	−1	−1	1	−1
13	24	1.5	70	110	3.2	−1	−1	1	1	1	1	−1	−1	−1	−1	−1	−1	1	1	1
14	46	1.5	70	110	2.4	1	−1	1	1	−1	−1	1	1	−1	−1	−1	1	1	−1	−1
15	24	2.5	70	110	2.4	−1	1	1	1	−1	−1	−1	−1	1	1	1	−1	1	−1	−1
16	46	2.5	70	110	3.2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 5
Experimental results for trials 1–16.

Trial no.	Front height, FH (mm)	Front width, FW (mm)	Back height, BH (mm)	Back width, BW (mm)
1	0.027	6.411	0.412	5.197
2	0.357	4.982	0.001	2.255
3	0.155	6.676	0.743	5.96
4	0.487	4.992	0.139	1.6
5	−0.179	7.432	0.593	7.058
6	−0.09	4.423	0.42	3.172
7	−0.077	7.46	0.82	7.809
8	0.38	5.231	0.397	2.817
9	−0.599	11.348	0.805	11.679
10	−0.339	7.335	0.619	7.52
11	−0.557	12.348	1.139	12.403
12	−0.01	6.396	0.536	6.197
13	−0.683	12.946	0.945	13.921
14	0.249	7.719	0.492	7.706
15	−0.623	11.767	1.128	12.86
16	−0.358	7.759	0.798	7.917

Table 6
Variable effects for trials 1–16.

	Weld bead shape parameters			
	Effects	Front width	Back height	Back width
E1	3.212	−27.551	−3.183	−37.703
E2	0.654	0.033	1.413	−0.945
E3	−0.902	4.249	1.199	10.449
E4	−3.98	30.011	2.937	44.335
E5	−1.32	2.123	0.597	3.007
E12	−0.010	−0.195	−0.737	−3.299
E13	0.274	−1.395	0.425	−2.369
E14	0.796	−10.849	0.039	−5.343
E15	−1.232	−1.761	0.503	−0.539
E23	−0.604	−0.639	−0.027	0.037
E24	−1.006	−2.189	0.067	−1.953
E25	0.506	2.855	−0.413	0.783
E34	1.082	1.279	−0.671	−1.239
E35	−0.750	−1.245	0.149	1.749
E45	−0.588	4.193	0.483	3.631

The relationships between the standardized variables and the experimental variables are:

$$
\begin{aligned}
X1 &= \frac{S-35.0}{21.0}\\
X2 &= \frac{\mathrm{WS}-2.0}{0.5}\\
X3 &= \frac{\mathrm{CP}-50.0}{20.0}\\
X4 &= \frac{C-95.0}{15.0}\\
X5 &= \frac{G-2.8}{0.4}
\end{aligned}
\qquad (1)
$$

The individual and interaction effects have been calculated by multiplying the appropriate standardized variable by the experimental result for each trial and summing the resultant values.

Table 6 shows the values of the individual effects and the two-factor interaction effects for each experimental result obtained from the 2^{5-1} fractional factorial design. According to the data in Table 6, E1, E2, E3, etc., mean the effectiveness of $X1$ (welding speed), $X2$ (wire speed), $X3$ (cleaning percentage), etc., respectively on the weld bead shape parameters. According to the notation, E12 means the effectiveness of the coupled variables of $X1$ and $X2$ on the weld bead shape parameters. Similarly other notations can be interpreted. The larger the absolute value of these effects, the more dominant is the effect on the weld bead geometric parameters.

From Table 6 it is evident that, the most dominant welding process variable on the weld bead shape parameters except back height is welding current. Front width and back width has got plus sign indicating that, these two parameters increases with increase in welding current, whereas for front height has got minus sign indicating that, it decreases with increase in welding current. Welding current is the second dominant variable for the back height, whereas welding speed is the second dominant variable for front height, front width and back width. Front width, front height and back width decreases with increase in welding speed. This could obviously be attributed to reduced line power per unit length of weld bead as welding speed increases. Also at higher welding speeds, the electrode wire travels faster and covers more distance per unit time. The combined effects of lesser line power and faster electrode travel speed results in decreased metal deposition rate per unit length of weld bead. In some cases coupled variables also has got substantial effects on the weld bead shape parameters. For example effectiveness corresponding to E14, i.e. the coupled variables welding speed and welding current has got substantial negative effect on front width. Similarly with the help of information on effectiveness of the other variables can be interpreted.

3.1. Regression equations for weld bead shape parameters

In the present work, the regression equations were developed for the bead shape parameters such as front height, front width, back height and back width of the beads formed during TIG welding process. For each of these features, linear regression equations were obtained by considering both main and two factor interaction effects. To obtain these equations, the experimental conditions presented in Table 4 and the experimental results presented in Table 5 were used. Weld bead shape features were then computed from these linear regression equations and compared with actual experimental values.

3.1.1. Linear regression equations

Four linear regression equations were postulated considering both main and two factor interaction effects for the bead shape parameters, based on the evaluation of the variable effects discussed in Section 3. The postulated equations for the bead shape parameters are:

- Equation for front height:

$$\begin{aligned} Y1 = {} & a_0 + a_1X1 + a_2X2 + a_3X3 + a_4X4 + a_5X5 + a_6X12 \\ & + a_7X13 + a_8X14 + a_9X15 + a_{10}X23 + a_{11}X24 \\ & + a_{12}X25 + a_{13}X34 + a_{14}X35 + a_{15}X45 \end{aligned} \tag{2}$$

where $Y1$ is the estimated front height; $a_0, a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, a_{10}, a_{11}, a_{12}, a_{13}, a_{14}$ and a_{15} are the estimated coefficients.

- Equation for front width:

$$\begin{aligned} Y2 = {} & b_0 + b_1X1 + b_2X2 + b_3X3 + b_4X4 + b_5X5 + b_6X12 \\ & + b_7X13 + b_8X14 + b_9X15 + b_{10}X23 + b_{11}X24 \\ & + b_{12}X25 + b_{13}X34 + b_{14}X35 + b_{15}X45 \end{aligned} \tag{3}$$

where $Y2$ is the estimated front width; $b_0, b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10}, b_{11}, b_{12}, b_{13}, b_{14}$ and b_{15} are the estimated coefficients.

- Equation for back height:

$$\begin{aligned} Y3 = {} & c_0 + c_1X1 + c_2X2 + c_3X3 + c_4X4 + c_5X5 + c_6X12 \\ & + c_7X13 + c_8X14 + c_9X15 + c_{10}X23 + c_{11}X24 \\ & + c_{12}X25 + c_{13}X34 + c_{14}X35 + c_{15}X45 \end{aligned} \tag{4}$$

where $Y3$ is the estimated back height; $c_0, c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{11}, c_{12}, c_{13}, c_{14}$ and c_{15} are the estimated coefficients.

- Equation for back width:

$$\begin{aligned} Y4 = {} & d_0 + d_1X1 + d_2X2 + d_3X3 + d_4X4 + d_5X5 + d_6X12 \\ & + d_7X13 + d_8X14 + d_9X15 + d_{10}X23 + d_{11}X24 \\ & + d_{12}X25 + d_{13}X34 + d_{14}X35 + d_{15}X45 \end{aligned} \tag{5}$$

where $Y4$ is the estimated back width; $d_0, d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10}, d_{11}, d_{12}, d_{13}, d_{14}$ and d_{15} are the estimated coefficients; and

$$\begin{aligned} & X12 = X1 * X2,\ \ X13 = X1 * X3,\ \ X14 = X1 * X4,\ \ X15 = X1 * X5, \\ & X23 = X2 * X3,\ \ X24 = X2 * X4,\ \ X25 = X2 * X5, \\ & X34 = X3 * X4,\ \ X35 = X3 * X5, \\ & X45 = X4 * X5 \end{aligned}$$

The estimated coefficients for Eqs. (2)–(5) are replaced in equations and the resulting equations are shown below (experimental variable terms were also substituted in to the equations by using the transforming equations 1 to change the standardized variables (X) to experimental variables (Y)):

- Front height:

$$\begin{aligned} \mathrm{FH} = {} & 1.6725 + 0.0349 * S + 0.6281 * \mathrm{WS} - 0.0030 * \mathrm{CP} \\ & - 0.0045 * C + 0.9648 * G - 0.0001 * S * \mathrm{WS} \\ & + 0.0001 * S * \mathrm{CP} + 0.0003 * S * C - 0.0175 * S * G \\ & - 0.0038 * \mathrm{WS} * \mathrm{CP} - 0.0084 * \mathrm{WS} * C + 0.1581 * \mathrm{WS} * G \\ & + 0.0002 * \mathrm{CP} * C - 0.0203 * \mathrm{CP} * G - 0.0061 * C * G \end{aligned} \tag{6}$$

- Front width:

$$\begin{aligned} \mathrm{FW} = {} & -4.4859 + 0.3281 * S - 0.4838 * \mathrm{WS} + 0.0371 * \mathrm{CP} \\ & + 0.1697 * C - 4.2402 * G - 0.0022 * S * \mathrm{WS} \\ & - 0.0004 * S * \mathrm{CP} - 0.0041 * S * C - 0.0250 * S * G \\ & - 0.0040 * \mathrm{WS} * \mathrm{CP} - 0.0182 * \mathrm{WS} * C + 0.8922 * \mathrm{WS} * G \\ & + 0.0003 * \mathrm{CP} * C - 0.0097 * \mathrm{CP} * G + 0.0437 * C * G \end{aligned} \tag{7}$$

- Back height:

$$\begin{aligned} \mathrm{BH} = {} & -0.1291 - 0.0288 * S + 0.7865 * \mathrm{WS} + 0.0099 * \mathrm{CP} \\ & + 0.0035 * C - 0.4348 * G - 0.0084 * S * \mathrm{WS} \\ & + 0.0001 * S * \mathrm{CP} + 0.0071 * S * G - 0.0002 * \mathrm{WS} * \mathrm{CP} \\ & + 0.0006 * \mathrm{WS} * C - 0.1291 * \mathrm{WS} * -0.0001 * \mathrm{CP} * C \\ & + 0.0012 * \mathrm{CP} * G + 0.0050 * C * G \end{aligned} \tag{8}$$

Table 7
Comparison of experimental and estimated results using two factor interaction effects regression equations of weld bead shape parameters for trials 1–16.

Front height, FH		Front width, FW		Back height, BH		Back width, BW	
Exptl.	Estimated	Exptl.	Estimated	Exptl.	Estimated	Exptl.	Estimated
0.027	0.027	6.411	6.411	0.412	0.412	5.197	5.197
0.357	0.357	4.982	4.982	0.001	0.001	2.255	2.255
0.155	0.155	6.676	6.676	0.743	0.743	5.960	5.960
0.487	0.487	4.992	4.992	0.139	0.139	1.600	1.600
−0.179	−0.179	7.432	7.432	0.593	0.593	7.058	7.058
−0.090	−0.090	4.423	4.423	0.420	0.420	3.172	3.172
−0.077	−0.077	7.460	7.460	0.820	0.820	7.809	7.809
0.380	0.380	5.231	5.231	0.397	0.397	2.817	2.817
−0.599	−0.599	11.348	11.348	0.805	0.805	11.679	11.679
−0.339	−0.339	7.335	7.335	0.619	0.619	7.520	7.520
−0.557	−0.557	12.348	12.348	1.139	1.139	12.403	12.403
−0.010	−0.010	6.396	6.396	0.536	0.536	6.197	6.197
−0.683	−0.683	12.946	12.946	0.945	0.945	13.921	13.921
0.249	0.249	7.719	7.719	0.492	0.492	7.706	7.706
−0.623	−0.623	11.767	11.767	1.128	1.128	12.860	12.860
−0.358	−0.358	7.759	7.759	0.798	0.798	7.917	7.917

- Back width:

$$
\begin{aligned}
\mathrm{BW} = & -7.7418 + 0.1081 * S + 2.0434 * \mathrm{WS} + 0.0420 * \mathrm{CP} \\
& + 0.1951 * C - 4.0279 * G - 0.0375 * S * \mathrm{WS} \\
& - 0.0007 * S * \mathrm{CP} - 0.0020 * S * C - 0.0077 * S * G \\
& + 0.0002 * \mathrm{WS} * \mathrm{CP} - 0.0163 * \mathrm{WS} * C + 0.2447 * \mathrm{WS} * G \\
& - 0.0003 * \mathrm{CP} * C + 0.0137 * \mathrm{CP} * G + 0.0378 * C * G \qquad (9)
\end{aligned}
$$

Using Eqs. (6)–(9), weld shape parameters were estimated. These results indicate that, the experimental and estimated values are found to be matching very closely as shown in Table 7.

These results are plotted and are depicted in Figs. 2–5. The results indicate that these regression equations can be used more effectively to predict the weld bead shape parameters viz., front height, front width, back height and back width.

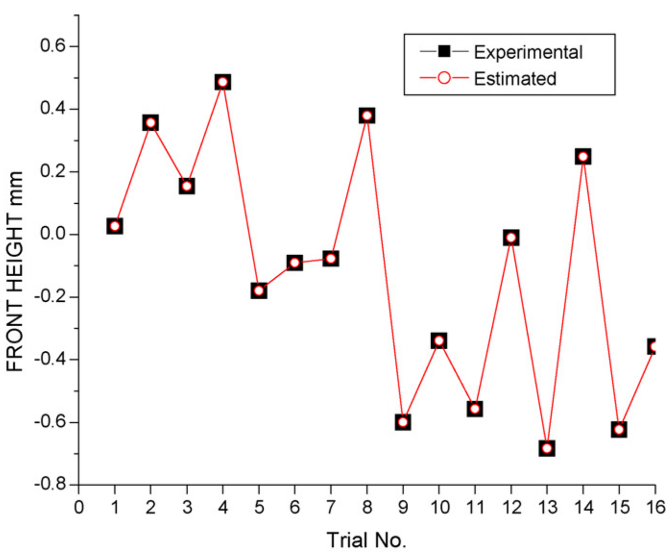

Fig. 2. Experimental and estimated values of front height.

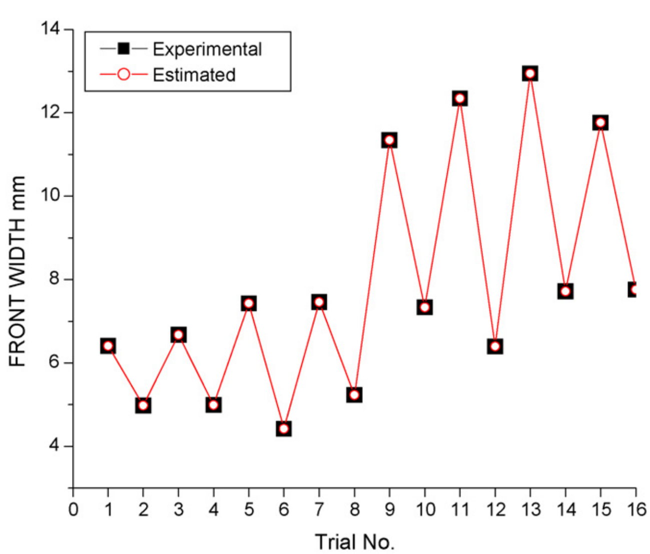

Fig. 3. Experimental and estimated values of front width.

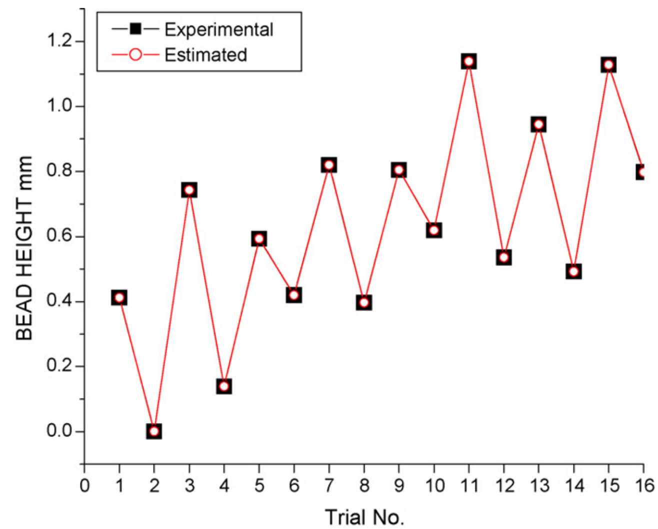

Fig. 4. Experimental and estimated values of back height.

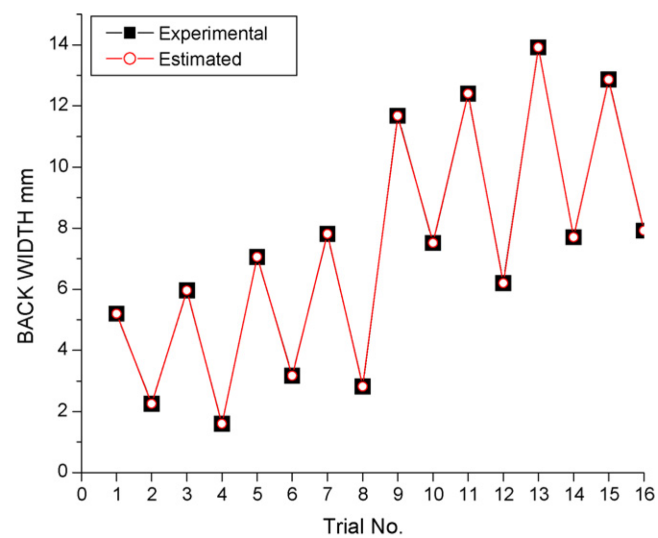

Fig. 5. Experimental and estimated values of back width.

4. Weld bead shape parameters prediction—ANN approach

The back-propagation neural network was used as basic structure for the application discussed here.

The performance of the artificial neural network depends on the number of hidden layers and number of neurones in the hidden layers. Therefore, many attempts need to be made in choosing the optimal structure for the neural network by changing the number of hidden layers as well as the number of neurones in each of these hidden layers. The appropriate neural network structure for predicting bead shape was chosen by trial-and-error method. In this study, the number of welding process variables were 5 and the output process parameters are the weld bead shape parameters, which are 4 in numbers. While deciding the neural network structure five neurones were selected for input layer and four neurones for output layer. The final structure of the neural network was 5–5–4–4 (five neurones in the *input layer*, five neurones in the 1st *hidden layer*, four neurones in the 2nd *hidden layer* and four neurones in the *output layer*). Learning rate was set at 0.02.

A multi layer back-propagation neural network consisting of *input layer*, *output layer* and 2 *hidden layers* used for predicting the weld bead shape parameters is as shown in Fig. 6. The input

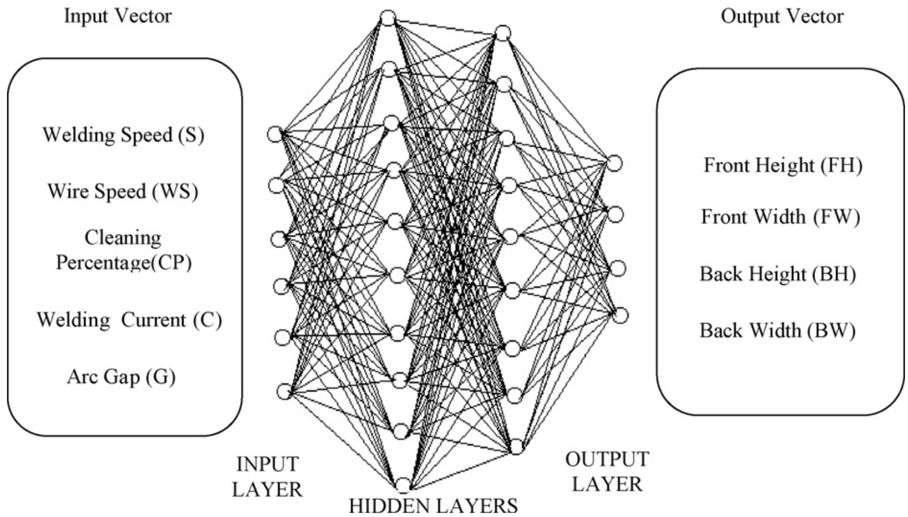

Fig. 6. Back-propagation neural network used for predicting bead shape parameter.

parameters to the network were welding speed (S), wire speed (WS), cleaning percentage (CP), welding current (C) and arc gap (G). The model outputs were weld bead shape parameters consisting of front height (FH), front width (FW), back height (BH) and back width (BW). The experimental data used to train the neural network were the same data which were used for developing regression equations, which are presented in Tables 4 and 5.

The neural network was trained for 11,000 iterations. Further training did not improve the modeling performance of the network. If the network is trained further, then with excessive training the neural network will be converged to memorization of the training data, rather than capturing the generalities of the process as stated in the previous chapters.

The predicted results of the neural network test are shown in Table 8. The experimental data reserved exclusively for testing are bold faced in the table. These test sets of data were not used while training the neural network. The errors in predicted values of bead shape parameters, occasionally exceeded 20% (5 out of 64 outputs i.e., about 7.8% of the total outputs), still the neural network was able to predict fairly accurately. With these results, we can safely conclude that the neural networks appear to constitute a workable model for predicting the weld bead shape parameters under given set of TIG welding conditions.

The predicted values of front height, front width, back height and back width of the weld joint using back-propagation neural networks along with the actual experimental values are shown in Figs. 7–10.

5. Optimization of tungsten inert gas welding process parameters—genetic algorithm approach

In this section of the present work genetic algorithms are used for optimizing the TIG welding process parameters with respect to desired front height to front width ratio (FH/FW) and back height to back width ratio (BH/BW) of the weld beads.

5.1. Program formulation and execution of genetic algorithms

In the present work, genetic algorithm is used to optimize the TIG welding process parameters for the set desired values of front height to front width ratio and back height to back width ratio of the weld beads obtained during TIG welding experiments listed in Table 4. Program formulation for this purpose had been made using various functions of the GA toolbox on MATLAB platform, so that the GA can generate a set of population, which can reproduce and cross among themselves to create a best possible solution in

Table 8
Comparison of experimental and neural network results of weld bead shape parameters for trials 1–16.

Front height, FH		Front width, FW		Back height, BH		Back width, BW	
Exptl.	Neural	Exptl.	Neural	Exptl.	Neural	Exptl.	Neural
0.027	0.0276	6.411	6.4525	0.412	0.4154	5.197	5.0637
0.357	0.3406	4.982	3.7486	0.001	0.0010	2.255	1.0933
0.155	0.1487	6.676	6.8041	0.743	0.7458	5.960	5.6813
0.487	0.4958	4.992	4.8854	0.139	0.1334	1.600	1.8834
−0.179	−0.1824	7.432	7.4967	0.593	0.5963	7.058	6.8780
−0.090	−0.0779	4.423	4.2696	0.420	0.4148	3.172	3.5529
−0.077	−0.2222	7.460	6.9799	0.820	0.9416	7.809	7.2538
0.380	0.3854	5.231	5.1709	0.397	0.3946	2.817	2.9661
−0.599	−0.6005	11.348	11.3479	0.805	0.8006	11.679	11.7494
−0.339	−0.3431	7.335	7.3922	0.619	0.6197	7.520	7.3832
−0.557	−0.5452	12.348	12.1331	1.139	1.1302	12.403	12.9215
−0.010	−0.0177	6.396	6.6017	0.536	0.5490	6.197	5.6351
−0.683	−0.6858	12.946	13.0110	0.945	0.9508	13.921	13.7316
0.249	−0.3679	7.719	8.0900	0.492	0.5585	7.706	7.9099
−0.623	−0.6218	11.767	11.7784	1.128	1.1300	12.860	12.8152
−0.358	−0.3566	7.759	7.7193	0.798	0.7935	7.917	8.0393

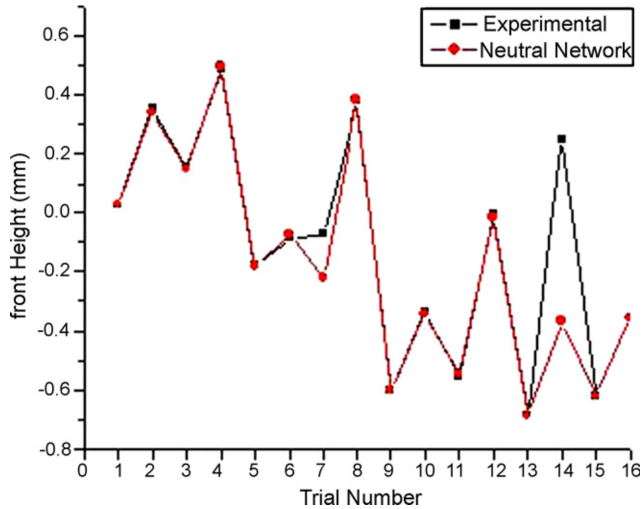

Fig. 7. Experimental and NN predicted values of front height.

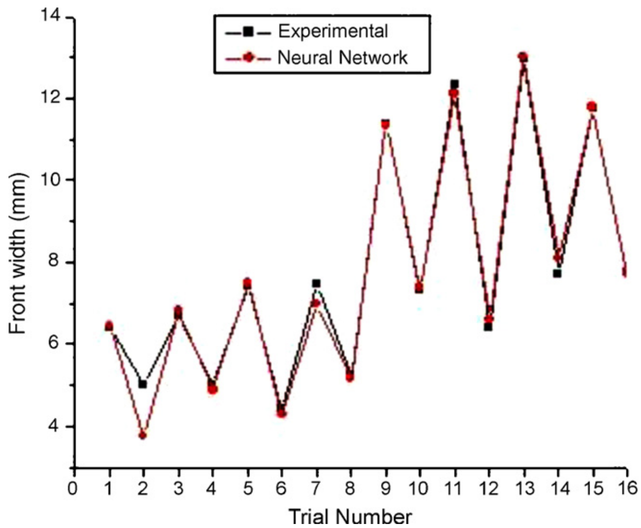

Fig. 8. Experimental and NN predicted values of front width.

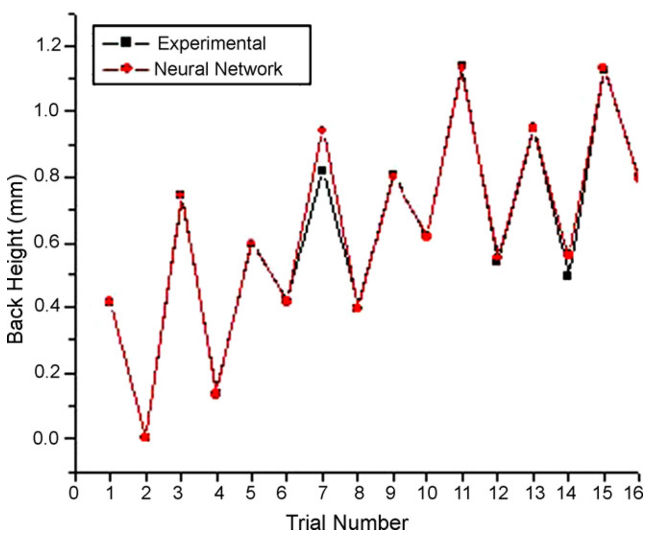

Fig. 9. Experimental and NN predicted values of back height.

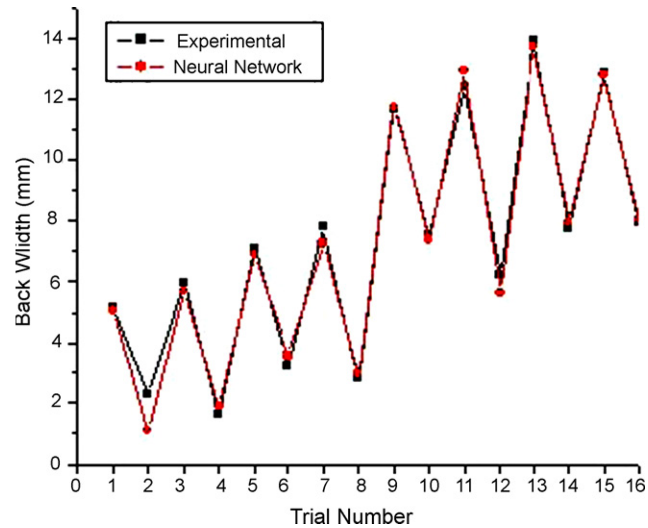

Fig. 10. Experimental and NN predicted values of back width.

a given number of generations. In the GA program for optimizing the process parameters of TIG welding process to get the desired values of front height to front width ratio and back height to back width ratio, the appropriate objective function has been defined. The type of genetic algorithm, the genetic algorithm parameters etc. had been set in the GA program. The program is executed after the program formulation is complete, to get the optimized process parameters for the desired height to width ratios of the bead shape parameters.

5.2. Optimization of process parameters for height to width ratios of weld bead shape parameters

The goal of this section is to obtain the optimized process parameters for the desired front height to front width ratio and back height to back width ratio using GA. The experimental conditions for this investigation are taken from Table 3 and the height to width ratios are calculated from the bead shape parameters and are presented in Table 9.

5.2.1. Defining the objective function, GA parameters for genetic algorithm

The equations obtained using regression analysis, considering the effects of main variables, were used for designing the objective function. The experimental data presented in Tables 3 and 9 were

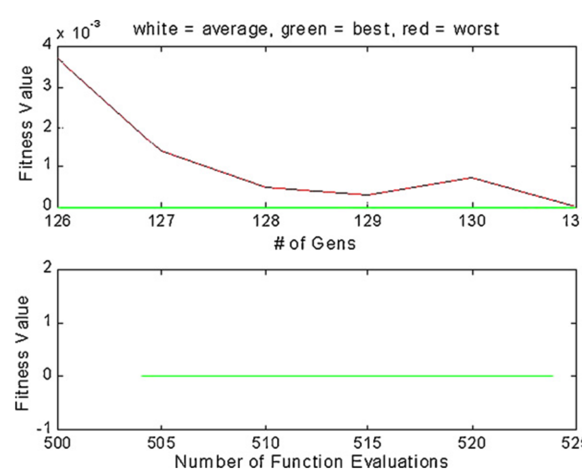

Fig. 11. Final phase plot of fitness value vs number of generations for FH/FW ratio.

Table 9
Front height to front width (FH/FW) and back height to back width (BH/BW) ratios for trials 1–16.

Trial no.	FH (mm)	FW (mm)	BH (mm)	BW (mm)	FH/FW ratio	BH/BW ratio
1	0.027	6.411	0.412	5.197	0.004212	0.079277
2	0.357	4.982	0.001	2.255	0.071658	0.000443
3	0.155	6.676	0.743	5.96	0.023217	0.124664
4	0.487	4.992	0.139	1.6	0.097556	0.086875
5	−0.179	7.432	0.593	7.058	−0.02409	0.084018
6	−0.09	4.423	0.42	3.172	−0.02035	0.132409
7	−0.077	7.46	0.82	7.809	−0.01032	0.105007
8	0.38	5.231	0.397	2.817	0.072644	0.14093
9	−0.599	11.348	0.805	11.679	−0.05278	0.068927
10	−0.339	7.335	0.619	7.52	−0.04622	0.082314
11	−0.557	12.348	1.139	12.403	−0.04511	0.091833
12	−0.01	6.396	0.536	6.197	−0.00156	0.086493
13	−0.683	12.946	0.945	13.921	−0.05276	0.067883
14	0.249	7.719	0.492	7.706	0.032258	0.063846
15	−0.623	11.767	1.128	12.86	−0.05294	0.087714
16	−0.358	7.759	0.798	7.917	−0.04614	0.100796

used for obtaining the mathematical model using regression analysis. For realizing the desired front height to front width ratio and back height to back width ratio, the objective functions were set to GA.

The experimental conditions presented in Table 3 are used to define the vector of minimum and maximum values of the controllable process variables and are shown below:

Vector of minimum values:

$$p\_\text{min} = \begin{bmatrix} 24 & 1.5 & 30 & 80 & 2.4 \end{bmatrix}$$

Vector of maximum values:

$$p\_\text{max} = \begin{bmatrix} 46 & 2.5 & 70 & 110 & 3.2 \end{bmatrix}$$

The genetic algorithm can choose the various process parameters used in the experimental work, to achieve the desired value of front height to front width ratio and back height to back width ratio from the vectors of minimum and maximum values. The desired values of front height to front width ratio and back height to back width ratio are set at 0.07 and 0.1 respectively for genetic algorithm to optimize the process parameters and are expressed as follows:

$$[\text{PI}] = pb1(X)$$

$$\text{er1} = (Y_\text{d} - Y)^2$$

$$\text{PI} = \text{er1}$$

where PI is the objective function (performance index); Y_d is the desired value of front height to front width ratio or, back height to back width ratio depending on the bead parameter ratio under study; Y is the estimated value of front height to front width ratio or, back height to back width ratio depending on the bead parameter ratio under study, using regression equations obtained for main variable effects. These equations are shown below:

$$Y(\text{FH/FW ratio}) = 0.188 + 0.002 * X1 + 0.016 * X2 - 4.771\text{E} - 4 * X3 - 0.002 * X4 - 0.029 * X5$$

$$Y(\text{BH/BW ratio}) = 0.006 - 9.011\text{E} - 5 * X1 + 0.031 * X2 + 0.001 * X3 - 4.281\text{E} - 4 * X4 + 0.014 * X5$$

where $X1$ is the welding speed (cm/min); $X2$ is the wire speed (cm/min); $X3$ is the cleaning percentage (%); $X4$ is the current (A); $X5$ is the arc gap (mm).

Several GA computational experimentations were conducted separately for front height to front width ratio and back height to back width ratio to arrive at the GA parameters, which can yield the desired set values of bead parameters ratio. After conducting these experimentations, the following lists of GA parameters were found to be able to optimize the process parameters:

GA parameters	
Type of GA	Regular GA
No. of generations for evolution	130
Population size	5
Type of selection	Tournament selection
Probability of cross over	0.95

The output of GA program executed after incorporating the above defined objective function, vectors of minimum and maximum values of process variables and the GA parameters are as follows:

- Front height to front width ratio:
  Desired value of front height to front width ratio set for GA: 0.07.

Output of GA program for front height to front width ratio

#of Gens = 2	Max = 0.0062958	Min = 0.0019669	Avg = 0.0037463
#of Gens = 3	Max = 0.0025664	Min = 0.0019669	Avg = 0.0022009
#of Gens = 4	Max = 0.0025856	Min = 0.0018174	Avg = 0.0020521
...	...	...	...
...	...	...	...
#of Gens = 129	Max = 0.00027204	Min = 8.2713E−013	Avg = 6.1851E−005
#of Gens = 130	Max = 0.0006958	Min = 8.2713E−013	Avg = 0.00013962
#of Gens = 131	Max = 2.1331E−006	Min = 8.2713E−013	Avg = 8.0467E−007

GA has optimized the welding parameters w.r.t. front height to front width ratio

Best possible front height to front width ratio is 0.0700
GA has also searched the five optimum input parameters which can yield the above best front height to front width ratio and the desired values in the remaining output parameters
Type "bp" and enter to obtain the above optimum input parameters
»bp
S = 44.3829 WS = 2.3504 CP = 30.0391 C = 80.2198 G = 2.4000

Table 10
Results of GA work.

	Desired Value	GA achieved value	GA optimized process parameters				
			S (cm/min)	WS (cm/min)	CP (%)	C (A)	G (mm)
FH/FW ratio	0.07	0.07	44.38	2.35	30.0	80.22	2.40
BH/BW ratio	0.1	0.1	27.89	2.22	31.1	100.81	2.85

The plot of fitness value v/s number of generations from the final phase of execution is shown in Fig. 11 for front height to front width ratio. The plot in Fig. 11 depicts that the genetic algorithm has searched the optimal TIG welding process parameters and was successful in arriving at the zero error between the desired and the achieved values in the fitness function in 130 generations.

Similarly in the case of back height to back width ratio also, the genetic algorithm was successful in arriving at the zero error between the desired and the achieved values in the fitness function. The GA program output for back height to back width ratio is as follows:

- Back height to back width ratio:
  Desired value of back height to back width ratio set for GA: 0.1.

Output of GA program for back height to back width ratio			
#of Gens = 2	Max = 0.00062913	Min = 2.0847E−006	Avg = 0.00018223
#of Gens = 3	Max = 2.5782E−005	Min = 1.6854E−007	Avg = 6.1471E−006
#of Gens = 4	Max = 1.1336E−005	Min = 9.561E−008	Avg = 4.6245E−006
...	...	...	...
...	...	...	...
#of Gens = 129	Max = 0.00084175	Min = 1.6636E−012	Avg = 0.00018587
#of Gens = 130	Max = 1.2618E−006	Min = 1.6636E−012	Avg = 3.0396E−007
#of Gens = 131	Max = 4.9593E−007	Min = 1.6636E−012	Avg = 1.649E−007

GA has optimized the welding parameters w.r.t. back height to back width ratio

Best possible back height to back width ratio is 0.1000
GA has also searched the five optimum input parameters which can yield the above best possible back height to back width ratio and the desired values in the remaining output parameters
Type "bp" and enter to obtain the above optimum input parameters
»bp
S = 27.8681 WS = 2.2165 CP = 31.0940 C = 100.8132 G = 2.8472

5.2.2. Results and discussions

TIG welding process parameters are optimized using GA, separately for front height to front width ratio and back height to back width ratio. Optimal process parameters were searched by the genetic algorithm to arrive at the desired front height to front width ratio and back height to back width ratio. The results of GA are summarized and shown in Table 10.

The results listed in the Table 10 indicate that all the five independent controllable process variables, which were optimized by the GA are having values between the vectors of minimum and maximum values of the controllable process variables. This is true for both the front height to front width ratio and back height to back width ratio cases. With these results, it is found that GA can be a powerful tool in experimental TIG welding optimization.

6. Conclusions

For estimating the bead shape parameters of tungsten inert gas (TIG) welding process, mathematical models were developed using regression analysis for front height, front width, back height and back width based on TIG welding process variables like welding speed, wire speed, cleaning percentage, welding current and arc gap. A two level fractional factorial design and multiple linear regression technique applied on the conventional experimental data have yielded reasonably accurate results. Multiple linear regression equations developed by considering both main and interaction effects are able to predict the weld bead shape parameters.

Modeling of the weld bead shape parameters of tungsten inert gas welding process was tried using a back-propagation neural network. A neural network with 5–5–4–4 architecture was able to predict the TIG welding bead shape parameters with reasonable accuracy. The analysis carried out for this confirms that artificial neural networks are powerful tools for analysis and modeling of TIG welding process.

Optimization of process parameters using GA for front height to front width ratio and back height to back width ratio yielded satisfactory results and it is felt that GA can be effectively used to determine input process parameters to get desired bead shape parameter ratio.

The proposed methods could be effectively used in determining the weld bead geometric descriptors for tungsten inert gas welding process.

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