

Estimation Of Optimum Dilution In The GMAW Process Using Integrated ANN-SA

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Abstract

To improve the corrosion resistant properties of carbon steel usually cladding process is used. It is a process of depositing a thick layer of corrosion resistant material over carbon steel plate. Most of the engineering applications require high strength and corrosion resistant materials for long term reliability and performance. By cladding these properties can be achieved with minimum cost. The main problem faced on cladding is the selection of optimum combinations of process parameters for achieving quality clad and hence good clad bead geometry.

This paper highlights an experimental study to optimize various input process parameters (welding current, welding speed, gun angle, contact tip to work distance and pinch) to get optimum dilution in stainless steel cladding of low carbon structural steel plates using Gas Metal Arc Welding (GMAW). Experiments were conducted based on central composite rotatable design with full replication technique and mathematical models were developed using multiple regression method. The developed models have been checked for adequacy and significance. In this study, Artificial Neural Network (ANN) and Simulated Annealing Algorithm (SA) techniques were integrated labels as integrated ANN-SA to estimate optimal process parameters in GMAW to get optimum dilution.

Key words: Mathematical model, cladding, GMAW, ANN, Clad bead geometry, corrosion, SA.

I. Introduction

Prevention of corrosion is a major problem in Industries. Even though it cannot be eliminated completely it can be reduced to some extent. A corrosion resistant protective layer is made over the less corrosion resistant substrate by a process called cladding. This technique is used to improve life of engineering components but also reduce their cost. This process is mainly now used in industries such as chemical, textiles, nuclear, steam power plants, food processing and petro chemical industries [1].

Most accepted method of employed in weld cladding is GMAW. It has got the following advantages [2].

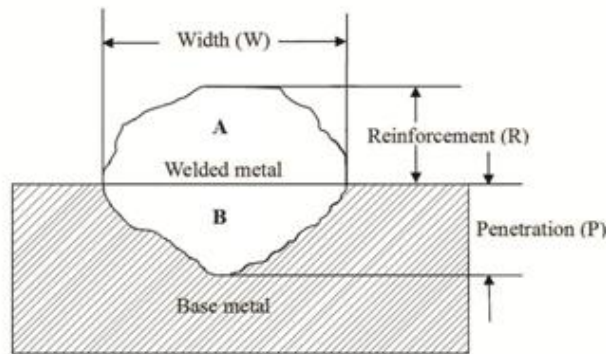
- High reliability
- All position capability
- Ease to use
- Low cost
- High Productivity
- Suitable for both ferrous and non ferrous metals
- High deposition rate
- Cleanliness and ease of mechanization

The mechanical strength of clad metal is highly influenced by the composition of metal but also by clad bead shape. This is an indication of bead geometry. Fig 1 shows the clad bead geometry. It mainly depends on welding current; welding speed, arc voltage etc. Therefore it is necessary to study the relationship between the process parameters and bead parameters to study clad bead geometry. Using mathematical models it can be achieved. This paper highlights the study carried out to develop mathematical and ANN-SA models to optimize clad bead geometry, in stainless steel cladding deposited by GMAW. The experiments were conducted based on four factor five level central composite rotatable designs with full replication technique [3]. The developed models have been checked for their adequacy and significance. Again using ANN-SA, the bead parameters were optimized to get optimum dilution.

Welding process is a very complex one. And this does not permit pure analytical and physical modelling. Basically models can be divided into three categories that are experimental models, analytical models and artificial intelligent models. Experimental and analytical models can be developed by conventional techniques such as multiple regression analysis. The artificial intelligent models can be developed by artificial neural

network, genetic algorithm fuzzy logic and simulated annealing algorithm. The abilities of ANN include that ANN can handle a nonlinear form of modelling that learns the mapping of inputs to outputs, in terms of speed, simplicity ANN is more successful, ANN models does not need any preliminary assumptions as to underlying mechanisms in the modelled process and there exists ANN tool box in MATLAB which makes the process simple.

Generally modelling is a process of establishing the minimum potential value of welding process while optimization is the process of establishing the potential minimum value of welding performance at optimal point of process parameters. There are some established techniques such as Genetic algorithm (GA), simulated annealing algorithm (SA). Tabu search (TS), and particle swarm optimization technique (PSO). One of the alternative in optimizing weld bead geometry is the use of Simulated annealing algorithm (SA). It is because SA program is easy and typically takes only few hundred lines of computer code, SA algorithm can be used to determine the global minimum more efficiently instead of tapping in a local minimum where objective function has surrounding boundaries and Sa search is independent of initial conditions. The integration system is a combination of two or more techniques with the target to obtain a more successful result. ANN technique and PSO optimization techniques were integrated in determining the optimum solution in conventional machining for pocket –milling and ball end milling process (EI-Mounayri, Kishawy & Briceño 2005). In this study an integration system is taken up to observe the possible improvement in the result that may be obtained particularly for GMAW process. With integrated ANN-SA it is expected that it can produce more significant result for dilution compared to the experimental, regression modelling and ANN single based modelling results.



$$\text{Percentage dilution (D)} = [B / (A+B)] \times 100$$

Fig 1. Clad bead geometry

II. Experimental Procedure

The following machines and consumables were used for the purpose of conducting experiment.

- 1) A constant current gas metal arc welding machine (Invtree V 350 – PRO advanced processor with 5 – 425 amps output range)
- 2) Welding manipulator
- 3) Wire feeder (LF – 74 Model)
- 4) Filler material Stainless Steel wire of 1.2mm diameter (ER – 308 L).
- 5) Gas cylinder containing a mixture of 98% argon and 2% oxygen.
- 6) Mild steel plate (grade IS – 2062)

Test plates of size 300 x 200 x 20mm were cut from mild steel plate of grade IS – 2062 and one of the surfaces is cleaned to remove oxide and dirt before cladding. ER-308 L stainless steel wire of 1.2mm diameter was used for depositing the clad beads through the feeder. Argon gas at a constant flow rate of 16 litres per minute was used for shielding. The properties of base metal and filler wire are shown in Table 1.

The selection of the welding electrode wire based on the matching the mechanical properties and physical characteristics of the base metal and weld size [4]. A candidate material for cladding which has excellent corrosion resistance and weldability is stainless steel. These have chloride stress corrosion cracking resistance and strength significantly greater than other materials. These have good surface appearance, good radiographic standard quality and minimum electrode wastage.

Table 1. Chemical Composition of Base Metal and Filler Wire

Materials	Elements wt %								
	C	SI	Mn	P	S	Al	Cr	Mo	Ni
IS 2062	0.150	0.160	0.870	0.015	0.016	0.031	-	-	-
ER 308L	0.03	0.57	1.76	0.021	0.008	-	19.52	0.75	10.02

III. Plan of Investigation

The research work was planned to be carried out in the following steps [5].

- 1) Identification of factors and responses.
- 2) Finding limits of process variables.
- 3) Development of design matrix.
- 4) Conducting experiments as per design matrix.
- 5) Recording the responses.
- 6) Development of mathematical models.
- 7) Checking the adequacy of developed models.
- 8) Conducting conformity tests.

3.1 Identification of factors and responses

The following independently controllable process parameters were found to be affecting output parameters. These are wire feed rate (W), welding speed (S), welding gun angle (T), contact tip to work to distance (N) and pinch (Ac), The responses chosen were clad bead width (W), height of reinforcement (R), Depth of Penetration. (P) and percentage of dilution (D). The responses were chosen based on the impact of parameters on final composite model.

The basic difference between welding and cladding is the percentage of dilution. The properties of the cladding are significantly influenced by dilution obtained. Hence control of dilution is important in cladding where a low dilution is highly desirable. When dilution is quite low, the final deposit composition will be closer to that of filler material and hence corrosion resistant properties of cladding will be greatly improved. The chosen factors have been selected on the basis to get minimal dilution and optimal clad bead geometry. Few significant research works have been conducted in these areas using these process parameters and so these parameters were used for experimental study.

3.2 Finding the limits of process variables

Working ranges of all selected factors are fixed by conducting trial runs. This was carried out by varying one of factors while keeping the rest of them as constant values. Working range of each process parameters was decided upon by inspecting the bead for smooth appearance without any visible defects. The upper limit of given factor was coded as -2. The coded value of intermediate values were calculated using the equation (2)

$$X_i = \frac{2[2X - (X_{max} + X_{min})]}{(X_{max} - X_{min})} \quad \text{----- (2)}$$

Where X_i is the required coded value of parameter X is any value of parameter from X_{min} - X_{max} . X_{min} is the lower limit of parameters and X_{max} is the upper limit parameters [4].

The chosen level of the parameters with their units and notation are given in Table 2.

Table 2. Welding Parameters and their Levels

Parameters	Unit	Notation	Factor Levels				
			-2	-1	0	1	2
Welding Current	A	I	200	225	250	275	300
Welding Speed	mm/min	S	150	158	166	174	182
Contact tip to work distance	mm	N	10	14	18	22	26
Welding gun Angle	Degree	T	70	80	90	100	110
Pinch	-	Ac	-10	-5	0	5	10

3.3 Development of design matrix

Design matrix chosen to conduct the experiments was central composite rotatable design. The design matrix comprises of full replication of $2^5 (= 32)$, Factorial designs. All welding parameters in the intermediate levels (0) constitute the central points and combination of each welding parameters at either is highest value (+2) or lowest (-2) with other parameters of intermediate levels (0) constitute star points. 32 experimental trails were conducted that make the estimation of linear quadratic and two way interactive effects of process parameters on clad geometry [5].

Table 3. Design Matrix

Trial Number	Design Matrix				
	I	S	N	T	Ac
1	-1	-1	-1	-1	1
2	1	-1	-1	-1	-1
3	-1	1	-1	-1	-1
4	1	1	-1	-1	1
5	-1	-1	1	-1	-1
6	1	-1	1	-1	1
7	-1	1	1	-1	1
8	1	1	1	-1	-1
9	-1	-1	-1	1	-1
10	1	-1	-1	1	1
11	-1	1	-1	1	1
12	1	1	-1	1	-1
13	-1	-1	1	1	1
14	1	-1	1	1	-1
15	-1	1	1	1	-1
16	1	1	1	1	1
17	-2	0	0	0	0
18	2	0	0	0	0
19	0	-2	0	0	0
20	0	2	0	0	0
21	0	0	-2	0	0
22	0	0	2	0	0
23	0	0	0	-2	0
24	0	0	0	2	0
25	0	0	0	0	-2
26	0	0	0	0	2
27	0	0	0	0	0
28	0	0	0	0	0
29	0	0	0	0	0
30	0	0	0	0	0
31	0	0	0	0	0
32	0	0	0	0	0

I - Welding current; S - Welding speed; N - Contact tip to work distance; T - Welding gun angle; Ac - Pinch

3.4 Conducting experiments as per design matrix

The experiments were conducted at SVS College of Engineering, Coimbatore, India. In this work thirty two experimental run were allowed for the estimation of linear quadratic and two-way interactive effects of corresponding each treatment combination of parameters on bead geometry as shown Table 3 at random. At each run settings for all parameters were disturbed and reset for next deposit. This is very essential to introduce variability caused by errors in experimental set up.

3.5 Recording of Responses

In order to measure clad bead geometry of transverse section of each weld overlays were cut using band saw from mid length. Position of the weld and end faces were machined and grinded. The specimen and faces were polished and etched using a 5% nital solution to display bead dimensions. The clad bead profiles were traced using a reflective type optical profile projector at a magnification of X10, in M/s Roots Industries Ltd. Coimbatore. Then the bead dimension such as depth of penetration height of reinforcement and clad bead width were measured [6]. The traced bead profiles were scanned in order to find various clad parameters and the percentage of dilution with help of AUTO CAD software. This is shown in Fig 4.

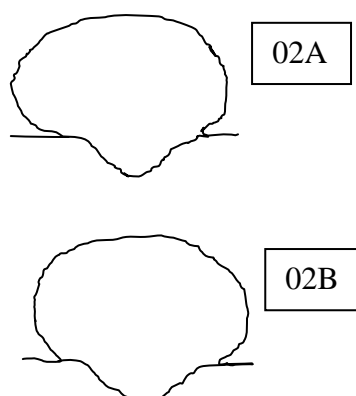


Fig. 4 Traced Profiles (Specimen No.2)

02A represents profile of the specimen (front side) and 02B represents profile of the specimen (rear side). The measured clad bead dimension and percentage of dilution is shown in Table 4.

Table 4 Design Matrix and Observed Values of Clad Bead Geometry

Trial No.	Design Matrix					Bead Parameters			
	I	S	N	T	Ac	W (mm)	P (mm)	R (mm)	D (%)
1	-1	-1	-1	-1	1	6.9743	1.67345	6.0262	10.72091
2	1	-1	-1	-1	-1	7.6549	1.9715	5.88735	12.16746
3	-1	1	-1	-1	-1	6.3456	1.6986	5.4519	12.74552
4	1	1	-1	-1	1	7.7635	1.739615	6.0684	10.61078
5	-1	-1	1	-1	-1	7.2683	2.443	5.72055	16.67303
6	1	-1	1	-1	1	9.4383	2.4905	5.9169	15.96692
7	-1	1	1	-1	-1	6.0823	2.4672	5.49205	16.5894
8	1	1	1	-1	-1	8.4666	2.07365	5.9467	14.98494
9	-1	-1	-1	1	-1	6.3029	1.5809	5.9059	10.2749
10	1	-1	-1	1	1	7.0136	1.5662	5.9833	9.707297
11	-1	1	-1	1	1	6.2956	1.58605	5.5105	11.11693
12	1	1	-1	1	-1	7.741	1.8466	5.8752	11.4273
13	-1	-1	1	1	1	7.3231	2.16475	5.72095	15.29097

14	1	-1	1	1	-1	9.6171	2.69495	6.37445	18.54077
15	-1	1	1	1	-1	6.6335	2.3089	5.554	17.23138
16	1	1	1	1	1	10.514	2.7298	5.4645	20.8755
17	-2	0	0	0	0	6.5557	1.99045	5.80585	13.65762
18	2	0	0	0	0	7.4772	2.5737	6.65505	15.74121
19	0	-2	0	0	0	7.5886	2.50455	6.4069	15.77816
20	0	2	0	0	0	7.5014	2.1842	5.6782	16.82349
21	0	0	-2	0	0	6.1421	1.3752	6.0976	8.941799
22	0	0	2	0	0	8.5647	3.18536	5.63655	22.94721
23	0	0	0	-2	0	7.9575	2.2018	5.8281	15.74941
24	0	0	0	2	0	7.7085	1.85885	6.07515	13.27285
25	0	0	0	0	-2	7.8365	2.3577	5.74915	16.63287
26	0	0	0	0	2	8.2082	2.3658	5.99005	16.38043
27	0	0	0	0	0	7.9371	2.1362	6.0153	15.18374
28	0	0	0	0	0	8.4371	2.17145	5.69895	14.82758
29	0	0	0	0	0	9.323	3.1425	5.57595	22.8432
30	0	0	0	0	0	9.2205	3.2872	5.61485	23.6334
31	0	0	0	0	0	10.059	2.86605	5.62095	21.55264
32.	0	0	0	0	0	8.9953	2.72068	5.7052	19.60811

W - Width; P - Penetration; R - Reinforcement; D - Dilution %

3.6 Development of Mathematical Models

The response function representing any of the clad bead geometry can be expressed as [7, 8, 9],

$$Y = f(A, B, C, D, E) \text{-----} (3)$$

Where, Y = Response variable

- A = Welding current (I) in amps
- B = Welding speed (S) in mm/min
- C = Contact tip to Work distance (N) in mm
- D = Welding gun angle (T) in degrees
- E = Pinch (Ac)

The second order surface response model equation can be expressed as below

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 D + \beta_5 E + \beta_{11} A^2 + \beta_{22} B^2 + \beta_{33} C^2 + \beta_{44} D^2 + \beta_{55} E^2 + \beta_{12} AB + \beta_{13} AC + \beta_{14} AD + \beta_{15} AE + \beta_{23} BC + \beta_{24} BD + \beta_{25} BE + \beta_{34} CD + \beta_{35} CE + \beta_{45} DE \text{-----} (4)$$

Where, β_0 is the free term of the regression equation, the coefficient $\beta_1, \beta_2, \beta_3, \beta_4$ and β_5 is are linear terms, the coefficients $\beta_{11}, \beta_{22}, \beta_{33}, \beta_{44}$ and β_{55} quadratic terms, and the coefficients $\beta_{12}, \beta_{13}, \beta_{14}, \beta_{15}$, etc are the interaction terms. The coefficients were calculated by using MINITAB 15. After determining the coefficients, the mathematical models were developed. The developed mathematical models are given as follows.

$$\text{Clad Bead Width (W), mm} = 8.923 + 0.701A + 0.388B + 0.587C + 0.040D + 0.088E - 0.423A^2 - 0.291B^2 - 0.338C^2 - 0.219D^2 - 0.171E^2 + 0.205AB + 0.405AC + 0.105AD + 0.070AE - 0.134BC + 0.225BD + 0.098BE + 0.26 CD + 0.086 CE + 0.012 DE \text{-----} (5)$$

$$\text{Depth of Penetration (P), mm} = 2.735 + 0.098A - 0.032B + 0.389C - 0.032D - 0.008E - 0.124A^2 - 0.109B^2 - 0.125C^2 - 0.187D^2 - 0.104E^2 - 0.33AB + 0.001 AC + 0.075AD + 0.005 AE - 0.018BC + 0.066BD + 0.087BE + 0.058CD + 0.054CE - 0.036DE \quad \text{----- (6)}$$

$$\text{Height of Reinforcement (R), mm} = 5.752 + 0.160A - 0.151B - 0.060C + 0.016D - 0.002E + 0.084A^2 + 0.037B^2 - 0.0006C^2 + 0.015D^2 - 0.006E^2 + 0.035AB + 0.018AC - 0.008AD - 0.048AE - 0.024BC - 0.062BD - 0.003BE + 0.012CD - 0.092CE - 0.095DE \quad \text{----- (7)}$$

$$\text{Percentage Dilution (D), \%} = 19.705 + 0.325A + 0.347B + 3.141C - 0.039D - 0.153E - 1.324A^2 - 0.923B^2 - 1.012C^2 - 1.371D^2 - 0.872E^2 - 0.200AB + 0.346 AC + 0.602 AD + 0.203 AE + 0.011BC + 0.465BD + 0.548 BE + 0.715 CD + 0.360CE + 0.137 DE \quad \text{----- (8)}$$

3.7 Checking the adequacy of the developed models

The adequacy of the developed model was tested using the analysis of variance (ANOVA) technique. As per this technique, if the F – ratio values of the developed models do not exceed the standard tabulated values for a desired level of confidence (95%) and the calculated R – ratio values of the developed model exceed the standard values for a desired level of confidence (95%) then the models are said to be adequate within the confidence limit [10]. These conditions were satisfied for the developed models. Values are shown in Table 5.

Table 5 Analysis of variance for Testing Adequacy of the Model

Parameter	1 st Order terms		2 nd order terms		Lack of fit		Error terms		F-ratio	R-ratio	Whether model is adequate
	SS	DF	SS	DF	SS	DF	SS	DF			
W	36.889	20	6.233	11	3.513	6	2.721	5	1.076	3.390	Adequate
P	7.810	20	0.404	11	0.142	6	0.261	5	0.454	7.472	Adequate
R	1.921	20	0.572	11	0.444	6	0.128	5	2.885	3.747	Adequate
D	506.074	20	21.739	11	6.289	6	15.45	5	0.339	8.189	Adequate

SS - Sum of squares; DF - Degree of freedom; F Ratio (6, 5, 0.5) = 3.40451; R Ratio (20, 5, 0.05) = 3.20665

IV. Artificial neural network modelling.

To develop ANN model for predicting the bead geometry a net work structure is illustrated as shown in Fig6.

MAT LAB 7 was used for tracing the network for the prediction of clad bead geometry. Statistical mathematical model was used compare results produced by the work. For normalizing the data, the goal is to examine the statistical distribution of values of each net input and outputs are roughly uniform in addition the value should scaled to match range of input neurons [16].

This is basically range 0 to 1 in practice it is found to between 0.1 and 0.9 [17]. In this paper data base are normalized using the Equation (9)

$$X_{norm} = 0.1 + \frac{(X - X_{min})}{1.25 (X_{max} - X_{min})} \quad \text{----- (9)}$$

X_{norm} = Normalized value between 0 and 1

X = Value to be normalized

X_{min} = Minimum value in the data set range the particular data set rage which is to be normalized.

X_{max} = Maximum value in the particular data set range which is to be normalized.

In this study five welding process parameters were employed as input to the network. The Levenberg-Marquardt approximation algorithm was found to be the best fit for application because it can reduce the MSE to a significantly small value and can provide better accuracy of prediction. So neural network model with feed forward back propagation algorithm and Levenberg-Marqudt approximation algorithm was trained with data collected for the experiment. Error was calculated using the equation (10).

$$\text{Error} = \frac{(\text{Actual value} - \text{Predicted value}) \times 100}{\text{Predicted value}} \quad \text{----- (10)}$$

The difficulty using the regression equation is the possibility of over fitting the data. To avoid this, the experimental data is divided in to two sets; one training set and other test data set .The ANN model is created using only training data the other test data is used to check the behavior the ANN model created. All variables are normalized using the equation (9).The data was randomized and portioned in to two one training and other test data.

$$y = \sum_i w_{ij} h_i + \theta \quad \dots\dots\dots (11)$$

$$h_i = \tanh (\sum_j w_{ij} x_j + \theta_i) \quad \dots\dots\dots (12)$$

Neural Network general form can be defined as a model shown above y representing the output variables and x_j the set of inputs, shown in equation [11, 12]. The subscript i represent the hidden units shown in Fig 6 and θ represents bias and w_j represents the weights. The above equation defines the function giving output as a function of input.

The training process involves the derivation of weights by minimization of the regularized sum of squared error.

The complexity of model is controlled by the number of hidden level values of regularization constants and is associated with each input one for biases and one for all weights connected to output.

4.1 Procedure for prediction

The effectiveness of ANN model is fully depends on the trial and error process. This study considers the factors that could be influencing the effectiveness of the model developed. In the MATLAB 7 tool there are five Influencing factors listed below.

1. Network algorithm.
2. Transfer function.
3. Training function.
4. Learning function.
5. Performance function.

The ANN structure consists of three layers which are input, hidden, output layer. It is known that ANN model is designed on trial and error basis. The trial and error is carried out by adjusting the number of layers and the number of neurons in the hidden structure. Too many neurons in hidden layer results a waste of computer memory and computation time, while too few neurons, may not provide desired data control effect. The process is conducted using 28 randomly selected samples. Seventeen data are used for training and eleven used for test the data. Table 4 shows randomized data with 1-11 for test data and 12-28 for training data.

It is suggested that following guide lines should be followed for selecting training and testing of data such as 90%:10%, 85%:15% and 80%:20% with a total of the 100% combined ratio. To fit the randomized sample of 28; preferred ratio selected is 70%:30%.

1. $(70/100) \times 28 = 19-20$ Training samples.
2. $(30/100) \times 28 = 8-9$ data testing samples.

It is necessary to normalize the quantitative variable to some standard range from 0-1. The number of neurons hidden layers should be approximately equal to $n/2$, n , $2n$ and $2n+1$ where n is the number of input neurons. Many different ANN network algorithms have been proposed by researchers but back propagation (BP) algorithm has found to be the best for prediction .Researchers developed the model by using feed forward BP and radial basis network algorithm and it were found that feed forward BP gives more accurate results. Basically a feed forward network based on BP is a multilayered architecture made up of one or more hidden layers placed between input and output layers, Shown in Fig 6.Transfer function, training function, learning function and performance function used in this study are logsig, traindgm, traingdx and MSE.

4.2 Determination of the best ANN model

In order to determine the best network structure of ANN prediction model the randomized data set is divided into two sets one training data set which is used for the prediction of the model, and the other test data which issued to validate the model. Seventeen data used for training set and eleven data for test set .This to avoid the over fitting of the data. An ANN model is created and trained using MATLAB 7 ANN tool box .The lowest MSE obtained is for twelve hidden neurons .So network structure 5-12-4, five input neurons, twelve hidden neurons and four output neurons. Then the test data is validated against the ANN model created, the results are shown in Table 6.Training data is shown in Table 7.

Table.6. Comparison of actual and predicted values of the clad bead parameters using neural network data (test)

Trial No.	Actual Bead Parameters				Predicted Bead Parameters				Error			
	W (mm)	P (mm)	R (mm)	D (%)	W (mm)	P (mm)	R (mm)	D (%)	W (mm)	P (mm)	R (mm)	D (%)
1	6.974	1.673	6.026	10.72	6.194		5.961	12.36	0.779	-	0.065	-
2	3	5	2	1	5	1.85	1	7	8	0.177	1	1.646
3	7.654	1.971	5.887	12.16	7.181	2.150	6.555	10.26	0.473	-	-	-
4	9	5	3	7	5	7	3	8	4	0.179	0.668	1.899
5	6.345	1.698	5.451	12.74	7.495	1.533	5.492	9.380		0.164		3.365
6	6	6	9	6	4	9	3	8	-1.15	7	-0.04	2
7	7.763	1.739	6.068	10.61	6.493		6.557	9.479	1.269	-	-	1.131
8	5	6	4	1	6	1.854	3	9	9	0.114	0.489	1
9	7.268		5.720	16.67	7.335	2.657	5.565	19.10	-	-	0.154	-
10	3	2.443	6	3	4	6	7	4	0.067	0.215	9	2.431
11	9.438	2.490	5.916	15.96	7.606	2.104	6.434		1.831		-	-
12	3	5	9	7	6	5	2	18.49	7	0.386	0.517	2.523
13	6.082	2.467		16.58	8.041	2.172	5.512	16.87	-		-	-
14	3	2	5.492	9	7	2	6	4	1.959	0.295	0.021	0.285
15	8.466	2.073	5.946	14.98	8.323	2.234	5.903	16.97		-	0.043	-
16	6	7	7	5	6	9	1	2	0.143	0.161	6	1.987
17	6.302	1.580	5.905	10.27	8.238	1.795	5.602	11.21	-	-	0.303	-
18	9	9	9	5	1	5	2	9	1.935	0.215	7	0.944
19	7.013	1.566	5.983	9.707	7.589	2.457		13.41	-	-	-	-
20	6	2	3	3	9	9	6.542	5	0.576	0.892	0.559	3.708
21	6.295		5.510	11.11	7.731	1.764	5.867		-	-	-	-
22	6	1.586	5	7	8	7	6	10.71	1.436	0.179	0.357	0.407

Table.7. Comparison of actual and predicted values of the clad bead parameters using neural network data (training)

Trial NO.	Actual Bead Parameters				Predicted Bead Parameters				Error			
	W (mm)	P (mm)	R (mm)	D (%)	W (mm)	P (mm)	R (mm)	D (%)	W (mm)	P (mm)	R (mm)	D (%)
1	7.741	1.846	5.875	11.427	7.335	2.098	6.079	10.82	0.406	-0.252	-0.204	0.605
2	6	2	3	7.335	6	2	22	0.406	-0.252	-0.204	1	0.605
3	7.323	2.164	5.720	15.290	6.821	2.061	5.694	14.93	0.501	0.103	0.026	0.353
4	1	75	95	97	4	7	6	79	7	05	35	07
5	9.617	2.694	6.374	18.540	9.371	2.898	6.408	17.45	0.245	0.203	-	1.082
6	1	95	45	77	3	2	4	78	8	25	0.033	97
7	6.633	2.308	5.554	17.231	7.430	2.292	5.623	15.79	-	0.016	-	1.440
8	5	9		38	6	7	2	08	0.797	2	0.069	58
9	10.51	2.729	5.464	20.875	7.899	2.515	5.807	18.06	2.614	0.214	-	2.809
10	4	8	5	5	1	4	8	64	9	4	0.343	1
11	6.555	1.990	5.805	13.657	6.576	1.915	5.786	14.20	-	0.074	0.019	-
12	7	45	85	62	1	8	7	39	0.020	65	15	0.546
13	7.477	2.573	6.655	15.741	7.393	2.719	6.711	14.75	0.084	-	-	0.988
14	2	7	05	21		1	2	25	2	0.145	0.056	71
15	7.588	2.504	6.406	15.778	7.594	2.431	6.383	15.98	-	0.072	0.023	-
16	6	55	9	16	3	7	4	81	0.005	85	5	0.209
17	7.501	2.184	5.678	16.823	7.465	2.281	5.767	16.57	-	-	-	0.249
18	4	2	2	49	2	4	4	44	0.036	0.097	0.089	09

10	6.142 1	1.375 2	6.097 6	8.9417 99	5.658 3	1.44	6.205 4	9.375 3	0.483 8	- 0.064 8	- 0.107 8	- 0.433 5
11	8.564 7	3.185 36	5.636 55	22.947 21	9.972 4	2.962	5.522 7	18.95 66	- 1.407 7	0.223 36	0.113 85	3.990 61
12	7.957 5	2.201 8	5.828 1	15.749 41	9.069 3	2.691 9	6.233 7	17.55 48	- 1.111 8	- 0.490 1	- 0.405 6	- 1.805 3
13	7.708 5	1.858 85	6.075 15	13.272 85	6.769 9	1.780 7	6.109	12.85 84	0.938 6	0.078 15	- 0.033 8	0.414 45
14	7.836 5	2.357 7	5.749 15	16.632 87	8.536 4	2.943 1	6.673 5	15.96 53	- 0.699 9	- 0.585 4	- 0.924 3	0.667 57
15	8.208 2	2.365 8	5.990 05	16.380 43	8.008 3	2.371	6.018 6	16.37 01	0.199 9	- 0.005 2	- 0.028 5	0.010 33
16	7.937 1	2.136 2	6.015 3	15.183 74	7.944 1	2.119 7	6.01	15.37 35	- 0.007	0.016 5	0.005 3	- 0.189 7
17	8.473 1	2.171 45	5.698 95	14.827 58	8.673 5	2.516 5	5.498 5	15.28 75	- 0.200 1	- 0.345 0	0.203 1	- 0.459 9

V. SIMULATED ANNEALING ALGORITHM OPTIMIZATION

Simulated annealing is a random search technique that able to escape local optima using a probability function (Kirkpatrick,Gelatte,&Vecchi 1983).Based on the iterative improvement ,the SA algorithm is A heuristic method with basic idea of generating random displacement from any feasible solution. This process accepts not only the generated solutions which improve the fitness function but also those which do not improve it with probability function; a parameter depending upon the fitness function.

SA is a method for solving unconstrained and bound-constrained optimization problems. It models the physical process of heating a material and then slowly lowering the temperature to decrease the defects, thus minimizing the system energy. At each of iteration of SA algorithm, new points randomly generated the distance of the new point from the current point or the extent of search is based on the probability distribution of the scale proportional to temperature. The algorithm accepted new scale that lowers the objective but also with the probability points that raise the objective. By accepting points that raises the objective, the algorithms avoids being trapped in the in a local minimum and it is able to globally for mean solutions. An annealing temperature is selected to systematically decrease the temperature as algorithm proceeds. As the temperature reduces the algorithm reduces the extent of its search to converge to a minimum. An important part of SA process is how in puts are randomised .The randomized process take place the previous input value and current temperature inputs. A higher temperature will result more randomization a lower temperature will result less randomization.

In this study Simulated Annealing (SA) which utilizes stochastic optimization is used for the optimization of clad bead geometry deposited by GMAW. The main advantage of using this stochastic algorithm is that global optimization point can be reached regardless of the initial starting point. Since the algorithm incorporates. The major advantage of SA is an ability to avoid being trapped at a local optimum point during optimization .The algorithm employs a random search accepting not only the changes that improve the objective function but also the changes that deteriorate it.Fig.7 shows simulated annealing algorithm [11].

VI. OPTIMIZATION OF CLAD BEAD GEOMETRY USING SA.

The experimental data related to welding current (I), welding speed(S), welding gun angle (T), Contact tip to work distance (N) and pinch (Ac) are used in the experiments conducted.

The aim of the study is to find optimum adjust welding current (I), welding speed (S), welding Gun angle (T), contact tip to work distance (N) and pinch (Ac) in a GMAW cladding process. The optimum parameters are those who deliver response, as close as possible of the cited values shown in Table 8. Table 9 shows the options used for study.

Table 8. SA Search ranges

Parameters	Range
Welding current (I)	200 - 300 Amps
Welding Speed (S)	150 - 182mm/min
Contact tip to work distance(N)	10 - 26mm
Welding gun angle(T)	70 - 110deg
Pinch(Ac)	-10 - 10

Table 9. Combination of SA Parameters Leading To Optimal Solution

Annealing Function	Boltzmann Annealing
Re annealing Interval	100
Temperature update Function	Exponential Temperature
Initial Temperature	100
Acceptance probability Function	SimulatedAnnealing Acceptance
Data Type	Double

The objective function selected for optimizing was percentage of dilution. The response variables bead width (W), Penetration (P), reinforcement (R) and Dilution (D) were given as constraint in their equation. The constrained non linear optimisation is mathematically stated as follows

Minimize f(x)

Subject to f (X (1), X (2), X (3), X (4), X (5)) < 0

Simulated Annealing algorithms are nowadays popular tool in optimizing because SA uses only the values of objective function. The aim of the study is to find the optimum adjusts for welding current, welding speed, pinch, welding angle, contact to tip distance. Objective function selected for optimization was percentage of dilution. The process parameters and their notation used in writing the programme in MATLAB 7 software are given below.

Minimize f(x)

Subject to (X (1), X (2), X (3), X (4), X (5)) < 0

- X (1) = Welding current (I) in Amps
- X (2) = Welding Speed (S) in mm/min
- X (3) = Contact to work piece distance (N) in mm
- X (4) = Welding gun angle (T) in degree
- X (5) = Pinch (Ac)

Objective function for percentage of dilution which must be minimized was derived from equation 5-8. The constants of welding parameters are given Table 2.

- Subjected to bounds
- $200 \leq X (1) \leq 300$
 - $150 \leq X (2) \leq 182$
 - $10 \leq X (3) \leq 26$
 - $70 \leq X (4) \leq 110$
 - $-10 \leq X (5) \leq 10$

6.1 Objective Function

$$f(x)=19.75+0.325*x(1)+0.347*x(2)+3.141*x(3)-0.039*x(4)-0.153*x(5)-1.324*x(1)^2-0.923*x(2)^2-1.012*x(3)^2-1.371*x(4)^2-0.872*x(5)^2+20.200*x(1)*x(2)+0.346*x(1)*x(3)+0.602*x(1)*x(4)+0.203*x(1)*x(5)+0.011*x(2)*x(3)+0.465*x(2)*x(4)+0.548*x(2)*x(5)+0.715*x(3)*x(4)+0.360*x(3)*x(5)+0.137*x(4)*x(5) \dots\dots\dots(13)$$

6.2 Constraint Equations

$$P=(2.735+0.098*x(1)-0.032*x(2)+0.389*x(3)-0.032*x(4)-0.008*x(5)-0.124*x(1)^2-0.109*x(2)^2-0.125*x(3)^2-0.187*x(4)^2-0.104*x(5)^2-0.33*x(1)*x(2)+0.001*x(1)*x(3)+0.075*x(1)*x(4)+0.005*x(1)*x(5)-0.018*x(2)*x(3)+0.066*x(2)*x(4)+0.087*x(2)*x(5)+0.058*x(3)*x(4)+0.054*x(3)*x(5)-$$

$$0.036*x(4)*x(5)-3 \dots\dots\dots(15)$$

(Depth of penetration (P) upper limit),

$$P=(2.735+0.098*x(1)-0.032*x(2)+0.389*x(3)-0.032*x(4)-0.008*x(5)-0.124*x(1)^2-0.109*x(2)^2-0.125*x(3)^2-0.187*x(4)^2-0.104*x(5)^2-0.33*x(1)*x(2)+0.001*x(1)*x(3)+0.075*x(1)*x(4)+0.005*x(1)*x(5)-0.018*x(2)*x(3)+0.066*x(2)*x(4)+0.087*x(2)*x(5)+0.058*x(3)*x(4)+0.054*x(3)*x(5)-0.036*x(4)*x(5))+2 \dots\dots\dots(16)$$

(Depth of penetration (P) lower limit),

$$f(x)-23.6334 \dots\dots\dots(20)$$

$$8.94441799-f(x) \dots\dots\dots(21)$$

(Dilution Upper and lower limit),

$$x(1),x(2),x(3),x(4),x(5) \leq 2; \dots\dots\dots(22)$$

$$x(1),x(2),x(3),x(4),x(5) \geq -2; \dots\dots\dots(23)$$

Other constraint equations bead width ,reinforcement are written in same format as penetration for writing the programme. MATLAB program in SA and SA function was used for optimizing the problem. The program was written in SA and constraints bounds were applied. The minimum percentage of dilution obtained from the results obtained running the SA tool. The minimum percentage of dilution obtained is 9.2342.the value of process parameters obtained is I=240amp, S=157mm/min, N=13mm, T=87egrees, Ac=4.5.The fitness function is shown in Fig 8.Fig 9 shows current value function.

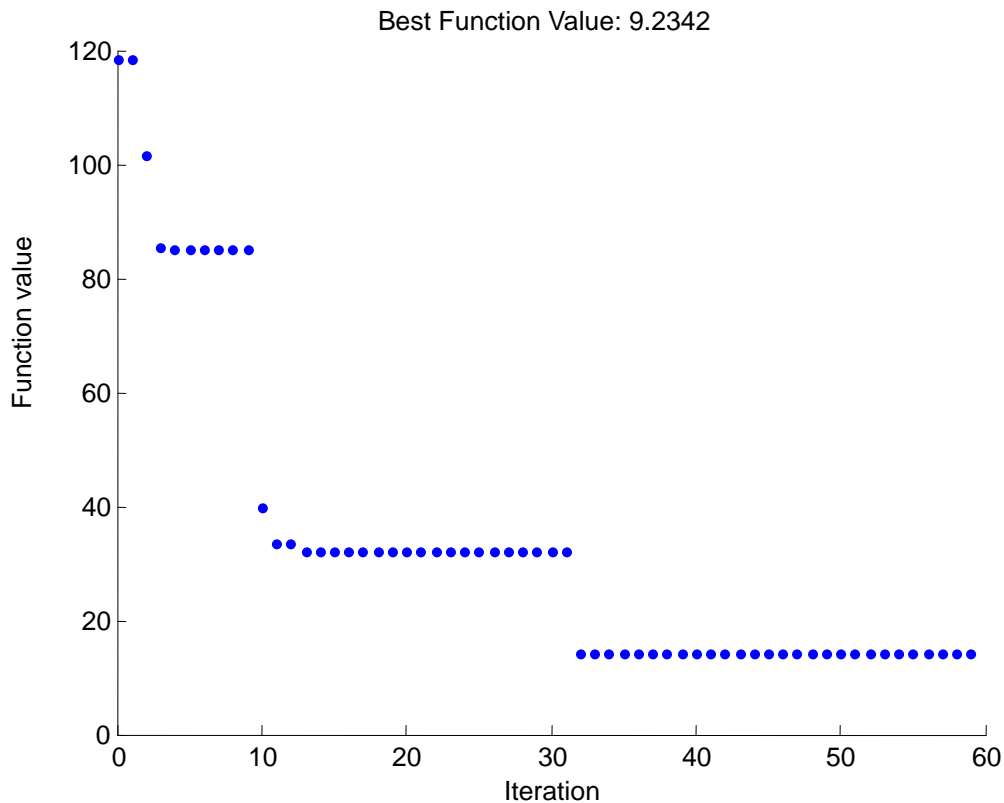


Fig 8. Fitness value of SA function

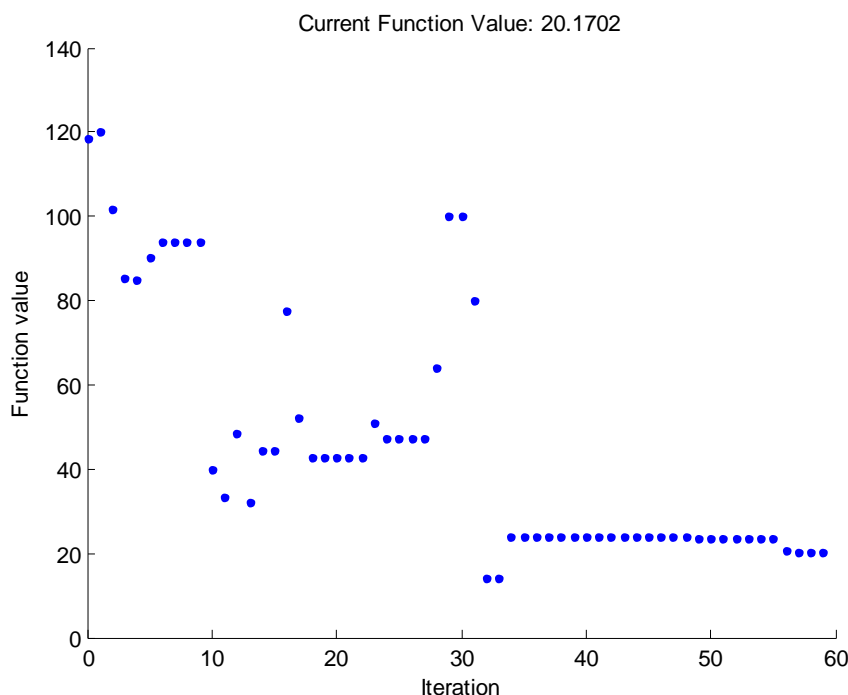


Fig 9.Current Value Function

VII. Methodology of integrated ANN-SA

The methodology applied in this study involves six cases [18]. They are experimental data, regression modelling, ANN single based modelling SA single based optimization, integrated ANN-SA-type-A based optimization and integrated ANN-SA-type-B based optimization. The objectives of type-A and type-B are.

1. To estimate the minimum value of cladding parameters compared to the performance value of the experimental data, regression modelling and ANN single based modelling.
2. To estimate the optimal process parameters values that has been within the range of minimum and maximum coded values for process parameters of experimental design that are used for experimental trial.
3. To estimate the optimal solution of the process parameters within the small number of iterations compared to the optimal solution of the process parameters with single based SA optimization.

The steps in order to implement the integrated ANN-GA -type-A and integrated ANN-GA type-B in fulfilling the three objectives are:

1. In the experimental data module the values of dilution for different combinations of process parameters used for modelling.
2. In the regression modelling schedule model was developed using cladding process parameters. A multilinear regression analysis was performed to predict dilution and a governing equation was constructed.
3. A predicted model was developed using ANN. The percentage if error was calculated between predicted and actual values.
4. In the single based SA optimization, the predicted equation of the regression model would become the objective function .The minimum and maximum coded values of the process parameters of the experimental design would define the boundaries for minimum and maximum values of the optimal solution.
5. In the integrated ANN-SA-type-A module that it was the first integration system proposed in this study. Similar to SA single based optimization process the predicted equation of the regression would become the objective function. This integration system process the optimal process parameters value of the single based SA optimization process combined with the process parameters of ANN system would define the foundries if minimum and maximum values for optimal solution.
6. In the integrated ANN-SA-type-B system which is the second integration system proposed in this study. Similar to type A the predicted regression equation would become the objective function and the optimal process parameters value of single based SA optimization combined with process parameters value of the ANN model would define the boundaries for the minimum and maximum values of the optimal solution

.This integration system proposes the process parameters values of the best ANN model to define the initial point for optimization solution [19].

7.1 Integrated ANN-SA-type-A optimization solution

The strategy of this study in implementing integrated ANN-GA-type-A is by proposing the optimal process parameters value of the SA combined with the non-optimal process parameters value of the ANN model to define the boundaries for the minimum and maximum value for optimization solution. As given in Table 6, the non-optimal process parameters values that yield to the minimum prediction, value of the ANN model for dilution are $D\%=9.353$, $I= 250\text{Amps}$, $S= 166\text{mm/min}$, $N = 10 \text{ mm}$, $T = 10\text{degree}$ and $Ac=0$. As given in Fig. 8, the values of optimal process parameters from SA are $I= 240 \text{ amps}$, $S= 157\text{mm/min}$, $N = 13 \text{ mm}$. $T = 87\text{degrees}$ and $Ac = 4.5$.

Three conditions could be stated for the non-optimal process parameters values of the ANN model (OptANN) and optimal process parameters values of the SA (OptSA) as classified in Table 10.

By using the conditions stated in Table 12, the decision to define the limitation constraint bound values of the optimization solution are given. Fulfilling the above condition Eqns. (24)- (28) are formulated to define the limitation constraint bounds for welding current, welding speed, contact tip to work distance, welding angle and pinch as process parameters, respectively. The limitation constraint bound for each process parameters are stated as follows [20]:

$$240 \leq I \leq 250 \tag{24}$$

$$157 \leq S \leq 166 \tag{25}$$

$$10 \leq N \leq 13 \tag{26}$$

$$87 \leq T \leq 90 \tag{27}$$

$$0 \leq Ac \leq 4.5 \tag{28}$$

As per Fig. 10 the optimal process parameters value that lead to the minimum cladding performance of the SA is proposed to define initial points for the integrated ANN-SA-type-A to search the optimal solution. The equations for the initial point of optimization solution for integrated ANN-SA-type A are given in Eq. (29), (30), (31), (32), (33) as follow. Fig 9 shows the values.

$$\text{Initial point of } I = 240 \tag{29}$$

$$\text{Initial point of } S = 157 \tag{30}$$

$$\text{Initial point of } N = 10 \tag{31}$$

$$\text{Initial point of } T = 87 \tag{32}$$

$$\text{Initial point of } Ac = 0 \tag{33}$$

Table 12. Condition to define limitation constraint bounds of integrated ANN-SA.

Condition	Decision	
	Lower bound	Upper bound
1 $(Opt_{ANN}) < (Opt_{SA})$	Opt_{ANN}	Opt_{SA}
2 $(Opt_{ANN}) > (Opt_{SA})$	Opt_{SA}	Opt_{ANN}
3 $(Opt_{ANN}) = (Opt_{SA})$	Nearest lower bound of the coded value of experimental design	Nearest upper bound of the coded value of experimental design

By using the objective function formulated in Eq. (13), the constraints Eq. 14-22, the limitation constraint bounds of process parameters formulated in Equations (24), (25), (26), (27), (28), the initial points formulated in Equation (29), (30), (31), (32), (33), and the same setting of parameters applied in SA that given in Table 12, results of the integrated ANN-SA-type-A by using MATLAB 7 Optimization Toolbox fitness function are obtained as shown in Figs. 11[20].

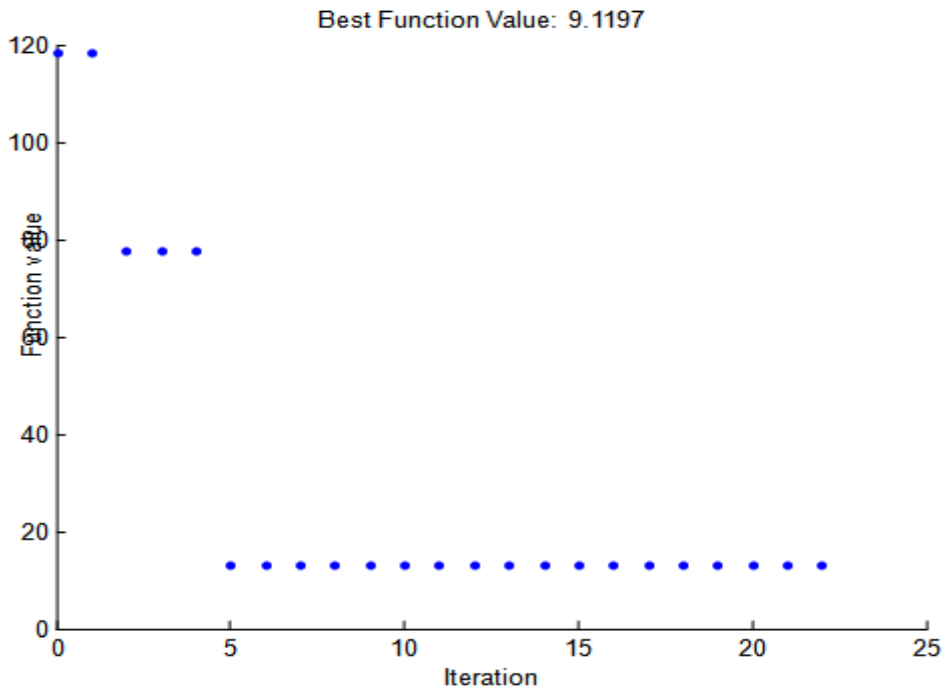


Fig11. Fitness value of ANN-SA Type-A

It can be seen that the set values of optimal process parameters that lead to the minimum dilution $D=9.1197\%$ are $I=274\text{amps}$, $S=152\text{mm/min}$, $N=12\text{mm}$, $T=73\text{degrees}$ and $Ac=1.4$.

7.2. Integrated ANN-SA-type-B optimization solution

Similar to integrated ANN-SA-type-A approach, the objective function formulate in Eq. (13), The basic difference to the integrated ANN-SA-type-A approach, the non-optimal process parameters value that lead to the minimum machining performance of the best ANN model that stated shown in Fig. 11 is proposed to define initial point for the integrated

ANN-SA-type-B is to search the optimal solution. Therefore, the equation for the initial point for integrated ANN-SA-type-B could be given in Eq. (32) to (36) as follows:

Initial point of $I = 250$ (32)

Initial point of $S = 166$ (33)

Initial point of $N = 10$ (34)

Initial point of $T = 90$ (35)

Initial point of $Ac = 0$ (36)

The results of the integrated ANN- SA-type-B by using MATLAB Optimization Toolbox fitness function are as shown in Fig.12.

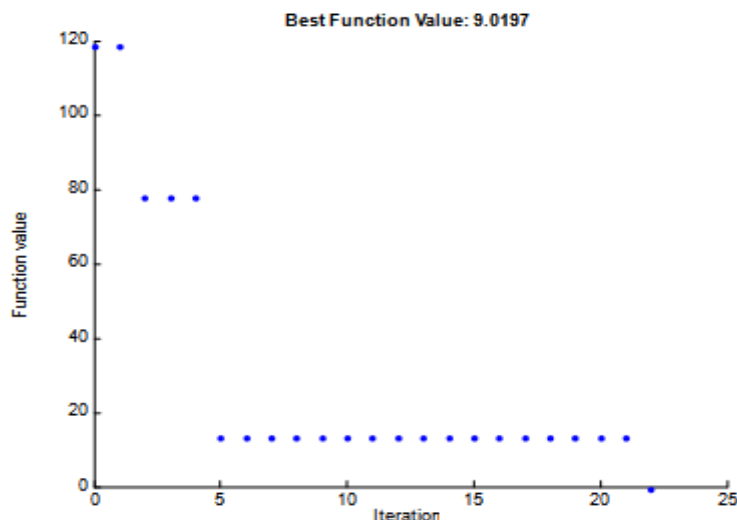


Fig 12. Fitness value of ANN-SA Type- B

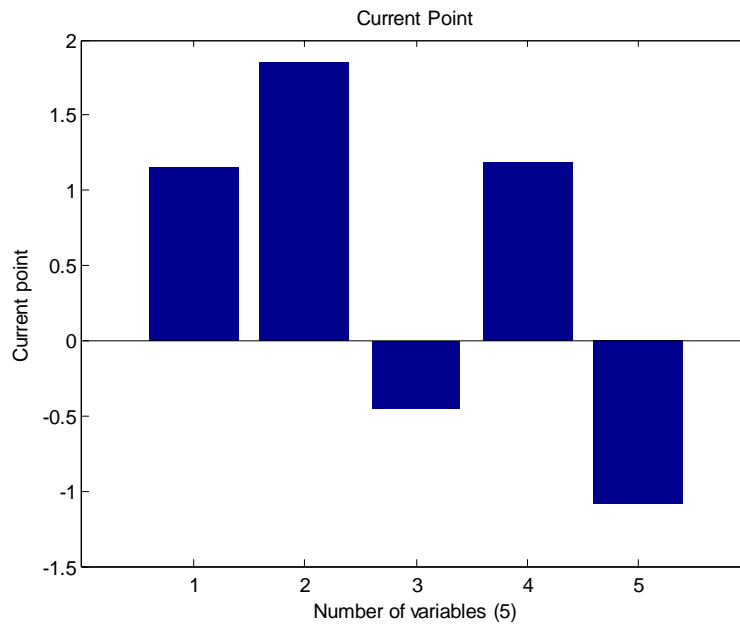


Fig 13. Current point

From Fig 12, it can be seen that the set values of optimal process parameters that lead to the minimum value of dilution $D = 9.0197$ are $I=212\text{amps}$, $v=138\text{mm/min}$, $N=16\text{mm}$, $T=78\text{degrees}$ and $Ac=1.5$. Fig.13 Shows current point.

7.3 ANN-SA Type-A

$$D=19.75+0.325*x(1)+0.347*x(2)+3.141*x(3)-0.039*x(4)-0.153*x(5)-1.324*x(1)^2-0.923*x(2)^2-1.012*x(3)^2-1.371*x(4)^2-0.872*x(5)^2-0.200*x(1)*x(2)+0.346*x(1)*x(3)+0.602*x(1)*x(4)+0.203*x(1)*x(5)+0.011*x(2)*x(3)+0.465*x(2)*x(4)+0.548*x(2)*x(5)+0.715*x(3)*x(4)+0.360*x(3)*x(5)+0.137*x(4)*x(5) \dots\dots\dots (37)$$

Optimum dilution obtained is 9.9532

7.4 ANN-SA Type-B

$$D=19.75+0.325*x(1)+0.347*x(2)+3.141*x(3)-0.039*x(4)-0.153*x(5)-1.324*x(1)^2-0.923*x(2)^2-1.012*x(3)^2-1.371*x(4)^2-0.872*x(5)^2-0.200*x(1)*x(2)+0.346*x(1)*x(3)+0.602*x(1)*x(4)+0.203*x(1)*x(5)+0.011*x(2)*x(3)+0.465*x(2)*x(4)+0.548*x(2)*x(5)+0.715*x(3)*x(4)+0.360*x(3)*x(5)+0.137*x(4)*x(5) \dots\dots\dots (38)$$

Optimum dilution obtained is 9.7895

VIII. Validation of the integrated ANN-SA result

Theoretically, to validate the result of the proposed approach this study, the optimal process parameters values of the integrated ANN-SA will be transferred into the regression model equation. Eq. (13), taken as the objective function of the optimization solution where I an optimal solution of the welding current. S an optimal solution of the welding speed; N is an optimal solution of contact to work distance. T is an optimal solution of the welding gun angle, and Ac an optimal solution of the pinch of integrated ANN-SA, this study discusses the calculation for validating the result of integrated ANN-SA-type-A and integrated ANN-SA-type-B.

IX. Evaluation of the integrated ANN-SA results

In this study, discussion is carried out to highlight all the objectives of the study is separated into three parts which are evaluation of the minimum Dilution value, evaluation of the optimal process parameters and evaluation of the number of iteration of the integrated ANN-SA results.

9.1. First objective: Evaluation of the minimum Dilution value

Fig. 11 and Fig. 12 show the minimum value of dilution for both integration systems, integrated ANN-SA-type-A and ANN-SA-type-B are 9.0197. For fulfilling the first objective of this study, evaluation against the minimum dilution is 9.237 by SA.

9.2. Experimental data vs. integrated ANN-SA

Optimum dilution should be between 8-15% from previous study .This objective is fulfilled in this case.

9.3. Regression vs. integrated ANN

The minimum predicted dilution value of the regression model is 9.9532. Therefore, with dilution is 9.0192. It can be concluded that both integration systems have given the more minimum result of the dilution compared to regression model. Consequently, integrated ANN-SA-type-A and integrated ANN-SA-type-B have reduced the value of dilution and optimized between 8 to15.

9.4. ANN vs. integrated ANN-SA

Minimum predicted Dilution value of the ANN model is9.353, it can he concluded that both integration systems have given the more optimum result of the Dilution compared to ANN model. Consequently, integrated ANN-SA-type-A and integrated ANN-SA-type-Aare well within the limits of standard dilution.

9.5. SA vs. integrated ANN-SA

The minimum predicted Dilution value of the SA was 9.375. Therefore, with Dilution 9.745, it can be concluded that both integrated systems have given the more minimum of the Dilution compared to SA technique.

9.6. Second objective: Evaluation of the optimal process parameters

For the second objective of this study, the optimal values of the integrated ANN-SA-type-A and integrated ANN-SA-type-B for each process parameter are within the range of minimum and maximum value of experimental design, thus, this study concludes that the second objective of this study is fulfilled.

9.7. Third objective: Evaluation of the number of iteration

Integrated ANN-SA-type-A and integrated ANN-SA-type-B are approximately same or lower than the number of iteration by SA, thus, this study concludes that the third objective of this study is fulfilled.

X. Conclusion

This study proposed two integration systems, integrated ANN-SA-type-A and integrated ANN-SA-type- B, in order to estimate the optimal solutions of process parameters that lead to minimum dilution is found to satisfy three conditions. The process parameters considered for this study are Welding current(I),Welding speed(S),Contact tip to work distance(N),Welding gun angle(T),and pinch(Ac).The outputs are Bead width(W),Penetration(P),Height of reinforcement(R) and Dilution(D).Each process parameters recommended by ANN-SA-type-A and integrated ANN-SA-type-B have satisfied within the minimum and maximum range of coded values for process parameters of experimental design. It also showed that number of iterations improved.

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