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Research Paper

SIMULATION AND PARAMETER OPTIMIZATION OF GMAW PROCESS USING NEURAL NETWORKS AND PARTICLE SWARM OPTIMIZATION ALGORITHM

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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 predict 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. Using Artificial Neural Network (ANN) the parameters were predicted and percentage of error calculated between predicted and actual values. The parameters were optimized using particle swarm optimization (PSO) algorithm.

Keywords: Mathematical model, Cladding, GMAW, ANN, Clad bead geometry, Corrosion, PSO

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

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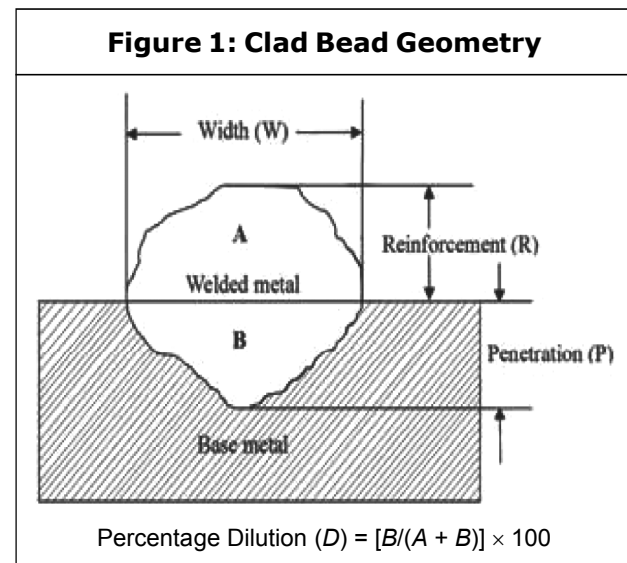
components but also reduce their cost This process is mainly now a day's used in industries such as chemical, textiles, nuclear steam power plants, food processing and petro chemical industries (Palani and Murugan, 2006).

Most accepted method of employed in weld cladding is GMAW. It has got the following advantages (Kannan and Murugan, 2006).

- High reliability
- All position capability
- Ease to use
- Law 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. Figure 1 shows the clad bead geometry. It mainly depends on wire feed rate, welding speed, arc voltage etc. Therefore it is necessary to study the relationship between in 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 models to predict 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 (Gunaraj and Murugan, 2005). The developed

models have been checked for their adequacy and significance. Again using ANN, the bead parameters were predicted. These predicted and actual parameters were compared. The parameters were optimized using PSO algorithm. The parameters were presented in Graphical form.



EXPERIMENTAL TECHNIQUE

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

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

Test plates of size 300 × 200 × 20 mm 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 1.2 mm 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 important and most difficult parameter found from trial run is wire

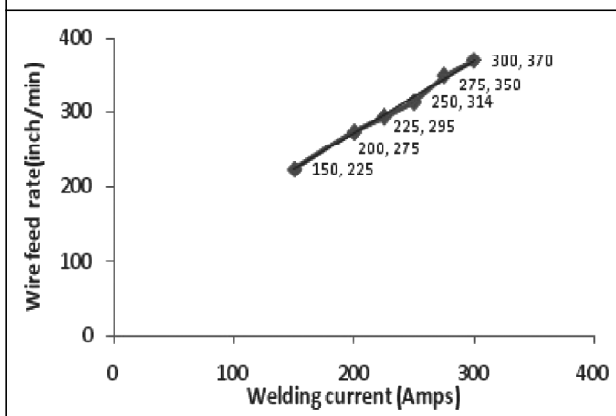
feed rate. The wire feed rate is proportional to current. Wire feed rate must be greater than critical wire feed rate to achieve pulsed metal transfer. The relationship found from trial run is shown in Equation (1). The formula derived is shown in Figure 2.

$$\text{Wire feed rate} = 0.96742857 * \text{Current} + 79.1 \quad \dots(1)$$

Table 1: Chemical Composition of Base Metal and Filler Wire

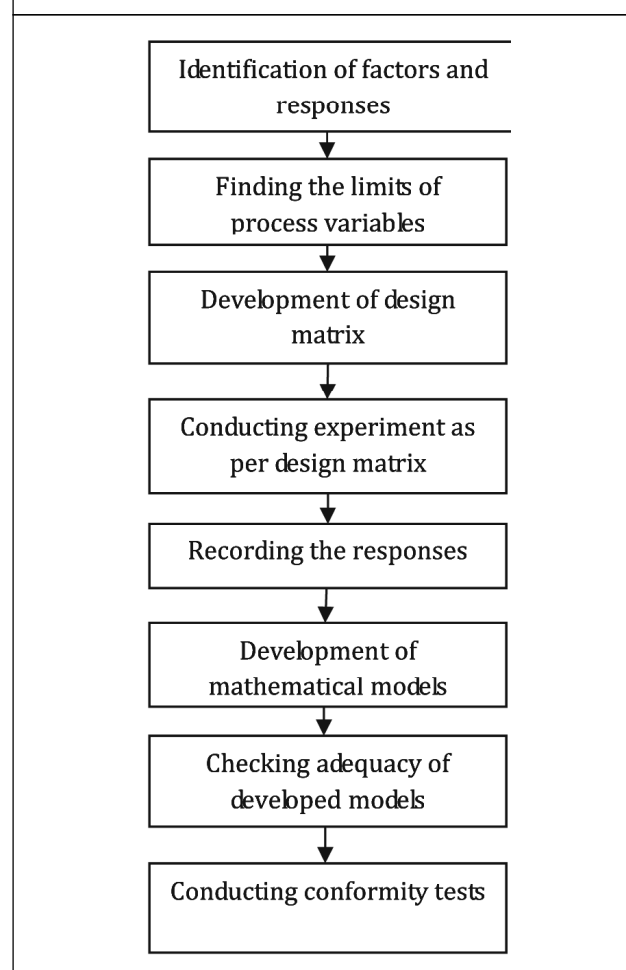
Elements, Weight%									
Materials	C	SI	Mn	P	S	Al	Cr	Mo	Ni
IS 2062	0.150	0.160	0.870	0.015	0.016	0.031	–	–	–
ER308L	0.03	0.57	1.76	0.021	0.008	–	19.52	0.75	10.02

Figure 2: Relationship Between Current and Wire Feed Rate



The selection of the welding electrode wire based on the matching the mechanical properties and physical characteristics of the base metal, weld size and existing electrode inventory (Kim *et al.*, 2003). 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

Figure 3: Experimental Design Procedure



electrode wastage. Experimental design procedure used for this study is shown in Figure 3 and importance steps are briefly explained.

PLAN OF INVESTIGATION

The research work was planned to be carried out in the following steps (Cochran and Coxz, 1987).

- Identification of factors and responses.
- Finding limits of process variables.
- Development of design matrix.
- Conducting experiments as per design matrix.
- Recording the responses.
- Development of mathematical models.
- Checking the adequacy of developed models.
- Conducting conformity tests.

Identification of factors and responses

DATA COLLECTION

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 is the 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.

No significant research work has been conducted in these areas using these process parameters and so these parameters were used for experimental study.

Working ranges of all selected factors are fixed by conducting trial run. 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).

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

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 (Kim *et al.*, 2003).

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

Design matrix chosen to conduct the experiments was central composite rotatable design. The design matrix comprises of full replication of 25(= 32), Factorial designs. All welding parameters in the intermediate levels (o) Constitute the central points and

Parameters	Unit	Notation	Factor Levels				
			-2	-1	0	1	2
			Welding Current	A	1	200	225
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

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 (Cochran and Coxz, 1987).

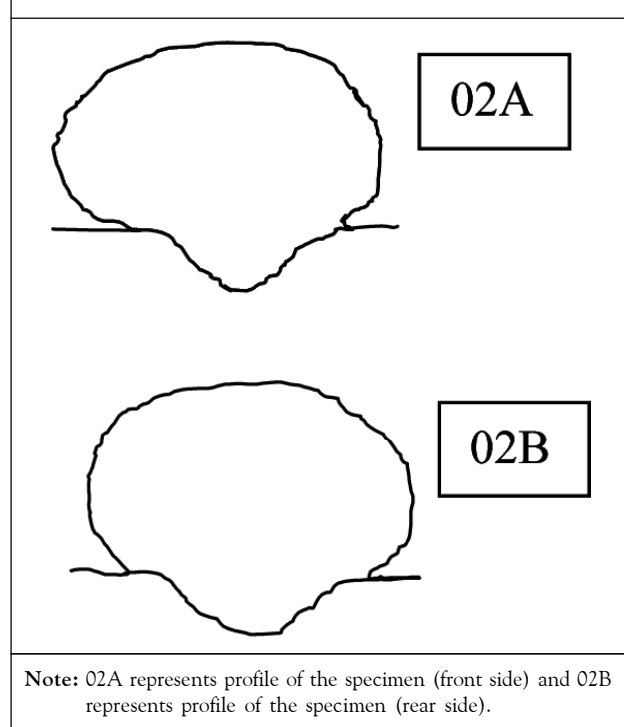
The experiments were conducted at SVS College of Engineering, Coimbatore, Tamilnadu, 642109, India. In this work Thirty two experimental run were allowed for the estimation of linear quadratic and two-way interactive effects of corresponding each treatment combination of parameters on bead geometry as shown Table 3 at random. At each

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

Note: I – Welding current; S – Welding speed; N – Contact tip to work distance; T – Welding gun angle; Ac – Pinch.

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. 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 (Serdar and Abdullah, 2008). 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 Figure 4.

Figure 4: Traced Profiles (Specimen No. 2)



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	1.673450	6.02620	10.720910
2	1	-1	-1	-1	-1	7.6549	1.971500	5.88735	12.167460
3	-1	1	-1	-1	-1	6.3456	1.698600	5.45190	12.745520
4	1	1	-1	-1	1	7.7635	1.739615	6.06840	10.610780
5	-1	-1	1	-1	-1	7.2683	2.443000	5.72055	16.673030
6	1	-1	1	-1	1	9.4383	2.490500	5.91690	15.966920
7	-1	1	1	-1	-1	6.0823	2.467200	5.49205	16.589400
8	1	1	1	-1	-1	8.4666	2.073650	5.94670	14.984940
9	-1	-1	-1	1	-1	6.3029	1.580900	5.90590	10.274900
10	1	-1	-1	1	1	7.0136	1.566200	5.98330	9.707297
11	-1	1	-1	1	1	6.2956	1.586050	5.51050	11.116930
12	1	1	-1	1	-1	7.7410	1.846600	5.87520	11.427300
13	-1	-1	1	1	1	7.3231	2.164750	5.72095	15.290970

Table 4 (Cont.)

Trial No.	Design Matrix					Bead Parameters			
	I	S	N	T	Ac	W (mm)	P (mm)	R (mm)	D (%)
14	1	-1	1	1	-1	9.6171	2.694950	6.37445	18.540770
15	-1	1	1	1	-1	6.6335	2.308900	5.55400	17.231380
16	1	1	1	1	1	10.5140	2.729800	5.46450	20.875500
17	-2	0	0	0	0	6.5557	1.990450	5.80585	13.657620
18	2	0	0	0	0	7.4772	2.573700	6.65505	15.741210
19	0	-2	0	0	0	7.5886	2.504550	6.40690	15.778160
20	0	2	0	0	0	7.5014	2.184200	5.67820	16.823490
21	0	0	-2	0	0	6.1421	1.375200	6.09760	8.941799
22	0	0	2	0	0	8.5647	3.185360	5.63655	22.947210
23	0	0	0	-2	0	7.9575	2.201800	5.82810	15.749410
24	0	0	0	2	0	7.7085	1.858850	6.07515	13.272850
25	0	0	0	0	-2	7.8365	2.357700	5.74915	16.632870
26	0	0	0	0	2	8.2082	2.365800	5.99005	16.380430
27	0	0	0	0	0	7.9371	2.136200	6.01530	15.183740
28	0	0	0	0	0	8.4371	2.171450	5.69895	14.827580
29	0	0	0	0	0	9.3230	3.142500	5.57595	22.843200
30	0	0	0	0	0	9.2205	3.287200	5.61485	23.633400
31	0	0	0	0	0	10.0590	2.866050	5.62095	21.552640
32.	0	0	0	0	0	8.9953	2.720680	5.70520	19.608110

Note: W – Width; P – Penetration; R – Reinforcement; D – Dilution.

REGRESSION ANALYSIS

The response function representing any of the clad bead geometry can be expressed as (Ghosh *et al.*, 1998; Gunaraj and Murugan, 1999; and Montgomery, 2003),

$$Y = f(A, B, C, D, E) \quad \dots(3)$$

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 equals can be expressed as below

$$Y = \beta_0 + \beta_1A + \beta_2B + \beta_3C + \beta_4D + \beta_5E + \beta_{11}A^2 + \beta_{22}B^2 + \beta_{33}C^2 + \beta_{44}D^2 + \beta_{55}E^2 + \beta_{12}AB + \beta_{13}AC + \beta_{14}AD + \beta_{15}AE + \beta_{23}BC + \beta_{24}BD + \beta_{25}BE + \beta_{34}CD + \beta_{35}CE + \beta_{45}DE \quad \dots(4)$$

where, β_0 is the free term of the regression equation, the coefficient $\beta_1, \beta_2, \beta_3, \beta_4$ and β_5 are linear terms, the coefficients $\beta_{11}, \beta_{22}, \beta_{33}, \beta_{44}$ and β_{55} quadratic terms, and the

coefficients β_{12} , β_{13} , β_{14} , β_{15} , etc., are the interaction terms. The coefficients were calculated using Quality America six sigma software (DOE-PC IV). After determining the coefficients, the mathematical models were developed. The developed mathematical models are given as follows.

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

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

$$\begin{aligned} \text{Height of Reinforcement (R), mm} = & 5.752 + 0.160A - 0.151B - 0.060C + 0.016D - \\ & 0.002E + 0.084A^2 + 0.037B^2 - 0.0006C^2 + \\ & 0.015D^2 - 0.006E^2 + 0.035AB + 0.018AC - \end{aligned}$$

$$\begin{aligned} & 0.008AD - 0.048AE - 0.024BC - 0.062BD - \\ & 0.003BE + 0.012CD - 0.092CE - 0.095DE \quad \dots(7) \end{aligned}$$

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

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 (Kannan, 2010). These conditions were satisfied for the developed models. The 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

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

Artificial Neural Networks (ANN)

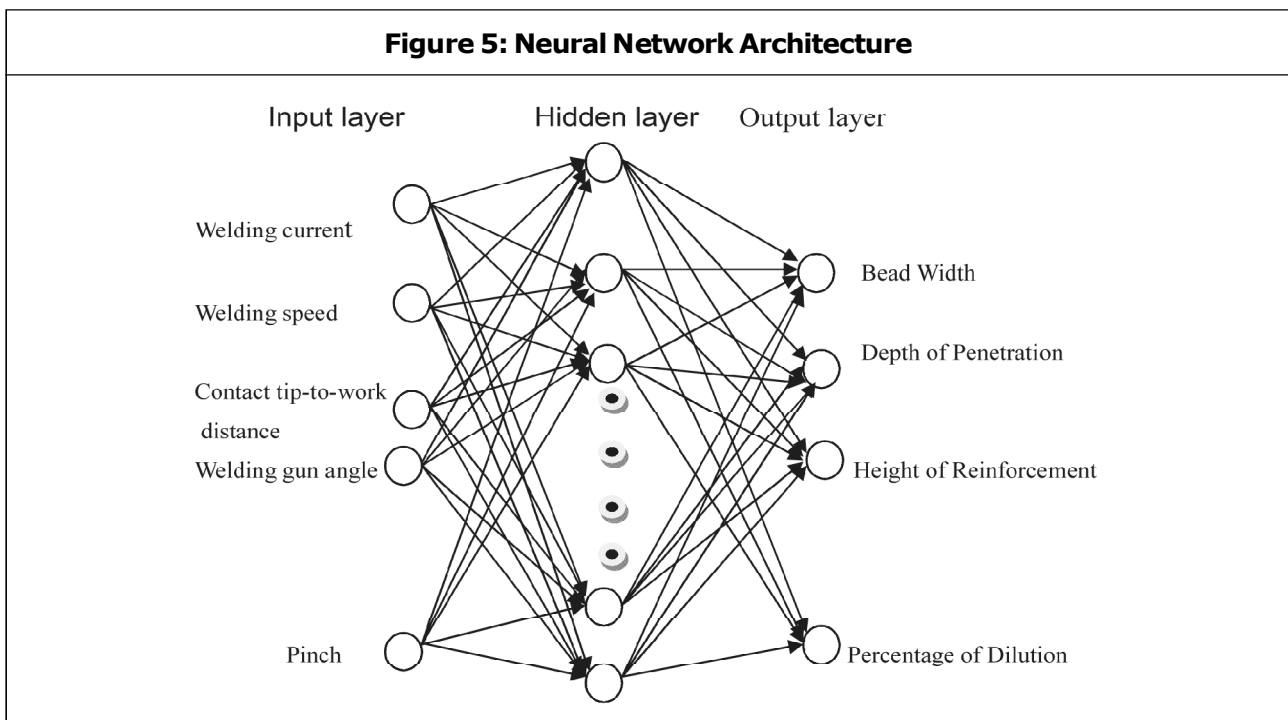
Neural network consists of many non-linear computational elements operating in parallel.

Basically it consists of neurons; it represents our biological nervous system. The basic unit of ANN is the neuron. The neurons are

connected to each other by link and are known as synapses which are associated to a weight factor. An artificial neuron receives signals from other neurons through the connection between them. Each connection strength has a synaptic connection strength which is represented by a weight of that connection strength. This artificial neuron receives a weighted sum of outputs of all neurons to which it is connected. The weighted sum is then compared with the threshold for an ANN and if it exceeds this threshold ANN fires. When it fires it goes to higher excitation state and a signal is send down to other connected neurons. The output of a typical neuron is obtained as a result of non-linear function of weighted sum. It is an adaptable system that can learn relationship through repeated presentation of data and is capable of generalizing a new previously unseen data. One of the most popular learning algorithms is the back propagation algorithm (Praikshit

and Dilip, 2007; and Hakan, 2007). In this study feedback propagation algorithm was used with a single hidden layer improved with numerical optimization technique called Levenbery Marguent approximation algorithm (LM) (Lee and Um, 2000). The architecture used in this study is 5-11-4 with 5 corresponding to input value 11 to the number of hidden layer and 4 corresponding to output. The topology of architecture of feed forward three Layers back propagations network is illustrated in Figure 5.

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 (Ananya and Asif, 2007).



This is basically range 0 to 1 in practice it is found to be between 0.1 and 0.9 (Deepak and Rajat, 2007). In this paper data are normalized using the Equation (9).

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

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 range which is to be normalized.

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

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-Marquardt approximation algorithm was trained with data collected for the experiment. Error was calculated using the Equation (10). Table 6 shows predicted test data using ANN.

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

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	6.9743	1.6735	6.0262	10.7210	6.1945	1.8500	5.9611	12.3670	0.7798	-0.1770	0.0651	-1.6460
2	7.6549	1.9715	5.8873	12.1670	7.1815	2.1507	6.5553	10.2680	0.4734	-0.1790	-0.6680	1.8990
3	6.3456	1.6986	5.4519	12.7460	7.4954	1.5339	5.4923	9.3808	-1.1500	0.1647	-0.0400	3.3652
4	7.7635	1.7396	6.0684	10.6110	6.4936	1.8540	6.5573	9.4799	1.2699	-0.1140	-0.4890	1.1311
5	7.2683	2.4430	5.7206	16.6730	7.3354	2.6576	5.5657	19.1040	-0.0670	-0.2150	0.1549	-2.431
6	9.4383	2.4905	5.9169	15.9670	7.6066	2.1045	6.4342	18.4900	1.8317	0.3860	-0.5170	-2.523
7	6.0823	2.4672	5.4920	16.5890	8.0417	2.1722	5.5126	16.8740	-1.9590	0.2950	-0.0210	-0.285
8	8.4666	2.0737	5.9467	14.9850	8.3236	2.2349	5.9031	16.9720	0.1430	-0.1610	0.0436	-1.987
9	6.3029	1.5809	5.9059	10.2750	8.2381	1.7955	5.6022	11.2190	-1.9350	-0.2150	0.3037	-0.944
10	7.0136	1.5662	5.9833	9.7073	7.5899	2.4579	6.5420	13.4150	-0.5760	-0.8920	-0.5590	-3.708
11	6.2956	1.5860	5.5105	11.1170	7.7318	1.7647	5.8676	10.7100	-1.4360	-0.1790	-0.3570	0.407

Particle Swarm Optimization

In particle swarm optimization algorithm PBest is the location of the best solution of a particle achieved so far. Best is the best location of the best solution that any neighbour achieved so far. Initially random numbers are generated for each particle and these values are considered as PBest and weights.

Velocity is calculated using the Equation (6), and added with the present weights in each link of the neural network. For each particle the newly calculated weights are compared with PBest weights and the minimum error produced by weights are stored in PBest. Initial velocity V is assumed to be 1 and GBest is the weights of minimum error produced

particle. New weights are calculated using Equation (7).

$$Velocity[] = wVelocity[] + C_1 rand_1(PBest[] - present[]) + C_2 rand_2(GBest[] - present[]) \dots(11)$$

$$Present [] = Present [] + Velocity [] \dots(12)$$

where C_1 and C_2 are two positive constants named learning factors. $rand_1$ and $rand_2$ are two random functions ranging from $[0, 1]$ w is an inertia weight to control over the impact of previous history of velocities on current velocities. The operator w plays the role of a balancing the global search and the local search; and was proposed to decrease linearly with time from a value of 1.4 to 0.5. As such global search starts with a large weight and then decreases with time to favour local search over global search. When the number of iterations is equal to the total number of particles, the goal is compared with the error

produced by GBest weights. If the error produced by GBest weights are less than or equal to goal weights in GBest are used for testing and prediction. Otherwise weights of minimum error are stored in GBest and iterations are repeated until goal is reached. Optimization procedure shown in Figure 6. $rand_1$ and $rand_2$ are two random functions in the range $[0, 1]$ where C_1 and C_2 are two positive constants named learning factors taken as 2 and ' w ' is the inertial weight taken as 0.5. The parameters used for PSO optimization are shown in Table 7.

Population Size	30
Dimension Size	5
Inertia Weight	0.4-0.9
Velocity Factors C_1, C_2	1.4
Number of Iteration Allowed	100

Method for developing PSO model

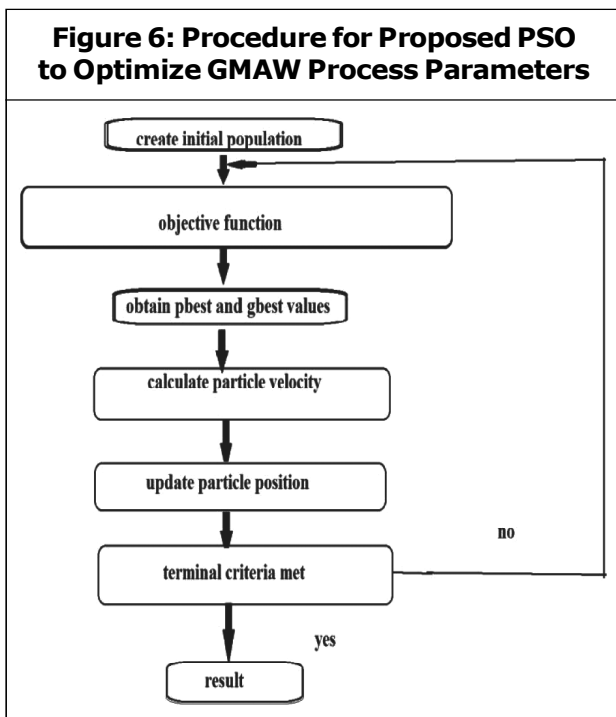
- Initiate each particle.
- Calculate fitness value of each particle. If the fitness value is better than the best fitness value (PBest) in history. Set the current value as new PBest.
- Calculate GBest.
- For each particle calculate the particle velocity.

Numerical Illustration for Developed PSO Model

The numerical illustration for the developed model to find optimal parameters for percentage of dilution as summarised below.

Welding current

$$I = I_{min} + (I_{max} - I_{min}) - rand()$$



Welding speed

$$S = S_{min} + (S_{max} - S_{min}) - rand()$$

Contact tip to work distance

$$N = N_{min} + (N_{max} - N_{min}) - rand()$$

Welding gun angle

$$T = T_{min} + (T_{max} - T_{min}) - rand()$$

Pinch

$$P = P_{min} + (P_{max} - P_{min}) - rand()$$

These values are substituted in Equation (8) and Dilution is obtained.

X(1) = A = Welding current (I) in amps

X(2) = B = Welding Speed (S) in mm/min

X(3) = C = Contact to work piece distance (N) in mm

X(4) = D = Welding gun angle (T) in degree

X(5) = E = Pinch (Ac)

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

Subjected to bounds

$$200 \leq X(1) \leq 300$$

$$150 \leq X(2) \leq 182$$

$$10 \leq X(3) \leq 26$$

$$70 \leq X(4) \leq 110$$

$$-10 \leq X(5) \leq 10$$

Objective Function

$$f(x) = 19.75 + 0.325*x(1) + 0.347*x(2) + 3.141*x(3) - 0.039*x(4) - 0.153*x(5) - 1.324*x(1)^2 - 0.923*x(2)^2 - 1.012*x(3)^2 - 1.371*x(4)^2 - 0.872*x(5)^2 - 0.200*x(1)*x(2) + 0.346*x(1)*x(3) +$$

$$0.602*x(1)*x(4) + 0.203*x(1)*x(5) + 0.011*x(2)*x(3) + 0.465*x(2)*x(4) + 0.548*x(2)*x(5) + 0.715*x(3)*x(4) + 0.360*x(3)*x(5) + 0.137*x(4)*x(5) \dots(13)$$

(This is the percentage of dilution)

Constraint Equations

$$W = (8.923 + 0.701*x(1) + 0.388*x(2) + 0.587*x(3) + 0.040*x(4) + 0.088*x(5) - 0.423*x(1)^2 - 0.291*x(2)^2 - 0.338*x(3)^2 - 0.219*x(4)^2 - 0.171*x(5)^2 + 0.205*x(1)*x(2) + 0.405*x(1)*x(3) + 0.105*x(1)*x(4) + 0.070*x(1)*x(5) - 0.134*x(2)*x(3) + 0.2225*x(2)*x(4) + 0.098*x(2)*x(5) + 0.26*x(3)*x(4) + 0.086*x(3)*x(5) + 0.12*x(4)*x(5)) - 3 \dots(14)$$

(Clad bead width (W) mm lower limit),

$$P = (2.735 + 0.098*x(1) - 0.032*x(2) + 0.389*x(3) - 0.032*x(4) - 0.008*x(5) - 0.124*x(1)^2 - 0.109*x(2)^2 - 0.125*x(3)^2 - 0.187*x(4)^2 - 0.104*x(5)^2 - 0.33*x(1)*x(2) + 0.001*x(1)*x(3) + 0.075*x(1)*x(4) + 0.005*x(1)*x(5) - 0.018*x(2)*x(3) + 0.066*x(2)*x(4) + 0.087*x(2)*x(5) + 0.058*x(3)*x(4) + 0.054*x(3)*x(5) - 0.036*x(4)*x(5)) - 3 \dots(15)$$

(Depth of penetration (P) upper limit),

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

(Depth of penetration (*P*) lower limit),

$$W = (8.923 + 0.701*x(1) + 0.388*x(2) + 0.587*x(3) + 0.040*x(4) + 0.088*x(5) - 0.423*x(1)^2 - 0.291*x(2)^2 - 0.338*x(3)^2 - 0.219*x(4)^2 - 0.171*x(5)^2 + 0.205*x(1)*x(2) + 0.405*x(1)*x(3) + 0.105*x(1)*x(4) + 0.070*x(1)*x(5) - 0.134*x(2)*x(3) + 0.225*x(2)*x(4) + 0.098*x(2)*x(5) + 0.26*x(3)*x(4) + 0.086*x(3)*x(5) + 0.012*x(4)*x(5)) - 10 \dots(17)$$

(Clad bead width (*W*) upper limit),

$$R = (5.752 + 0.160*x(1) - 0.151*x(2) - 0.060*x(3) + 0.016*x(4) - 0.002*x(5) + 0.084*x(1)^2 + 0.037*x(2)^2 - 0.0006*x(3)^2 + 0.015*x(4)^2 - 0.006*x(5)^2 + 0.035*x(1)*x(2) + 0.018*x(1)*x(3) - 0.008*x(1)*x(4) - 0.048*x(1)*x(5) - 0.024*x(2)*x(3) - 0.062*x(2)*x(4) - 0.003*x(2)*x(5) + 0.012*x(3)*x(4) - 0.092*x(3)*x(5) - 0.095*x(4)*x(5)) - 6 \dots(18)$$

(Height of reinforcement (*R*) lower limit),

$$R = (5.752 + 0.160*x(1) - 0.151*x(2) - 0.060*x(3) + 0.016*x(4) - 0.002*x(5) + 0.084*x(1)^2 + 0.037*x(2)^2 - 0.0006*x(3)^2 + 0.015*x(4)^2 - 0.006*x(5)^2 + 0.035*x(1)*x(2) + 0.018*x(1)*x(3) - 0.008*x(1)*x(4) - 0.048*x(1)*x(5) - 0.024*x(2)*x(3) - 0.062*x(2)*x(4) - 0.003*x(2)*x(5) + 0.012*x(3)*x(4) - 0.092*x(3)*x(5) - 0.095*x(4)*x(5)) + 6 \dots(19)$$

(Heights of reinforcement (*R*) upper limit),

$$f(x) - 23 \dots(20)$$

$$-f(x) + 8 \dots(21)$$

(Dilution Upper and lower limit),

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

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

Calculation of Pbest Value

The minimum percentage of dilution for each individual solution is considered as PBest value. This is the best value for the particular solution only.

Calculation of Gbest Value

The minimum dilution for initial solution or the whole iteration is considered as Gbest value. Table 8 shows PBest values and Table 9 shows velocity of particle. A program on MATLAB 7 is created and run to get optimal dilution. Figure 7 shows convergence of PSO for optimal dilution.

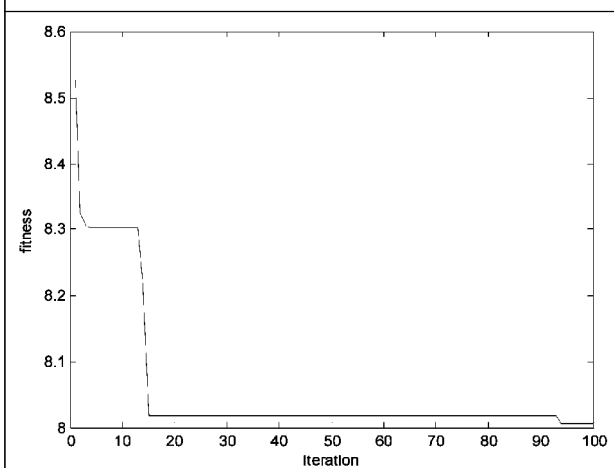
Table 8: PBest Value				
I	S	T	N	Ac
0.6241	1,1490	-1.9241	-0.3936	-0.5707
0.6213	1,1414	-1.9139	-0.4406	-0.5562
-0.7617	1,2651	-1.8204	-0.3466	0.5956
1.1993	0.4661	-1.4140	0.4173	-0.1746
0.6213	1.1368	-1.9224	-0.4496	-0.5725
1.2525	1,5324	-0.1270	-0.9208	0.6041
0.6188	1,1379	-1.9242	-0.4524	-0.5750
0.6196	1,1364	-1.9284	-0.4547	-0.5780
0.6230	1,1385	-1.9187	-0.4487	-0.5717
0.6223	1,1368	-1.9227	-0.4507	-0.5761
0.6182	1,1378	-1.9227	-0.4507	-0.5761
0.6182	1.1378	-1.9221	-0.4511	-0.5754
0.6256	1,1393	-1.9129	-0.4459	-0.5675
0.6230	1.1385	-1.9187	-0.4487	-0.5717

Table 9: Velocity of Particles				
I	S	T	N	Ac
-0.0766	-0.0000	0.0000	0.0000	0.0000

Table 9 (Cont.)

I	S	T	N	Ac
-0.0737	-0.0000	0.0000	0.0000	0.0000
-0.0278	-0.0953	-0.0960	-0.3871	-0.3927
0.0369	-0.0000	-0.6304	-0.5643	-0.6966
-0.0611	-0.1051	-0.1121	-0.4074	-0.4324
-0.0732	-0.0000	0.0000	0.0000	0.0000
-0.0000	-0.0000	0.0000	0.0000	0,0000
-0.0195	-0,0000	0.0000	0.0000	0,0000
-00517	-0,0940	-0.1307	-0.3794	-0.4224
-0.0296	-0.0000	0.0000	0.0000	0.0000
-0.0344	-0,0000	0.0000	0.0000	0,0000
-0.0766	-0.1135	-0.0974	-0.4006	-0.4197
-0.0211	-0.0000	0.0000	0.0000	0,0000

Figure 7: Convergence of PSO for Optimal Dilution



Dilution obtained is 8.2% and optimal process parameters shown in Table 10.

Table 10: Optimal Process Parameters

Parameters	Range (Coded Value)	Actual
Welding Current (I)	0.6196	265 A
Welding Speed (S)	-1.1364	174 mm/min
Contact Tip to Work Distance (N)	-1.9284	10 mm
Welding Gun Angle (T)	-0.4547	88 degree
Pinch (Ac)	-0.5780	-6

RESULTS AND DISCUSSION

Experiments were conducted using GMAW to produce cladding on austenitic stainless steel material. From the experimental results a mathematical model was developed using regression model. Further to enhance scope of work ANN model was developed by using feed forward back propagation algorithm.

In this study a feedback propagation neural network model to predict clad bead geometry was developed. To ensure accuracy of model developed to predict width, depth of penetration, reinforcement and dilution the experimental and predicted results using the developed model are compared. The percentage of error which gives the deviation of the predicted model and actual model were calculated and presented in Table 6.

The comparison of actual data and predicated data of clad bead width, depth of penetration height of reinforcement and percentage of dilution are shown from Figures 8 to 11. It can be seen that final results obtained by experimental method and predicted model are very close.

It can be see that ANN models can be effectively used to model cladding parameters.

Figure 8: Observed and Predicted Bead Width Using ANN Model

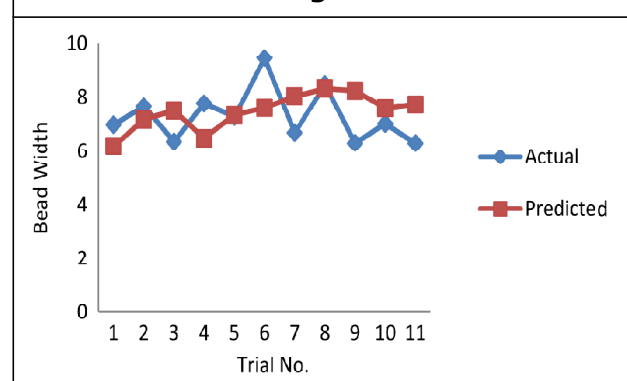


Figure 9: Observed and Predicted Penetration Using ANN Model

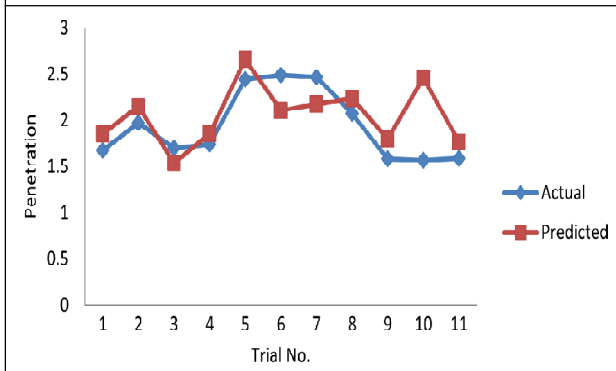


Figure 10: Observed and Predicted Reinforcement Using ANN Model

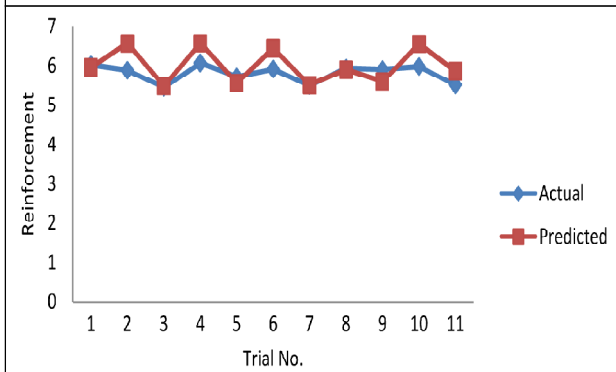
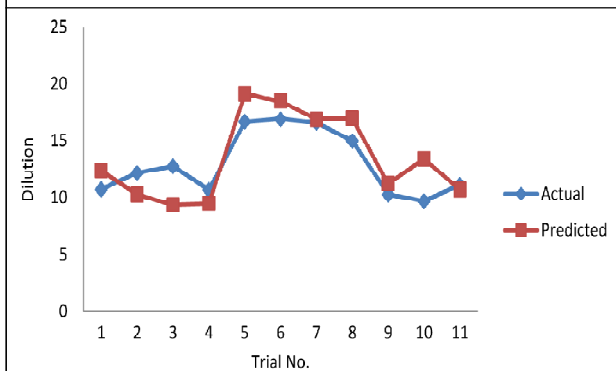


Figure 11: Observed and Predicted Dilution Using ANN Model



These predicted values can be directly used in automatic cladding in the forms of programs and for real time quality control and for the entire cladding process control application to improve bead geometry.

The objectives are optimized satisfactorily by PSO algorithm and the percentage of error was found to be very small.

CONCLUSION

- A neural network model has been developed from the experimental data to achieve desired clad bead geometry. Neural network models are capable of making prediction of clad bead geometry with reasonable accuracy.
- The developed models are able to predict process parameters required to achieve the desired clad bead geometry of stainless steel cladding deposited by GMAW and prediction of ANN models are within the limits of $\pm 1\%$ accuracy.
- In this study the following steps were applied for prediction of stainless steel clad bead geometry using GMAW; (a) Data collection using experimental studies, (b) Analysing and processing of data, (c) Training the neural network, (d) Test of trained neural network, and (e) Use of trained neural network for prediction of data.
- The percentage of error for bead width, penetration, reinforcement and dilution are very small. To conclude the main quality indicator of neural network is its generalised ability to predict accurately the output of unseen verification of data.
- The aim of the study was to show the possibility of the use of neural networks for calculation of clad bead geometry of stainless steel cladding deposited by GMAW method. The results showed that neural network models can be used as an alternative tool according to the present conventional calculation methods.

- In this study parameter optimization of weld bead geometry in GMAW process on 316 L material was done. Bead on plate weld runs were performed as per central composite rotatable design. The results were fed to the ANN algorithm for establishing a relationship between input and output parameters. The results were then embedded into PSO algorithm which optimized the process parameters.

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