Estimation of Bead on Plate Geometry of Super Duplex Stainless Steel on Low Carbon Steel using Artificial Neural Networks

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Abstract

Bead on plate geometry gives a priori knowledge about weld characteristics. In the current work, bead on plate experimental data are taken from one previously published work and different training algorithms are applied to get trained with the experimental data. Experiments were done using four-factor, five-level central composite rotatable design with full replication technique using response surface methodology. The working range of each parameter was decided upon by inspecting the weld bead for smooth appearance and the absence of visible defects. Bead of Super Duplex Stainless Steel was deposited on low carbon steel substrate using flux cored arc welding. An attempt is made in this work to predict the bead geometry parameters using Artificial Neural Networks (ANN). Effectiveness of three different ANN training functions are compared to choose the best model of these three. TRAINLM (Levenberg-Marquardt) algorithm is found to be the most appropriate training function for prediction of bead geometry in this work.

Keywords: Welding, FCAW, Bead on Plate welding, Super Duplex Stainless Steel, Neural Networks, ANN, Prediction.

1.0 INTRODUCTION

Various engineering components and structures are subjected to corrosive, or erosive, type hostile environment, and they fag out fast that need to be repaired or replaced in a frequent manner. It costs lot of money and time. To get rid of this problem, either this structure or component is to be made of good corrosion resistive alloys or coated with a layer of desired thickness of these alloys. The first one is quite costlier than the other one. There are various surface improvement methods by which it can have enhanced corrosion resistance properties of the components. Cladding is a type of thermal surface improvement method by which increment in corrosion resistance property can be achieved to some extent. Arc welding process is one of the ways by which cladding can be done [1,2].

Flux cored arc welding is an efficient, semi-automatic arc welding process that is quite similar to gas metal arc welding (GMAW) process. Like GMAW, this process also depends upon various parameters. Proper selection and observation of these process parameters helps to achieve a desired welding joint. This process is quite useful and reliable than the other existing arc welding processes. Basically Flux Cored Arc Welding (FCAW) is a fusion welding operation obtained by an electrical arc made between a nonstop electrode and the workpiece to generate the weld pool [1-4]. In this welding process, tubular electrode is endlessly complied and has a fluxed core that contribute extra shielding capacities to the welding method with or without extra safeguard from an outwardly equipped protection gas. The core is especially made by excrement formers, deoxidizers, arc pacifiers, and alloying elements.

FCAW technique have received great consideration from welders as a result of flux cored wire have heaps of benefits like exceptional productivity, top quality welds, deep penetration, less spatter attachment behaviour, greater deposition rates, larger welding speed and value blessings Cary et al. [4]. According to Palani et al. [5], the operational criteria for FCAW ought to be considered and classified to facilitate welding automation. Getting required weld quality needs admissible method to adopt to get required bead geometry and shape. Also other researchers outlined the scope of utilization of FCAW employing duplex stainless steel in fabrication of chemical cargo carriers [6].

A number of research works was carried out [7-11] by a group led by Das on the formation of weld bead of austenitic and duplex stainless steel on low carbon steel. After obtaining optimal bead profile corresponding to high bead width and height of reinforcement, they went forward for weld cladding to have desired corrosion resistance. Otherwise, high depth of penetration is required in a weld bead if one wishes to have good weld strength [1,2]. While Saha et al. [8], Bose and Das [10] and Saha et al. [11] carried out bead on plate experiments using austenitic stainless steel wire electrode to explore the desired bead geometry to go forward to cladding through GMAW process, Mondal et al. [7] and Saha and Das [9] studied the effect of heat input on corrosion aversion of duplex stainless steel (E2209 T0-1) cladding on low carbon steel flats by flux cored arc welding (FCAW) process.

Optimization is widely used in finding out the optimum solution without conducting repeated physical operations. Classical methods of optimization are less used nowadays as they are time-taking and vital to collect data from experiments. Therefore, some heuristic algorithms are introduced as a modern optimization technique. They are powerful learning tools and widely used for further operation, prediction, developing mathematical models, etc. Among many heuristic algorithms, the following are pretty standard- Artificial Neural Networks (ANN), Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and many more.

Artificial Neural Networks (ANN) is a parallel operating system simulating the neurons of a human being. They are connected with coefficients or weights which construct the structure of the Neural Networks (NN) [12]. The processing elements have weighted inputs, transfer function and outputs for processing information. Each neuron always receives information from the neurons of the previous layer and after performing computations on that information transfers it to the neurons of the next layer. Among many models of NN, the Back Propagation Neural Networks (BPNN) is a known model for fault detection and prediction in different applications [13-30]. ANN was applied in estimation of melt temperature profile [13] as well as for pressure control [14] in injection moulding, and also in finding out bend angle of sheet metal bending by laser beam [15], monitoring of cutting tool wear [17-19,22], weld bead geometry determination [21,23,28], surface roughness estimation during machining [24], estimating drilling burr formation [25], finding out performance of abrasive jet drilling [26], etc. In another work, ANN was reported to have determined the weld sequence to obtain minimum distortion [27], while ANN was also applied to determine the viscosity of multi-phase fluid flow system to facilitate transportation of magnetite ore-water slurry [20].

In a recent work, weld characteristics was tried [29] to estimate using regression analysis and neural networks related to dissimilar welding of AISI 304 and EN 8 steels through metal active gas welding. In another recent research work [30], possibilities of Artificial Intelligence-Enabled Feedback Control System in Robotized Gas Metal Arc Welding were explored using ANN.

MATLAB software can be used to design the ANN [31]. For complex problems, Multi-Layer Perceptron (MLP) is the best model as it overcomes the drawback of the single-layer perceptron by adding more hidden layers. In a feed forward multilayer perceptron network, input signals are multiplied by the connection weights, summed up and then directed to a transfer function to give output for that neuron. The transfer function (purelin, Tan-sigmoid, or logi-sigmoid) executes on the weighted sum of the input of neuron(s). In the present work, different training algorithms and different number of neurons in the hidden layer are tried to find out the minimum error model of ANN to estimate bead geometry parameters accurately as far as possible.

2.0 TRAINING FUNCTION

There are three types of training algorithm generally used in ANN tool box. These are Gradient Descent algorithm, Conjugate Gradient algorithm, and Quasi-Newton algorithm [12,16].

2.1 Gradient Descent algorithms

Among three algorithms, Gradient Descent algorithm is the most powerful training algorithm. It uses negative gradient of performance function to updates weights and biases.

Gradient Descent back propagation algorithm (traingd) measures the outcome of different errors and by adjusting the weight in the descending gradient direction calculates the gradient of the error. Gradient Descent along with Momentum (traingdm) algorithm acts like low pass filter, that means, it will ignore small deviation in error surface [32]. Resilience back propagation (trainrp) training function completely omits the effect of magnitude of partial derivative [33].

2.2 Conjugate Gradient algorithms

When a search is performed along the conjugate direction, the basic gradient descent is called by Conjugate gradient algorithm. This type of algorithm consumes little more disk space than the other algorithms. So, it is good for use in a network with large number of weights [34].

Like other conjugate training functions, Scaled Conjugate Gradient (trainscg) does not need to search a line at each iteration. To avoid line search per learning iteration, step size scaling mechanism is used. This training function does require more iterative steps than any other conjugate gradient algorithm. However, number of computations at each iteration decreases as no line search is conducted [35]. Ratio of norm square of current gradient to norm square of previous gradient is called as Conjugate Gradient back propagation with Fletcher-Reeves Updates (traincgf). This training function is faster than any other algorithm, however it is problem dependent [36]. Ratio of the inner product of previous change in gradient with current gradient to norm square of previous gradient is called Conjugate Gradient back propagation with Polak-Riebre Updates (traincgp) training function.

2.3 Quasi-Newton algorithms

The method introduced by Newton shows faster evaluation of optimal point than the conjugate gradient method. Hessian matrix with second derivatives is used in this type of algorithm. In Quasi-Newton algorithm, it doesn't require calculation of second order derivatives. In each iteration, it updates Hessian matrix for obtaining better results.

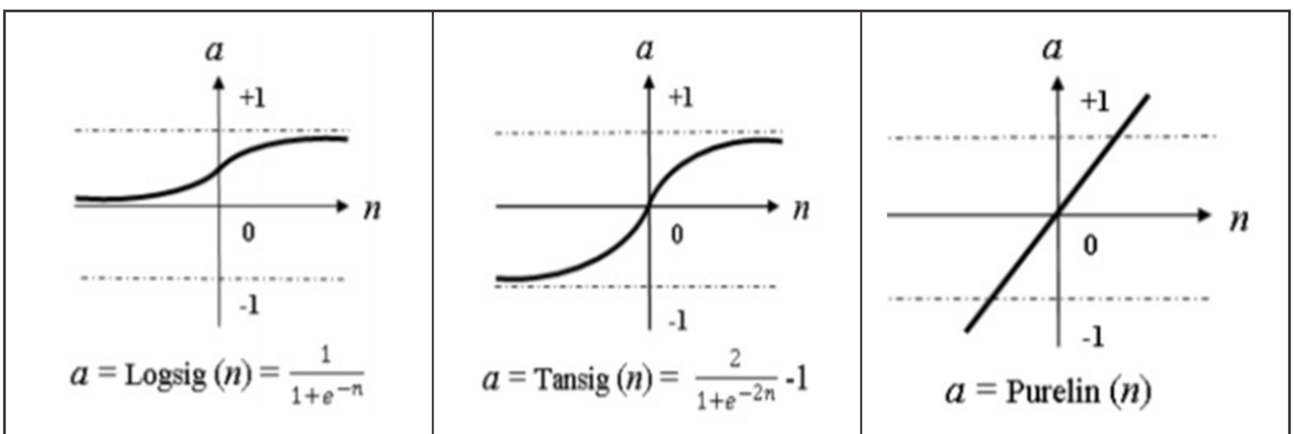
BFGS (Broyden–Fletcher–Goldfarb–Shanno) (trainbfg) method follows hill-climbing optimization system. Necessary parametric combination to achieve optimal point is gradient set to be zero [32]. It needs large storage as well as rigorous computation compared to conjugate gradient method.

Levenberg–Marquardt back propagation (trainlm) is a combination of multivariate, sum of squares of non-linear real-valued functions. In each iteration, it reduces the performance function. That is why Trainlm is the fastest and mostly used training algorithm. It is suitable for moderate size of networks [37].

3.0 TRANSFER FUNCTION

In the Linear time invariant system, relations between input and output data are represented by Transfer function. Three types of Transfer functions are found in MATLAB (Neural network tool box).

Log-sigmoid transfer function or LOGSIG **(Fig. 1(a))** becomes a commonly used transfer function. Input values lie between + and - and output value lies between 0 and 1 respectively. As the function is differentiable, it is used in back propagation algorithm.



(a) Log-Sigmoid (b) Tan-Sigmoid (c) Purelin

Fig. 1 : Different transfer functions used in ANN

Hyperbolic tangent transfer function or TANSIG **Fig. 1(b)** is related to bipolar sigmoid. It has output value range of -1 to +1. This function runs faster than other transfer functions and difference between predicted to experimental values are usually quite low [12,16,31,32].

Sometimes, experimental models are designed in such a manner that when operated within nominal parameters, behave close enough to linear. In this case, PURELIN transfer function can be imposed.

4.0 EXPERIMENTAL RESULTS AND DISCUSSION

For this ANN modelling, experimental data are taken from the work as reported by Balan et al. [38]. Height of reinforcement (R), depth of penetration (P), bead width (W) which are standard weld bead geometry parameters, are observed in this work. Detail of experiment is given in **Table 1** and **Table 2**. Experiments were done [38] following central composite rotatable design technique of RSM (Response Surface Methodology).

Table 1 : Bead on plate experimental details [38]

Welding process	FCAW							
Base material	Low carbon steel (IS: 2062), Carbon Eqv.: 0.42.							
Electrode	1.2mm Flux Cored Super Duplex Stainless Steel (FC250716) wire							
Shielding gas	80% Argon+ 20% CO_2							
Input parameter	Wire Feed rate		Torch travel speed		Nozzle tip distance		Torch angle	
	Coded value	Value (inch/min)	Coded value	Value (inch/min)	Coded value	Value (inch/min)	Coded value	Value (inch/min)
	-2	150	-2	100	-2	16	-2	90
	-1	175	-1	120	-1	18	-1	100
	0	200	0	140	0	20	0	110
	1	225	1	160	1	22	1	120
	2	250	2	180	2	24	2	130

In the current work, different training algorithms are utilized to train experimental data obtained from Balan et al. [38].

All these tests related to ANN based estimation are conducted on Windows 10 (64-bit) operating system having Intel i5 (8th Generation) processor with 8GB RAM. MATLAB ANN toolbox is employed for the prediction or estimation.

Three training algorithms with 8 training functions are used to predict the most suitable combination by which it can be used for further investigation. For learning process, data are separated into 70% for training set, 15% for validation set and 15% for testing set. The ANN is set as follows for training stage: Max epochs = 1000, show = 5, performance goal = 0, time = Infinitive, max fail = 6. No. of epochs at the end of the training, least square error during training, validation and testing are also checked. Number of neurons in hidden layer is set according to 10, 20, and 30. Training of the network is continued thorough an iterative process till 'mean square error' becomes quite less.

Table 3 shows the outcome obtained through these training functions. Number of neurons in hidden layer and training functions adversely affect the Network simulation. TRAINRP and TRAINSCG do not show considerable change with the increase in hidden nodes in hidden layer. Closeness of ANN output with the target (actual value of outputs) is found out by least square error method in the Regression analysis. Correlation coefficient (R) close to one indicates the ANN to be appropriate. **Table 3** clearly specifies TRAINLM training function with PURELIN transfer function to qualify for appreciably good prediction ability as the R value is near to 1.0 compared to any other combination.

Table 1 : Bead on plate experimental details [38]

Sl. No	Wire feed rate	Welding Speed	Nozzle-to-plate distance	Welding gun angle	Bead width, W (mm)	Reinforce-ment R (mm)	Penetration, P (mm)
1	-1	-1	-1	-1	8.38	4.13	0.371
2	1	-1	-1	-1	9.76	4.61	0.420
3	-1	1	-1	-1	8.04	3.37	0.376
4	1	1	-1	-1	8.43	3.78	0.443
5	-1	-1	1	-1	8.51	4.27	0.327
6	1	-1	1	-1	10.09	4.77	0.378
7	-1	1	1	-1	8.49	3.68	0.342
8	1	1	1	-1	8.99	3.92	0.379
9	-1	-1	-1	1	8.69	3.96	0.330
10	1	-1	-1	1	10.12	4.15	0.407
11	-1	1	-1	1	8.52	3.36	0.338
12	1	1	-1	1	8.60	3.62	0.431
13	-1	-1	1	1	8.92	3.99	0.318
14	1	-1	1	1	10.28	4.68	0.362
15	-1	1	1	1	8.66	3.50	0.330
16	1	1	1	1	9.61	3.87	0.363
17	-2	0	0	0	7.71	3.74	0.327
18	2	0	0	0	10.00	4.09	0.550
19	0	-2	0	0	10.13	4.83	0.419
20	0	2	0	0	8.16	3.40	0.498
21	0	0	-2	0	7.74	3.16	0.834
22	0	0	2	0	9.61	4.09	0.267
23	0	0	0	-2	8.92	3.77	0.377
24	0	0	0	2	9.78	3.52	0.178
25	0	0	0	0	8.43	3.87	0.707
26	0	0	0	0	7.86	3.87	0.707
27	0	0	0	0	8.44	4.28	0.707
28	0	0	0	0	8.43	3.86	0.707
29	0	0	0	0	8.44	3.87	0.529
30	0	0	0	0	8.44	3.86	0.707
31	0	0	0	0	8.43	3.86	0.707

Table 1 : Bead on plate experimental details [38]

Algorithm	Transfer Function	Training Function	No. of neurons	Best validation MSE at epoch	Epochs	R on training	R on validation	R on test
Gradient Descent	PURELIN	TRAINGD	10	0.090267 at 815	1000	0.99752	0.99681	0.99727
			20	0.24418 at 180		0.99206	0.992	0.98572
			30	0.039882 at 1000		0.9974	0.99846	0.99478
		TRAINGDM	10	0.31005 at 40		0.99098	0.98829	0.98921
			20	0.094818 at 1000		0.9975	0.99695	0.99684
			30	0.10132 at 1000		0.99755	0.99591	0.9978
		TRAINRP	10	0.08526 at 23		0.99753	0.99747	0.99835
			20	0.1229 at 16		0.99734	0.99619	0.99748
			30	0.055085 at 17		0.99791	0.99792	0.99594
Conjugate Gradient	PURELIN	TRAINSCG	10	0.45338 at 43	1000	0.99376	0.99149	0.98765
			20	0.063111 at 18		0.99712	0.9979	0.99505
			30	0.068664 at 19		0.9977	0.99889	0.99807
		TRAINCGP	10	0.15168 at 1		0.9918	0.9969	0.99786
			20	0.88383 at 4		0.99169	0.98387	0.9895
			30	0.069294 at 6		0.99766	0.99741	0.99778
		TRAINCGF	10	0.11129 at 8		0.99469	0.99749	0.98602
			20	0.11235 at 7		0.99413	0.99609	0.99047
			30	0.34604 at 3		0.99077	0.99097	0.9901
Quasi Newton	PURELIN	TRAINBFG	10	0.2166 at 10	1000	0.99661	0.99417	0.99582
			20	0.118 at 7		0.99784	0.99588	0.99285
			30	0.39778 at 4		0.98178	0.98818	0.98449
		TRAINLM	10	0.02861 at 5		0.99696	0.99873	0.9989
			20	0.079523 at 4		0.99765	0.99744	0.99612
			30	0.062682 at 4		0.99795	0.9984	0.99438

5.0 MODELLING AND PREDICTION USING ANN

Artificial Neural Networks (ANN) is employed widely as a tool for prediction of the responses where clear physical explanation may be absent, and performing rigorous, time consuming experiment is difficult. Thirty one experimental data generated from the experimental runs following Central Composite Design (CCD) method of Response Surface Methodology (RSM) are used for neural networks modelling. To train the neural network for predicting the Bead width, Reinforcement and Penetration, back propagation algorithm was used. The input layer of the network used the TRAINLM function, when the output layer used the linear (purelin) function. Hidden nodes were of 10 in number in a single hidden layer model. Learning rate chosen was 0.01, momentum coefficient was 0.1, target error, MSE was 0.01, maximum number of iterations of 1000 epochs was set. Input data were split into training data (70%), validation data (15%) and testing data (15%). Trainlm follows Levenberg-Marquardt algorithm. The optimal architecture of ANN was generated as shown in **Fig. 2**.

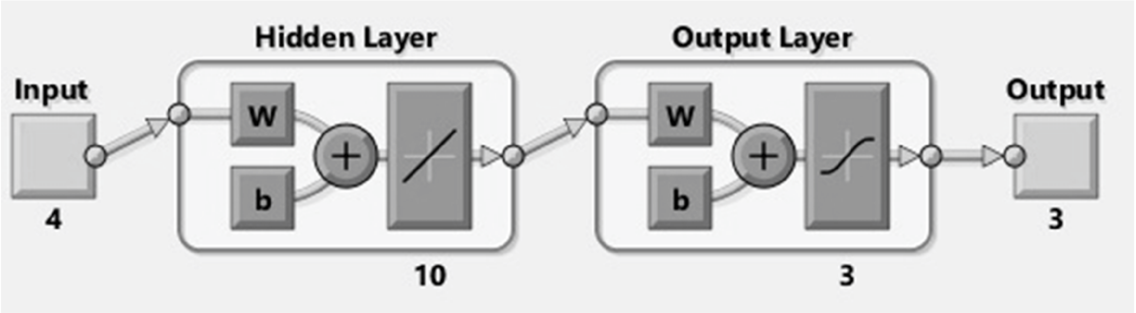


Fig. 2 : artificial neural network architecture

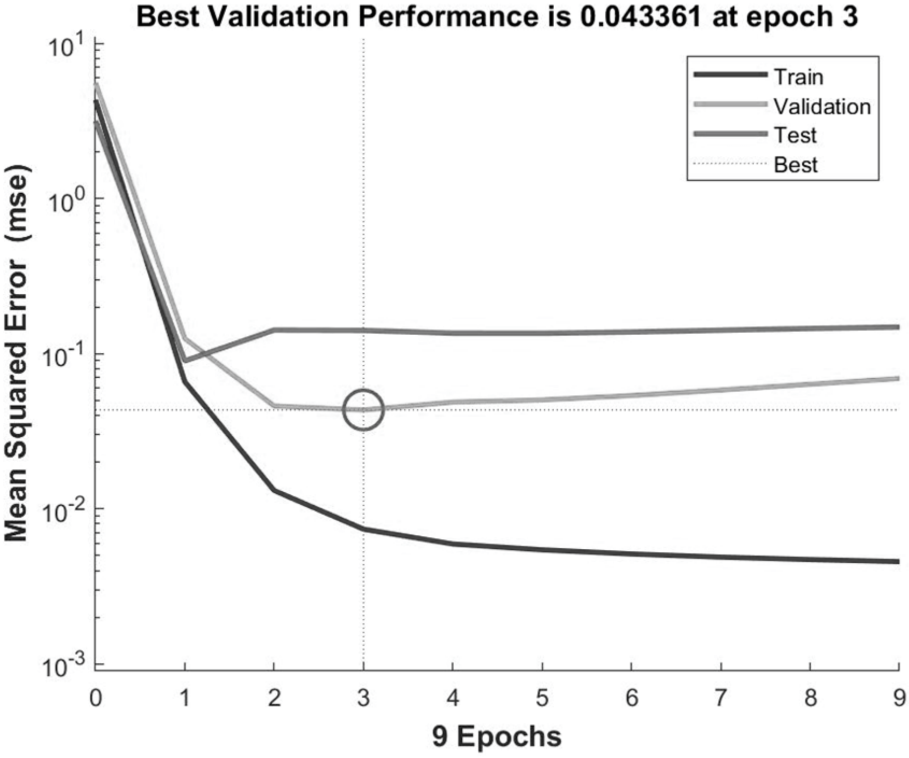


Fig. 3 : Performance curve of trained network for predicting the weld bead geometry

From the network training sequence, the number of iterations needed to achieve minimum error can be seen as 9 only as depicted in **Fig. 3.** The gradient function of 0.00238 has been found. Training gain is 0.0001. Validation checking is done with 6 data. Fig. 4 presents the trend of change in training, validation and testing errors with number of iterations.

Over fitting is not seen. Somewhat similar trend is observed for training, validation and testing plots. A low error value of 0.043361 at epoch 3 is visible clearly. Nature of change in gradient function, training gain (Mu) and validation check with progress of iteration is presented in **Fig. 4**. Lowest gradient value of 0.0023756 is evaluated indicating minimal error contributed by each neuron. Momentum gain (Mu) is a control parameter to train the ANN and its value should be <1. Momentum gain of 0.0001 indicates good capacity of prediction. Regression plots presented in **Fig. 5** show quite good correlation existing between the input and the target.

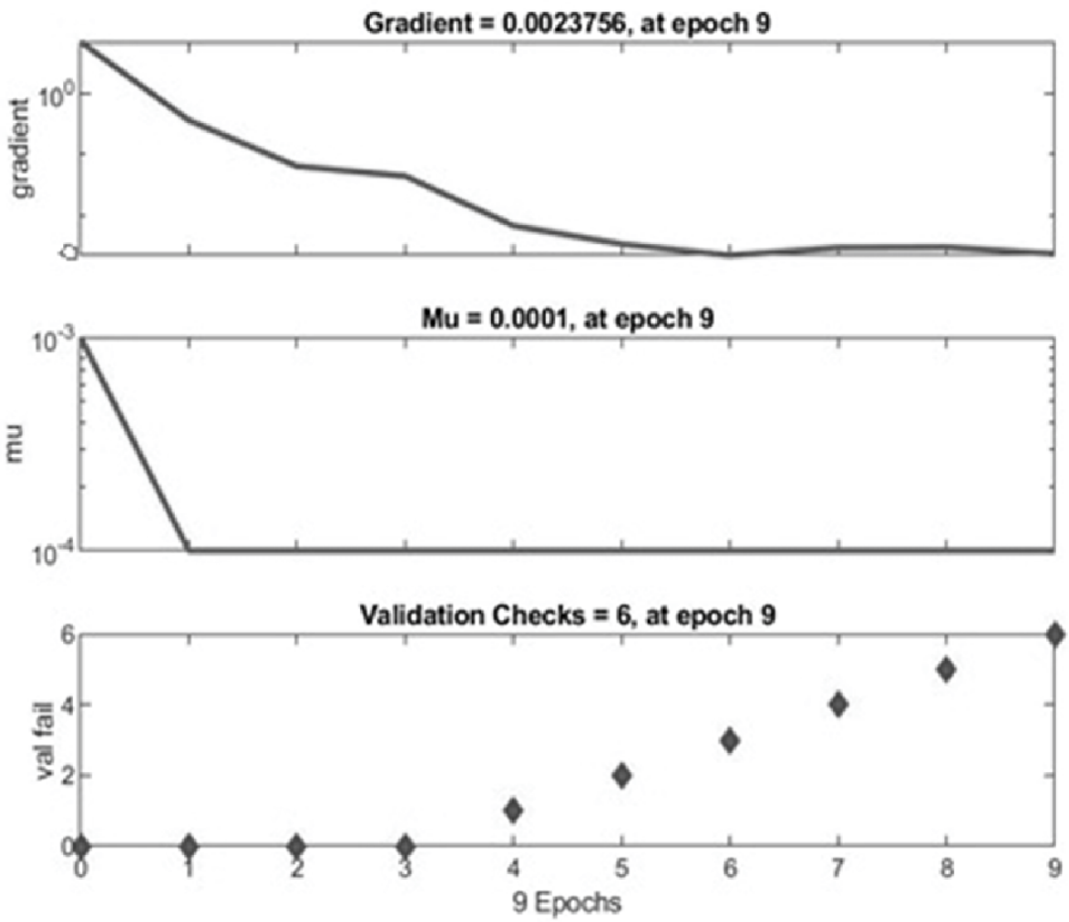


Fig. 4 : Training state of Neural Networks for predicting weld bead geometry

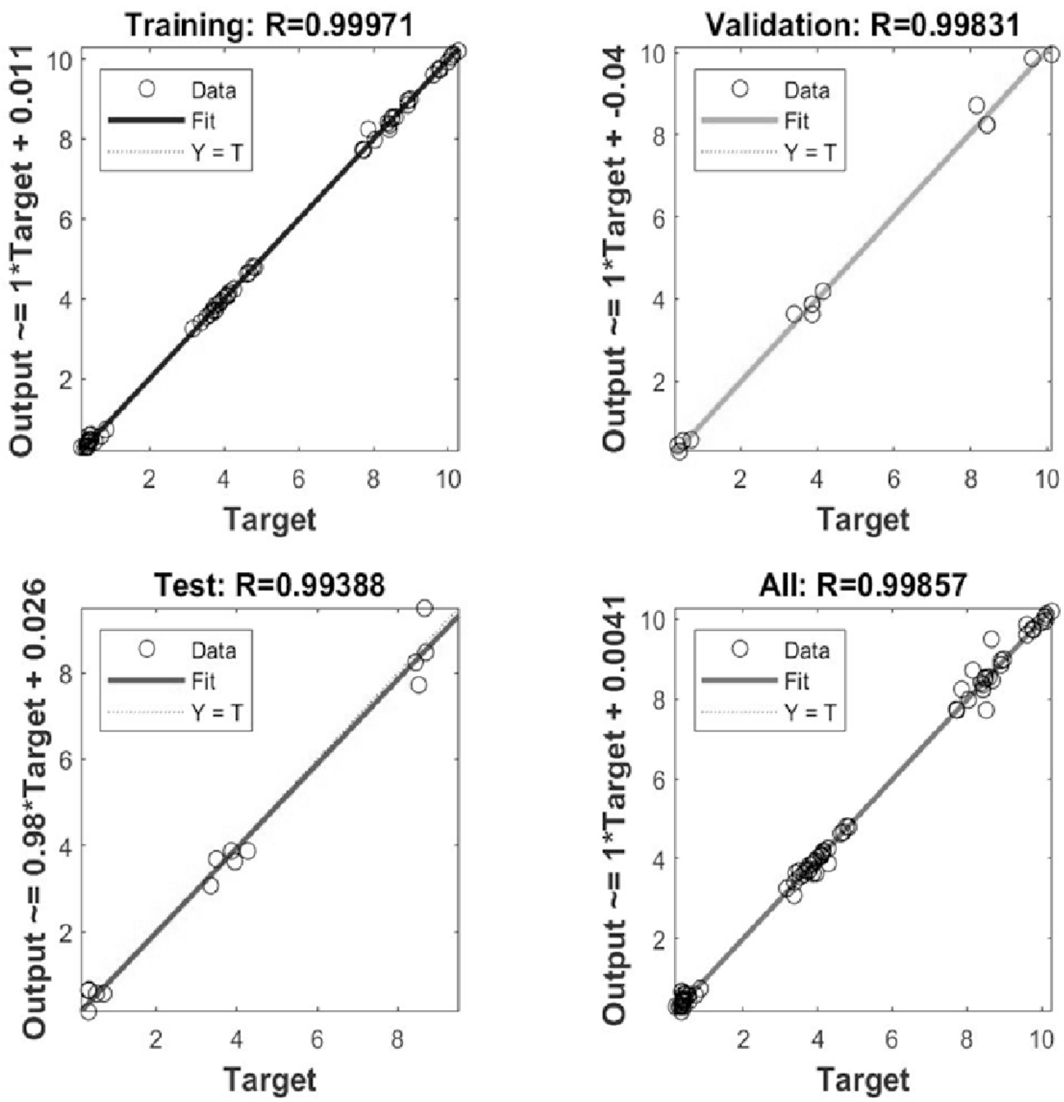


Fig. 5 : Regression plot showing the progress of training, validation and testing

6.0 RESULTS AND DISCUSSION

Table 3 shows correlation among the experimental values of Bead width and Predicted values obtained from Artificial Neural Networks operation. The maximum Bead width of 10.28 and 10.20 mm are obtained from Experimental No. 14 in both experimental and predicted approach. Those numbers are quite similar in nature as error percentage is only -0.80. The maximum and minimum error % are only +9.70 and +0.01. In **Fig. 6**, column chart also shows closely between Experimental and predicted values.

Table 4 : Different data sets of experimental and predicted values of weld bead width

Sl. No	Wire feed rate	Welding speed	Nozzle-to plate distance	Welding gun angle	Bead width W (mm)	Predicted Bead width (mm)	% Error
1	-1	-1	-1	-1	8.38	8.41	0.30
2	1	-1	-1	-1	9.76	9.76	0.01
3	-1	1	-1	-1	8.04	7.97	-0.78
4	1	1	-1	-1	8.43	8.35	-0.91
5	-1	-1	1	-1	8.51	8.54	0.40
6	1	-1	1	-1	10.09	10.05	-0.42
7	-1	1	1	-1	8.49	8.54	0.16
8	1	1	1	-1	8.99	8.99	-0.02
9	-1	-1	-1	1	8.69	8.47	-2.51
10	1	-1	-1	1	10.12	9.96	-1.55
11	-1	1	-1	1	8.52	7.72	-9.40
12	1	1	-1	1	8.60	8.55	-0.61
13	-1	-1	1	1	8.92	8.96	0.46
14	1	-1	1	1	10.28	10.20	-0.80
15	-1	1	1	1	8.66	9.50	9.70
16	1	1	1	1	9.61	9.86	2.65
17	-2	0	0	0	7.71	7.73	0.30
18	2	0	0	0	10.00	9.93	-0.73
19	0	-2	0	0	10.13	10.13	-0.03
20	0	2	0	0	8.16	8.72	6.86
21	0	0	-2	0	7.74	7.72	-0.30
22	0	0	2	0	9.61	9.61	-0.01
23	0	0	0	-2	8.92	8.85	-0.74
24	0	0	0	2	9.78	9.73	-0.56
25	0	0	0	0	8.43	8.24	-2.22
26	0	0	0	0	7.86	8.24	4.87
27	0	0	0	0	8.44	8.24	-2.34
28	0	0	0	0	8.43	8.24	-2.22
29	0	0	0	0	8.44	8.24	-2.34
30	0	0	0	0	8.44	8.24	-2.34
31	0	0	0	0	8.43	8.24	-2.22

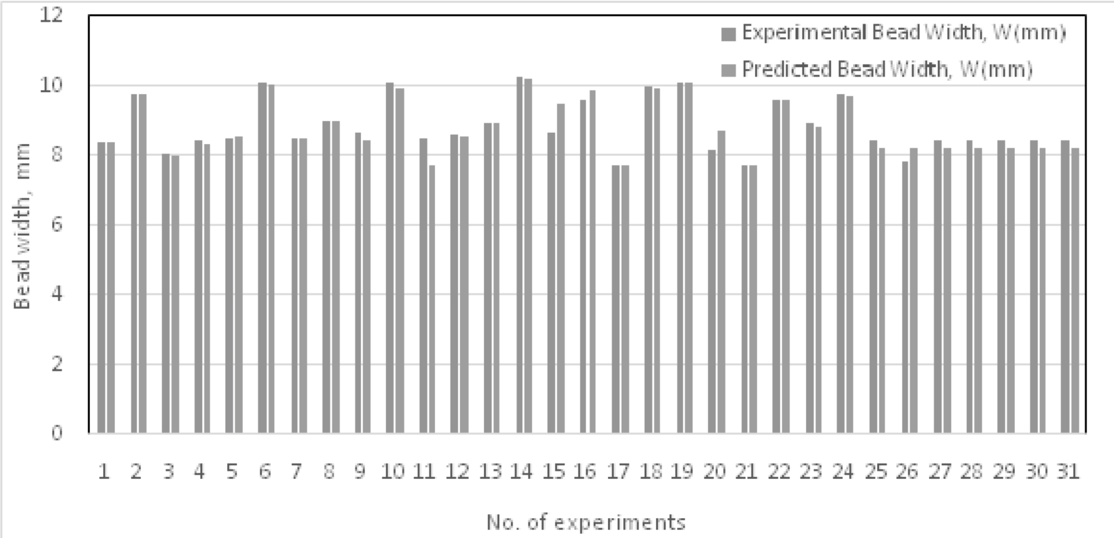


Fig. 6 : Column diagram of Experimental and Predicted vales of bead width

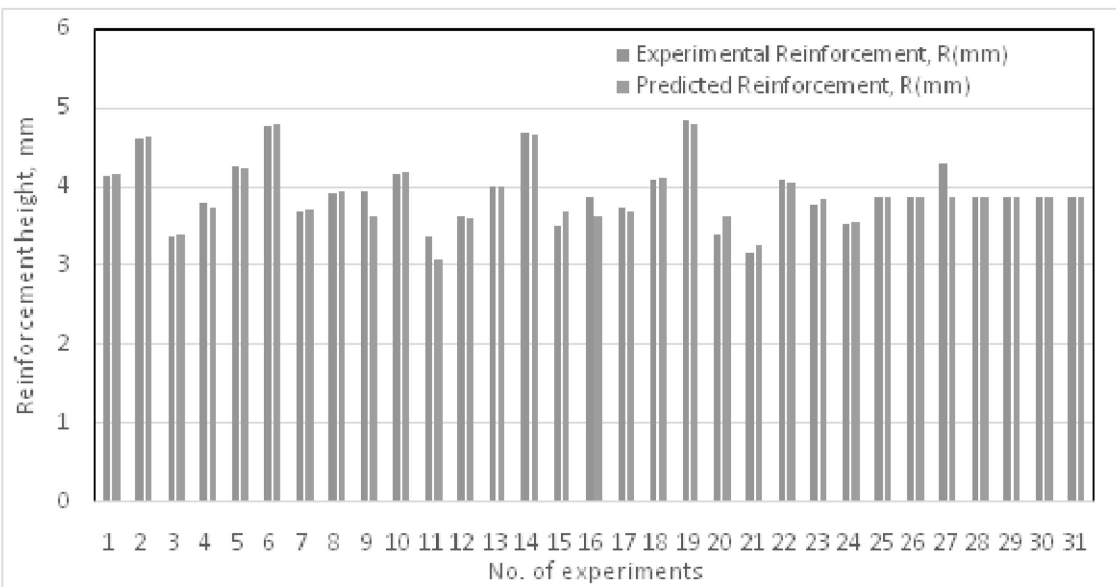


Fig. 7 : Column diagram of Experimental and predicted values of Reinforcement height

Table 5 shows correlation between the Experimental values of Reinforcement height and Predicted values obtained from Artificial Neural Networks operation. The maximum Reinforcement height of 4.83 and 4.79 mm as obtained from Experimental No. 19 in both experimental and predicted approach. Those numbers are quite similar in nature as well as error percentage is only 0.04. The maximum and minimum error % are only +0.33 and 0.01. In Fig. 7, column chart also shows quite close between Experimental and predicted values.

Table 6 shows correlation among the Experimental values of depth of penetration and predicted values obtained from Artificial Neural Networks operation. The maximum depth of penetration of 0.834 and 0.73 mm are obtained from Experimental No. 21 in both experimental and predicted approach. Those numbers are not so similar in nature as well as error percentage is a bit high at 12.34. The maximum and minimum error % are -95.57 and -3.44. In Fig. 8, column chart also shows some deviations between Experimental and predicted values.

Table 5 : Different data of experimental and predicted values of Reinforcement height

Sl. No	Wire feed rate	Welding speed	Nozzle-to plate distance	Welding gun angle	Reinforcement R (mm)	Predicted Reinforcement (mm)	% Error
1	-1	-1	-1	-1	4.13	4.15	-0.02
2	1	-1	-1	-1	4.61	4.63	-0.02
3	-1	1	-1	-1	3.37	3.40	-0.03
4	1	1	-1	-1	3.78	3.73	0.05
5	-1	-1	1	-1	4.27	4.25	0.02
6	1	-1	1	-1	4.77	4.80	-0.03
7	-1	1	1	-1	3.68	3.71	-0.03
8	1	1	1	-1	3.92	3.94	-0.02
9	-1	-1	-1	1	3.96	3.63	0.33
10	1	-1	-1	1	4.15	4.19	-0.04
11	-1	1	-1	1	3.36	3.07	0.28
12	1	1	-1	1	3.62	3.61	0.01
13	-1	-1	1	1	3.99	4.01	-0.02
14	1	-1	1	1	4.68	4.66	0.02
15	-1	1	1	1	3.5	3.69	-0.19
16	1	1	1	1	3.87	3.63	0.24
17	-2	0	0	0	3.74	3.68	0.06
18	2	0	0	0	4.09	4.09	-0.01
19	0	-2	0	0	4.83	4.79	0.04
20	0	2	0	0	3.4	3.64	-0.24
21	0	0	-2	0	3.16	3.25	-0.09
22	0	0	2	0	4.09	4.05	0.04
23	0	0	0	-2	3.77	3.83	-0.06
24	0	0	0	2	3.52	3.54	-0.02
25	0	0	0	0	3.87	3.87	-0.01
26	0	0	0	0	3.87	3.87	-0.01
27	0	0	0	0	4.28	3.87	0.40
28	0	0	0	0	3.86	3.87	-0.02
29	0	0	0	0	3.87	3.87	-0.01
30	0	0	0	0	3.86	3.87	-0.02
31	0	0	0	0	3.86	3.87	-0.02

Table 6 : Different data sets of experimental and predicted values of Penetration depth

Sl. No	Wire feed rate	Welding speed	Nozzle-to plate distance	Welding gun angle	Penetration P (mm)	Predicted Penetration (mm)	% Error
1	-1	-1	-1	-1	0.371	0.48	-28.92
2	1	-1	-1	-1	0.42	0.44	-5.68
3	-1	1	-1	-1	0.376	0.45	-20.32
4	1	1	-1	-1	0.443	0.59	-34.16
5	-1	-1	1	-1	0.327	0.28	13.62
6	1	-1	1	-1	0.378	0.40	-5.70
7	-1	1	1	-1	0.342	0.30	11.75
8	1	1	1	-1	0.379	0.58	-54.33
9	-1	-1	-1	1	0.33	0.65	-95.57
10	1	-1	-1	1	0.407	0.28	29.58
11	-1	1	-1	1	0.338	0.67	-97.14
12	1	1	-1	1	0.431	0.48	-11.24
13	-1	-1	1	1	0.318	0.30	4.64
14	1	-1	1	1	0.362	0.32	11.92
15	-1	1	1	1	0.33	0.16	52.82
16	1	1	1	1	0.363	0.44	-20.14
17	-2	0	0	0	0.327	0.31	6.05
18	2	0	0	0	0.55	0.44	20.60
19	0	-2	0	0	0.419	0.45	-6.74
20	0	2	0	0	0.498	0.55	-9.57
21	0	0	-2	0	0.834	0.73	12.34
22	0	0	2	0	0.267	0.29	-7.02
23	0	0	0	-2	0.377	0.39	-3.44
24	0	0	0	2	0.178	0.28	-59.95
25	0	0	0	0	0.707	0.57	18.91
26	0	0	0	0	0.707	0.57	18.91
27	0	0	0	0	0.707	0.57	18.91
28	0	0	0	0	0.707	0.57	18.91
29	0	0	0	0	0.529	0.57	-8.38
30	0	0	0	0	0.707	0.57	18.91
31	0	0	0	0	0.707	0.57	18.91

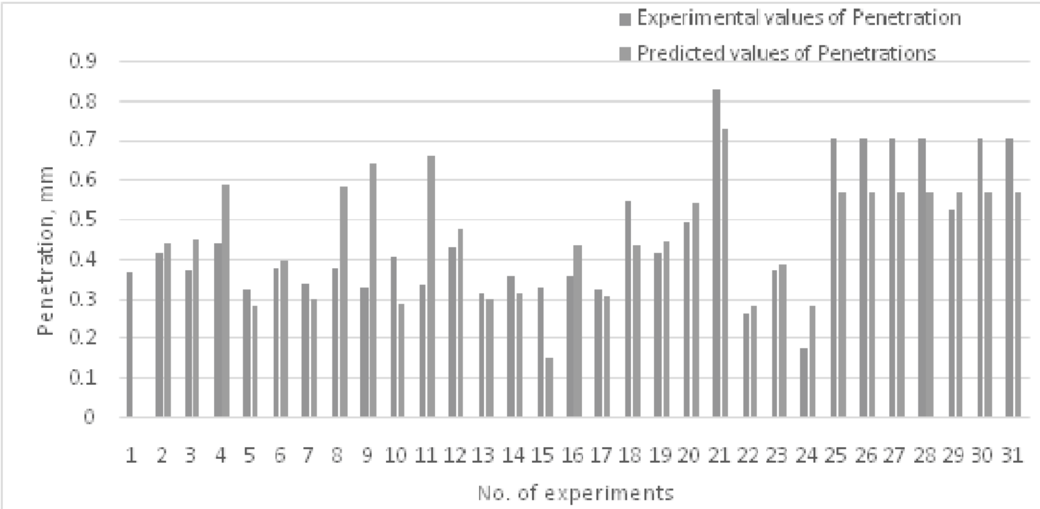


Fig. 8 : Column diagram of experimental and predicted values of penetration depth

7.0 CONCLUSIONS

In the context of bead on plate process performance for low carbon steel substrate using flux cored super duplex stainless steel filler wire. An attempt is made to predict output parameters using Artificial Neural Networks (ANN). The following conclusions are made after the investigations:

- By comparison between the chosen three ANN functions, TRAINLM (Levenberg-Marquardt) is found to be the most appropriate training function for prediction of bead geometry.
- Various comparison table are found to be stated that, Experimental and predicted values of Bead geometry are significant to each other. There values are quite similar.
- Also column chart shows similarity to Experimental and predicted values.
- Column chart of experimental and predicted values of penetration depth shows dissimilarity. Thus not adequate to predict the bead geometry correctly. So it is not recommended to further future work.
- Therefore, it can be summarized that bead geometry can well be estimated using an ANN algorithm.

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