RESEARCH ARTICLE

Comprehensive Development and Comparison of two Feed Forward Back Propagation Neural Networks for Forward and Reverse Modeling of Aluminum Alloy AA5083; H111 TIG Welding Process

Suneel RamachandraJoshi *, Dr.J.P.Ganjigatti **
* *Research school,Departmen of Industrial Engineering and Management,SIT,TumkurKarnataka,India.*
** *Professor, Departmen of Industrial Engineering and Management,SIT,TumkurKarnataka,India.*

ABSTACT
The development of an intelligent system for the establishment of relationship between input parameters and the responses utilizing both reverse and forward modeling of artificial neural networks is the main objective of the present research work. Prediction of quality characteristics such as front width, back width, front height and back height of the weld bead geometry in Tungsten Inert Gas welding process of AA5083; H111 Aluminum alloy is the aim in forward modeling from known set of process parameters such as current, %balance, welding speed, arc gap, gas flow rate, and frequency. Reverse modeling meets the industrial requirements of automatic welding to predict the recommended weld bead geometry characteristics. Comprehensive approach for the development of two back propagation networks viz. feed forward back propagation (FFBP) and Elman back propagation (EBP) neural networks is adopted. 212 Face centered central composite design based experimental data is utilized for the development of both supervised learning networks with batch mode training approach. A comparison of performance of FFBPP and EBP neural networks are made with that of stepwise multiple regression statistical modeling. Analysis of results showed that both neural network modeling outperformed the statistical approach in making better predictions and the models are efficient in selection of parameters effectively for the desired responses. FFBP performance found to marginally better than that of EBP neural network. Also the forward modeling performance was better than that of reverse modeling in both neural networks.
Key Words: Artificial Neural Networks, TIG welding, weld bead Characteristics, forward feed back propagation (FFBP) & Elman Back Propagation (EBP) Networks.

I. INTRODUCTION

Some of the quality requirements such as corrosion resistance, high strength to weight ratio, toughness and formability have made aluminum as the best material in most of the fabrication industries. One of the aluminum alloy, AA5083 ; H111 famously known as pressure vessel alloy and strongest non heat treated wrought alloy finds lot of application in cryogenic corrosion resistant applications, low temperature transport vessels & radioactive water waste tanks fabrication, ship building and general transport vehicles industries. TIG welding because of its superior weld quality plays an important role in modern manufacturing especially in aerospace, automobile and ship building industries. TIG welding is utilized for the welding of aluminum, magnesium, stainless steel and titanium materials. The heat generated by the electric arc established between the tungsten electrode and the base metal with inert-gas shielding produces the coalescence. As it plays an important role in determining the mechanical properties of weldment, the weld bead geometry strongly characterizes the final quality of the TIG welding. Welding process parameters such as current, welding speed, stand-off distance and gas flow rate affect the quality of weld bead geometry. The weld bead geometry parameters may include front width, back width, front height, back height, penetration, and HAZ etc. This clearly indicates the complex, multivariate, multi response nature of the TIG welding process. The literature confirms TIG welding as highly non linear and strongly coupled process with never ending interest in researching for input-output relations to obtain high level of quality under different circumstances. A manufacturing process like TIG welding needs to be automated to ensure both high productivity and good quality which in turn requires a proper tested model. Many researchers have applied different statistical techniques successfully for this purpose. But the automation of any process requires input-output relationships to be known in both forward and reverse directions. As the transformation matrix turns singular and might not be invertible always, the backward prediction i.e. determination of process parameters to predict the desired outputs, might become difficult through the conventional statistical techniques. Soft computing techniques like neural networks (NN), genetic algorithms(GA) and Fuzzy logic(FL) etc. have made the generation of an integrated system that estimates two or more responses simultaneously and reverse prediction modeling , a possibility. In recent past, application of neural networks for modeling input - output relationships for complicated manufacturing processes like casting, machining and various welding processes has started to replace the earlier statistical techniques. This is due to the shear ability of neural networks to learn and generalize (interpolate) the complicated input-output relations. Several researchers have attempted to use neural networks for various welding process modeling

II. LITERATURE SERVEY

T.G Lim, and H.S cho, [1] proposed a neural network model for the estimation of Weld pool sizes in GMA welding of 200×60×4 hot rolled AISI 1025 Plates. Utilizing the variable polarity plasma arc data of aluminum welding, George.E.Cook, Robert Joel Barnett, Kristinn Andersen, and Alvin M Strauss, [2] used artificial neural networks (ANN) in its modeling, analysis & control application. S.C. Juang, Y.S.Tarng, and H.R. Lii, [3] described both back-propagation (BPNN) and counter-propagation (CPNN) networks for modeling TIG Welding process of pure Aluminum 1100 sheet of 1.6mm with a single pass with reasonable accuracy & found BPNN with better generalization & CPNN with better learning ability. . Kim et al [4] proposed two different neural networks using two different training algorithms for predicting the weld bead width as a function of key process parameters and found Lavenberg-Marquardt algorithm to perform better over error back propagation. . D.S Nagesh & Datta [5] explored the use of Back Propagation Neural Network to model SMAW process of grey C.I plates with M.S electrodes to relate welding process variables with bead geometry. The network achieved good agreement with the training data & yielded satisfactory generalization. . Parikshit Dutta, and Dilip Kumar Pratihar [6] proposed two neural network-based approaches (i.e., back-propagation neural network and genetic-neural system) Both the NN-based approaches were found to be more adaptive compared to the conventional regression analysis, for the test cases. Genetic-neural (GA-NN) system outperformed the BPNN in most of the test cases (but not all). Taking the results of submerged arc welding process from V.Gunarajan & N.Murugan, K.Manikya Kanti, and P.Shrinivasa Rao [7] developed back propagation neural network model for the prediction of weld bead geometry in pulsed gas metal arc welding process with correlation coefficient of 0.99. Amarnath & Pratihar [8] solved forward and reverse mapping problems of the tungsten inert gas (TIG) welding process using radial basis function neural networks (RBFNNs). Nagesha & Datta[9] developed a back-propagation neural network & Ganetic algorithm to optimize the process parameters for front height to front width ratio and back height to back width ratio yielded satisfactory results and it is felt that these are powerful tools for analysis and modeling of TIG welding process. Vidyut Dey,Dilip Kumar Pratihar, and G.L.Datta [10] could find back – propagation neural network (BPNN) to show better performance than genetic-neural (GA-NN) in predicting the bead profiles in Electron beam bead on plates welding. Y.S.Tarng, J.L.Wu, S.S. Yeh, and S.C. Juang [11] described application of Neural Network & Simulated annealing (SA) algorithm to model & optimize the GTAW process of pure 1.6mm aluminum 1100 sheet. As CPN is equipped with good learning ability, CPN is selected to model the process & SA applied to search for welding process parameter with optimal weld pool features Ghosh and Sarkar [12] have proposed a neural network model to predict the yield characteristics of submerged arc weldments. R.J.Praga-Alejo,L.M.Torres-Trevino, and M.R.Pina-Monarrez [13] found the performance of neural network plus GA algorithm a little better than response surface methodology with canonical analysis. R.P.Singh, R.C.Gupta, and S.C.Sarkar [14] used artificial neural network technique to predict the tensile strength of weld for the given welding parameters. I.U. Abhulimen & J.I. Achebo[15] used Artificial neural network in the prediction and optimization of the Tungsten inert gas weld of mild steel pipes. Neural network model was generated using the Levenberg-Marquardt algorithm with feed ward back propagation learning rule. Results show that the generated neural network model was able to predict tensile and yield strength to a mean square error of 34.2. K. Anand [16] utilized neural networks for predicting the friction welding process parameters to weld Incoloy 800H.Lin & Chou [17] adopted neural network with a Levenberg - Marquardt back-propagation (LMBP) algorithm was then adopted to develop the relationships between the welding process parameters and the tensile-shear strength of each weldment

The literature survey revealed absence of a comprehensive and efficient neural network modeling process with limited application in reverse modeling and comparison of various learning, training algorithms and transfer functions was found not adopted for better model development. The application of Elman back propagation neural network was rare in weld process modeling as per literature survey. The present research work provides a comprehensive method for developing two different backward propagation neural networks, feed forward back propagation and Elman back propagation, both in forward & reverse modeling and the comparison of their performance in reverse modeling along with the comparison of their performance in forward mapping with stepwise regression modeling performance by taking into account of upper said findings in the development of neural network models.

III. EXPERIMENTAL PROCEDURE

Response surface methodology (RSM) based design of experiment, Face centered central composite design with 53 total runs comprising of 32 half factorial points plus 9 center points and 12 star points was employed for conducting the experiments. The experiment was conducted as per the above design matrix available in MINITAB 16 at random to take care of systematic errors infiltration. The experimentation is carried out in the fabrication shop of Siddhivinayak fabricators, Bengaluru. Single pass autogenous bead on plate welding procedure is followed to simulate tight butt joint welding on 5 mm thick AA 5083; H111 aluminum alloy with current, % balance, welding speed arc gap, shielding gas flow rate and frequency as process parameters and front width(FW), back width(BW), front height(FH), back height(BH) as weld bead characteristics (responses). The welding of plate is carried out normal to the rolled direction. A gas mixture of 75% Helium and 25% Argon is used as shielding gas along with 0.2% Zirconiated tungsten rod of 3.2 mm diameter as electrode. To simulate the actual robot welding operation the welding torch was made to move along the precise aluminum railings pertaining to ESAB automatic gas cutter .The experiment was conducted by varying the current in the range of 145-185 ampere , the % balance in the range of 32-68 % , the gap in the range of 1.5-2 mm , welding speed in the range of 230-330 mm/min, the gas flow rate in the range of 15-20 L/min and frequency in the range of 30-110 Hz. The experimental set up is shown in Figure 1. Then the weld bead geometry quality characteristics such as, were measured in millimeters using Project profilometer after preparing specimen following the standard metallographic procedures. Four replicates are taken for each run totaling 212 input data.

Fig. 1: Experimental set up of TIG welding process

Table 1: Design matrix with input parameters at ctual values [23]

RUNS	Current	% balance	gap	speed	Flow. Rate	Frequency
DP41	165	50	1.75	280	15	70
DP13	145	32	2	330	15	30
DP22	185	32	2	230	20	110
DP43	165	50	1.75	280	17.5	30
DP50	165	50	1.75	280	17.5	70
DP37	165	50	1.5	280	17.5	70
DP8	185	68	2	230	15	110
DP44	165	50	1.75	280	17.5	110
DP51	165	50	1.75	280	17.5	70
DP35	165	32	1.75	280	17.5	70

DP6	185	32	2	230	15	30
DP23	145	68	2	230	20	110
DP25	145	32	1.5	330	20	30
DP14	185	32	2	330	15	110
DP10	185	32	1.5	330	15	30
DP9	145	32	1.5	330	15	110
DP46	165	50	1.75	280	17.5	70
DP42	165	50	1.75	280	20	70
DP40	165	50	1.75	330	17.5	70
DP19	145	68	1.5	230	20	30
DP48	165	50	1.75	280	17.5	70
DP28	185	68	1.5	330	20	30
DP33	145	50	1.75	280	17.5	70
DP24	185	68	2	230	20	30
DP31	145	68	2	330	20	30
DP36	165	68	1.75	280	17.5	70
DP18	185	32	1.5	230	20	30
DP39	165	50	1.75	230	17.5	70
DP27	145	68	1.5	330	20	110
DP11	145	68	1.5	330	15	30
DP1	145	32	1.5	230	15	30
DP15	145	68	2	330	15	110
DP21	145	32	2	230	20	30
DP7	145	68	2	230	15	30
DP12	185	68	1.5	330	15	110
DP30	185	32	2	330	20	30
DP52	165	50	1.75	280	17.5	70
DP3	145	68	1.5	230	15	110
DP26	185	32	1.5	330	20	110
DP2	185	32	1.5	230	15	110
DP45	165	50	1.75	280	17.5	70
DP49	165	50	1.75	280	17.5	70
DP20	185	68	1.5	230	20	110
DP47	165	50	1.75	280	17.5	70
DP17	145	32	1.5	230	20	110
DP53	165	50	1.75	280	17.5	70
DP34	185	50	1.75	280	17.5	70
DP4	185	68	1.5	230	15	30
DP38	165	50	2	280	17.5	70
DP29	145	32	2	330	20	110
DP16	185	68	2	330	15	30
DP32	185	68	2	330	20	110
DP5	145	32	2	230	15	110

IV. PROCESS MODELING USING STATISTICAL APPROACH [23]

Utilizing MINITAB Statistical software version 16 the mathematical models are developed for all the quality characteristics using stepwise regression analysis which eliminates the insignificant model terms automatically with stepwise selection of terms α to enter = 0.15, α to remove = 0.15. The method is dealt by Douglas.C.Montogomory [18]. Considering linear, square and 2 way interactions the following response equations are developed for each quality characteristics.

$$FW = 2.52 + 0.5874D - 0.1510A - 45.68T - 0.15951P + 3.254M - 0.05035R - 0.002193D^2 + 0.001440A^2 + 13.146T^2 + 0.000028P^2 - 0.07074M^2 - 0.000099R^2 + 0.000150DA + 0.02667DT + 0.000447DP - 0.001877DM - 0.01595AT - 0.000032AP + 0.001905AM - 0.000223AR + 0.018494TP - 0.4564TM - 0.012805TR + 0.000684PM + 0.000280PR + 0.000854MR$$

$$FH = - 2.474 - 0.01388D + 0.03874A - 5.761T + 0.04493P + 0.1652M - 0.03681R - 0.000284A^2 + 2.128T^2 - 0.000102P^2 + 0.000071R^2 - 0.000047DA - 0.003188DT + 0.000101DP - 0.000584DM + 0.000024DR - 0.001215AT - 0.000424AM + 0.000087AR - 0.002625TP - 0.01325TM - 0.001062TR - 0.000161PM + 0.000064PR + 0.000095MR$$

$$BW = - 9.90 + 0.1653D - 0.0272A - 10.78T - 0.04756P + 2.975M - 0.10527R - 0.000710D^2 + 0.000578A^2 + 1.517T^2 - 0.000054P^2 - 0.09523M^2 + 0.000278R^2 - 0.000246DA + 0.01608DT + 0.000178DP + 0.000107DR - 0.000084AP + 0.001977AM + 0.000067AR + 0.012856TP - 0.00432TR + 0.000946PM + 0.000123PR + 0.000855MR$$

$$BH = 11.38 - 0.1005D - 0.06271A + 5.32T - 0.05544P + 0.310M + 0.02810R + 0.000307D^2 + 0.000445A^2 - 2.615T^2 + 0.000046P^2 -$$

$$0.02395M^2 - 0.000108R^2 - 0.000183DA + 0.000018DP + 0.000792DM - 0.000073DR + 0.000091AP + 0.001536AM - 0.000093AR + 0.007494TP + 0.08512TM + 0.000852TR + 0.000504PM - 0.000005PR + 0.000220MR$$

V. MODELING OF TIG WELDING PROCESS USING ARTIFICIAL NEURAL NETWORKS

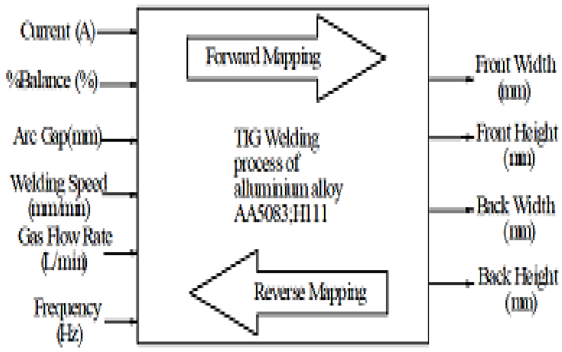


Figure2: Forward and reverse TIG welding process modeling.

Artificial neural network (ANN) is one of the computational based artificial intelligence techniques (AI) that copies the behavior of human brain. It has the self learning capability, adaptation characteristic and is basically non linear in nature. Hence ANN is applied as an excellent tool for handling complex non linear engineering processes by R.J.Praga-Alejo, L.M.Torres-Trevino, and M.R.Pina-Monarrez [13] Development of ANN consists of 5 basic steps 1) collecting data 2) preprocessing data 3) creating the network 4) training the network 5) simulate the network response to new inputs. As stated by Rakesh Malviya,and Dilip Kumar Pratihar [19], in order to automate any process, knowing input-output relation ships both in reverse and forward direction is required, on line.

5.1 Forward modeling- Feed forward back propagation neural network (FFBPNN)

The most common and successful ANN architecture with feed forward network topology is multilayer perceptron (MLP).Multilayer back propagation algorithm (FFBP) is the most common supervised learning technique used for training ANNs. FFBP network minimizes the errors between obtained outputs and desired target values by feeding back the derivatives of network error with respect to networks and adjusting the weights so that the error decreases with each iteration and the ANN model gets closer and closer to the desired target values. 212 input and output data obtained as a result of the real experimentation is utilized for training and testing of the neural networks. For training both the back propagation neural networks in forward and reverse modeling, the training parameters utilized are goal-0,min_grad--1 x 10^{-7},max_fail-6,mu-0.001,mu_dec-0.1,mu_inc-10, mu-max—1 x 10^{10} and 1000 epochs. Neural network tool box of MATLAB R2013a was utilized for the whole modeling process.

In this research work, preprocessing was done to scale the inputs and targets to fall within a specified range (-1 to +1) by using minmax technique so that accuracy of subsequent numeric computation enhances by avoiding effect of high valued variables on lower magnitude variable during training. Creating the network means finalizing the number of layers and the number of neurons in hidden layer. S.C Juang et al.[3] have found that many researchers have confirmed experimentally that single hidden layer is sufficient to provide better convergence in the modeling of TIG welding process, in the present research work a three layer feed forward neural network architecture consisting of six input, four output neurons and a hidden layer is utilized. During the network construction, the data set was divided into training, validation and test data in proportion of 0.7, 0.15 and 0.15respectively. For gradient computation and weights & bias updating, training set was used. For improving generalization, validation set and for validating the network performance, test set was utilized. The selection of data in each set is done randomly and then the network was created .As the finalization of number of neurons in the hidden layer is crucial for efficient modeling as found by Ill-Soo Kim et al [20] six data selected randomly, are utilized for

calculating simulating error of each architecture during the finalization of neurons in hidden layer and remaining 6 data are used in calculating absolute % of prediction error (APPE) for the model finalized through comprehensive method. a comprehensive methodology is adopted. Out of 212 data, 200 data has been utilized for the modeling. During finalization of architecture, the conducted parametric analysis is shown in Table 1. During the parametric
analysis, trainlm, learngdm and mse are used as training; adaptation learning and performance function respectively. Tan sigmoid was used as transfer function for hidden and output layers. Five trainings were conducted and the architecture with minimum mean square error (MSE) with minimum percentage of simulation error was chosen to avoid over fitting.
The analysis of the table 2 yielded the final architecture for forward mapping as 6-20-4. This architecture was again trained using 12 different back propagation training algorithms to select an efficient algorithm for training the ANN. Then afterwards, various transfer functions and adaptation learning algorithms are considered for creating the network. The neural model with best prediction capacity having Pearson Correlation Coefficients above 0.98 for the training, validation and test sets was taken as performance criteria. The analysis is shown in table 3, 4 and 5 respectively.

Table2: Parametric analysis for architecture finalization

Architecture	MSE	%Simulating error	Average absolute error	Architecture	MSE	%Simulating error	Average absolute error
6--5—4	0.0359	2.8489	7.34745	**6--20--4**	0.00187	0.4841	**0.6655075**
	0.0396	17.786			0.0017	1.16	
	0.0371	-7.5426			0.00177	-0.1033	
	0.0393	-1.2123			0.00188	-0.91463	
	0.0378				0.00168		
6--10—4	0.00947	-0.4169	2.07601	6--25--4	0.0019	0.49815	0.80853
	0.0109	-4.365			0.00176	1.72026	
	0.011	-0.2814			0.0019	-0.18139	
	0.00845	3.2407			0.00203	-0.83432	
	0.00823				0.00184		
6--15--4	0.00203	-1.2439	1.6248				
	0.00226	4.564					
	0.00215	0.02723					
	0.00239	0.66417					
	0.00222						

Analysis of above table yielded a neural network as shown in Figure 3. It is a feed forward back propagation network of 6-20-4 neuron configuration with a Lavenberg-Marquardt training algorithm (trainlm), gradient descent BP with momentum as adoptive learning algorithm (traingdm) and tan-sigmoid (tan-sig) as transfer function for both hidden & output layers. The Levenberg-Marquard approximation algorithm was found to be the best fit for application. Similar results found in literature by P.Sreeraj, T.kannan, and S.Maji [21]

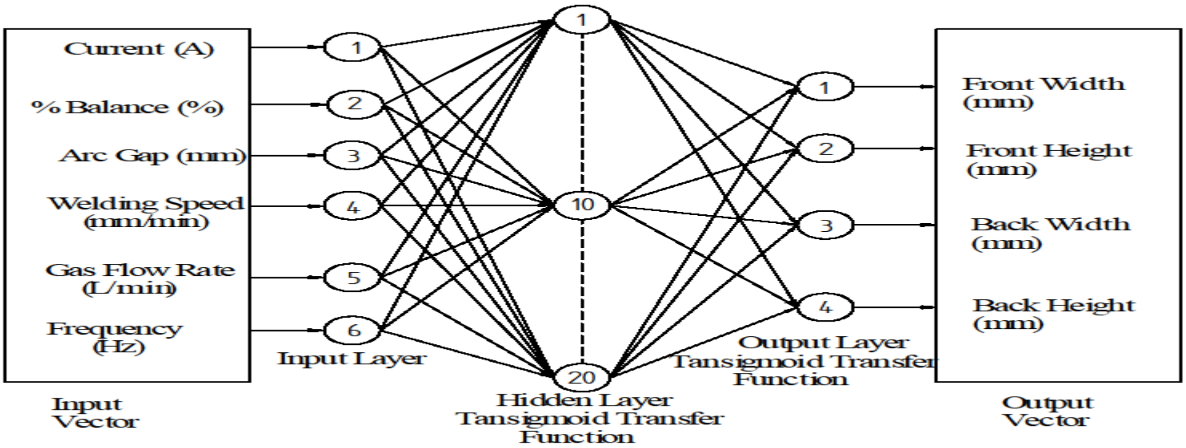


Figure 3: Configuration of back propagation neural network for forward modeling of TIG weldin

5.2 Reverse modeling- Feed forward back propagation neural network (FFBPNN)

Following the similar procedure as that of forward modeling, reverse modeling is performed**.** The finalized architecture is a feed forward back propagation network of 4-20-6 neuron configuration with a Lavenberg-Marquardt training algorithm (trainlm), gradient descent BP with momentum as adoptive learning algorithm (traingdm) and tan-sigmoid (tan-sig) as transfer function for both hidden & output layers.

6 ELMAN'S BACK PROPAGTION NEURAL NETWORK (EBPNN)

Jeffrey Elman proposed this network. It is a neural network with semi recursive character which recognizes patterns from a sequence of values by back propagation through time learning algorithm. It is basically a recurrent neural network that enables sequential learning and identification of patterns in series of values or events that unfold over time and can be predicted. Elman's neural network consists of a recurrent first layer opposed to a conventional two layer network. Values from a previous step can be stored as context and used in the current time step. The stored information can be used in future and this enables temporal and spatial pattern learning. Following the similar procedure as that of earlier back propagation neural network generation, Elman's back propagation neural networks are generated both for forward and reverse modeling. During network finalization with respect to various training & adaptation learning algorithms and transfer functions, mean square error (MSE) is used as the performance criteria.

6.1 Forward modeling (EBP)

Finalized network is Elman back propagation network of 6-25-4 neuron configuration with a Lavenberg-Marquardt training algorithm (trainlm), gradient descent BP with momentum as adoptive learning algorithm (traingdm) and log-sigmoid (log-sig) as transfer function for hidden & pure lin for output layer as shown in Figure 4.

6.2 Reversed modeling (EBP)

The analysis yielded the final architecture for reverse mapping as 4-25-6. This architecture was again trained using different learning algorithms, transfer functions and training algorithms Finalized network is Elman back propagation network of 4-25-6 neuron configuration with a Lavenberg-Marquardt training algorithm (trainlm), gradient descent BP with momentum as adoptive learning algorithm (traingdm) and log-sigmoid (log-sig) as transfer function for hidden & pure lin for output layer.

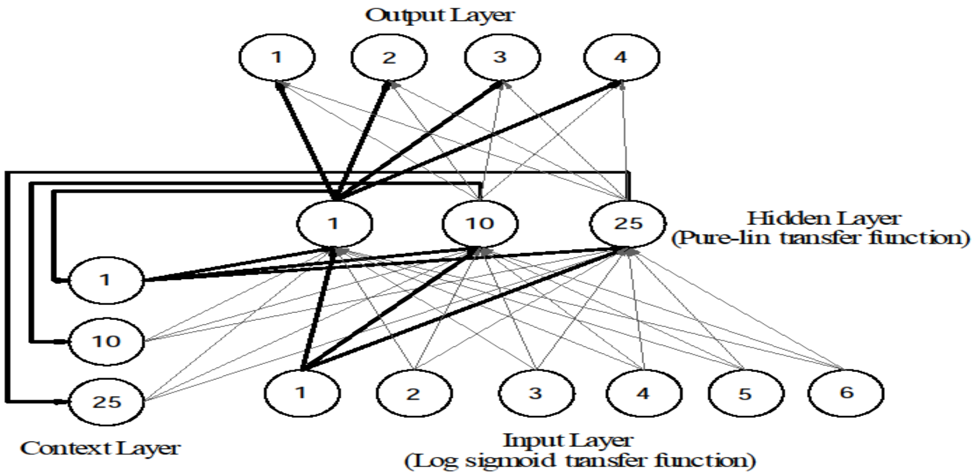


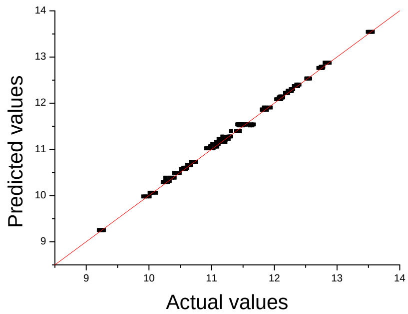
Figure 4: Configuration of Elman back propagation neural network for forward modeling of TIG welding

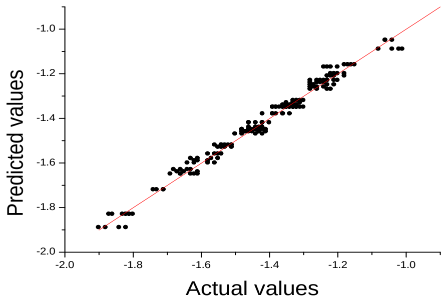
7 RESULTS AND DISCUSIONS

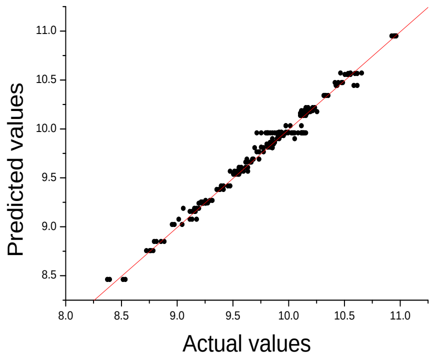
Forward and reverse modeling of TIG welding of aluminum alloy AA5083: H111 have been carried out using the artificial neural networks developed through FFBP and EBP. Results of the modeling are stated and discussed below.

7.1 Results of forward modeling

Once the networks are trained with the finalized parameters, algorithms and transfer functions, the networks are simulated with six unused data, network outputs are noted and the predicted vs. the actual plots for all the four quality characteristics FW, BW, FH, and BH are drawn respectively. The entire predicted vs. actual plots give an indication that the models developed are adequate as points are scattered randomly and closure to the 45 degree line as shown in Figure 6







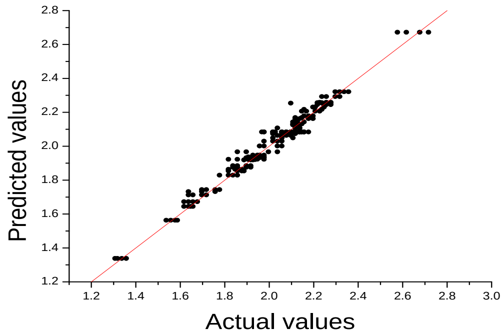


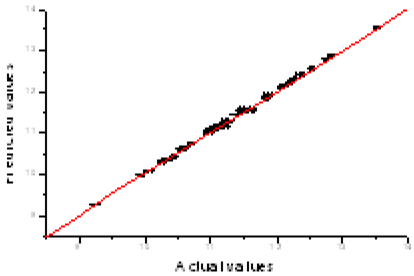
Fig 5 : predicted vs. the actual values plots for all the four quality characteristics FW, FH, BW, and BH respectively (BPNN)

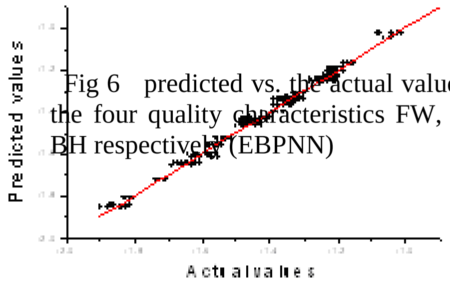
Then the absolute percentage of prediction error (APPE) is calculated for the simulated results and compared with corresponding RSM statistical model results and the comparison is shown in table 6. The analysis of the table reveals that the both back propagation neural networks predict the results accurately. The percentage of prediction errors found in FFBP is smaller than that of EBP. And the performance of both the neural networks found to be better than that of statistical method in three quality characteristics except front height. Experimental errors and measurement errors could be the reason in case of front height.

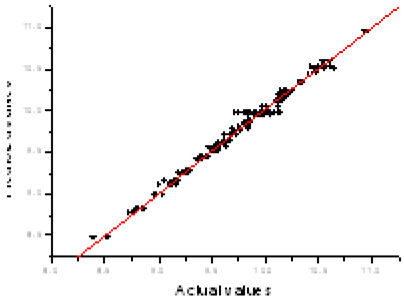
Table 6: Comparison of APPE for FFBP and EBP forward modeling of welding process

FW				FH			
Experimental	RSM	EBPP	FFBP	Experimental	RSM	EBPP	FFBP
11.12	11.035	11.043	11.0618	-1.31	-1.316	-1.346	-1.35
11.42	11.519	11.52	11.5282	-1.38	-1.351	-1.34	-1.354
11.28	11.274	11.24	11.2348	-1.64	-1.611	-1.611	-1.594
11.22	11.173	11.2	11.1985	-1.05	-1.048	-1.06	-1.05
11.58	11.519	11.52	11.5282	-1.36	-1.3509	-1.34	-1.35
11.916	11.8682	11.889	11.8943	-1.68	-1.6749	-1.656	-1.65
APPE	0.34%	0.46%	**0.44%**	APPE	**1.40625**	1.8728	1.7

BW				BH			
Experimental	RSM	EBPP	FFBP	Experimental	RSM	EBPP	FFBP
9.26	9.217	9.246	9.2374	1.96	1.9713	1.924	1.917
9.92	9.977	9.991	9.9522	2.08	2.083	2.102	2.081
9.27	9.292	9.26	9.2456	2.21	2.1793	2.229	2.255
9.01	9.106	9.015	9.0158	1.7	1.75	1.73	1.729
9.96	9.977	9.991	9.9522	2.08	2.15	2.102	2.081
10.13	10.09	10.15	10.181	2.24	2.2368	2.282	2.242
APPE	0.48	0.253	**0.2466**	APPE	1.4266	1.405	**1.013**







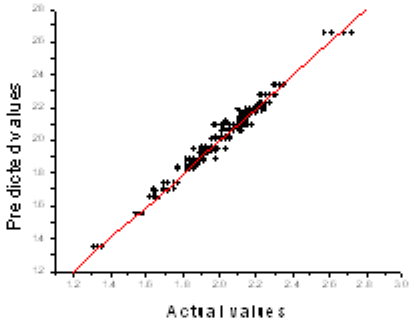


Fig 6 predicted vs. the actual values plots for all the four quality characteristics FW, FH, BW, and BH respectively (EBPNN)

7.2 Reverse modeling results

On the same lines as that of forward modeling, following results are obtained for reverse modeling and are depicted in Figure 7 and Figure 8 respectively for FFBPNN and EBPNN

Table 7: Comparison of APPE for FFBP and EBP reverse modeling of welding process.

Current			% Balance			Gap		
ual	BPNN	EBP	actual	BPNN	EBP	actual	BPNN	EBP
5	183.29	184.96	50	45.855	62.4542	1.75	1.7542559	1.6284
5	162.97	158.8	50	52.5567	44.049	1.75	1.7791983	1.7357

185	184.91	179.954	68	56.2772	51.2951	1.5	1.7613236	1.6
185	185	184.998	68	67.8162	67.9879	1.5	1.622845	1.9
145	180.98	145.212	68	66.5043	52.4638	1.5	1.7131567	1.6
165	163.56	164.8	50	52.0795	56.6171	1.75	1.7818084	1.7
APPE	6.3417	**3.141769**	**APPE**	**6.212**	16.2459	**APPE**	**7.2585**	8.8

Speed			Gas flow rate			Frequency		
ual	BPNN	EBP	actual	BPNN	EBP	actual	BPNN	EBP
30	305.03	249.988	15	15.3171	16.5187	70	24.609148	38.2077
30	271.23	275.753	17.5	17.6578	18.1394	20	2[illegible]37746646	70.945
30	330	257.977	20	16.3975	16.6112	30	31.483593	77.6979

330	330	329.703	15	15.0151	15.3297	110	107.78938	109.
230	230	235.849	15	18.3615	18.9418	110	109.27331	108
280	272.86	276.815	17.5	17.4879	18.0923	70	65.085587	69.4
APPE	**2.437**	6.305	**APPE**	**7.268**	10.43	**APPE**	**4.1447**	34.7

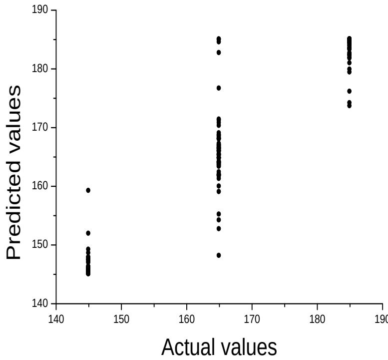
Analysis of the table 7 reveals that absolute percentage error of prediction of both networks found accurate enough except frequency prediction, which was slightly out of limit. BPNN found better than EBP in prediction of five characteristics except current. And also comparisons of forward and reverse modeling found that the forward modeling accuracy was far better than that of the reverse modeling.

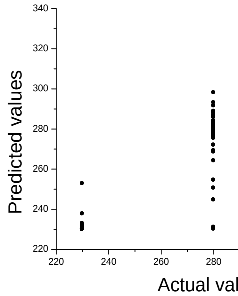
8 CONFIRMATION EXPERIMENTS RUNS (FORWARD MODELING)

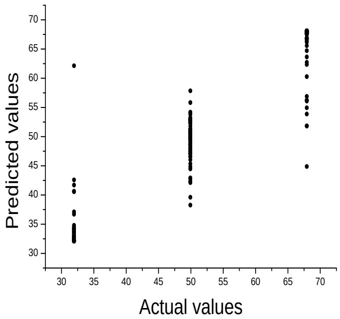
Using composite desirability approach, optimal parameter setting obtained was current 145 A,% balance 37.0909,gap of 1.6667 mm, welding speed of 330 mm/min,20 L/min gas flow rate and 38.0808 Hz frequency. And the optimal setting yielded the experimental results which were compared with that predicted by FFBP and EBP forward modeling approaches and the results are shown in table 8 with absolute percentage prediction error(APPE) as evaluation criteria. Accuracy of prediction found better in FFBP network in most cases than RSM and EBP approaches.

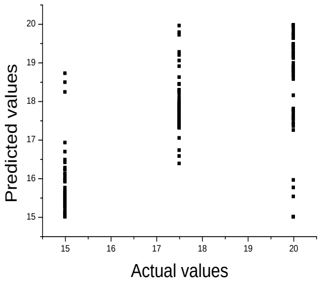
Table 8: Comparison of APPE for FFBP and EBP forward modeling at optimum condition

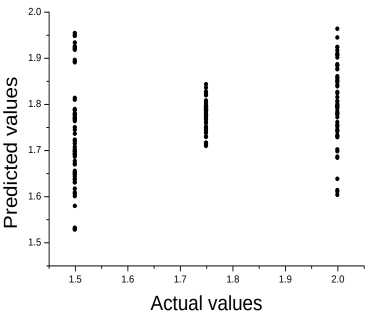
FW				FH			
Expmtl.	RSM	FFBP	EBP	Expmtl	RSM	FFBP	EBP
9.93	9.21	10.0261	9.7291	-1.48	-1.6	-1.5616	-1.5743
APPE	7.81%	**0.95%**	2.06%	APPE	7.50%	**5.23%**	5.99%
BW				BH			
Expmtl	RSM	FFBP	EBP	Expmtl	RSM	FFBP	EBP
8.22	8.83	8.514	8.6243	1.58	1.68	1.4655	1.5695
APPE	6.90%	**3.40%**	4.68%	APPE	5.95%	7.80%	**0.67%**











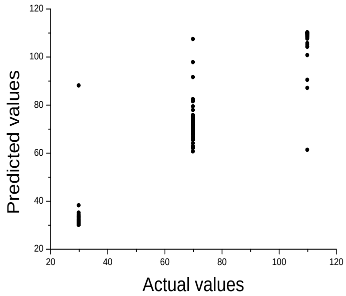


Fig 7: predicted vs. the actual values plots for all the four quality characteristics FW, FH, BW, and BH respectively
(FFBPNN)

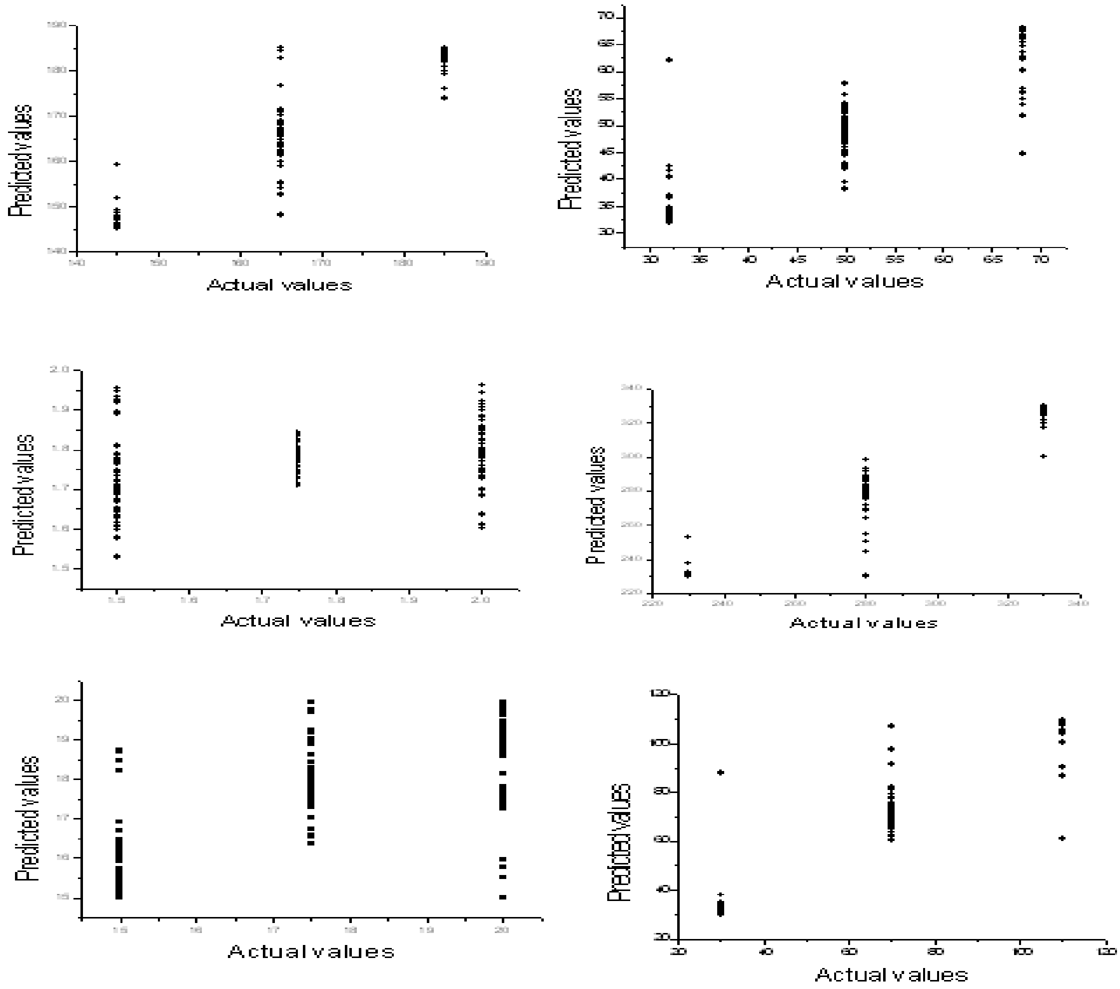


Fig 8: predicted vs. the actual values plots for all the four quality characteristics FW, FH, BW, and BH respectively (EBPNN)

9 CONCLUSIONS

The present work proposes two artificial intelligence techniques, feed forward back propagation and Elman's back propagation artificial neural network as effective methods of conducting both forward and reverse modeling of TIG welding process of aluminum alloy AA5083:H111 to enable the automation of the process. The prediction results found in this work are in good agreement with the actual measurements with low absolute percentage of error performance index. The good results indicate that both the artificial neural networks are capable of accurately modeling weld bead geometry. The construction, training and simulating process of theses ANN models was very complicated so as the architecture finalization. A comprehensive way adopted in this work was to use some trail and error method and thoroughly understand the theory of back propagation for designing the neural networks efficiently to generate accurate predicting results. Both the approaches found to have more adoptive nature than the statistical approach which may be due to their ability to carry out interpolation within the parameter ranges. Both the neural network models found to possess better predictive ability than the step wise regression analysis based statistical approach. These two ANNs were found to be viable methods of predicting the parameters in both forward and reverse modeling as their accuracy has been tested by the comparison of the simulated results with that of the real experimental data of TIG welding process. Modeling by BPNN found to be more accurate in more cases in both reverse and forward modeling than EBP. Confirmation test during forward modeling emphasizes this superiority. Prediction accuracy in forward modeling found to be more than reverse modeling in both neural networks. Similar results are found by many authors in literature like Billy Chan ,Jack Pacey, and Malcolm Bibby [22]

REFERENCES

[1]. T.G Lim, and H.S cho, *"Estimation of weld pool sizes in GMA welding process using neural Networking" Journal of system & control Engineering Proc Instn. Mech Engrs Korea vol 207- IMechE 1993*.

[2]. George.E.Cook, Robert Joel Barnett, Kristinn Andersen, and Alvin M Strauss, *"Weld modeling and control using artificial Neural Networking," IEEE Transactions on industry applications, vol31, No.6 Novklee-1995*

[3]. S.C. Juang, Y.S.Tarng, and H.R. Lii, *"A comparison between the back-propagation and counter-propagation networks in the modeling of the TIG welding process," Journal of Materials processing Technology 75(1998)54-62*

[4]. I.S. Kim, J.S. Son, C.E. Park, C.W. Lee, Yarlagadda, and K.D.V.Prasad, *"A study on prediction of bead height in robotic arc welding using a neural geometry," Journal of materials processing Technology 130-131(2002) 229-234*

[5]. D.S. Nagesha, and G.L. Datta, *"Genetic algorithm for optimization of welding variables for height to width ratio and application of ANN for prediction of bead geometry for TIG welding process," Applied Soft Computing 10 (2010) 897–907*

[6]. Parikshit Dutta, and Dilip Kumar Pratihar, *"Modeling of TIG welding process using conventional regression analysis and neural network-based approaches," Journal of Materials Processing Technology 184 (2007) 56–68*

[7]. K.Manikya Kanti, and P.Shrinivasa Rao, *"Prediction of bead geometry in pulsed GMA using back propagation neural networks,"Journal of Materials Processing Technology 200 (2008) 300-305*

[8]. M V Amarnath, and D K Pratihar, *"Forward and reverse mappings of the tungsten inert gas welding process using radial basis function neural networks," Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 2009 223: 1575*

[9]. D.S. Nagesha, and G.L. Datta, *"Genetic algorithm for optimization of welding variables for height to width ratio and application of ANN for prediction of bead geometry for TIG welding process," Applied Soft Computing 10 (2010) 897–907*

[10]. Vidyut Dey,Dilip Kumar Pratihar, and G.L.Datta, *"Prediction of weld bead profile using neural network,"*

[11]. Y.S.Tarng, J.L.Wu, S.S. Yeh, and S.C. Juang, *"Intelligent modeling & optimization of the gas tungsten arc Welding process," Journal of intelligent manufacturing (1999) 10, 73-79*

[12]. A.Ghosh, S.Chattopadhyay, and P.K.Sarkar, *"Effects of input parameters on weld bead geometry of SAW process," ICME2007, Dhaka, Bangladesh*

[13]. R.J.Praga-Alejo,L.M.Torres-Trevino, and M.R.Pina-Monarrez*,"Optimization of welding process parameters through response surface, neural network and genetic algorithms"*

[14]. R.P.Singh, R.C.Gupta, and S.C.Sarkar*,"Application of artificial neural network to analyze and predict the tensile strength of shielded metal arc welded joints under the influence of external magnetic field," Int J. of engineering and science ISBN: 23189-6483,ISSN: 2278-4721,Vol. 2 Issue 1 Jan.2013,pp 53-57*

[15]. I.U. Abhulimen, and J.I. Achebo, *"Application Of Artificial Neural Network In Predicting The Weld Quality Of A Tungsten Inert Gas Welded Mild Steel Pipe Joint," International journal of scientific & Technology Research Vol.3 Issue 1, January 2014 ISSN 2277-8616*

[16]. K. Ananda, Birendra Kumar Barik , K. Tamilmannan, and P. Sathiya *, "Artificial neural network modeling studies to predict the friction welding process parameters of Incoloy 800H joints," Engineering Science and Technology, an International Journal 18 (2015) 394e407*

[17]. Hsuan-Liang Lin, and Chang-Pin Chou, *"Optimization of the GTA welding process using combination of the Taguchi method and a neural-genetic approach," Materials and manufacturing processes, 25:631-636, 2010*

[18]. Douglas.C.Montogomory*,"Design and analysis of experiments," Seventh edition published by John Wiley& Sons, INC,UK.*

[19]. Rakesh Malviya,and Dilip Kumar Pratihar*,"Tuning of neural networks using particle swarm optimization to model MIG welding process," Swarm and Evolutionary Computation 1 (2011) 223–235*

[20]. Ill-Soo Kim, Joon-Sik Son ,Sang-Heon Lee,Prasad K.D, and V.Yaralagadda , *"Optimal design of neural networks for control in robotic arc welding," Robotics and computer integrated manufacturing 20(2004) 57-63*

[21]. P.Sreeraj, T.kannan, and S.Maji, *"Genetic algorithm for the optimization of welding variables for percentage of dilution & application of ANN for prediction of weld bead geometry in GMAW process," Mechanical confab vol.2 No.1 Jan 2013*

[22]. Billy Chan ,Jack Pacey, and Malcolm Bibby, *"Modeling gas metal arc weld geometry using artificial neural network Technology," Canadian Metallurgical Quarterly , Vol 38 No 1, pp. 43-51*

[23]. Suneel.R.Joshi, and Dr.J.P.Ganjigatti, *"Simultaneous optimization of multiple quality characteristics in TIG welding of AA5083; H111 Aluminu Alloy using Response Surface Methodology coupled with composite desirability function"* International Journal of Applied Engineering Research ISSN 0973-4562 Volume 11, Number 9 (2016) pp 6525-6541 *(IN PRESS)*