Prediction of Welded Joint Strength in Plasma Arc Welding: A Comparative Study Using Back-Propagation and Radial Basis Neural Networks

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Abstract:

Welding input parameters such as current, gas flow rate and torch angle play a significant role in determination of qualitative mechanical properties of weld joint. Traditionally, it is necessary to determine the weld input parameters for every new welded product to obtain a quality weld joint which is time consuming. In the present work, the effect of plasma arc welding parameters on mild steel was studied using a neural network approach. To obtain a response equation that governs the input-output relationships, conventional regression analysis was also performed. The experimental data was constructed based on Taguchi design and the training data required for neural networks were randomly generated, by varying the input variables within their respective ranges. The responses were calculated for each combination of input variables by using the response equations obtained through the conventional regression analysis. The performances in Levenberg-Marquardt back propagation neural network and radial basis neural network (RBNN) were compared on various randomly generated test cases, which are different from the training cases. From the results, it is interesting to note that for the above said test cases RBNN analysis gave improved training results compared to that of feed forward back propagation neural network analysis. Also, RBNN analysis proved a pattern of increasing performance as the data points moved away from the initial input values.

Key words: Plasma arc welding, Regression analysis, Back propagation neural network, Radial basis neural network.

1. Introduction

Plasma arc welding is an urbanized from of TIG welding process. While in TIG welding, the arc burns freely between a non-consumed tungsten electrode and the work piece, in plasma welding it is additionally constricted by a nozzle and a gas stream. Comparing the features of the different processes, positive-pole welding emerges as the best. The current strength required is low, so that less heat is introduced into the parent metal and distortion is minimized. Production-related component tolerances can be controlled and the welder is not exposed to noise. Typical applications are processing of sections, pipes and sheet metal. During welding, it is very important to determine the influence of various input parameters on the responses. For this several modelling techniques like regression analysis, neural networks etc were employed by various researchers.

Multi-layer feed forward neural network is one of the simplest, robust and highly non-linear modeling techniques, and it is especially appropriate for model based supervision of uncertain systems. This technique has been extensively used for mapping input and output parameters of arc welding process. Andersen et al. [1] pioneered the application of neural network for modelling the arc welding process. Cook et al. [2] used two back propagation network models for variable polarity plasma arc welding process modeling and control. Moreover, Chi et al. [3] develop an intelligent decision support system for plasma arc welding based on fuzzy Radial Basis Function (RBF) neural network approach. Juang et al. [4] made a comparison between back-propagation and counter propagation networks in the modelling of the TIG welding process. Lee et al. [5] made a comparison of back-bead prediction of the GMAW process using multiple regression analysis and ANN analysis. Further, Seshank et al. [6] used ANN and Taguchi methods to predict the bead geometry parameters using pulsed current GTAW. Pal et al. [7] developed ANN model for prediction of weld properties in pulsed metal inert gas welding and compared the results with multiple regression analysis. Dutta et al. [8] compared regression analysis, BPNN, GA-NN for modelling of TIG welding process. Rakesh et al. [9] modelled MIG welding process by using neural networks and particle swarm optimization techniques. Sathiya et al. [10] modeled laser beam butt welding process parameter using artificial neural networks and genetic algorithm techniques.

In the present study an attempt has been made to model the plasma arc welding process by using regression analysis, Back propagation neural networks (BPNN) and Radial basis function Neural networks (RBFNN). In the present study, the input process parameters, such as current, gas flow rate and torch angle are considered as inputs and ultimate tensile strength and hardness of the welded joints are treated as outputs. It is paying attention to note that the prediction results obtained from the above models are comparable.

2. Experimental Details

The experimental details related to the welding of mild steel plates using plasma arc welding are explained in the subsequent sub-sections.

2.1. Specimen preparation

In the present work, mild steel specimens of size 75 mm x 12.5 mm x 6 mm of each are used as workpiece. These specimens are prepared with 45^{o} V-shaped groove angle with root gap and root face as 2 mm respectively. 32 pairs of specimens were prepared.

2.2. Equipment used

A manual plasma arc welding machine is used for the present work with the following specifications.

Polarity : DCEN
Mode of Operation : Pulse mode
Max power consumption : 2500W
Max jet flame temperature: 8000^{o}C
Electrode : Tungsten
Plasma gas : Argon
Torch position : Vertical

The levels of the input process parameters considered in this study are given in Table. 1.

Table 1. Input welding parameters and their ranges

Input parameter	Units	Minimum value	Maximum value
Current	A	150	180
Gas flow rate	Lit/min	5	20
Torch angle	Degrees	86	94

2.3 Input-Output data for Plasma Arc Welding:

Experiments are conducted based on the concept of design of experiments in which current, gas flow rate and torch angle are considered as input parameters, and each factor is considered to have four levels between their respective ranges. Based on a full-factorial design which was adopted in the present work, a total of $2^4 = 16$ combinations of experiments are conducted. Two responses, namely ultimate tensile strength and Rockwell hardness (RC) are considered as outputs for the analysis. A set of 16 experiments as shown in Table 2 are used for conducting the experiments related to the plasma arc welding. The sample specimens are shown in Figure 1.

Figure 1. Weld specimens prepared using plasma arc welding

Table 2. Experimental Data

S.No	Current (amp)	Gas flow rate (lit/min)	Torch angle(◦) Degrees	Ultimate tensile strength (N/mm^2)	Hardness RHC
1.	150	5	86	133.33	63
2.	150	10	88	213.33	54
3.	150	15	92	266.66	58
4.	150	20	94	106.66	52
5.	160	5	92	186.66	56
6.	160	10	94	186.66	59
7.	160	15	86	386.66	56
8.	160	20	88	200.00	51
9.	170	5	94	240.00	58
10.	170	10	92	320.00	53
11.	170	15	88	160.00	53
12.	170	20	86	280.00	65
13.	180	5	88	173.33	52
14.	180	10	86	240.00	55
15.	180	15	94	200.00	60
16.	180	20	92	226.66	56

3. Modeling of Plasma Arc welding process

In the present work, three modelling techniques, such as multiple regression analysis and artificial neural network (that is, both BPNN and RBFNN) are used to model the plasma welding process.

3.1. Multiple Regression analysis

Two linear regression models are developed for ultimate tensile strength (UTS) and hardness (RHC). The response equations were the result of this regression analysis done using MINITAB statistical analysis software. The linear regression equations obtained are as follows:

UTS = -12650 + 69*Current + 1606*GFR + 140*Torch angle - 8.8*Current*GFR- 0.75*Current*Torch angle- 17.5*GFR*Torch Angle+ 0.096*Current*GFR*Torch angle

RHC = 1823 - 11.10*Current - 161.0*GFR - 18.9*Torch angle + 1.006*Current*GFR + 0.1187*Current*Torch angle + 1.71*GFR*Torch angle - 0.01072*Current*GFR*Torch angle

3.2. Artificial Neural Network

Artificial neural network is a very useful tool to develop models which give the inter-relationship between inputs and outputs. Various types of artificial neural networks, namely back-propagation neural network, radial basis function and self-organizing map are used for modelling. In the present study, the input layer consists of three neurons which represent welding current, gas flow rate and torch angle and the output layer consists of two neurons which represent ultimate tensile strength and hardness of the weld bead. The number of neurons in the hidden layer is selected based on a systematic data study. In the present study, both BPNN and RBFNN are used to model the input-output relationship. In order to train these neural networks, 1000 sets of data which are different from experimental data are randomly generated with the help of regression equations. Another set of 16 experiments, different from training cases are conducted as shown in table 3. MATLAB software is used for training and simulating the neural networks.

Table 3. Test data used to evaluate the developed models

S.No	Current (amp)	Gas flow rate (lit/min)	Torch angle(◦) Degrees	Ultimate tensile strength (N /mm$^{2)}$	Hardness RHC
1.	150	5	90	141.11	56
2.	150	10	90	132.35	52
3.	150	15	90	121.40	49
4.	150	20	90	124.55	47
5.	160	5	90	242.07	48
6.	160	10	90	145.06	50
7.	160	15	90	130.00	47
8.	160	20	90	185.62	53
9.	170	5	90	247.13	51
10.	170	10	90	161.00	53
11.	170	15	90	171.30	49
12.	170	20	90	282.82	49
13.	180	5	90	291.30	56
14.	180	10	90	270.35	48
15.	180	15	90	204.08	51
16.	180	20	90	280.73	55

3.2.1. Back-Propagation Neural Network

In BPNN, linear transfer functions used in the input layer and Tan-sigmoid function is used for both hidden and output layers of the network, respectively. The details of these functions are given below:

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Input Layer : y =x
Hidden Layer : y (n) = 2/ (1+exp (-2*n))-1
Output Layer : y (n) = 2/ (1+exp (-2*n))-1
Momentum Constant : 0.9
Learning Rate : 0.2

3.2.2. Radial Basis Function Neural Network

For the radial basis function neural network, the input and output layers are provided with linear transfer function and hidden layer is provided with Gaussian function for mapping inputs and outputs of the plasma welding process.

Input Layer : y = x
Hidden Layer : y (n) = exp (-n^2)
Output Layer : y = x
Spread Constant : 9

4. Results and Discussion

From the experimental investigations, it has been observed that when the value of current increases the ultimate tensile strength of a specimen increases and by increasing gas flow rate up to 10(lit/min) ultimate tensile strength increases and then decreases. Moreover, when the value of torch angle varies from 88 to 94^{o} the ultimate tensile strength of the welded joint is increased. Further, the hardness of the specimen is increases by increasing the current up to certain level and then decreases. Similar observations are seen for the change in gas flow rate and torch angle. In the present research, modelling of plasma arc welding has been carried out with the help of regression analysis, BPNN and RBFNN. The predicted values are plotted against the target values and shown on a scatter plot for the above three models (Figure 2&3). Percentage error was calculated for each test case and shown in Tables 4 and 5.

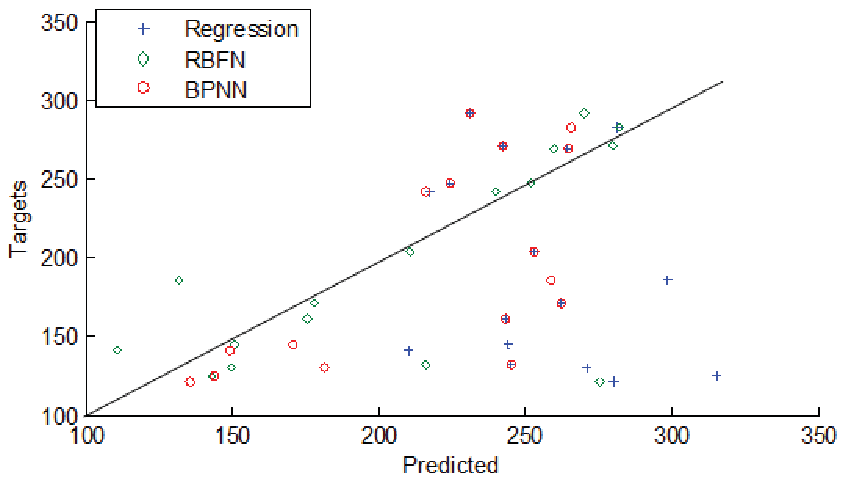

Figure 2. Scatter plot showing the predicted values of ultimate tensile strength for the developed approaches

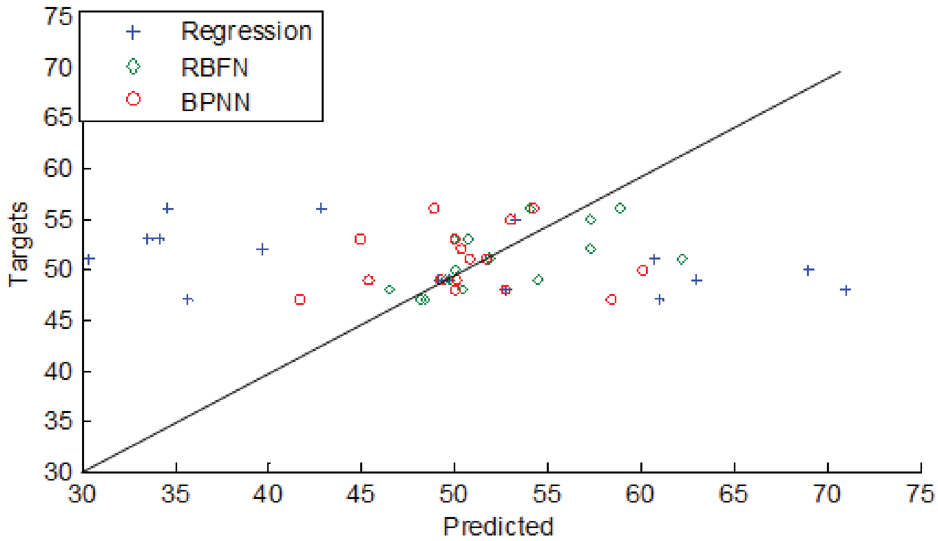

Figure 3. Scatter plot showing the predicted values of hardness for the developed approaches

From the scatter plots (Figures 2 & 3) and the Tables 4 and 5, it can be concluded that all the developed models are able to predict the responses with a reasonably good accuracy.

Table 4. Percentage error in predicting ultimate tensile strength by the developed approaches

S.No	Targets	Regression		BPNN		RBFNN	
		Predicted	%error	Predicted	%error	Predicted	%error
1.	141.11	210	48.82	149.02	5.61	110.37	-21.78
2.	132.35	245	85.12	244.95	85.08	215.84	63.09
3.	121.40	280	130.60	135.30	11.44	275.09	126.60
4.	124.55	315	152.90	143.62	15.31	142.64	14.53
5.	242.07	217	-10.36	215.84	-10.83	239.45	-1.08
6.	145.06	244	68.21	170.34	17.43	150.36	3.65
7.	130.00	271	108.46	181.33	39.48	149.29	14.84
8.	185.62	298	60.54	258.65	39.34	131.63	-29.08
9.	247.13	224	-9.36	223.86	-9.41	251.74	1.87
10.	161.00	243	50.93	242.95	50.90	175.30	8.88
11.	171.30	262	52.95	261.96	52.93	177.86	3.83
12.	282.82	281	-0.64	265.32	-6.19	282.00	-0.29
13.	291.30	231	-20.70	230.93	-20.22	270.06	-7.29
14.	270.35	242	-10.49	241.86	-9.80	279.48	3.38
15.	204.08	253	23.97	252.94	23.95	210.51	3.15
16.	280.73	264	-5.95	264.51	-5.77	259.72	-7.48

Table 5. Percentage error in predicting hardness by the developed approaches

S.No	Targets	Regression		BPNN		RBFNN	
		Predicted	%error	Predicted	%error	Predicted	%error
1.	56	42.85	-23.48	54.28	-3.06	58.94	5.25
2.	52	39.67	-23.70	50.41	-3.04	57.32	10.23
3.	49	63.01	28.60	45.37	-7.39	54.53	11.29
4.	47	60.98	29.74	41.74	-11.17	48.18	2.53
5.	48	52.74	9.88	52.79	9.99	50.44	5.09
6.	50	68.98	37.96	60.09	20.18	50.03	0.06
7.	47	35.67	-24.09	58.48	24.43	48.48	3.16
8.	53	33.56	-36.67	44.93	-15.21	50.05	-5.55
9.	51	60.76	19.15	50.80	-0.39	51.88	1.74
10.	53	34.15	-35.56	50.01	-5.62	50.71	-4.31
11.	49	49.67	1.37	50.12	2.29	49.75	1.53
12.	49	49.19	0.39	49.25	0.52	49.54	1.11
13.	56	34.56	-38.28	48.88	-12.70	54.09	-3.40
14.	48	70.98	47.88	50.03	4.23	46.52	-3.08
15.	51	30.43	-40.32	51.72	1.41	62.23	22.02
16.	55	53.26	-3.16	53.00	-3.62	57.36	4.29

It can be observed that the percentage deviation in regression model is found to be more when compared with the other non-traditional modeling tools, namely BPNN and RBFNN. It is interesting to note that these regression models are not convenient for modeling multi input and multi outputs and is also difficult to obtain optimal common process parameters that satisfy the individual responses. In order overcome this drawback, BPNN and RBFNN are tried and it has been observed that RBFNN is found to perform better than other two models that are regression and BPNN. It may be due to the reason that RBFNN tries to model multi-input-multi-output systems after considering the dynamic interactions between various inputs and outputs, whereas the regression models are failed to model the dynamic interactions between the responses, if any.

5. Conclusion

The present study explored two neural network based approaches to model the plasma arc welding process. These models were trained with the help of training data generated using regression model. The performances of BPNN and RBFNN are compared among themselves with the help of 16 experimental test cases. It is observed that RBFNN has offered more adaptability compared to BPNN, owing to the local multi-modal distribution of the experimental data.

6. References

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