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Comparison Between RSM and ANN Models To Predict Carbon Content Equivalent In a Tig Weld

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Abstract

Prediction of process parameters beyond design of experiment is a limitation for some traditional models like the response surface methodology. In this study a comparative analysis between the response surface methodology and the artificial neural network algorithm to predict carbon content present in welding process of mild steel was presented. The RSM model explored its numerical and graphical techniques to predict the carbon content. The results obtained showed that the RSM prediction did not fit perfectly into the observed values; the ANN model was also used to predict the carbon content. The ANN employed the process of training, validation and testing with the help of hidden neurons. The ANN model predictions fit perfectly into the plot of the observed values. The ANN is a better predictive model compared to the RSM.

1. Introduction

In tungsten inert gas welding, an electric arc is formed when electric current is passed through the system connection of the electrode and work piece in the presence of an inert gas. TIG is the most preferred welding technique today because of the low fumes and spatter produced during welding. Understanding the relationship between the welding process parameters can help to predict the outcome of the welded structure [1]. An artificial neural network algorithm was developed to control and monitor the bead profile of plasma arc welding, the result obtained showed that the ANN model possessed a higher accuracy than other traditional models [2]. A predictive study was carried out on neodymium doped yttrium aluminium garment (Nd YAG) welding process. The network predicted the weld penetration width and cross-sectional area of the weld bead profile, a conclusion was made that this method was excellent for real time predictions [3]. A study was carried out to compare between back propagation neural networks and the counter propagation neural networks. This models was applied to predict the weld bead height and width of tungsten inert gas welding process of aluminium,the results obtained showed that the back propagation network was a better predictive tool[4].The back propagation network was employed to predict bead width and height for gas metal arc welding of low carbon steel, the welding parameters considered are voltage, travel speed, current and plate thickness. The result obtained showed that the backward propagation has adequate capacity to accurately predict the desired responses [5]. A hybrid model was developed, which was a combination of the back propagation network and the supervised learning vector algorithm and used to predict weld undercut and distortion of laser welding [6]. Artificial neural network model was used to predict the bead depth and bead penetration of grey cast iron welded structure. The results showed that the predicted result has a close correlation with the experimental value [7]. Different numerical and statistical optimization approach has been used to analyze different welding processes and this includes Response surface methodology, genetic algorithm and artificial neural network [8]. An experimental study of flux core arc welding parameters using mathematical models to predict the percentage dilution and bead penetration ratio. The fraction factorial technique was employed which produced reliable results [9] The correlation between the weld bead penetration size and the process parameters of robotic gas metal arc welding was understudied using fractional factorial mathematical model. The results revealed that the welding parameters has significant effect on the bead penetration [10].

2.Methodology

In this study welding experiments was performed to determine carbon content equivalent present in a tungsten inert gas mild steel welded plate. The mild steel plates are cut into desired sizes, the weld samples are cleaned to remove dust, rust and grease. A design of experiment was generated to help determine the total number of welding experiments to be performed. The mild steel samples were welded with the TIG process and thereafter the carbon content was measured and recorded.

2.1. Identification of Range of Input Parameters

In this study the process parameters are current, voltage and gas flow rate, the upper and lower limit for the range of values was also determined as shown in Table 1.

. **Table 1: Range of input process factors**

Parameters	Unit	Symbol	lower	upper
Current	Amp	A	110	150
Gas flow rate	Lit/min	F	25	28
Voltage	Volt	V	11	15

2.2. Method of Data Collection

The data used for this study is the results of the experiments performed, the design expert software was used to generate a matrix to guide the experimentation, the design expert 2.0 software was employed to produce the most suitable experimental design, central composite design selected as the best design for the experiment .20 sets of experiment was conducted with each experiment having a different combination of input parameters value. The carbon content value was measured and recorded for each run as shown in Table 2.

Table 2: carbon content Experimental data

S/N	I, Amp	V, Volt	GFR, L/min	CE, %
1	150.23	26.50	12.50	1.1
2	125.00	26.50	12.50	5.2
3	125.00	26.50	12.50	5.4
4	125.00	26.50	12.50	5.6

5	140.00	25.00	11.00	5
6	125.00	23.98	12.50	6
7	140.00	25.00	14.00	4.5
8	125.00	26.50	15.02	6.7
9	140.00	28.00	11.00	4.2
10	110.00	25.00	14.00	4.9
11	125.00	29.02	12.50	5.7
12	125.00	26.50	12.50	5.7
13	125.00	26.50	9.98	6.2
14	110.00	25.00	11.00	4.8
15	99.77	26.50	12.50	4.3
16	125.00	26.50	12.50	4.8
17	140.00	28.00	14.00	3.25
18	125.00	26.50	12.50	5
19	110.00	28.00	11.00	6.23
20	110.00	28.00	14.00	6.35

2.3. Experimental procedure

The experimentation starts by cutting the mild steel plates into desired size and shape, the edges were then beveled in order to obtain a v shaped groove joint. The welding machine was switched on by setting the input parameters according to the experimental design for each experiment. For each experiment 5 samples were used so as to avoid errors. A total of 100 weld samples was produced. The TIG welding employed the use of a tungsten electrode and argon gas to shield the weld pool.

2.4. Method of data analysis

a. Response Surface Methodology

RSM is one of the most commonly used optimization techniques that employs the theory of ANOVA and regression that can be used to explain the relationship between welding process parameters. RSM makes use of some graphical tools for prediction like contour plots.

b. Artificial Neural Network

Artificial neural network is a data mining tool which can be used to make predictions of welding process parameters beyond experimental boundaries.

3. Results and Discussion

In this study a comparison between the response surface methodology and the artificial neural network was done. The RSM model employs some statistical diagnostics which helps us to check the acceptability and reliability the diagnostics statistics is shown in Table 3.

Table 3: Diagnostics case statistics report for carbon content

					Internally	Externally	Influence on		
Standard	Actual	Predicted			Studentized	Studentized	Fitted Value	Cook's	Run
Order	Value	Value	Residual	Leverage	Residual	Residual	DFFITS	Distance	Order
1	4.80	4.85	-0.046	0.670	-0.216	-0.205	-0.292	0.009	14
2	5.00	4.93	0.073	0.670	0.346	0.330	0.470	0.024	5
3	6.23	6.23	-3.235E-003	0.670	-0.015	-0.015	-0.021	0.000	19
4	4.20	3.85	0.35	0.670	1.659	1.848	* 2.63	0.558	9
5	4.90	5.31	-0.41	0.670	-1.958	-2.365	* -3.37	0.777	10

6	4.50	4.56	-0.060	0.670	-0.283	-0.270	-0.385	0.016	7
7	6.35	6.49	-0.14	0.670	-0.645	-0.625	-0.890	0.084	20
8	3.25	3.27	-0.018	0.670	-0.083	-0.079	-0.112	0.001	17
9	4.30	3.97	0.33	0.607	1.413	1.498	1.863	0.309	15
10	1.10	1.34	-0.24	0.607	-1.025	-1.028	-1.279	0.163	1
11	6.00	5.77	0.23	0.607	1.019	1.021	1.270	0.161	6
12	5.70	5.85	-0.15	0.607	-0.631	-0.611	-0.760	0.062	11
13	6.20	6.45	-0.25	0.607	-1.099	-1.112	-1.383	0.187	13
14	6.70	6.36	0.34	0.607	1.487	1.598	1.988	0.342	8
15	5.20	5.29	-0.086	0.166	-0.256	-0.244	-0.109	0.001	2
16	5.00	5.29	-0.29	0.166	-0.852	-0.839	-0.375	0.014	18
17	5.60	5.29	0.31	0.166	0.936	0.929	0.415	0.017	4
18	5.70	5.29	0.41	0.166	1.234	1.271	0.568	0.030	12
19	4.80	5.29	-0.49	0.166	-1.447	-1.544	-0.690	0.042	16
20	5.40	5.29	0.11	0.166	0.340	0.324	0.145	0.002	3

A contour plot was produced to shows the interaction between the carboncontent response versus currnt and voltageas shown in Figure 1.

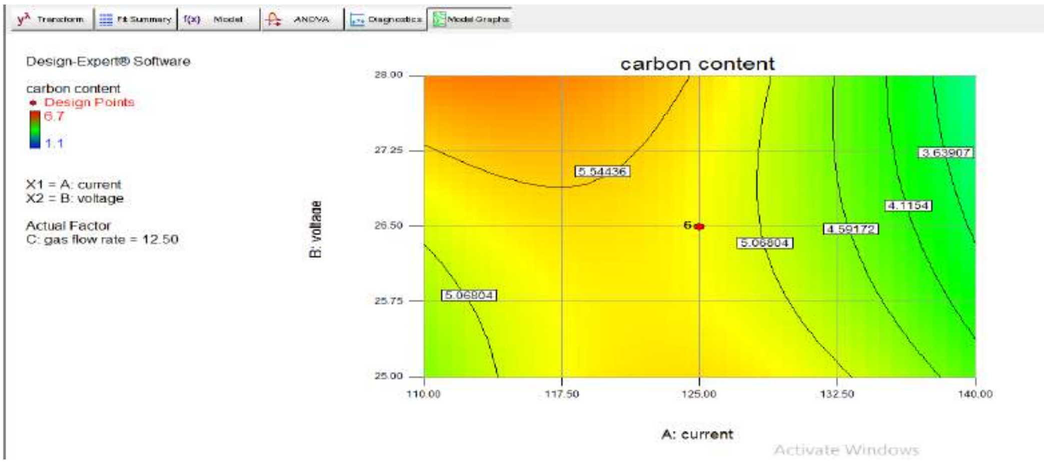

Figure 1: Contour plot for carbon content,current and voltage

The contour plots showing carbon content response variable against the current and gas flow rate is presented in Figure 2.

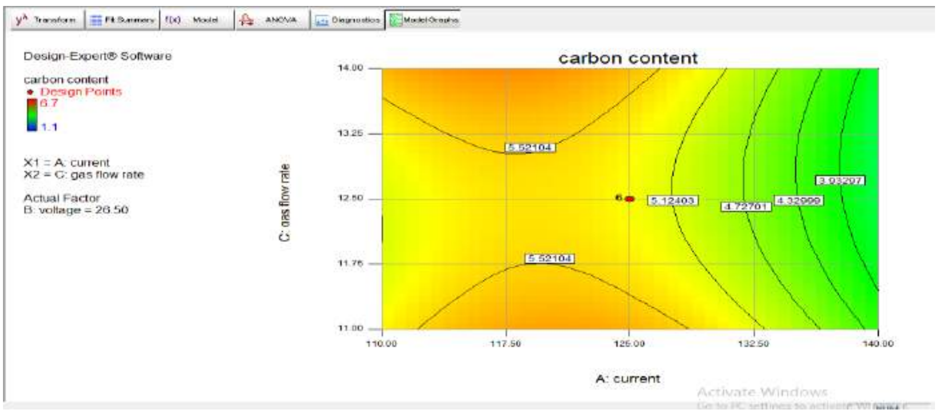

Figure 2: Contour plot for carbon content,current and gas flow rate

contour plot was produced show the interaction between carbon content response ,voltage and gas flow rate as shown in Figure 3.

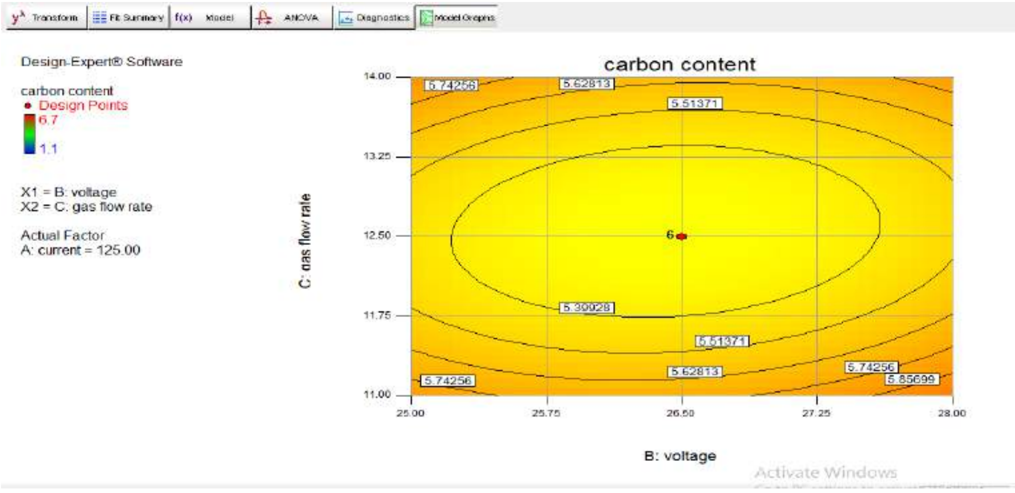

Figure 3: Contour plot for carbon content voltage and gas flowrate

The experimental data used for the RSM modelling was also used for the ANN modeling.To employ the ANN model the data needs to be trained, here the feed forward back propagation algorithm was used for the prediction of carbon content as shown in Figure 4.

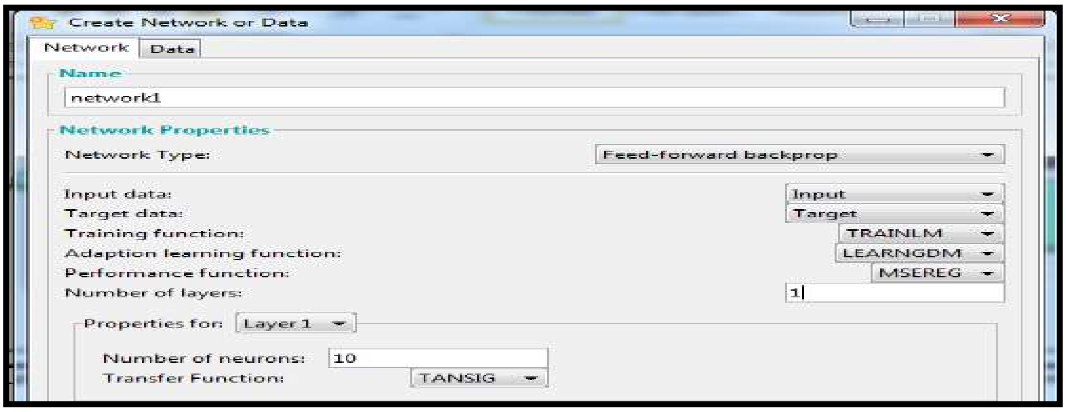

Figure 4: Carbon content Network training diagram

Secondly, an appropriate neural network architecture is required to help develop the best predictive network.The network architure generated to predict the carbon content is shown in Figure 5.

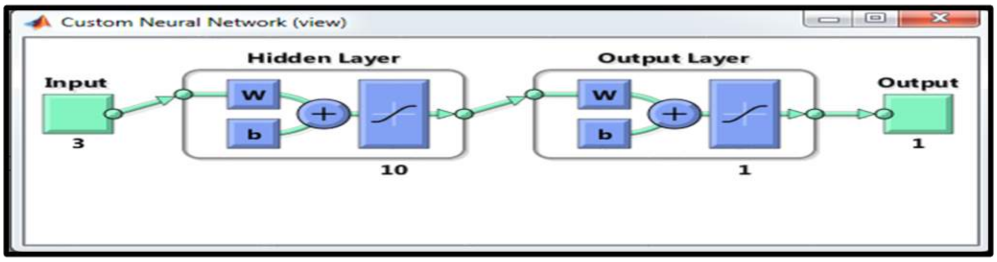

Figure 5: Carbon content network architecture

After training the data, a performance evaluation plot which shows the progress of training, validation and testing is produced as shown in Figure 6.

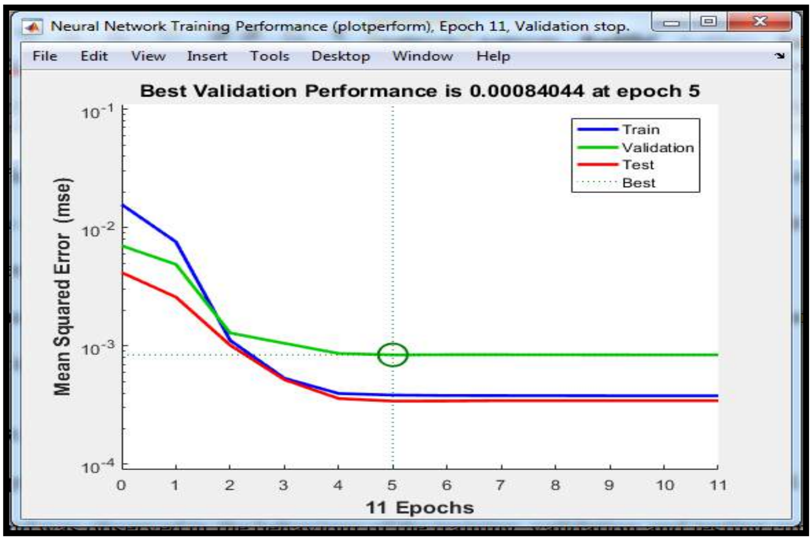

Figure 6: Carbon content Performance plot

From the performance plot of Figure 6 shows that the network has a low mean square error and no over fitting is an evidence that the network can adequately predict the carbon content response. The training state which helps us to support our claim of the networks capacity is shown in Figure 7.

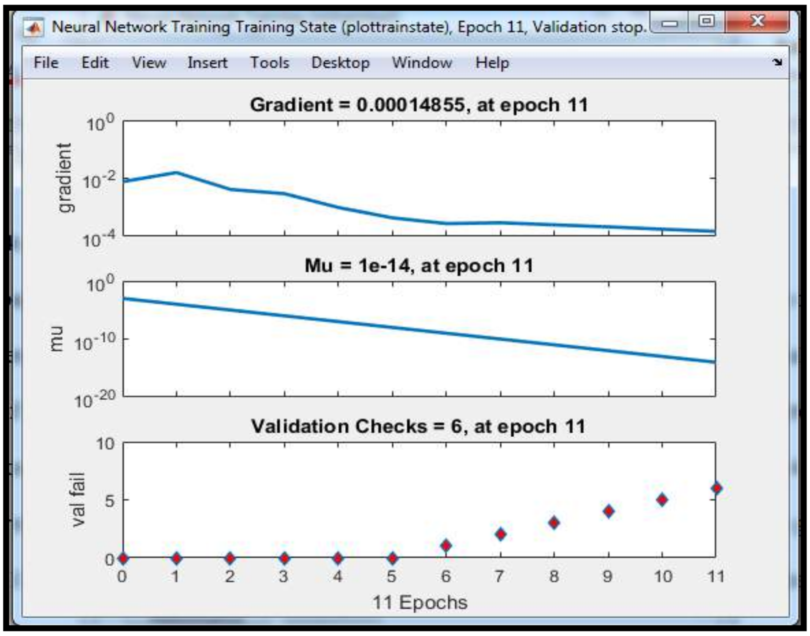

Figure 7: Neural network training state for predicting carbon content

To check for the network accuracy a regression plot is produced which shows the progress of training, validation and testing as shown in Figure 8.

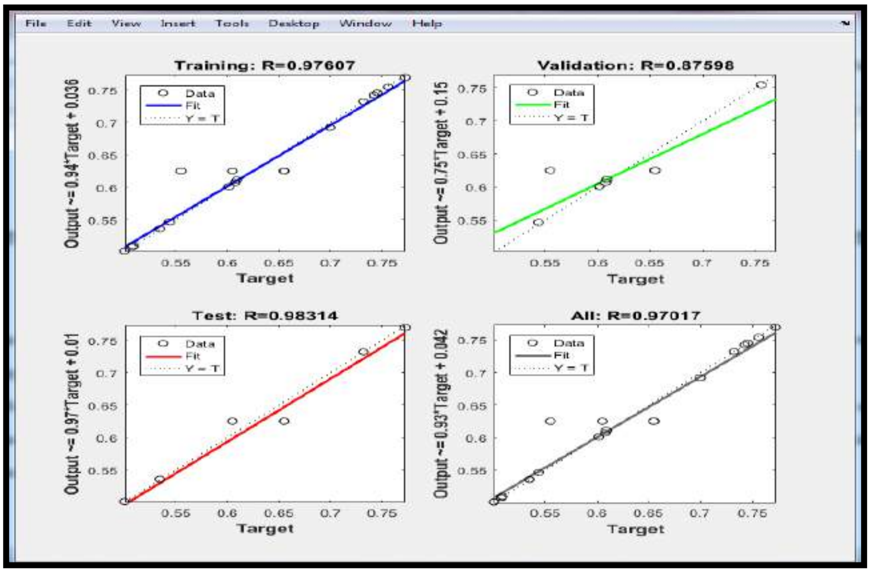

Figure 8: Regression plot for predicted and observed carbon content

To evaluate the performance of ANN in predicting the carbon content, a comparative analysis between ANN and response surface methodology (RSM) was done as presented in Table 4.

Table4:Prediction of carbon content using ANN and RSM

Run No.	Current (A)	Voltage (V)	Gas Flow Rate (L/min)	Carbon content Experimental Values	carbon content ANN Predicted Values	carbon content RSM Predicted Values
1	150.23	26.50	12.50	4.80	4.77	4.85
2	125.00	26.50	12.50	5.00	5.05	4.93
3	125.00	26.50	12.50	6.23	6.27	6.23
4	125.00	26.50	12.50	4.20	4.25	3.85
5	140.00	25.00	11.00	4.90	5.00	5.31
6	125.00	23.98	12.50	4.50	5.02	4.56
7	140.00	25.00	14.00	6.35	6.35	6.49
8	125.00	26.50	15.02	3.25	3.23	3.27
9	140.00	28.00	11.00	4.30	4.27	3.97
10	110.00	25.00	14.00	1.10	1.12	1.34
11	125.00	29.02	12.50	6.00	5.86	5.77
12	125.00	26.50	12.50	5.70	5.73	5.85

13	125.00	26.50	9.98	6.20	6.24	6.45
14	110.00	25.00	11.00	6.70	6.64	6.36
15	99.77	26.50	12.50	5.20	5.17	5.29
16	125.00	26.50	12.50	5.00	5.09	5.29
17	140.00	28.00	14.00	5.60	5.50	5.29
18	125.00	26.50	12.50	5.70	5.65	5.29
19	110.00	28.00	11.00	4.80	4.83	5.29
20	110.00	28.00	14.00	5.40	5.44	5.29

A plot comparing the artificial neural network predicted values and the observed values of carbon content is presented in Figure 9.

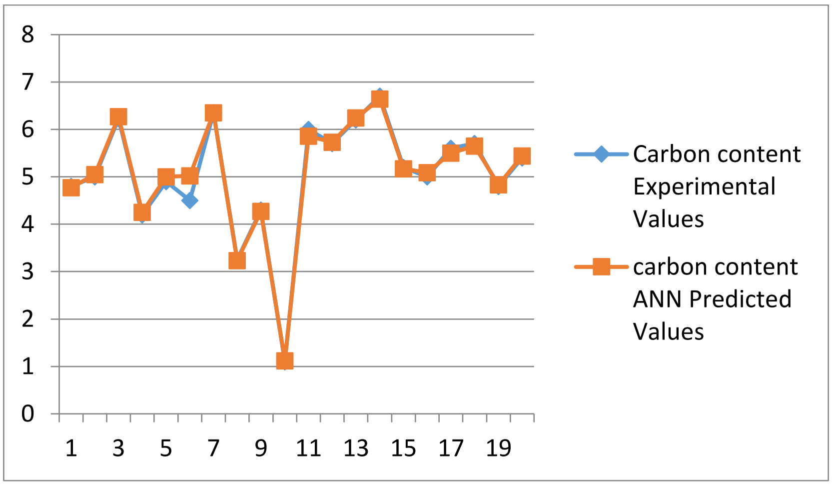

Figure 9: Plot of ANN predicted values versus observed values for carbon content

A plot comparing the response surface methodology predicted values and the observed values of carbon content is presented in Figure 10.

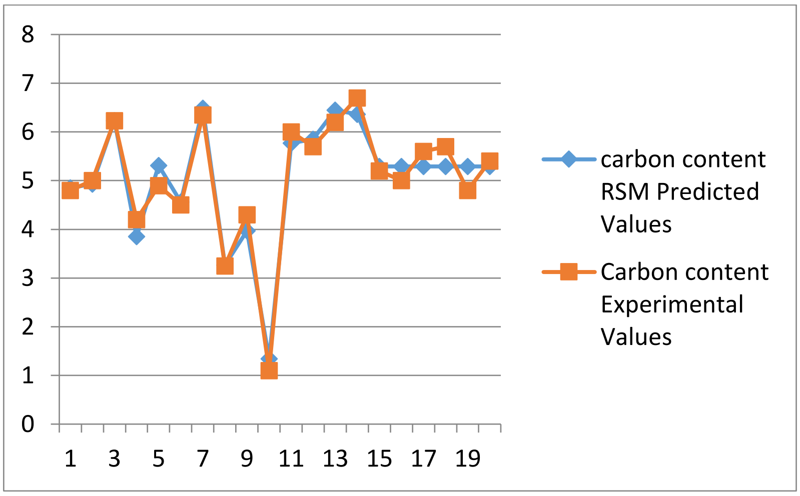

Figure 10: Plot of RSM predicted values versus observed values for carbon content

4. Conclusion

In this study a comparative analysis between the response surface methodology and the artificial neural network algorithm to predict carbon content present in a welding process of mild steel was presented. The RSM model explored its numerical and graphical techniques to predict the carbon content. The RSM prediction did not perfectly fit into the observed values, the ANN model was also used to predict the carbon content. The ANN used atraining, validation and testing approach with the help of hidden neurons. The ANN model predictions perfectly fit into the plot of the observed values. The ANN is a better predictive model compared to the RSM,and this is in reasonable agreement with the findings of Nagesh and Datta (2002).

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