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A Comparative Analysis between Artificial Neural Network and Response Surface Methodology in Predicting Tool Wear Rate in a Turning Operation

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Abstract: *In turning operation, tool wear has to be controlled and should be kept within the desired limits for any machining process. Besides, in order to maximize gains from a manufacturing process, an accurate process model is required. This research work was carried out to compare the ability of Response Surface Methodology and Artificial Neural Network in the prediction of tool wear rate in a turning operation, using the machining parameters of spindle speed, feed rate and depth of cut. A CNC lathe machine was used to carry out the turning operations for 20 experimental runs, as generated by the design matrix. The experimental results (data) were recorded and analysed with Response Surface Methodology of Design Expert software, version 7.0 and Artificial Neural Network of MATLAB 2013a. The rule of "the higher the better" was employed to select the better model for predicting the tool wear rate. The results obtained revealed that with a coefficient of determination (R^2) of 0.9956, Artificial Neural Network was acclaimed a better model for predicting tool wear rate ahead of Response Surface Methodology which has a coefficient of determination of 0.9894.*

Keywords: *Response Surface Methodology, Artificial Neural Network, Tool Wear Rate, Turning Operation.*

INTRODUCTION

The productivity of a machining system, as well as quality, the integrity of the machined surface, machining cost, and profit strongly depend on tool wear. Sudden failure of cutting tools leads to loss of productivity, rejection of parts and consequential economic losses. The maximum utilization of cutting tool is one of the ways for an industry to reduce its manufacturing cost. Hence, tool wear has to be controlled and should be kept within the desired limits for any machining process. Tool wear mainly depends upon the machining parameters used for turning work piece material. In order to maximize gains from a manufacturing process, an accurate process model is required. Seeman *et al.* (2010) carried out an experimental investigation to establish the influence of cutting speed, feed rate, machining time and depth of cut on tool wear rate in a turning operation. They used LM 25 aluminum alloy as a work piece and carbide tool insert (K10) as tool.

The flank wear and surface roughness were investigated, using regression analysis and response surface methodology. Their findings showed that cutting speed and feed rate have significant influence on tool wear rate. Suresh *et al.* (2012) conducted an experiment to correlate the cutting parameters such as cutting speed, feed rate and depth of cut, to predict power, tool wear, machining force, specific cutting force and surface roughness in a turning operation, with AISI 4340 steel as work piece material. The analysis was carried out with Taguchi and response surface methodology and the result inferred that cutting force and feed rate have significant effect on the rate at which the cutting tool wears. Senthil kumaar *et al.* (2012) carried out optimization, using Artificial Neural Network (ANN) and ANOVA in a facing operation, with Inconel 718 as work piece material. The cutting parameters used are cutting speed, feed, and depth of cut and the objective function is to minimize flank wear and surface roughness. Result showed that feed rate is the only input parameter that has influence on tool wear. Attanasio et al. (2012) conducted an orthogonal hard turning tests, to study the effects of cutting speed and feed rate on flank tool wear in the turning of white and dark layer formation in hardened AISI 52100 bearing steel, using PCBN inserts. Finite Element model was use to carry out the analysis. The result showed that cutting speed is the most influencing parameter on tool wear. Rajesh, (2013) carried out an experimental investigations and effects of cutting speed, feed rate, depth of cut and nose radius on the responses (power consumption and tool life), in the turning of 7075 Al alloy as work piece. Response surface methodology was employed to accomplish the objective of the experimental study and the results showed that cutting speed was the most significant factor followed by depth of cut, feed and nose radius on tool life.

MATERIALS AND METHODS

Materials

The materials and equipment used in this research work are as follow:

i. CNC lathe (power rating of 10 KW, with spindle speed range of 100 to 2500 rpm) [**Fig. 1**].

Fig.1: ENC Lathe machine

ii. M42 HSS single point cutting tool

iii. EN8 mild steel (size 100 mm diameters and length 60 mm)

iv. Tool maker's microscope (**Fig. 2**)

Fig.2: Tool maker's microscope

Methods

Three cutting parameters of spindle speed (A), feed rate (B), and depth of cut (C), with their respective ranges of 105 to 220 rev/min, 0.12 to 0.18 mm/min and 0.50 to 1.50 mm were considered for the turning process. The three input parameters and their respective ranges were fed into the graphical user interface of design expert software to generate the design matrix, which was used to set up the machine for turning for all the experimental runs. The quality characteristic (Tool wear rate) was got, using the tool maker's microscope in Fig. 2.

RESULTS AND DISCUSSION

The results of design matrix and experimental values for tool wear rate are presented in **Table 1.** Quadratic model was suggested from the sequential model sum of squares [Type II] for the response, (tool wear rate). The experimental data were analysed with ANOVA, to identify the factor(s) that significantly influence the performance measure, as shown in **Tables 2.** The ANOVA output fortool wear rate (TWR). It is observed that the model is significant, with significant model terms of A, B, C, AB, AC, A^2 and B^2. The model has an R-Squared value of 0.9894, implying that about 98.94% of the variability in TWR can be explained by the model.

Final equation in terms of actual factor is given by Equation (1).

$$\textbf{Tool Wear Rate } (\boldsymbol{TWR}) = +3.33542 - 0.012899 * A - 30.27331 * B - 1.17229 * C + 0.035299 * A * B + 6.61304E - 003 * A * C + 3.80833 * B * C + 1.92759E - 005 * A^2 + 78.22458 * B^2 + 0.019595 * C^2 \quad (1)$$

Table 1: Design matrix and and experimental values for Tool wear rate

Run No.	Spindle Speed(rpm)	Feed Rate (mm/min)	Depth of cut (mm)	TWR (mm^3/min) Experimental Values
1	162.5	0.15	1	0.307
2	162.5	0.15	1	0.393
3	162.5	0.15	1	0.348
4	162.5	0.15	1	0.368
5	162.5	0.15	1	0.273
6	162.5	0.15	1	0.402
7	65.79691	0.15	1	0.041
8	259.2031	0.15	1	1.113
9	162.5	0.099546	1	0.236
10	162.5	0.200454	1	0.501
11	162.5	0.15	0.1591	0.029
12	162.5	0.15	1.8409	0.807
13	105	0.12	0.5	0.044
14	220	0.12	0.5	0.245
15	105	0.18	0.5	0.067
16	220	0.18	0.5	0.374
17	105	0.12	1.5	0.177
18	220	0.12	1.5	0.98
19	105	0.18	1.5	0.27
20	220	0.18	1.5	1.496

Tables 2: Results of ANOVA for tool wear rate

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	2.8	9	0.31	50.54	< 0.0001	significant
A-Spindle Speed	1.42	1	1.42	231.02	< 0.0001	
B-Feed Rate	0.069	1	0.069	11.22	0.0074	
C-Depth of cut	9.00E-01	1	9.00E-01	1.46E+02	< 0.0001	
AB	3.20E-02	1	3.20E-02	5.26	0.0448	
AC	0.29	1	0.29	46.98	< 0.0001	
BC	2.60E-02	1	2.60E-02	4.24	0.0665	
A^2	5.60E-02	1	5.60E-02	9.05	0.0132	
B^2	4.40E-02	1	4.40E-02	7.19	0.0231	
C^2	3.42E-04	1	3.42E-04	0.056	0.8183	
Residual	6.20E-02	10	6.16E-03			
Lack of Fit	4.90E-02	5	9.78E-03	3.87	0.082	not significant
Pure Error	1.30E-02	5	2.53E-03			
Cor Total	2.86	19				

The model equation was used to predict the values of TWR as presented in Table 3. Three dimensional surface plots of TWR as a function of two inputs at a time are presented in Fig. 3-Fig.5.

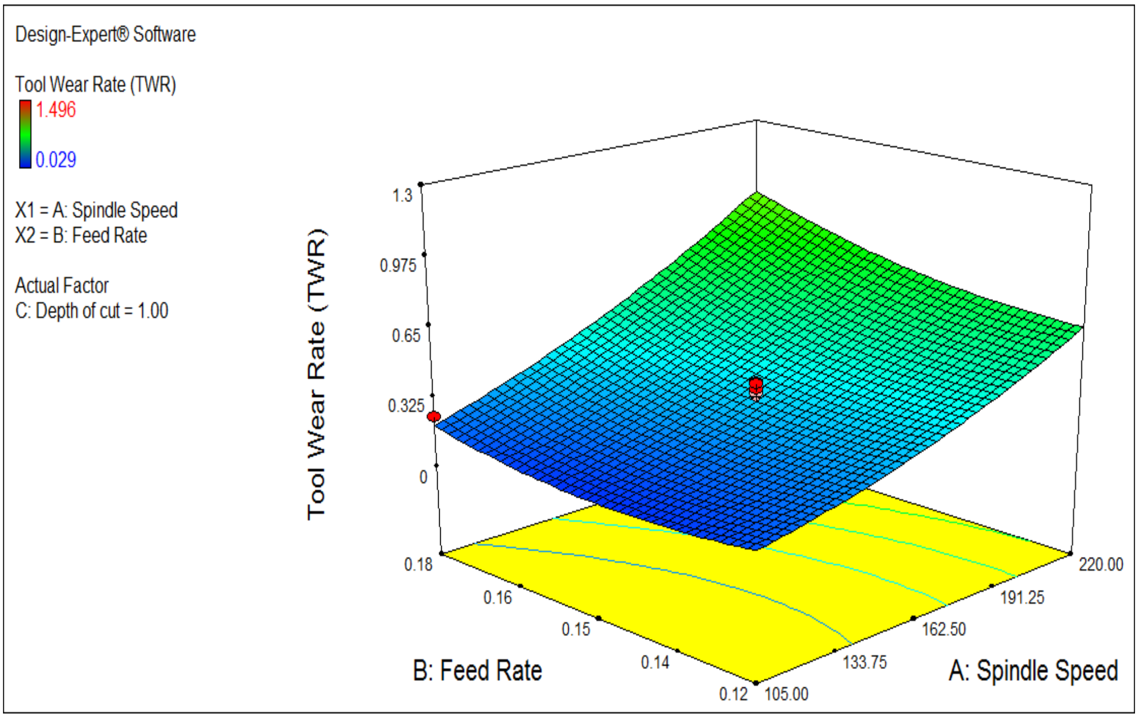

Fig 3: Three dimensional surface plot as a function of A and B

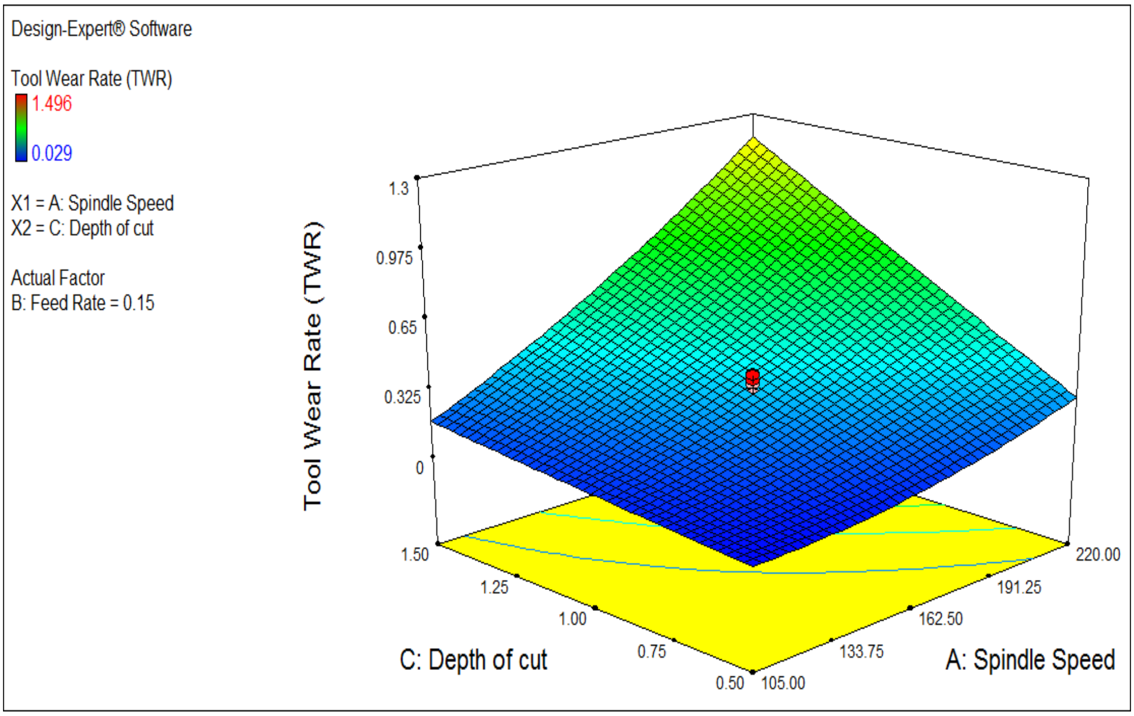

Fig 4: Three dimensional surface plot as a function of A and C

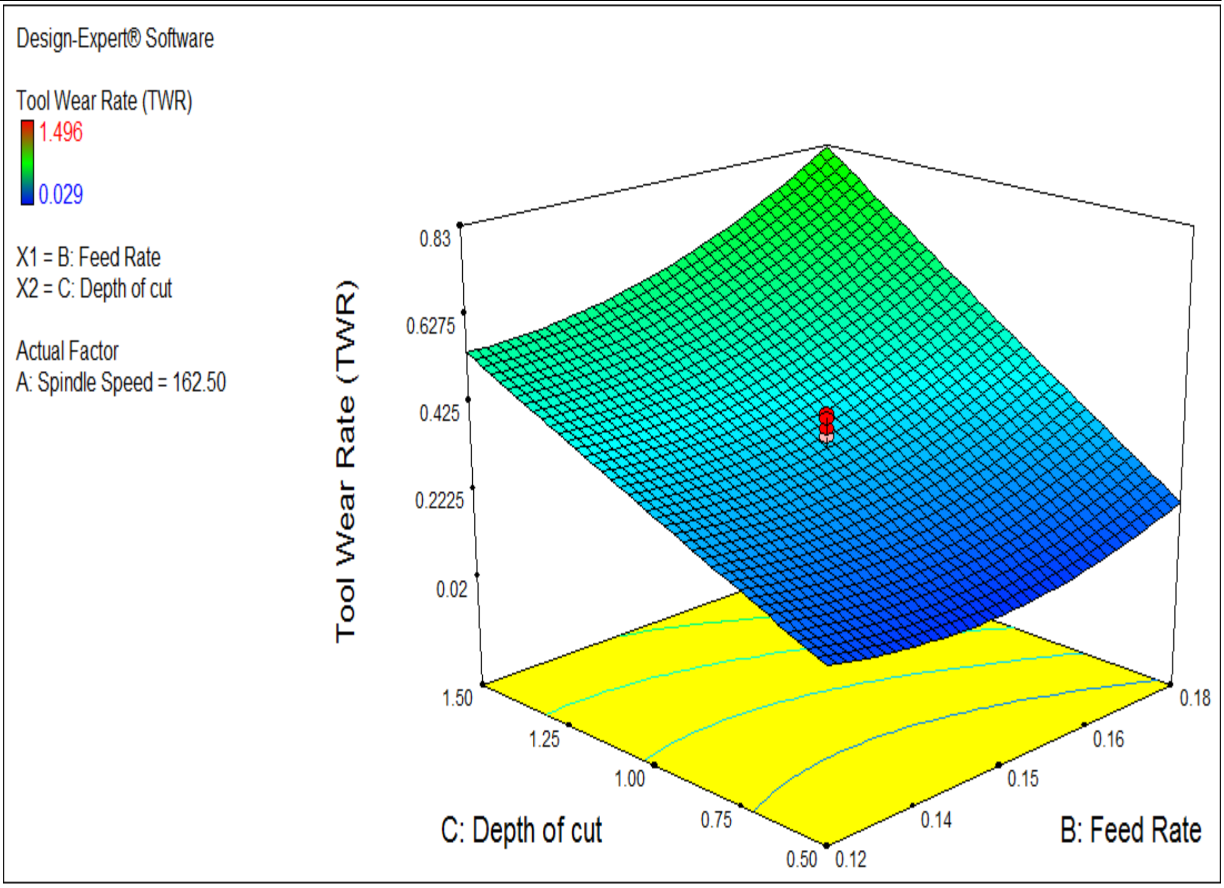

Fig 5: Three dimensional surface plot as a function of B and C

It can be inferred from **Fig. 3-Fig.5** that the spindle speed, feedrate and depth of cut have significant influence on tool wear rate: an increase in any of them will lead to an increase in the rate of tool wear.

A. *Modelling and Prediction of Tool Wear Rate (TWR), using Artificial Neural Network (ANN)*

Response surface methodology was effective in determining the exact mathematical relationship between the input variables (A, B and C) and response variables, tool wear rate. One of the fundamental challenges with response surface methodology (RSM) is the inability to accurately predict the response variables without design of experiment. It means therefore that the performance of RSM is dependent on the beauty of experimental design. Therefore, to predict the response variables beyond the scope of experimentation, predictive model such as artificial neural network (ANN) was employed. Sixty (60) experimental data generated by replicating the design matrix from the CCD was used for the neural network modelling. The experimental data were first normalized to avoid the problem of weight variation that may consequently results in overtraining. The network training diagram generated for the prediction of tool wear rate (TWR) using back propagation neural network is presented in **Fig.6**.

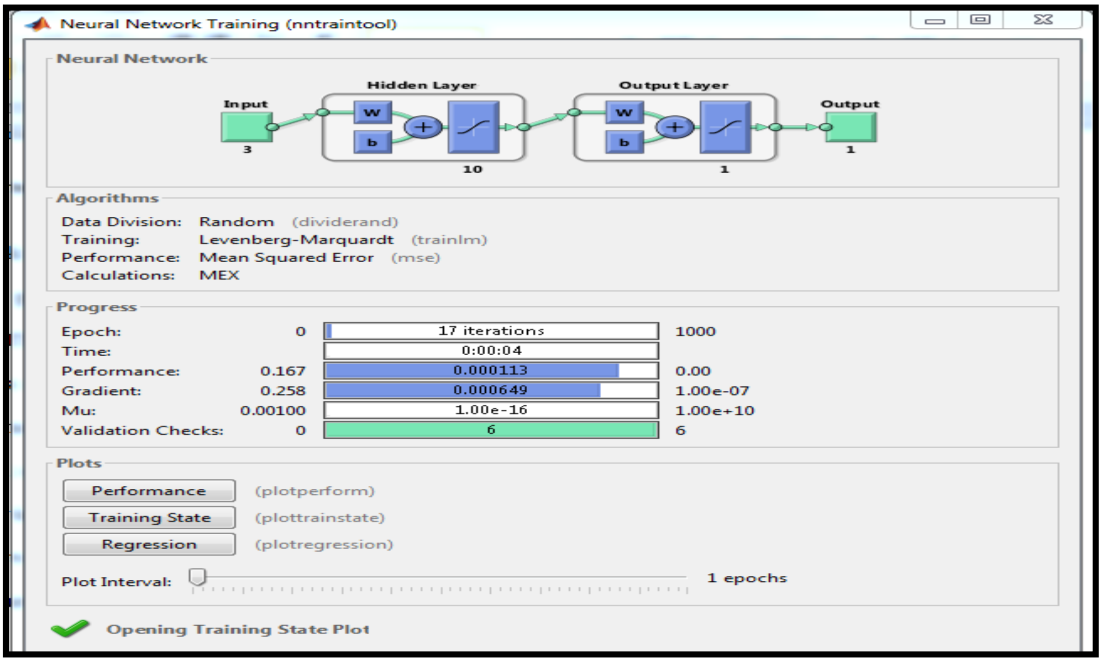

Fig 6: Network training diagram for predicting tool wear rate (TWR)

From the network training diagram of Fig. 6, it was observed that the network performance was significantly good with a performance error of 0.000113 which is far lesser than the set target error of 0.01. The maximum number of iteration needed for the network to reach this performance was observed to be 17 iterations which is also less than the initial 1000 epochs. The gradient function was calculated to be 0.000649 with a training gain (Mu) of 1.00e-16. Validation check of six (6) was recorded which is expected since the issue of weight biased had been addressed via normalization of the raw data. A performance evaluation plot which shows the progress of training, validation and testing is presented in Fig.7.

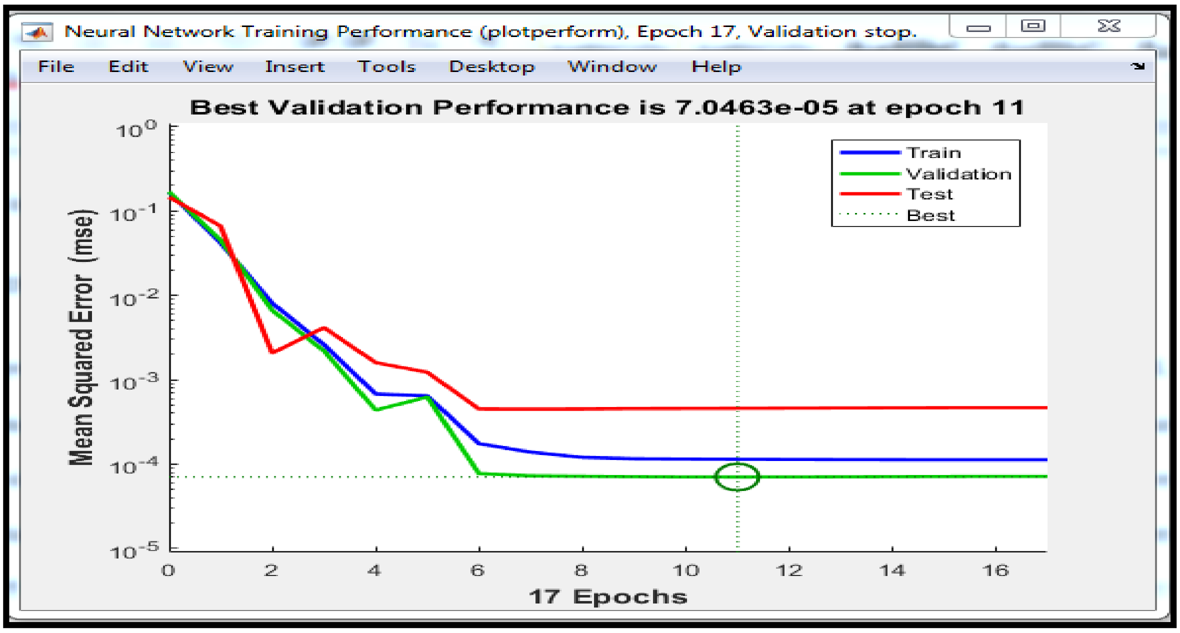

Fig 7: Performance curve of trained network for predicting tool wear rate

From the performance plot of Fig. 7, no evidence of over fitting was observed. In addition, similar trend was observed in the behaviour of the training, validation and testing curve which is expected since the raw data were normalized before use. Lower mean square error is a fundamental criterion used to determine the training accuracy of a network. An error value of 7.0463e-05 at epoch 11 is an evidence of a network with strong capacity to predict the tool wear rate (TWR). The training state, which shows the gradient function, the training gain (Mu) and the validation check, is presented in Fig. 8.

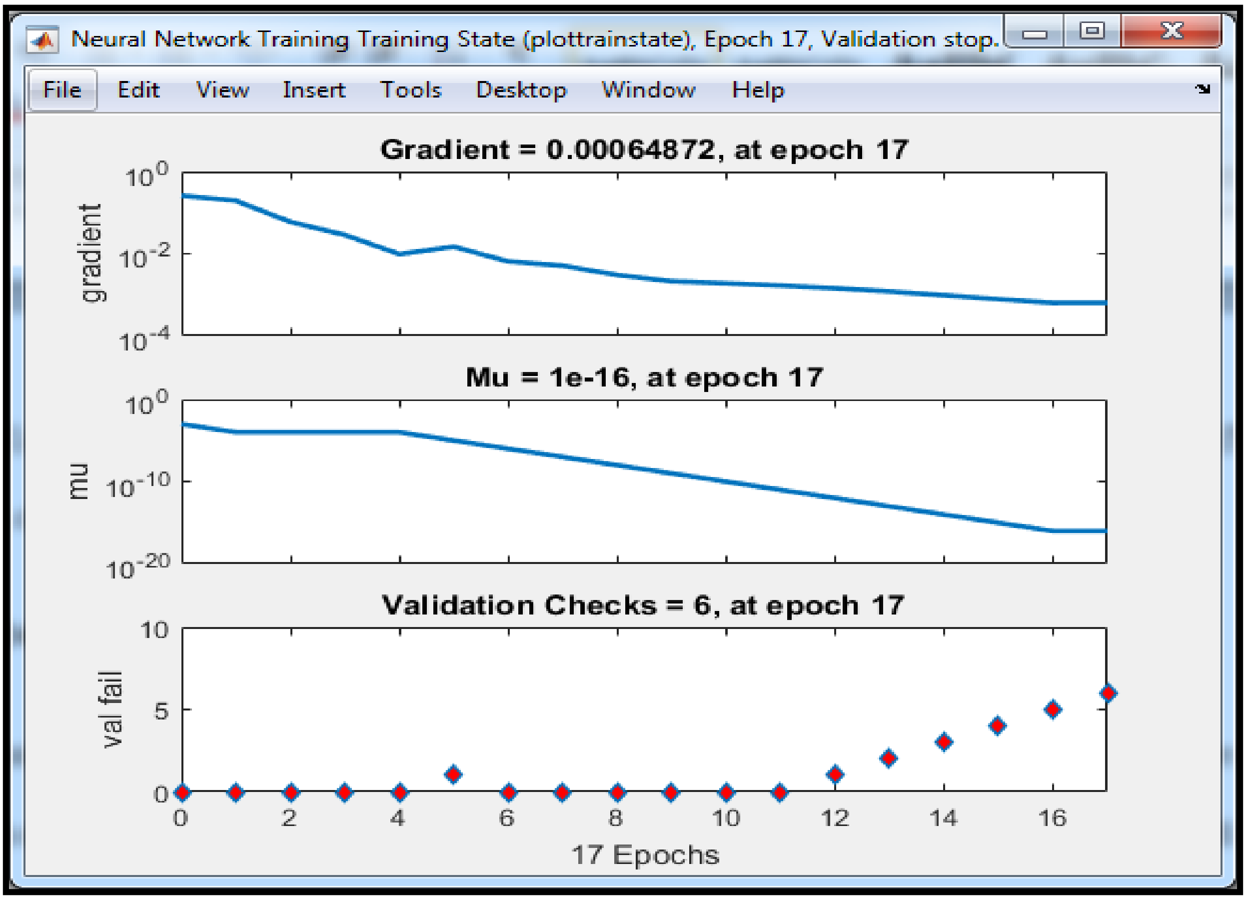

Fig 8: Neural network training state for predicting tool wear rate

The back propagation Neural Networks calculates the error contribution of each neuron after a batch of data training. Technically, the neural network calculates the gradient of the loss function to explain the error contribution of each of the selected neuron. Computed gradient value of 0.00064872, at epoch 17, as observed in **Fig. 8** indicates that the error contribution of each selected neurons is very minimal. Momentum gain (Mu) is a control parameter for the algorithm used to train the neural network. It is the training gains and its value must be less than unity. Momentum gain of 1e-16, at epoch 17, shows a network with high capacity to predict tool wear rate. The regression plot which shows the correlation between the input variables (spindle speed, feed rate, and depth of cut) and the target variable (TWR) is presented in Fig. 9.

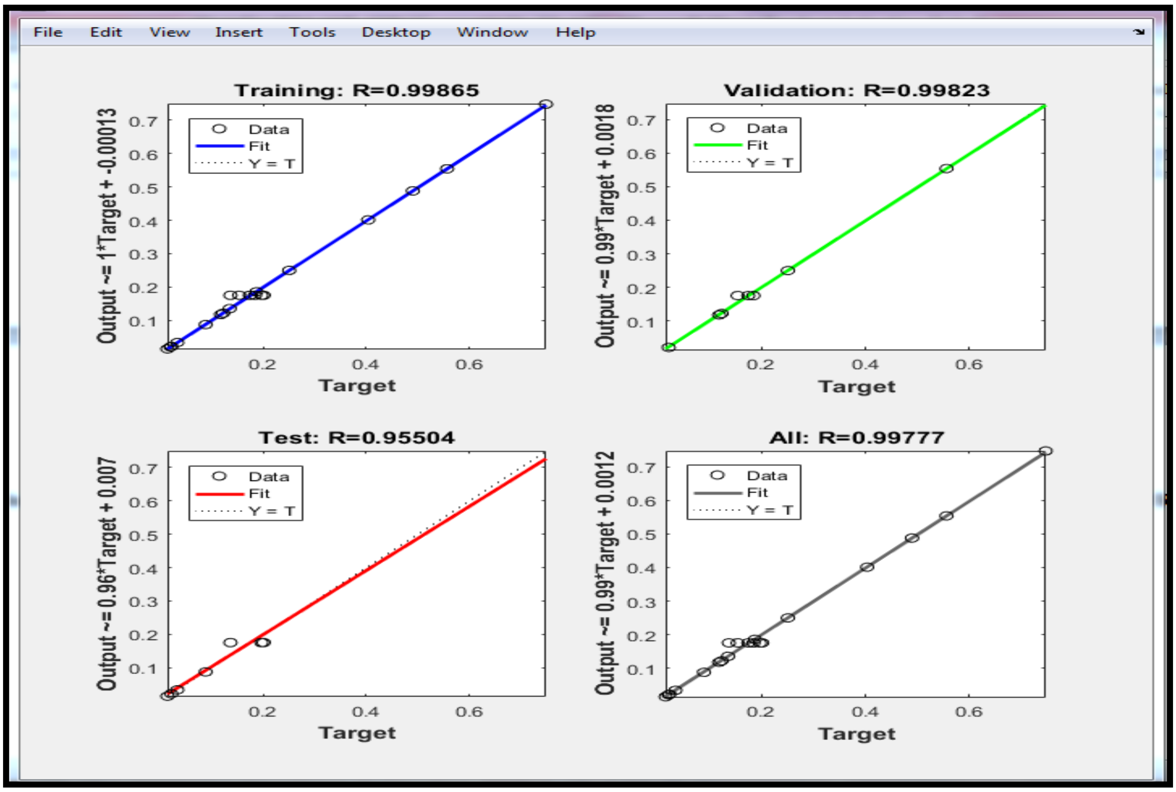

Fig 9: Regression plot of input variables (spindle speed, feed rate, depth of cut) versus target variable (TWR)

Based on the computed values of the correlation coefficient (R) as observed in Fig. 9, it was concluded that the network has been accurately trained and can be employed to predict the tool wear rate (TWR). To test the reliability of the trained network, the network was thereafter employed to predict its own values of tool wear rate using the same set of input parameters generated from the central composite design. Based on the observed and the predicted values of tool wear rate, a regression plot of outputs was thereafter generated as presented in Fig. 10.

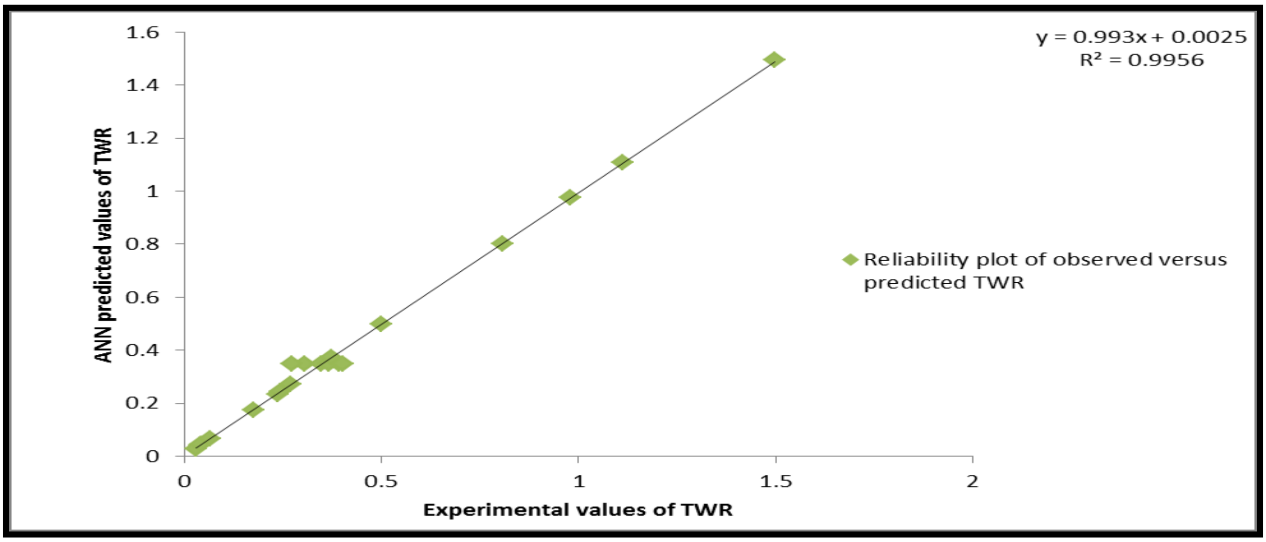

Fig 10: Regression plot of observed versus predicted tool wear rate

B. Comparative Analysis between Artificial Neural Networks (ANN) and Response Surface Methodology (RSM)

To evaluate the performance of ANN in predicting the tool wear rate (TWR), a comparative analysis between artificial neural networks (ANN) and response surface methodology (RSM) was done as follows:

i. Prediction of tool wear rate (TWR) using selected variable combinations was done using artificial neural networks and response surface methodology
ii. A regression plot of output between the experimental values of tool wear rate (TWR) and the predicted values of tool wear rate (TWR) using ANN and RSM was done, as presented in Fig. 11, and
iii. Coefficient of determination (R^2) was calculated for ANN predicted tool wear rate (TWR) and RSM predicted tool wear rate (TWR).
iv. The rule of higher the better was employed to select the best model for predicting the tool wear rate (TWR).

Table 3 shows the result of using ANN and RSM to predict the tool wear rate (TWR).

Table 3: Prediction of tool wear rate (TWR) using ANN and RSM

Run No.	Spindle Speed(rpm)	Feed Rate (mm/min)	Depth of cut (mm)	TWR (mm^3/min) Experimental Values	TWR (mm^3/min) RSM Predicted Values	TWR (mm^3/min) ANN Predicted Values
1	162.5	0.15	1	0.307	0.348639002	0.350384
2	162.5	0.15	1	0.393	0.348639002	0.350384
3	162.5	0.15	1	0.348	0.348639002	0.350384
4	162.5	0.15	1	0.368	0.348639002	0.350384
5	162.5	0.15	1	0.273	0.348639002	0.350384
6	162.5	0.15	1	0.402	0.348639002	0.350384
7	65.79691	0.15	1	0.041	0.040128547	0.041043
8	259.2031	0.15	1	1.113	1.109010466	1.108284
9	162.5	0.099546	1	0.236	0.217471777	0.235108
10	162.5	0.200454	1	0.501	0.514667236	0.499606
11	162.5	0.15	0.159104	0.029	0.015619688	0.029038
12	162.5	0.15	1.840896	0.807	0.846758701	0.802272
13	105	0.12	0.5	0.044	0.109194755	0.043908
14	220	0.12	0.5	0.245	0.232255747	0.24322
15	105	0.18	0.5	0.067	0.039408232	0.067297
16	220	0.18	0.5	0.374	0.426969224	0.371498
17	105	0.12	1.5	0.177	0.127468013	0.174685
18	220	0.12	1.5	0.98	1.011029005	0.975933
19	105	0.18	1.5	0.27	0.28618149	0.270563
20	220	0.18	1.5	1.496	1.434242482	1.495846

Coefficient of determination (R^2) values of 0.9956, as observed in Fig. 10, was employed to draw a conclusion that the trained network can be used to predict the tool wear rate (TWR) beyond the limit of experimentation. Besides, from the regression plot of output between the experimental values of tool wear rate (TWR) and the predicted values of tool wear rate (TWR) using ANN and RSM as presented in **Fig. 11**, it can be seen that ANN has a coefficient of determination of 0.9956 and RSM, 0.9894.

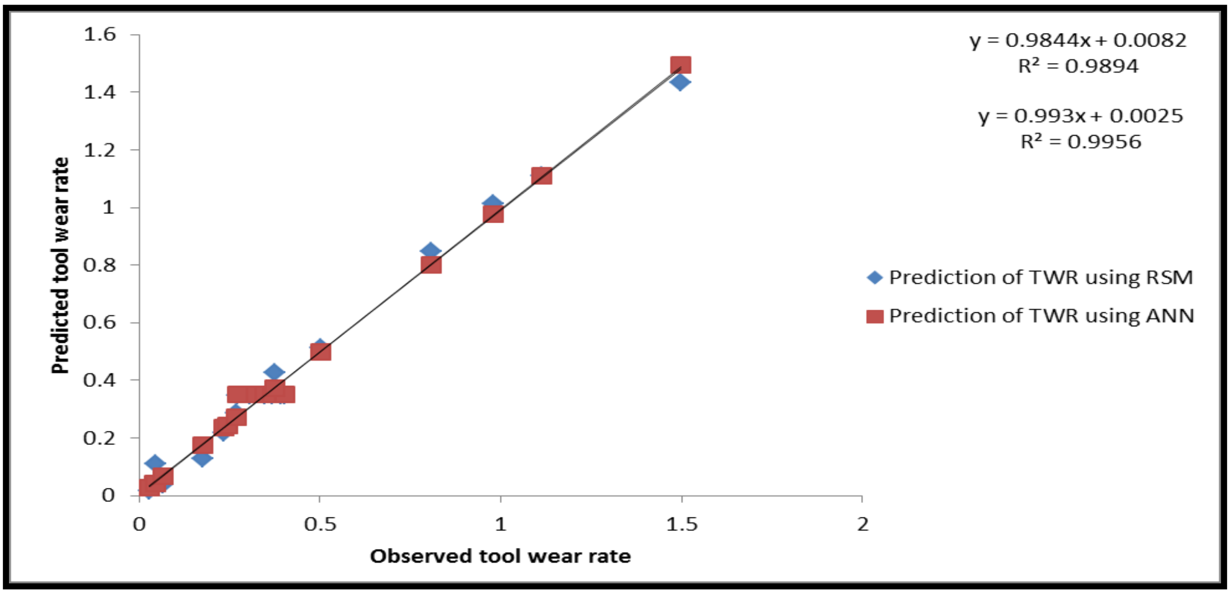

Fig. 11: Performance of ANN and RSM in predicting tool wear rate (TWR)

CONCLUSION

In this research work, a comparative analysis between artificial neural network and response surface methodology in predicting tool wear rate in a turning operation was successfully carried out. The outcome of the research work revealed that the spindle speed, feed rate and depth of cut have significant influence on the rate of tool wear. An increase in any of the evaluated parameters will lead to an increase in the rate of tool wear. Besides, artificial neural network and response surface methodology are good predictive tools but judging by the percentage of variability in tool wear rate that can be explained by each. Artificial neural network with a coefficient of determination of 0.9956 was acclaimed a better model for predicting tool wear rate ahead of response surface methodology having coefficient of determination of 0.9894.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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