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Modeling and Prediction of Tool Wear Using Artificial Neural Network for Turning of Mild Steel

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Abstract: Nowadays in the world of manufacturing machine tool is an important factor since tool wear affects productivity. Prior information about tool wear helps in maintaining product quality and minimizing the manufacturing cost. In this research work an Artificial Neural Network (ANN) model is developed to predict the tool wear during turning of mild steel. The cutting parameters spindle speed, feed and depth of cut are taken as input parameters and tool wear is the output parameter of the network. No of hidden neurons were selected by minimum error criteria. A feed forward back propagation algorithm was used to train the network. Experiment was conducted with 27 combinations of input parameters of which 18 sets were used to train, test and validate the developed network and rest 9 sets were used to test the prediction capacity of the network. From the result it was found that the ANN predicted results and the experimentally measured values for tool wear are very close to each other with an accuracy of 94.25%. It implies that the ANN model can be used to successfully monitor the tool wear condition by forecasting tool wears under different operating condition.

Keywords — Speed, Feed, Depth of cut, Tool wear, Mild steel, Artificial neural network, Prediction, Training

I. INTRODUCTION

In present technical environment machine tool is a very important factor for improving the product quality of an industry. It will minimize total manufacturing cost and produce best quality in phase with the demand. Several parameters such as speed, feed, depth of cut, vibration, temperature at chip-tool interface, surface roughness etc. influence its working condition. ANN (artificial neural network) method is widely used for both modeling and optimizing the performance of the manufacturing technologies.

II. REVIEW OF EARLIER RESEARCH

An experiment was carried out where modeling and optimization of milling process was done by using RSM (Response Surface Methodology) and ANN method. Effects of selected parameters on process variables (surface roughness and material removal rate) were investigated using RSM and ANN. Optimum machining parameters were carried out using RSM and compared to the experimental results. The obtained results indicate the appropriate ability of RSM and ANN methods for milling process modeling and optimization [3]. Another experiment for prediction of tool wear and surface roughness was done by using ANN in turning steel under minimum quality lubrication. A feed-forward back propagation network with 25 hidden neurons have been selected as the optimum network. The results imply that the model can be used easily to forecast tool wear and surface roughness in response to cutting parameters [4]. A milling experiment was carried out to predict the tool life which was based on three parameters of cutting speed, feed rate and depth of cut. The coefficient of correlation between the predicted and experimental data was 0.969 for train and 0.949 for test [5]. An experiment was carried out for prediction of tool wear using regression and ANN models in end milling of AISI304 Austenitic stainless steel. Predicted values of response by both models, i.e. regression and ANN were compared with the experimental values. The predictive neural network model was found to be capable of better predictions of tool flank wear within the trained range [6]. A research was carried out where modeling and prediction of surface roughness was done during dry turning process using ANN. Cutting parameters (cutting speed, feed rate, and depth of cut) were used as network inputs. The developed ANN model can predict surface roughness with regression value 98.641% b/w measured and predicted values and average error 5.4% [7].

III. EXPERIMENTATION

A. Experimental Details

Mild steel bars of length 13cm and diameter 16.5mm was

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used as work-piece for the turning operation performed in a semi-automatic Lathe machine. High speed steel was used as cutting tool. After each turning operation tool wear was measured by a digital vernier caliper.

B. Design of Experiment

The ranges of the control parameters were set in accordance with the normal working condition. As the turning operation is mainly influenced by cutting speed, feed and depth of cut, these three parameters were taken as the control parameters. The control parameters and their ranges are given in the table 1

Control parameters	Low	medium	High
Spindle speed (v) (rpm)	240	550	950
Feed rate (f) (mm/rev)	0.08	0.16	0.32
Depth of cut (d) (mm)	0.4	0.6	0.8

Table 1 Control parameters and their limits

In the present work of turning of mild steel, cutting speed, feed and depth of cut were selected as the design factors having three levels of design, low, medium and high. Hence a three level full factorial i.e 3^3=27 no of experiments were designed and conducted. The combination of various parameters along with the experimental values are presented in table 2

SI no	Spindle speed (v) (rpm)	Feed rate (f) (mm/rev)	Depth of cut (d) (mm)	Tool wear (mm)
1	240	0.08	0.4	0.02
2	240	0.08	0.6	0.03
3	240	0.08	0.8	0.04
4	240	0.16	0.4	0.03
5	240	0.16	0.6	0.04
6	240	0.16	0.8	0.05
7	240	0.32	0.4	0.04
8	240	0.32	0.6	0.05
9	240	0.32	0.8	0.06
10	550	0.08	0.4	0.03
11	550	0.08	0.6	0.04
12	550	0.08	0.8	0.05
13	550	0.16	0.4	0.04
14	550	0.16	0.6	0.05
15	550	0.16	0.8	0.06
16	550	0.32	0.4	0.05
17	550	0.32	0.6	0.06
18	550	0.32	0.8	0.08
19	950	0.08	0.4	0.05
20	950	0.08	0.6	0.06
21	950	0.08	0.8	0.07
22	950	0.16	0.4	0.06
23	950	0.16	0.6	0.07
24	950	0.16	0.8	0.08
25	950	0.32	0.4	0.07
26	950	0.32	0.6	0.09
27	950	0.32	0.8	0.1

Table 2 Experimental Data by DOE

IV. DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK MODEL

Here 18 sets of experimental data were used to develop the ANN model which were taken from the 27 sets of experimental data. Cutting speed, feed and depth of cut were taken as the input parameters of the model and tool wear was the output parameter of the ANN model. MATLAB software was used to train the given model

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	Input Data			Target Data
SI no	speed (v) (rpm)	feed (f) (mm/rev)	Depth of cut(d) (mm)	Tool wear (mm)
1	250	0.08	0.4	0.02
2	250	0.08	0.6	0.03
3	250	0.16	0.6	0.04
4	250	0.16	0.8	0.05
5	250	0.32	0.4	0.04
6	250	0.32	0.8	0.06
7	550	0.08	0.4	0.03
8	550	0.08	0.6	0.04
9	550	0.16	0.6	0.05
10	550	0.16	0.8	0.06
11	550	0.32	0.4	0.05
12	550	0.32	0.8	0.08
13	930	0.08	0.4	0.05
14	930	0.08	0.6	0.06
15	930	0.16	0.6	0.07
16	930	0.16	0.8	0.08
17	930	0.32	0.4	0.07
18	930	0.32	0.8	0.1

Table 3 Parameter combinations used to developed the model

The model contains one hidden layer whose no of neurons were calculated by the following error formula.

$$\textbf{Error} = \frac{1}{N}\sum_{i=1}^{N}(O-T)^2$$

Where N = no of samples.

O = network output.

T = target value

SI no	Number of Hidden neurons	Network structure	Error (μ-mm)
1	8	3-8-1	18.563
2	9	3-9-1	27.251
3	10	3-10-1	20.466
4	**11**	**3-11-1**	**16.453**
5	12	3-12-1	21.728

Table 4 Selection of Hidden Neurons

From the given table it was found that the minimum error took place for 11 no hidden neurons. So the preferred network structure was 3-11-1 that means 3 input neurons, 11 hidden neurons and 1 output neuron.

The network structure is given below:

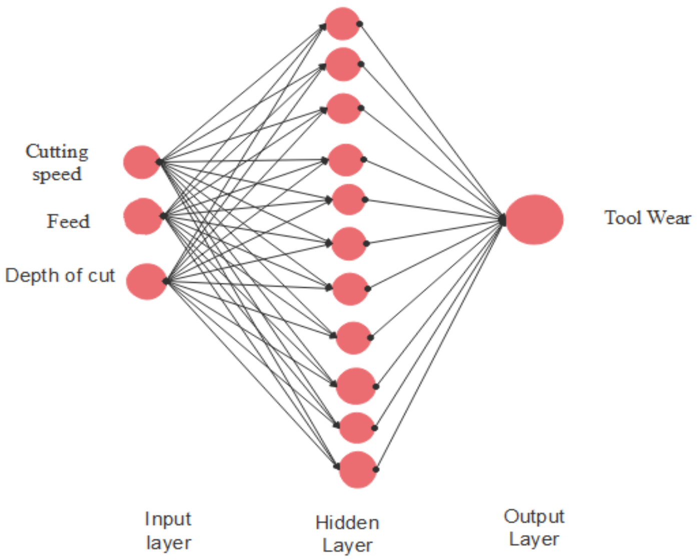

Fig 1 Developed ANN Model

V. TRAINING OF DEVELOPED MODEL

MATLAB 7.7 b Software was used to train the developed model.

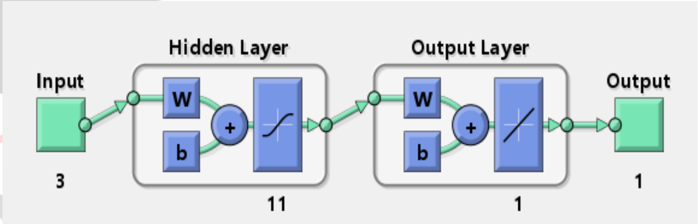

Fig 2 ANN Model

A. Training parameters

Following are the training parameters:

Training Algorithm	Feed-forward back propagation
Activation function	sigmoid
Weights range	(0.133 - 4.30)
No of epochs	1000
Bias range	(0.8- 5.6)
Input neuron	3
Output neuron	1
No of hidden layer	1
Hidden neuron	11
Learning rate	0.01

B. Training Algorithm

The proposed model was trained by Feed Forward Back Propagation Algorithm. The flow chart of the algorithm is given below

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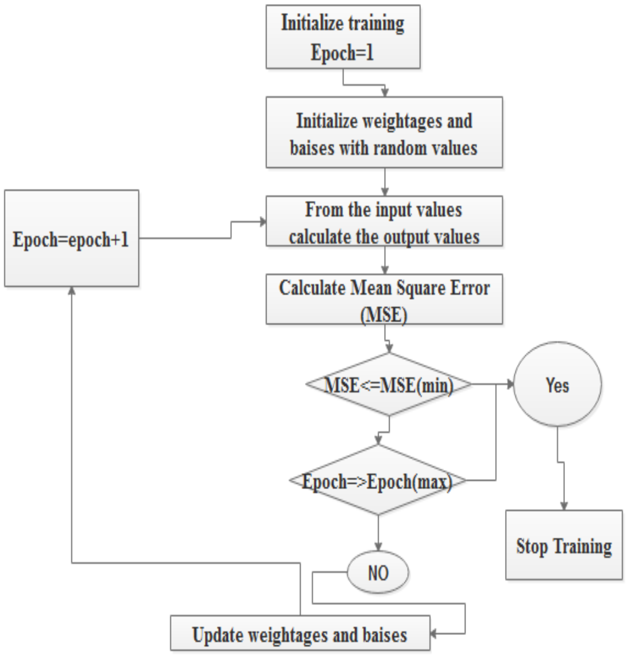

Fig 3 Flow chart for Feed Forward Back Propagation Algorithm

VI. RESULTS AND DISCUSSIONS

From the 18 sets of data 70% was used to train the network, 15% was used to validate the network and the remaining 15% was used to test the network.

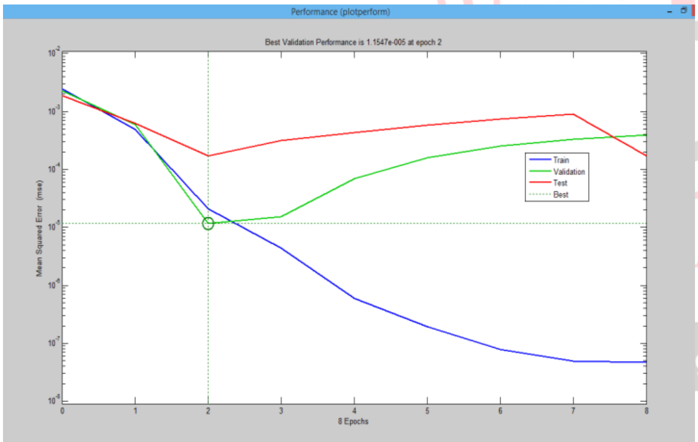

Fig 4 Performance Plot

Here the blue line indicates the training error, green line indicates the validation error and the red line indicates testing error. The error refers to the Mean Square Error (MSE). MSE for single epoch and n no of outputs is given by:

$$\mathrm{MSE}=\frac{1}{2}\sum_{i=1}^{n}(T-O)^2$$

Where T = Target value.

O = Network output.

From fig 4 it can be seen that the training error decreases with more no of epochs. The result is reasonable because the final Mean Square Error is small, the test set error and validation set error has similar characteristics. The best validation performance is at 2nd epoch where the validation error in minimum ($1.1547e^{-005}$). The validation error continues to increases and the training stops after 8 iterations when the error is very large.

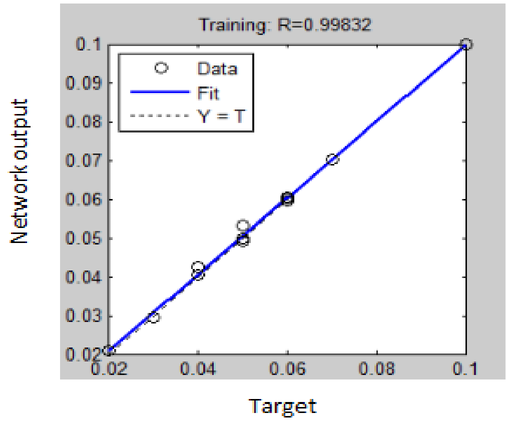

Fig 5 Regression plot for training

The above fig. represents the regression plot for training. It will define how well the network is trained. Here the coefficient of correlation (R) represents the relationship between the network output and target. Here the R value is 0.99832 means it is very close to the target.

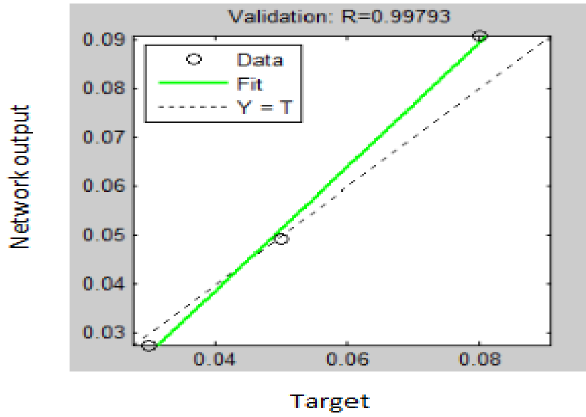

Fig 6 Regression plot for validation

The above fig. represents the Regression plot for validation. Validation data is used during training to assess how well the network is currently performing. Its value R= 0.99793 means the accuracy of the network is brilliant.

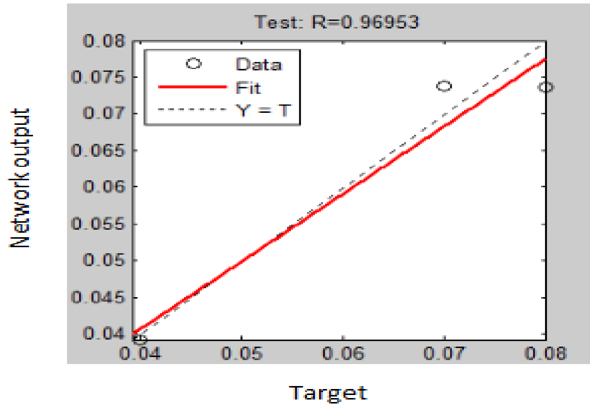

Fig 7 Regression plot for testing

The above fig. represents the regression plot for testing.

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Test data is used for prediction i.e. for finding the class of unknown samples. Here R= 0.96953 means its prediction capacity is exceptionally well.

A. Prediction of unknown samples

9 set of sample parameters which are different from training parameters were used for testing the prediction capacity of the network, which are given below:

SI no	Spindle speed(v) (rpm)	Feed(f) (mm/rev)	Depth of cut(d) (mm)
1	250	0.08	0.8
2	250	0.16	0.4
3	250	0.32	0.6
4	550	0.08	0.8
5	550	0.16	0.4
6	550	0.32	0.6
7	930	0.08	0.8
8	930	0.16	0.4
9	930	0.32	0.6

Table 5 Samples for testing

Prediction of tool wear corresponding to this sample was done by the developed network and is given below:

Test trail no	Measured tool wear (mm)	ANN predicted tool wear (mm)	Absolute prediction error(APE)	Accuracy in %
1	0.04	0.041692	4.23	95.77
2	0.03	0.0312	4	96
3	0.05	0.053126	6.25	93.75
4	0.05	0.054383	8.76	91.24
5	0.04	0.038723	3.19	96.81
6	0.06	0.064876	8.12	91.88
7	0.07	0.063596	9.14	90.86
8	0.06	0.057995	3.34	96.66
9	0.09	0.085693	4.78	95.22

Table 6 Prediction of unknown samples

The absolute prediction errors were calculated by the formula given below

$$\text{APE} = \frac{Measured - predicted}{Measured} \times 100$$

The experimentally measured values were compared with the ANN predicted values for tool wear in the above table. From which it was found that the average absolute prediction error is 5.75

So the accuracy of the model is 94.25%.

The graphs corresponding to the experimentally measured values and ANN predicted values of tool wear for different no of experiments are shown below in fig.8

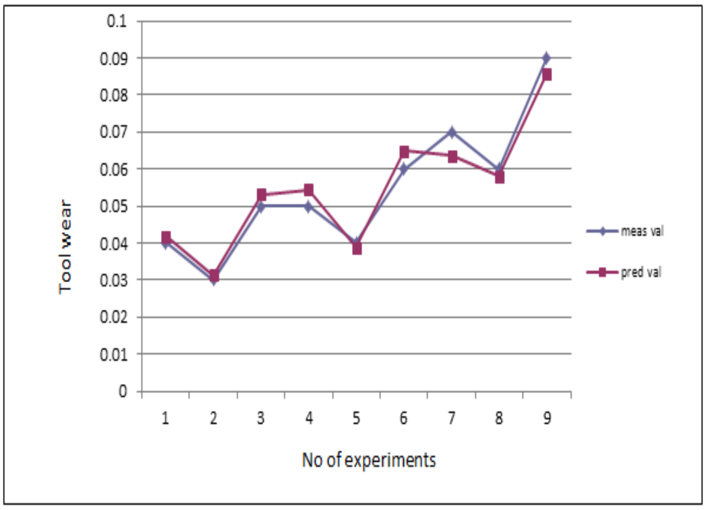

Fig 8 Graph between measured and predicted values

In the above graph the blue line represents the experimentally measured values and the red line represents the ANN predicted values for tool wear. From the graph it is clearly visible that the measured values and ANN predicted values are very close to each other for all 9 experiments.

VII. CONCLUSION

From the present research work it can be concluded that artificial neural network (ANN) is an extremely good soft computing machine learning tool for prediction of tool wear. It can also provide good results for image recognition, function approximation and optimization works. From the comparison of experimental and predicted values it can be seen that the average absolute prediction error for tool wear is 5.75 which is very low and its prediction accuracy is 94.25% which is exceptional. Hence ANN can be safely used for prediction of tool wear in the manufacturing industry.

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