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Experimental Analysis of Tool Wear in Drilling of EN-31 Using Artificial Neural Network

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Abstract : *Tool wear in drilling is an important parameter with respect to surface quality of hole and failure of material. Operation performed with worn out tool may increase manufacturing cost. In this work, an attempt has been made to measure the wear of tool with the help of stereoscopic microscope and the results obtained have been compared with a statistical model in which tool wear is assumed as the function of thrust force, machining time, speed and feed. And also compared with ANN model in which input neurons are drill diameter, torque, thrust force, machining time, feed and speed, whereas output is tool wear. Comparison between these three results has also been made. It is found that ANN gives best result and can be used for online tool monitoring. Experiments performed from 1 to 40th hole while drilling operations have performed on EN-31.*

Keywords : *Tool Wear; Torque; EN-31;Thrust force; artificial neural network; feed; speed;*

I. INTRODUCTION

Drilling is one of the most common and fundamental machining processes. Drilling operation in manufacturing industries contributes near about 30 to 40 % of all cutting operations. Worn drills produce poor quality holes and in extreme cases a broken drill can destroy an almost finished part [3]. A drill begins to wear as soon as it is placed into operation. As it wears, cutting forces will increases, the temperature of the drill rises and this accelerates the physical and chemical processes associated with drill wear and therefore drill wears faster. Different types of drill wear, such as flank wear, crater wear and chisel edge wear and margin wear, can be observed on drill because of the geometry of the drill and the cutting conditions vary along the cutting lips from the margin to the chisel edge The use of the tool after worn out condition will lead to increase the manufacturing cost due to the wastage of work piece material as well as a tool. Depends a lot on the finish produced by the drilling process. Worn out tool also causes rough surface finish, so it is necessary to replace or regrind tool at the right time during metal cutting operation. Cutting force can be represented by thrust and torque in drilling operations. Thrust and torque depend upon drill wear, drill size, feed rate and spindle speed.

In this work, tool wear is calculated manually by stereoscopic microscope after every fifth hole and this is also being compared with a model in which tool wear is proposed to be a function of thrust force, speed, torque, machining time. Tool wear is also compared with results obtained by artificial neural network (ANN) which gives more accurate results in terms of minimum error.

II. EXPERIMENTAL SETUP

The Work piece was made of EN-31 which has cylindrical shape (Length 70 mm & Diameter 40 mm). EN-31 also known as bearing metal, is high quality alloy of steel having good ductility and shock absorbing capacity with resistance to wear. Hardness of this material is higher than low carbon steel because it consists of nickel (Ni) and chromium (Cr) which leads to increase hardness of material. Tool made of HSS (High speed steel) has been used to make a hole in work piece. Point angle of tool is 135◦ and diameter of tool is 10mm. The radial drilling machine used was primarily intended for drilling medium to large and heavy work piece. The optical microscope used was variant designed for low magnification observation of a sample, typically using light reflected from the surface of an object rather than transmitted through it. A coordinate measuring machine (CMM) was also used to measure wear. A dynamometer (digital type) was used to measure thrust force (i.e. cutting force) and torque. The twist drill of 10 mm diameter and made of HSS (high speed steel) has been used. The work piece material is EN-31 (known as bearing metal) and drill depth is to be kept constant 20 mm. The work piece was of cylindrical shape, having diameter 40 mm and length 70 mm. The number of holes were carried out 1 to 40. Two tests were conducted using various combination of speed (13.71 m/min or 440 Rpm & 18.22 m/min or 580 Rpm) and feed (0.12 mm/rev and 0.2 mm/rev). Tool geometry, work piece hardness, tool geometry, rigidity of machine and temperature are the main parameters that influences the tool wear. These parameter are assumed as constant in the different set of tests. Wear measurements is carried out by using stereoscopic microscope with incident illumination. Wear land was observed under 100x magnification and wear land width was measured by means of a measuring eyepiece. The microscope has a resolution of 20m under 80x magnifications. Some pictures of twist drill before and after use was taken by CMM (coordinate measuring machine). The experimental data are as shown in Table 1 & Table 2. Fig.1 shows the tool image of used tool taken from CMM after 40th hole for reading A.

Two sets of reading are obtained which are as follows:
Reading set A - Diameter 10 mm, feed .12 mm/rev, speed 13.71mm/min or 440 RPM
Reading set B - Diameter 10 mm, feed .12 mm/rev, speed 18.22mm/min or 580 RPM

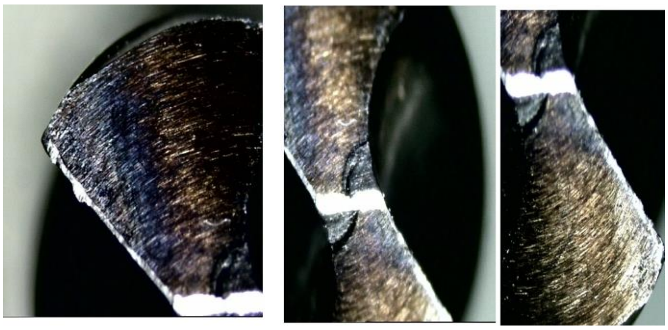

Fig.1. Tool image of used tool taken from CMM after 40th hole for reading A

III. ANALYSIS BY STATISTICAL METHOD

Tool wear is assumed to be proportional to the variables, such as cutting speed, feed, machining time and cutting force [8] in eq.1. The functional relationship between the response parameters, such as cutting speed, feed, time and thrust force for the cutting operation and the integrated independent variables which are given by:

Tw = k va f b Fc Td .... (1)

where Tw is the tool wear in mm, v the cutting speed in m/min, f the feed in mm/rev, Fc the cutting force in N and T is the machining time in min.

The form of equation (1) is non-linear, The software used for statistical analysis was Micro soft EXCEL. The equations obtained for tool wear by statistical analysis are as follows:

TW = 0.987× F0.8123× T-0.854×v-1.065 ×f 2.5
(Diameter 10 mm, feed 0.12 mm/rev speed 13.81 mm/min or 440 Rpm)

TW = 0.816× F0.7642× T-07765.×v-0.98 ×f-3.2
(Diameter 10 mm, feed 0.2 mm/rev speed 18.22 mm/min or 580 Rpm)

The modified regression equations were obtained for calculating the estimated values of tool wear are as shown below:

TW == 0.0069× F0.29× T0.7999 (Diameter 10 mm, feed 0.12 mm/rev speed 13.81 mm/min or 440 Rpm)

Modified Regression equation for reading set B is given as
TW== 0.00911× F 0.29× T 0.98
(Diameter 10 mm, feed 0.2 mm/rev speed 18.22 mm/min or 580 Rpm)

Table 1 Tool wear measured from microscope for reading set A
(Diameter 10 mm, feed .12 mm/rev, speed 13.71 mm/min or 440 RPM)

No. of holes	Machine time (min)	Force (N)	Torque (N-m)	Tool wear (mm)
1	0.415	1814.5	5.886	0.001
5	2.076	1932.57	6.867	0.1
10	4.151	2040.48	7.848	0.18
15	6.226	2089.53	8.004	0.25
20	8.301	2118.96	8.25	0.33
25	10.376	2226.27	8.63	0.45
30	12.541	2374.02	9.123	0.52
35	14.941	2481.93	9.613	0.56
40	16.601	2658.51	10.3	0.61

Table 2 Tool wear measured from microscope for reading set B
(Diameter 10 mm, feed .2 mm/rev, speed 18.22 mm/min or 580 RPM)

No. of hoes	Machining time (min)	Thrust (N)	Torque (N-m)	Tool wear (mm)
1	0.189	3021.48	10.305	0.001
5	0.946	3090.81	10.791	0.09
10	1.891	3149.01	11.772	0.17
15	2.836	3207.87	12.753	0.29
20	3.781	3305.97	12.753	0.38
25	4.726	3374.64	13.734	0.47
30	5.671	3443.31	14.715	0.54
35	6.616	3531.6	15.696	0.62
40	7.561	3688.56	16.677	0.68

Table 3 Estimated tool wear obtained from statistical analysis for reading set A
(Diameter 10 mm, feed .12 mm/rev, speed 13.71 mm/min or 440 RPM)

No. of hole s	Machini ng time	Force (N)	Torqu e (N-m)	Tool wear (mm)	Estimate d Tool wear
5	2.076	1932.57	6.867	0.1	0.108329
10	4.151	2040.48	7.848	0.18	0.191557
15	6.226	2089.53	8.004	0.25	0.266758
20	8.301	2118.96	8.25	0.33	0.337134
25	10.376	2226.27	8.63	0.45	0.408823
30	12.541	2374.02	9.123	0.52	0.484687
35	14.941	2481.93	9.613	0.56	0.564794
40	16.601	2658.51	10.3	0.61	0.626824

Table 4 Estimated tool wear obtained from statistical analysis for reading set B
(Diameter 10 mm, feed .12 mm/rev, speed 18.22 mm/min or 580 RPM)

No. of holes	Machining time	Force (N)	Torque (N-m)	Tool wear (mm)	Estimated Tool wear
5	0.946	3090.81	10.791	0.09	0.088718
10	1.891	3149.01	11.772	0.17	0.175852
15	2.836	3207.87	12.753	0.29	0.263011
20	3.781	3305.97	12.753	0.35	0.351698
25	4.726	3374.64	13.734	0.42	0.440259
30	5.671	3443.31	14.715	0.59	0.529454
35	6.616	3531.6	15.696	0.56	0.620317
40	7.561	3688.56	16.677	0.66	0.716002

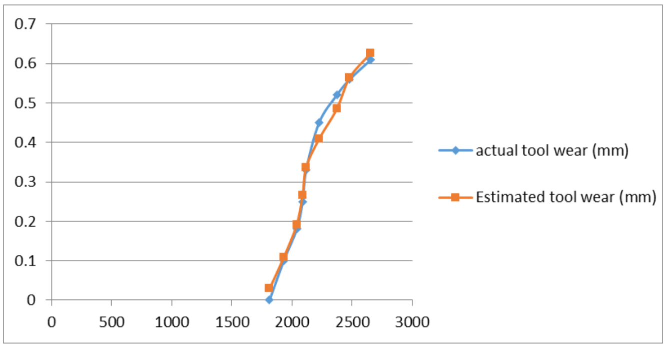

Fig.2. Comparison between actual tool wear & estimated tool wear for reading set A

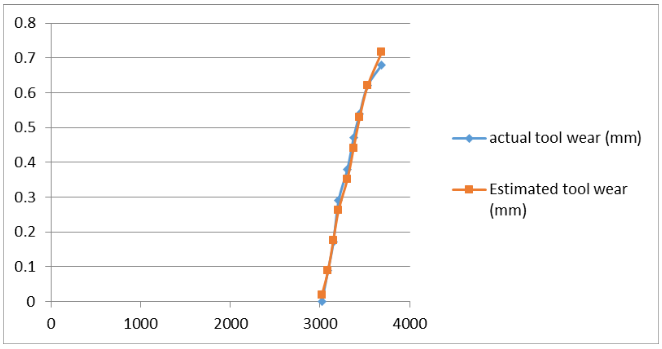

Fig.3. Comparison between actual tool wear & estimated tool wear for reading set B

IV. ANALYSIS BY ARTIFICIAL NEURAL NETWORK METHOD

These networks are designed to stimulate the information processing of the human brain. These networks have been successfully applied to industrial problems in the areas of pattern classification and automatic control. An ANN that uses back propagation algorithms for modelling tool wear has been developed using machining process parameters as inputs and tool wear as output.

The first step of analysis in ANN is to normalize all the raw or input data data to values between 0.1 and 0.9. Two data sets obtained from table 1 and table 2 has been used for the training of neural network, the learning rate is used 0.08, and no smoothing factor has used. Initially weights are assigned randomly from 0.1 to 0.8; the learning process was stopped after 2000 iterations. The number of neurons in the hidden layer are selected from 10, 15 and 20.

The first step of the calculation is to normalize all the raw input data to values between 0.1 and 0.9 as shown in the following equation.

$$a_i = \frac{0.8}{d_{\max} - d_{\min}}(d_i - d_{\min}) + 0.1$$

where d_{max} and d_{min} are the maximum and minimum input data, respectively, and d_i is the i^{th} input data.

The input of the each i^{th} neuron on the hidden layer I_{bi} is calculated by :

$$I_{bi} = \sum_{i=1}^{m} w_{ab} a_i$$

where m is the number of neurons in the input layer and w_{ab} is the numerical weight value of the connection between the two neurons. a_i is the i_{th} normalized output value from the input layer.
The output of the ith neuron on the hidden layer b_i is calculated by applying an activation function to the summed input to that neuron. The output of the each ith neuron on the hidden layer then becomes,

$$b_i = f(b_i) = \frac{1}{1 + e^{-s(I_{bi})}}$$

where s is the slope of the sigmoid function.
The values received by the output layer I_c are the outputs of the hidden and input layers.

$$I_{ci} = \sum_{i=1}^{m} w_{ac}\ a_i + \sum_{i=1}^{n} w_{bc} b_i$$

where m, the number of neurons in the input and n,the number of neurons in hidden layers. W_{ac} and w_{bc} are the weights between the input and output layer and between the hidden layer and output layer respectively. The actual output for the output layer is calculated by applying the same sigmoid function as in the hidden layer,

$$c_i = f(I_{ci})$$

The error i between the actual and desired output in the output layer is calculated by

$$\delta_{ci} = f^{'}(I_{ci})(X_i - c_i)$$

where X_i is the i^{th} training input to the neuron and f is the derivative of the sigmoid function.
Calculation of the error (δ_{bi}) For each neuron on the hidden layer is,

$$\delta_{bi} = f(I_{bi}) \sum_{i=1}^{K} \delta_{ci} w_{bc}$$

where K is the number of neurons in the output layer. MATLAB 2013 and neural tool box has been used to analyze the ANN application in the drilling problem of tool wear. The different test data is used for training the neural network structures. In order to find that which neural set will be the best neural network structure of ANN, a simple criteria can be used. Criteria is that the on increasing the no. of neurons on hidden layer optimises the result which gives minimum mean square error from actual tool wear.
For calculating updated new weight following step is to be done,

$$\Delta w_{bc}{}^{new} = (1-\beta)\alpha\delta_{ci}b_i + \beta\Delta w_{bc}{}^{old}$$

Similarly for w_{ab} and w_{ac} equation can be written.
α is learning rate. By increasing the learning rate number of iteration is required minimum and improves efficiency and β is smoothing constant.

Table 5. Tool wear obtained from ann analysis for reading set A
(Diameter 10 mm, feed 0.12mm/rev, speed 13.71 mm/min or 440 RPM)

No. of holes	MT (min)	Force (N)	Torque (N-m)	Tool wear (mm)	6×10×1 Tool Wear (mm)	6×15×1 Tool wear (mm)	6×20×1 Tool Wear (mm)
5	2.076	1932.57	6.867	0.1	0.1392	0.1324	0.1221
10	4.111	2040.48	7.848	0.18	0.1987	0.1888	0.1849
15	6.226	2089.53	8.004	0.25	0.2590	0.2523	0.2517
20	8.301	2118.96	8.25	0.33	0.3351	0.3319	0.3304
25	10.376	2226.27	8.63	0.45	0.4518	0.4504	0.4502
30	12.541	2374.02	9.123	0.52	0.5207	0.5204	0.5203
35	14.941	2481.93	9.613	0.56	0.5620	0.5609	0.5603
40	16.601	2658.51	10.3	0.61	0.6172	0.6113	0.6105

Table 6. Tool wear obtained from ann analysis for reading set B
(Diameter 10 mm, feed 0.2mm/rev, speed 18.22 mm/min or 580 RPM)

No. of holes	MT (min)	Force (N)	Torque (N-m)	Tool wear (mm)	6×10×1 Tool Wear (mm)	6×15×1 Tool wear (mm)	6×20×1 Tool Wear (mm)
5	0.946	3090.81	10.791	0.09	0.1350	0.1233	0.1153
10	1.891	3149.01	11.772	0.17	0.1903	0.1820	0.1753
15	2.836	3207.87	12.753	0.29	0.2954	0.2917	0.2905
20	3.781	3305.97	12.753	0.35	0.3850	0.3805	0.3813
25	4.726	3374.64	13.734	0.42	0.4209	0.4210	0.4202
30	5.671	3443.31	14.715	0.56	0.5615	0.5510	0.5503
35	6.616	3531.6	15.696	0.59	0.5913	0.5911	0.5910
40	7.561	3688.56	16.677	0.66	0.6614	0.6614	0.6608

A comparison graph is plotted is shown in Fig.5. It compares actual value with estimated Value calculated from statistical analysis and also compare with ANN structure (6x10x1) for reading set A. (diameter 10 mm, speed 13.71 mm/min or 440 RPM, feed .12 mm/rev).

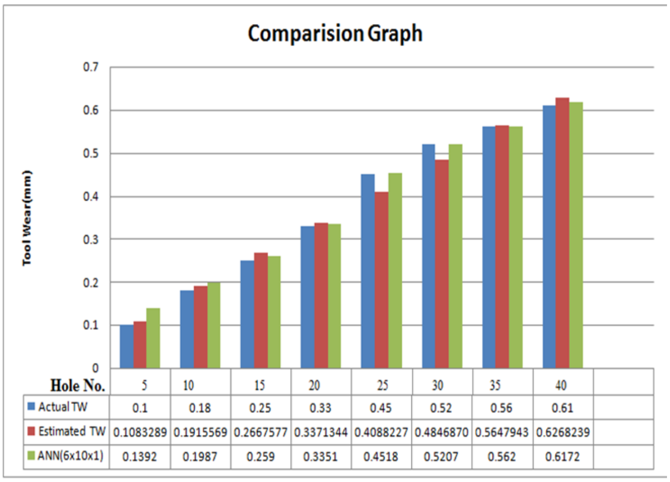

Fig.4. Tool wear comparison for reading set A

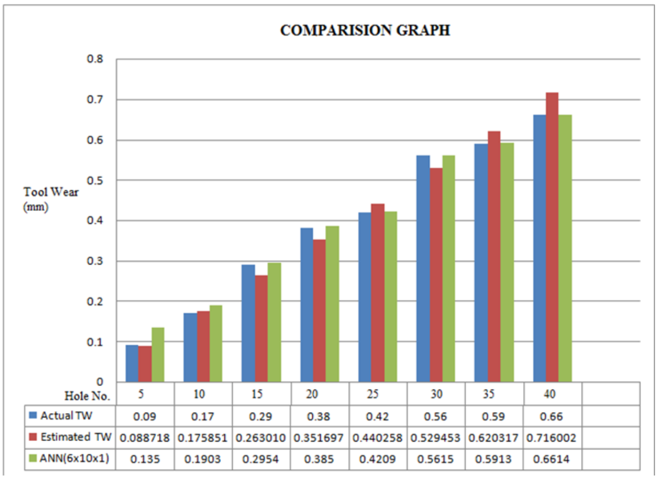

Fig.5. Tool wear comparison for reading set B

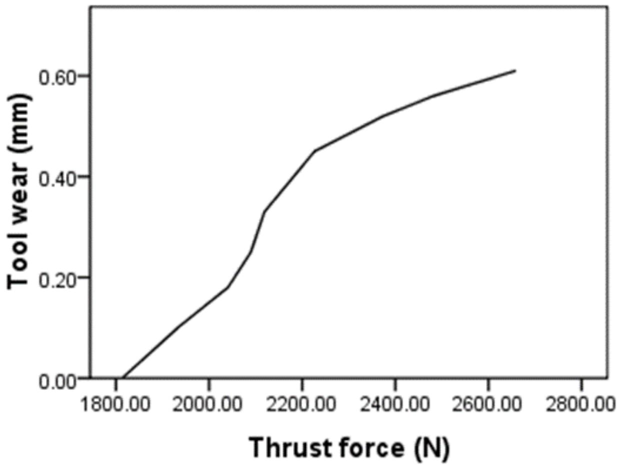

Fig.6. Graph between tool wear and thrust force for reading set A

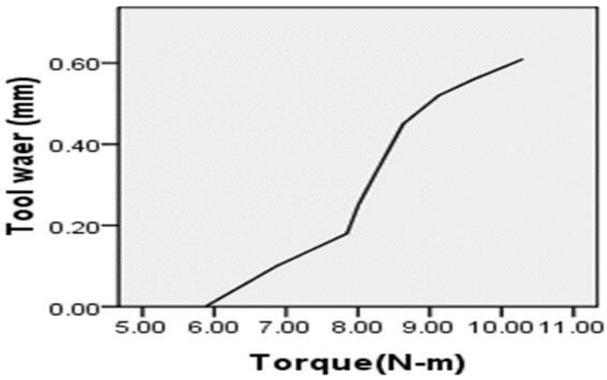

Fig.7. Graph between tool wear and torque for reading set A

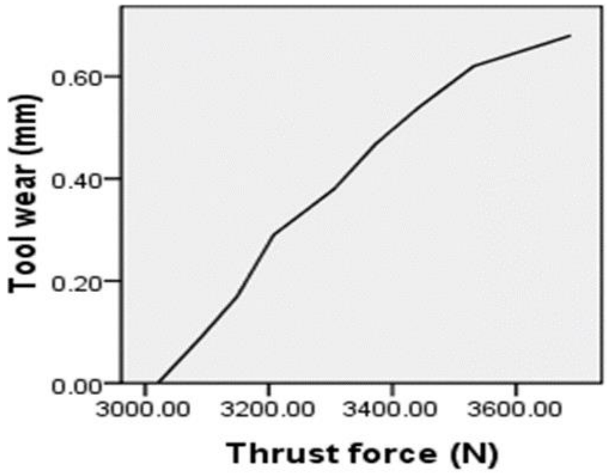

Fig.8. Graph between tool wear and thrust force for reading set B

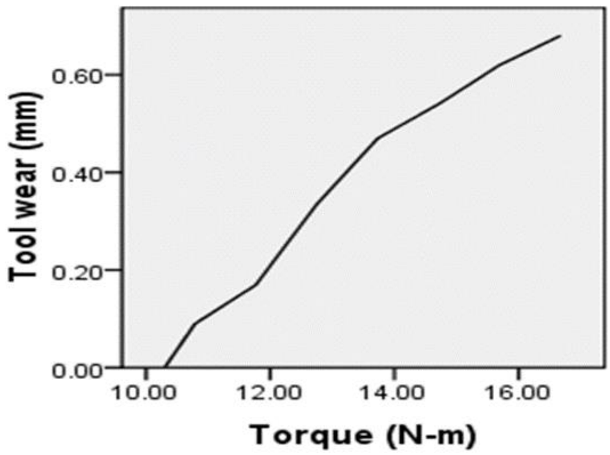

Fig.9. Graph between tool wear and torque for reading set B

A comparison graph is plotted is shown in Fig.6. it compares actual value with estimated value calculated from statistical analysis and also compare with ANN structure (6x10x1) for reading set B.
Graphs are plotted between tool wear and different parameter like thrust force and torque for both of the reading sets A and B. Fig. 6 and Fig.7 demonstrates that torque and thrust force increase as tool wear increases. Graphs for variation of tool wear with respect to thrust force and toque in Fig. 6 and Fig.7 respectively (Diameter 10mm, feed .12 mm/rev, speed 13.72 mm/min or 440 rpm). Graphs for variation of tool wear with respect to thrust force and torque (Diameter 10mm, feed .2 mm/rev, speed 18.22 mm/min or 580 rpm) is shown with graphs in Fig.8 and Fig.9.

V. CONCLUSION

Based on the observation Tables 3 and 4, following observations is made regarding statistical analysis:

- The focus of the work is on 10 mm drill diameter. It is assumed that tool wear depends on the cutting speed, feed, machining time and thrust force. The regression equations obtained is statistically justified in statistical sense and the modified regression equations is used for estimating the values of tool wear. A back propagation algorithm is used for the prediction of tool wear. It is assumed that tool wear depends on drill diameter, cutting speed, feed, machining time, thrust force and torque.

- Following observations were made regarding neural networks:
- Drill diameter, feed, cutting speed, time, force and torque is given as inputs and flank is estimated using different structures of ANN (Tables 5 and 6). These input can be used to train the neural network for getting the estimated values of tool wear. The work has demonstrated that tool wear depends on these variables. In both set of reading i.e. A and B, 6x20x1 gives best result because of minimum error from actual value. Here it is cleared that on increasing the number of neurons on hidden layer gives more accurate results.

- The comparative analysis has been done between the actual values of tool wear and the estimated values obtained by statistical analysis and neural network analysis. As per the Fig.4 and Fig.5, the estimated values obtained by neural network structures, are comparing well with the actual values obtained during experimentation for all the combinations of cutting speed and feed.

- Experimental results show that this method can be effectively employed in practice as the algorithm is easy and reliable. Neural network has shown the capability of generalization and has the ability for its application in tool wear analysis.

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