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Article *in* The International Journal of Advanced Manufacturing Technology · April 2008

DOI: 10.1007/s00170-007-0948-5

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Int J Adv Manuf Technol (2008) 37:29–41
DOI 10.1007/s00170-007-0948-5

ORIGINAL ARTICLE

Prediction of tool wear using regression and ANN models in end-milling operation

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Received: 25 February 2006 / Accepted: 12 January 2007 / Published online: 16 February 2007

Abstract Tool wear prediction plays an important role in industry for higher productivity and product quality. Flank wear of cutting tools is often selected as the tool life criterion as it determines the diametric accuracy of machining, its stability and reliability. This paper focuses on two different models, namely, regression mathematical and artificial neural network (ANN) models for predicting tool wear. In the present work, flank wear is taken as the response (output) variable measured during milling, while cutting speed, feed and depth of cut are taken as input parameters. The Design of Experiments (DOE) technique is developed for three factors at five levels to conduct experiments. Experiments have been conducted for measuring tool wear based on the DOE technique in a universal milling machine on AISI 1020 steel using a carbide cutter. The experimental values are used in Six Sigma software for finding the coefficients to develop the regression model. The experimentally measured values are also used to train the feed forward back propagation artificial neural network (ANN) for prediction of tool wear. Predicted values of response by both models, i.e. regression and ANN are 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.

Keywords Tool wear · Design of Experiments (DOE) · Regression model · Artificial neural network (ANN)

Nomenclature

b	Axial depth of cut, mm
b_r	Radial depth of cut, mm
D	Diameter of cutting tool, mm
f	Feed per tooth, mm/tooth
V	Cutting speed, m/minute
Y	Tool wear, mm
Z	Number of flutes on the cutter
W_{ih}	Weight values between input and hidden layers
W_{ho}	Weight values between hidden and output layers

1 Introduction

The productivity of a machining system and machining cost, as well as quality, the integrity of the machined surface and profit strongly depend on tool wear and tool life. Sudden failure of cutting tools leads to loss of productivity, rejection of parts and consequential economic losses. Flank wear occurs on the relief face of the tool and is mainly attributed to the rubbing action of the tool on the machined surface. The flank wear predominantly occurs in cutting tools, so the life of a particular tool used in the machining process depends upon the amount of flank wear. But the crater wear is prevalent only under certain cutting conditions, i.e. higher cutting speeds and feeds lead to more

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crater wear. In this case, tool life is evaluated by means of crater wear. As the flank face of the cutting tool performs a rubbing action against the work piece materials, the surface finish of the machined work piece primarily depends upon the amount of flank wear. An increase in the amount of flank wear leads to a reduction in nose radius of the cutting tool, which in turn reduces the surface finish. The dominating wear mode for the tools considered in this work is excessive flank wear, which gives increased cutting forces and vibrations in the milling process. The maximum utilisation 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 milling of a particular work piece material. In order to maximise gains from a manufacturing process, an accurate process model must be constructed for an end milling process with speed, feed, and depth of cut as input machining parameters and tool flank wear as the output variable.

Experiments have been conducted to measure tool wear based on Design of Experiments (DOE) for five level three factors full factorial technique. Design of Experiments (DOE) is a scientific approach of planning and conducting experiments to generate, analyse and interpret data so that valid conclusions can be drawn efficiently and economically. After determining the significant coefficients using Quality America PC IV, the final regression model is constructed to predict the tool wear. The value of the regression coefficients in the regression model gives an idea as to what extent the control variables affect the responses quantitatively. The accuracy of the model has been tested using the analysis of variance techniques (ANOVA). The regression mathematical model has been used to plot the contour and surface plots for different combinations of machining parameters in SYSTAT 10.2 software. The validity of the final regression models is further tested using the ANN model, which compares measured and predicted values. Knowledge of tool wear will help the operator in selecting machining parameters to minimise tool wear.

2 Literature survey

Yongjin and Fischer [1] developed tool wear index (TWI) and the tool life model for analysing wear surface areas and material loss from the tool using micro-optics and image processing/analysis algorithms. They proposed optimal control strategy demonstrates how production cost can be minimized by adjusting machining parameters and extending the tool usage within the constraints for specific machining conditions. Oraby and Hayhurst [2] developed models for wear and tool life determination using non-linear regression analysis techniques in terms of the variation of a ratio of force components acting at the tool tip. Shao et al. [3] developed a cutting power model for tool wear monitoring with variable cutting conditions in face milling operations. The cutting power model is verified with experiments. It is shown with the simulations and experiments that the simulated power signals predict the mean cutting power better than instantaneous cutting power. Richetti et al. [4] investigated the effect of the number of tools used in face milling operations and related it to the establishment of tool life under specified cutting conditions. Flank wear was evaluated for AISI 1045 and 8640 steels using 1, 2, 3 and 6 inserts in a face milling cutter. Test results show that reduction in the number of inserts in the milling cutter leads to a reduction in the amount of material removed and also tends to increase tool life when machining at the same feed per tooth.

Kuo et al. [5] proposed an on-line estimation system applied in the area of tool wear monitoring through integration of two promising technologies: artificial neural network and fuzzy logic. The proposed system is able to accurately predict the amount of tool wear. The results showed that the proposed system can significantly increase the accuracy of the product profile when compared to the conventional approaches. Srinivasa et al. [6] presented tool wear estimation in face milling operations using the resource allocation network (RAN). Acoustic emission (AE) signals, surface roughness parameters and cutting conditions (cutting speed, feed) have been used to formulate input patterns. The results obtained using (RAN) are very encouraging and are compared with those obtained from a multi-layer perceptron (MLP) network. RAN has faster learning ability and is able to fairly and accurately estimate the tool wear. The results of MLP indicate it to be much more robust and accurate in estimating the values of tool wear when compared with RAN. Choudhury et al. [7] predicted the response variables flank wear, surface finish and cutting zone temperature in turning operations using Design of Experiments and the neural network technique and the values obtained from both methods were compared with the experimental values of the response variables to determine the accuracy of the predictions. Koshy et al. [8] proposed the effectiveness of two innovative techniques designed to rapidly optimise a milling application. One of them relates to quantifying the relative wear of different insert grades concurrently in a single cutting test, by mounting the inserts in the same cutter, for a quick comparative performance evaluation. The other technique refers to rapid identification of the optimum feed/tooth that corresponds to maximum tool life. This entails a test wherein individual inserts in the cutter are subjected to feed/tooth that are multiples of a base value, by selectively leaving an appropriate number of consecutive insert pockets unoccupied.

Wang et al. [9] investigated the performance and the wear mechanism of the binderless cubic boron nitride (BCBN) tool when slot milling the titanium alloy in terms of cutting forces, tool life and wear mechanism. This type of tool manifests longer tool life at high cutting speeds. Based on the comparison with tool life of cubic boron nitride (CBN) and PCD tools, BCBN would appear to be the most functionally satisfactory cutting tool material now available for machining titanium. Sohyung et al. [10] developed and implemented a tool breakage detection system using a support vector regression in a milling process. To fulfill the diverse customer needs, multiple sensors have been used to establish the model. The breakage detection rate has been compared to a model developed using the traditional multiple variable regression (MVR) approach. It is observed that the proposed support vector regression (SVR) model performs well with a tight threshold value for tool breakage determination. Po-Tsang et al. [11] developed a multiple regression model in detecting the tool breakage based on the resultant cutting forces in end milling operations. The feed rate and depth of cut are particularly influenced by the force in the regression model. Srinivas and Kotaiah [12] developed a neural network model to predict tool wear and cutting force in turning operations for cutting parameters cutting speed, feed and depth of cut.

Chattopadhyay [13] has used the forward back propagation artificial neural network for evaluation of wear in turning operations using carbide inserts taking speed, feed and depth of cut as input parameters. Pekelharing [14] has stated that one of the causes of the excessive chipping of the carbide tools used in milling operations is a phenomenon which he called “foot forming”. When the tool edge is ready to exit the workpiece, it causes a rotation of the primary shear plane, making its angle negative and instantaneously increasing the force on the edge. Kang and Chi [15] constructed an automatic monitoring system for on-line detection of tool breakage in milling processes. A simulation approach is adopted which means analytical models are used to generate the simulated signals instead of real measurements. A variety of simulation examples are presented to demonstrate the efficiency of the proposed system. Danko et al. [16] considered the application of the radial basis function neural network (RBFNN) for tool wear determination in the milling process. Tool wear, i.e. flank wear zone width, has been estimated in two phases using two types of RBFNN algorithms. In the first phase, a RBFNN pattern recognition algorithm is used in order to classify tool wear features in three wear level classes (initial, normal and rapid tool wear). On behalf of these results, in the second phase, the RBFNN regression algorithm is utilised to estimate the average amount of flank wear zone widths.

Prediction of tool wear is an important study in metal cutting in order to maximise the utilisation of the tool and minimise the machining cost. In order to maintain the tool life, the proper setting of machining parameters is crucial before the process takes place. The user of the machine tool must know how to choose cutting parameters in order to minimise tool wear. The main goal of this work is to study the influence of cutting conditions such as cutting speed, feed per tooth and depth of cut on tool wear in the end milling process. In order to increase the efficiency and reduce the cost of machining, it is necessary to improve understanding of the metal cutting process. The regression and ANN models have been developed to predict tool wear in end-milling. Researchers have used many methods to predict tool wear, but comparisons of these methods have not been done for milling. In the present work, the predictions from the regression and ANN models are compared with the experimental results to determine prediction accuracy.

3 Role of flank wear in tool life evaluation

Flank wear occurs on the relief face of the tool and is mainly attributed to the rubbing action of the tool on the machined surface. A milling cutter is assumed to have more single point cutting tools. The flank wear predominantly occurs in the cutting tool, so the life of a particular tool used in a machining process depends upon the amount of flank wear. But crater wear is prevalent only under certain cutting conditions, i.e. higher cutting speeds and feeds lead to more crater wear, and in this case tool life is evaluated by means of crater wear. As the flank face of the cutting tool undergoes a rubbing action against the work piece materials, the surface finish of the work piece machined mostly depends upon the amount of flank wear. If the amounts of flank wear increases, a reduction in nose radius of the cutting tool occurs, which in turn reduces the surface finish of the product. Among the aforesaid wears, the principal flank wear is the most important because it raises the cutting forces and related problems. ISO standard 3685 [17] dictates that the end of useful tool life is determined when a tool ceases to produce a desired part size and surface quality. In this work, the flank wear is only considered to evaluate the tool condition during the machining process. The life of the tool is estimated by flank wear.

3.1 Development of regression model

In this work, a regression model is developed to predict tool wear based on experimentally measured tool wear. The coefficients for the regression model are determined using

Six Sigma software. The experiment is conducted using Design of Experiments (DOE).

3.1.1 Design of Experiments (DOE)

The experiment should provide the required information with minimum time and effort. Therefore, the experimental plan and program must be well prepared and designed to conduct experiments. Experimental design is an important tool to aid the experimenter in coping with the complexities of technical investigation. This is an organised approach to the collection of information.

The various steps involved in the design of experiments are given below:

- Identifying the important process control variables
- Finding the upper and the lower limits of the selected control variables
- Development of the design matrix
- Conducting the experiments as per the design matrix
- Evaluation of regression coefficients for the mathematical model
- Development of regression mathematical model

3.1.2 Identification of the process variables

Specifications of the CNC milling trainer, cutter and work piece material used for the experiment are given in Table 1. Machining conditions set by various process parameters influence the tool wear which in turn affect the overall quality. The identification of correct process parameters is of paramount importance in obtaining better surface finish with minimum tool wear. Desired tool life may be achieved by properly selecting the independently controllable process variables or factors which influence the surface quality. Among the many independently controllable process parameters affecting tool wear, cutting speed (V), feed rate (f) and depth of cut (b) are selected as factors to carry out the experimental works and the development of mathematical models.

3.1.3 Finding the limits of the process variables

The working ranges of all process variables selected had to be determined to fix their levels and to develop the design matrix. This is achieved with the assistance of trial runs carried out by varying one of the process variables while keeping the rest of them at constant value. A large number of trial runs have been conducted for tool wear at different machining parameters. In conducting the experiment, the upper limit of a factor was coded as +1.682 and the lower limit as −1.682, the coded values for intermediate values were calculated from the following relationship

$$X_i = \frac{1.682(2X - (X_{\max} + X_{\min}))}{(X_{\max} - X_{\min})} \tag{1}$$

where X_i is the required coded value of a variable X, X is any value of the variable from $X_{\min}$ to $X_{\max}$, $X_{\min}$ is the lower limit of the variable and $X_{\max}$ is the upper limit of the variable.

The coded values for intermediate values have been calculated using Eq. 1. The selected process parameters of the experiment for tool wear, with their limits, units and notations, are given in Table 2.

Table 1 Specifications of CNC milling machine, cutter and work piece material

Sl no	Parameters	Value
1	Power of spindle motor	0.37 kW
2	Speed rage of spindle motor	0–3600 rpm
3	Power of feed motor (X & Y dir)	0.18 kW
4	Torque of spindle and feed motor	20 kg.m
5	Feed (X & Y dir)	0–450 mm/min
6	Material of cutter	Uncoated tungsten carbide (P20 grade)
7	Number of flutes	4
8	Diameter of cutter	15 mm
9	Rake angle of flute	12°
10	Helix angle of flute	30°
11	Work piece material	AISI 1020 steel
12	Brinell hardness	90 BHN
13	Size of work piece	120×50×10 mm
14	Radial depth of cut	10 mm

3.1.4 Development of design matrix

In factorial design, the experiments are conducted for all possible combinations of the parameter levels and these combinations, written in the form of a table where the rows correspond to different trials and the columns to the levels of the parameters, form a design matrix. The design matrix selected for experiment is a three factor five level central composite rotatable design consisting of 20 sets of coded conditions. The design for the above said models comprises a full replication of 2^3 (=8) factorial design plus six centre points and six star points; these correspond to the first eight rows, the last six rows and rows nine to fourteen, respectively, in the design matrix.

All process parameter variables at the intermediate (0) level constitute the centre points and the combinations of each of the process parameter variables at either its lowest

Table 2 Process variables and their levels (three factors, five levels)

Process parameters	Units	Notation	Limits				
			−1.682	−1	0	+1	+1.682
Cutting speed	m/min	V	10	28	55	82	100
Feed	mm/tooth	f	0.05	0.09	0.15	0.21	0.25
Depth of cut	mm	b	0.5	0.9	1.5	2.1	2.5

(−1.682) or highest (+1.682) with two other variables of the intermediate levels constitute the star points. In this matrix, twenty experimental runs provide ten estimates for the effect of three parameters. One estimate for the mean effect of all the three parameters, three linear estimates for main effects, three quadratic estimates due to main effects, and three estimates for the two factor interactions are included. Thus the design matrix has allowed the estimation of linear, quadratic and two-way interactive effects of the selected process parameter variables on tool wear.

3.1.5 Conducting the experiment as per the design matrix for the measurement of tool wear

Machining experiments have been carried out in a CNC mill trainer as per the design matrix on AISI 1020 steel work piece material using an uncoated tungsten carbide end mill (ISO designation P20 grade, axial rake angle = +18°, nose radius = 0.40 mm) with a diameter of 15 mm and having 4 flutes. The effective rake angle is found to be +18° with reference to Milton C. Shaw [18]. The work piece is 50 mm wide and 120 mm long and is placed with its longitudinal axis aligned with the direction of feed. The tests have been conducted along a 120 mm edge. The combination of process parameters in each experimental run and the number of experiments to be conducted corresponds to the design matrix table.

The flank wear values (Y_{max}) have been measured off-line with a tool maker's microscope (Metzer-1395, Metzer, India; size travel up to 50 mm in each direction, least count 0.001 mm) for each combination of cutting conditions in accordance with the ISO standards 8688 [19]. Milling was carried out in the climb milling mode with cutter centre offset with respect to the work centerline to ensure that the exit of the cut was outside the domain that renders the inserts prone to edge failure due to fracture. The position of the inserts was verified using a dial indicator. The acceptable radial deviation was 0.01 mm. Cutting was started with a sharp insert and stopped every 5 runs (passes) of cut for tool flank wear measurement using a toolmaker's microscope. Flank wear was recorded at 40 times magnification with a microscope that allows the measurement without removing the inserts from the milling cutter. Tool wear is measured for two cutting edges, and the average flank wear is calculated for each experiment. After measuring, the tool is clamped in the tool holder in the same orientation every time. The measured values of tool wear for 20 experiments are presented in Table 3.

3.1.6 Evaluation of coefficients for regression mathematical model

The process models relate the input process variables to the response variables of the process. Hence, it is possible to predict the response of the process for the input variables. The relationships between these input and response variables have to be determined by developing a regression based mathematical model. Hence, X_1, X_2 and X_3 are coded values of cutting speed, feed and depth of cut, respectively. Y is the tool wear. The regression model is obtained using a set of experimental data. Polynomial models are widely used as approximating functions and normally a second order polynomial is used to form mathematical models. The second order model for three selected factors is given in Eq. 2:

$$Y = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_{11}X_1^2 + B_{22}X_2^2 + B_{33}X_3^2 + B_{12}X_1X_2 + B_{13}X_1X_3 + B_{23}X_2X_3 \qquad (2)$$

where Y is the measure of response (tool wear), X_1, X_2, X_3 represent the coded values of the process parameters and B_0, B_1, B_2, etc. represent the regression coefficients to be determined.

The coefficients of the polynomials such as B_0, B_1, B_2 have to be determined for the development of the regression based mathematical model. Substitution of the determined coefficients in the polynomial (Eqs. 3–6) gives the required model for the process. Once the model is formed, the coded values of the actual process variables have to be substituted in the equation to get the predicted response of the process. The resultant mathematical models for tool wear in coded form are given such that:

$$B_0 = 0.142857\sum Y - 0.035714\sum\sum (X_{ii}Y) \qquad (3)$$

$$B_1 = 0.041667\sum (X_iY) \qquad (4)$$

Table 3 Design matrix values and responses (three factors, five levels)

	Design matrix values			Tool wear (mm)			% Error	
Exp no	Cutting speed	Feed	Depth of cut	Measured values	Predicted values using regression	Predicted values using ANN	Using regression model	Using ANN model
1	−1	−1	−1	0.125	0.121	0.123	3.20	1.60
2	+ 1	−1	−1	0.157	0.158	0.157	−0.64	0.00
3	−1	+ 1	−1	0.172	0.170	0.174	1.16	−1.16
4	+ 1	+ 1	−1	0.201	0.204	0.199	−1.49	1.00
5	−1	−1	+ 1	0.135	0.138	0.135	−2.22	0.00
6	+ 1	−1	+ 1	0.180	0.176	0.175	2.22	0.57
7	−1	+ 1	+ 1	0.194	0.196	0.193	−1.03	0.52
8	+ 1	+ 1	+ 1	0.222	0.226	0.219	−1.80	1.35
9	−1.682	+ 0	+ 0	0.144	0.145	0.143	−0.86	0.69
10	+ 1.682	+ 0	+ 0	0.206	0.202	0.209	1.74	−1.46
11	+ 0	−1.682	+ 0	0.131	0.132	0.131	−0.59	0.00
12	+ 0	+ 1.682	+ 0	0.217	0.216	0.217	0.52	0.00
13	+ 0	+ 0	−1.682	0.160	0.153	0.157	4.37	1.87
14	+ 0	+ 0	+ 1.682	0.197	0.190	0.195	3.81	1.02
15	+ 0	+ 0	+ 0	0.171	0.171	0.170	0.00	1.16
16	+ 0	+ 0	+ 0	0.172	0.171	0.170	0.58	1.16
17	+ 0	+ 0	+ 0	0.169	0.171	0.170	−1.18	−0.59
18	+ 0	+ 0	+ 0	0.168	0.171	0.170	−1.79	−1.19
19	+ 0	+ 0	+ 0	0.172	0.171	0.170	0.58	1.16
20	+ 0	+ 0	+ 0	0.171	0.171	0.170	0.00	1.16

$$B_2 = 0.03125\sum(X_{ii}Y) + 0.035714\sum\sum(X_{ii}Y) - 0.035715\sum Y \tag{5}$$

$$B_3 = 0.0625\sum\left(X_{ij}Y\right) \tag{6}$$

The above models are used to predict the regression coefficients of tool wear. It has been found that the model is adequate at 94% confidence level. The regression coefficients are determined using Six Sigma software for developing the mathematical model.

The value of the regression coefficients gives an idea as to what extent the control variables affect the responses quantitatively. The less significant coefficients can be eliminated along with their responses with which they are associated, without affecting much of the accuracy of the model. To achieve this, the students t-test has been used. As per this test, when the calculated value of t corresponding to a coefficient exceeds the standard tabulated value for the desired level of confidence limit, the coefficient becomes significant. After finding the significant coefficients using the Quality America DOE PC 1 V software package [20], the final model is to be developed using only these significant coefficients.

3.1.7 Regression mathematical model for tool wear

The regression mathematical model for tool flank wear (Y) is developed based on the coefficients determined using Six Sigma software:

$$Y = 0.17 + 0.017X_1 + 0.025X_2 + 0.01X_3 + 0.001X_1^2 + 0.001X_2^2 + 0.002X_3^2 - 0.002X_1X_2 + 0.001X_1X_3 + 0.001X_2X_3 \tag{7}$$

where X_1 is a coded value of cutting speed in m/min, X_2 is a coded value of feed in mm/tooth and X_3 is a coded value of depth of cut in mm.

The mathematical model developed as per the regression coefficients are then analysed for the most significant coefficients. The backward elimination of 0.75 criteria has been used for determining the significant coefficients in the Six Sigma software technique. The final mathematical model for tool wear after backward elimination of 0.75 probability criteria without scarifying the accuracy is given by Eq. 8:

$$Y = 0.172 + 0.017X_1 + 0.025X_2 + 0.01X_3 + 0.002X_3^2 - 0.002X_1X_2 + 0.001X_1X_3 \tag{8}$$

The predicted tool wear values obtained using Eq. 8 are compared with the actual measured tool wear and percentage of error for each experiment is given in Table 3.

Table 4 Calculation of variance for testing the adequacy of the model

Parameter	1st order terms (SS)	df	1st order terms (SS)	df	Lack of fit (SS)	df	Error (SS)	df	F-ratio	R-ratio	Whether the model is adequate
Tool wear	0.014	19	0.014	19	0.001	8	0.003	13	4.91	86..27	Adequate

3.1.8 Checking the adequacy of the developed model

The accuracy of the model has been tested using the analysis of variance techniques (ANOVA). As per this technique [21]: (i) the calculated value of the F-ratio of the model developed should not exceed the standard tabulated value of the F-ratio for a desired level of confidence (say 95%), and (ii) if the calculated value of the R-ratio of the model developed exceeds the standard tabulated value of the R- ratio for the desired level of confidence (say 95 %), then the model may be considered adequate within the confidence limit. From Table 4, it is found that the model is adequate.

3.1.9 Interaction effect of machining parameters on tool wear

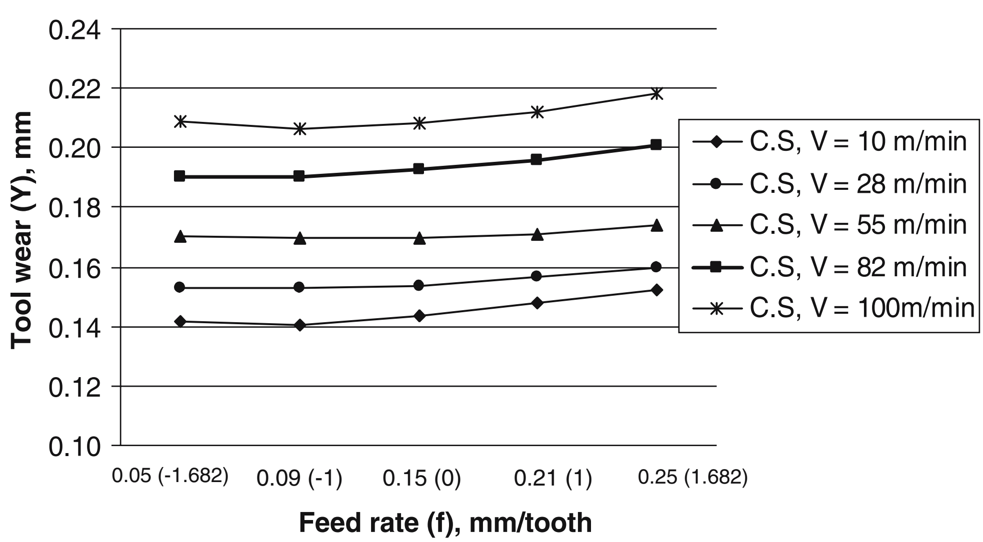
The regression mathematical model has been used to plot the contour and surface plots for different combinations of machining parameters in SYSTAT 10.2 software.

3.1.9.1 Interaction effect of feed rate and cutting speed on tool wear Figure 1 shows the interaction effect of feed rate *f* and cutting speed *V* on tool wear *Y*. From the figure, it is clear that *Y* decreases with increase in *f* up to a −1 limit then increases with an increase of *f* for all values of *V*. Also, the increase in *Y* is almost similar (about 0.010 mm) when *V* is at the lower limit of −1.682 and (about 0.010 mm) when V is at the higher limit (+1.682). These effects are further explained with the help of response surface plots, as shown in Fig. 2. It is evident from the contour surface that *Y* is maximum (about 0.016 mm) when *f* and *V* are at their higher limits (+1.682) and is minimum (about 0.1406 mm) when *f* is at the −1 limit and *V* is at the lower limit (−1.682).

3.1.9.2 Interaction effect of depth of cut and feed rate on tool wear Figure 3 shows the interaction effect of depth of cut *b* and feed rate *f* on tool wear *Y*. From the figure, it is clear that *Y* increases with increase in *b* for all values of *f*. Also, the increase in *Y* is almost similar (about 0.005 mm) when *b* is at the lower limit of −1.682 and (about 0.025 mm) when *b* is at the higher limit (+1.682). Tool wear tends to increase with increasing depth of cut. When the depth of cut is lower, there is less work piece material adhered to the flank than at larger depth of cut. Since the heat and the forces generated during the cutting process are higher at larger depth of cut, it is reported that the higher temperature and the higher force are the main reasons that cause the adhesion of work piece material onto the tool flank face, thus accelerating the tool wear. These effects are further explained with the help of response surface plots, as shown in Fig. 4. It is evident from the contour surface that *Y* is maximum (about 0.226 mm) when *b* and *f* are at their higher limits (+1.682) and is minimum (about 0.126 mm) when *b* and *f* are at their lower limits (−1.682).

3.1.9.3 Interaction effect of cutting speed and depth of cut on tool wear Figure 5 shows the interaction effect of

Fig. 1 Interaction effect of cutting speed and feed rate on tool wear



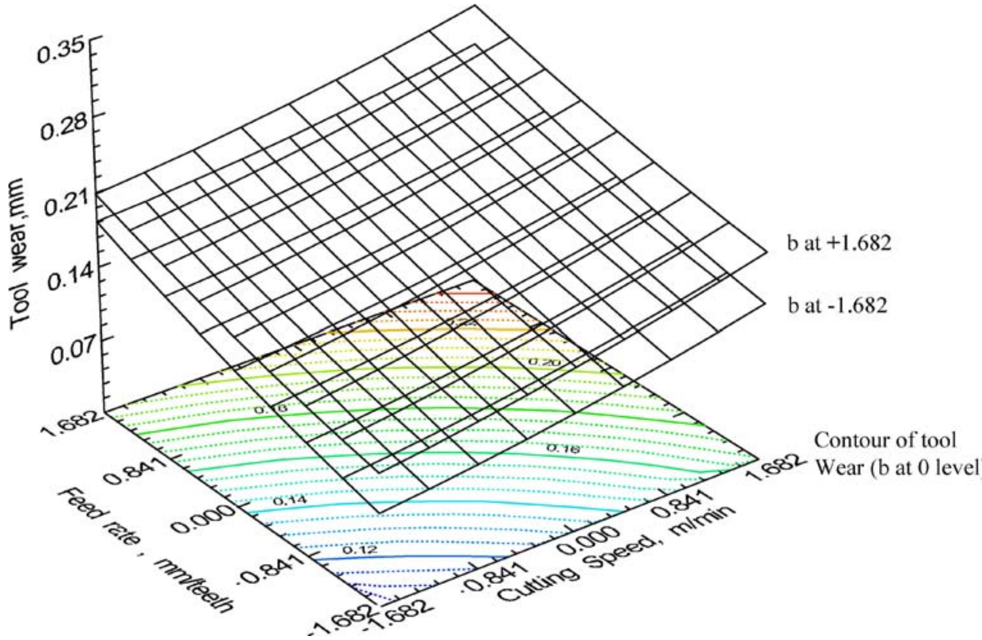


Fig. 2 Contour plot and response surface plot for the interaction effect of feed rate and cutting speed on tool wear

cutting speed V and depth of cut b on tool wear Y. From the figure, it is clear that Y increases with increase in V for all values of b. Also, the increase in Y is almost similar (about 0.051 mm) when b is at the lower limit of −1.682 and (about 0.062 mm) when b is at the higher limit (+1.682). Tool wear tends to increase with increasing cutting speed. It has been reported by Eldem et al. [22] that increase in cutting speed accelerates thermally activated wear mechanisms in addition to generating more intense mechanical impact. These promote an increase in the thermal gradient which tends to increase tool wear as thermal crack generation rate increases [23]. The tendency of tool wear to increase with increasing cutting is found to be predominant. These effects are further explained with the help of response surface plots, as shown in Fig. 6. It is evident from the contour surface that Y is maximum (about 0.226 mm) when V and b are at their higher limits (+1.682) and is minimum (about 0.136 mm) when V and b are at their lower limits (−1.682).

Among the various machining parameters, the cutting speed has more effect on tool wear because increase cutting speed accelerates thermally activated wear mechanisms. An average flank wear height of at least 0.3 mm or the maximum wear height of 0.6 mm was considered to be a worn edge. This limit was selected in accordance with the criteria recommended by ISO 8688 which defines effective tool life for carbide tools [19]. Knowledge about tool wear variation helps the operator in selecting suitable machining parameters in order to minimize tool wear.

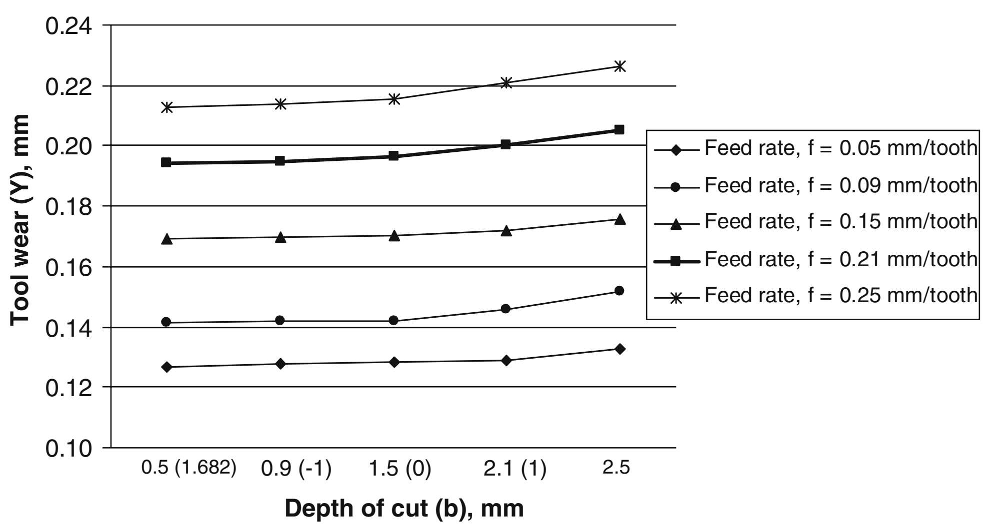


Fig. 3 Interaction effect of depth of cut and feed rate on tool wear

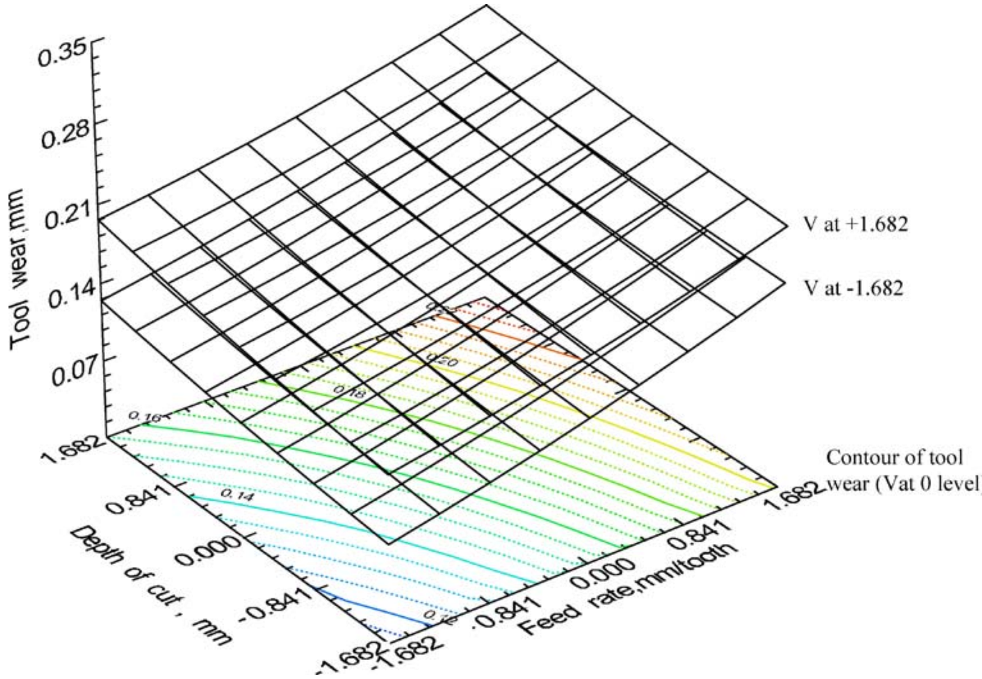


Fig. 4 Contour plot and response surface plot for the interaction effect of feed rate and depth of cut on tool wear

3.2 Artificial neural network (ANN)

Artificial neural networks are powerful tools for the identification of systems typically encountered in the structural dynamics field. Artificial neural networks have been originally developed to simulate the function of the human brain or neural system. Artificial neural networks are massive parallel-interconnected networks that consist of basic computing elements called neurons interconnected via unidirectional signal channels called connection that imitates the human brain. Each processing element has a single output connection that branches into as many collateral connections as desired. Each neuron carries the same signal —the processing output signal. It has the capability to organise its structural constituents, known as neurons, to perform certain computations many times faster than the fastest digital computer in existence today through a process of learning. Neural networks are physical cellular systems, which can acquire, store and utilise experimental knowledge.

In the present paper, the most widely used technique, the feed forward back propagation neural network, is adapted for the prediction of tool wear in the end-milling operation. It is a gradient descent error-correcting algorithm, which updates the weights in such a way that the network output error is minimized [24]. The feed forward back propagation network consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationship

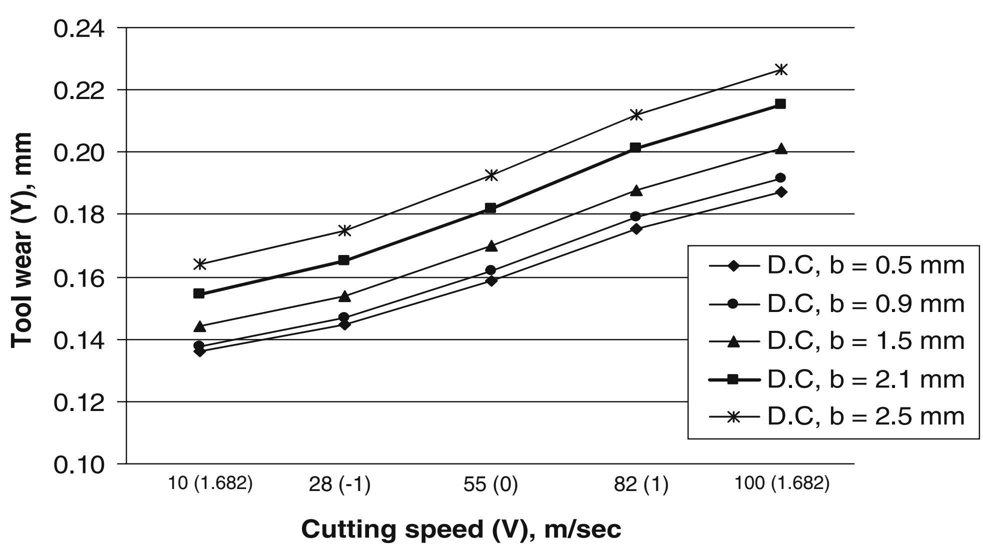


Fig. 5 Interaction effect of cutting speed and depth of cut on tool wear

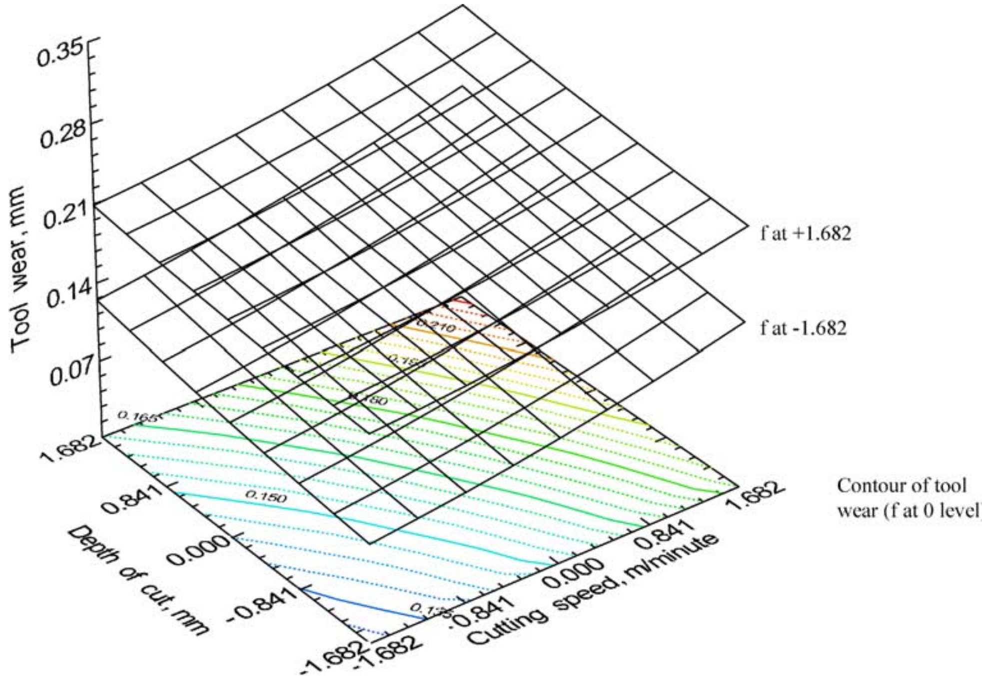


Fig. 6 Contour plot and response surface plot for the interaction effect of depth of cut and cutting speed on tool wear

between the inputs and outputs are determined and represented by synaptic weights) and an output layer (which emits the outputs of the problem).

Training of an ANN plays a significant role in designing the direct ANN-based prediction. The accuracy of the prediction depends on how it is trained. The training of the neural network using a feed-forward back propagation algorithm has been carried out. The network performs two phases of data flow. First the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow of data, it produces an output. Then the error signals resulting from the difference between the computed and the actual are back propagated from the output layer to the previous layers for them to update their weights. The number of neurons in the hidden layer is intentionally chosen to start with one neuron and hidden neurons are added to the hidden layer incrementally. The addition of hidden neurons continues until there is no further improvement in network performance. The accuracy of the network was evaluated by mean sum of squared error (MSE) between the measured and the predicted values for the training. The feedback from that processing is called the

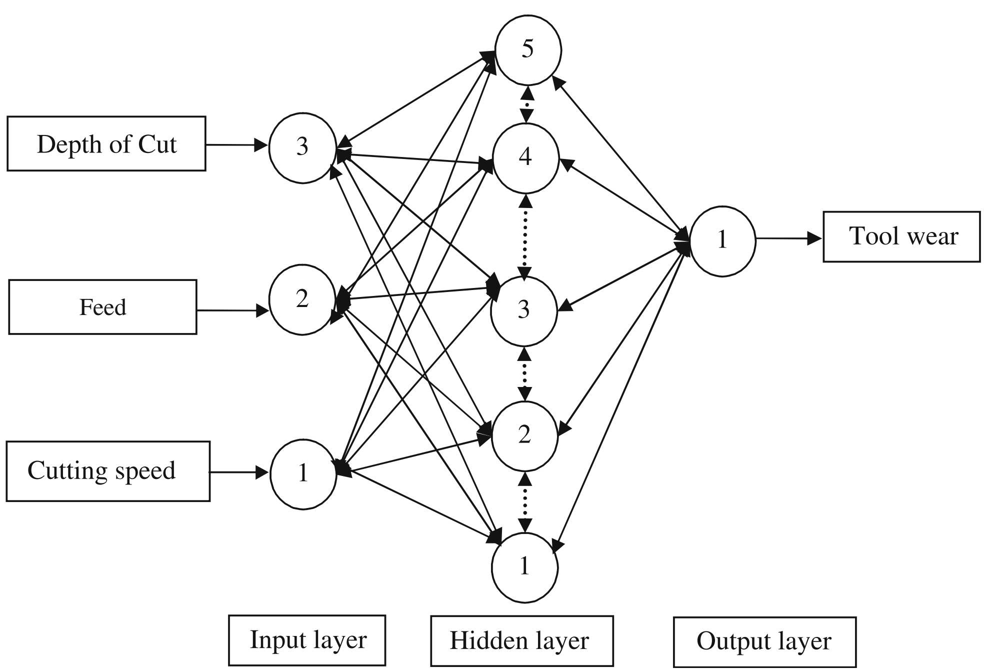


Fig. 7 ANN model structure

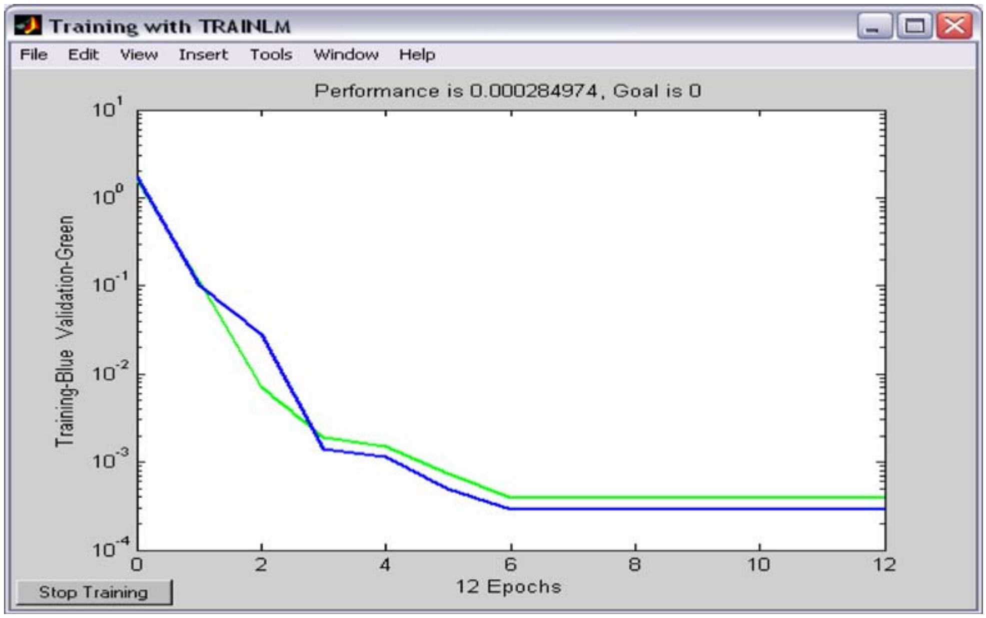


Fig. 8 ANN training performance graph (five nodes)

"average error" or "performance". Once the average error is below the required goal, the neural network stops training and is, therefore, ready to be verified.

3.2.1 Topology of the neural network

The topology architecture of feed-forward three-layered back propagation neural network is illustrated in Fig. 7. The foundation of a neural network is the neuron, which is also called as node or neurode. In a standard architecture, neurons are grouped into different layers including the input, hidden and output layers. The ANN configuration is represented as 3:5:1, that is, the input layer consists of three inputs, the hidden layer five neurons and the output layer one output. The number of neurons in the input layer consists of depth of cut, feed and spindle speeds, which are used to assess the tool wear of the end-milling process. The number of neurons in the hidden layer is determined by investigating many different neural networks, but finally five hidden layers have been selected as an optimum number. There is no fixed rule for determining the number of neurons in the hidden layer. The number of neurons in this layer must be large enough to allow for enough partitions of the non-linear evaluation space. The number of output nodes is taken to be one, so as to indicate the value of tool wear.

3.2.2 Training the neural network

MATLAB 6.1 has been used for training the network model for tool wear prediction. The inter-connections between all three layers are established by training the weights w_{ih} and

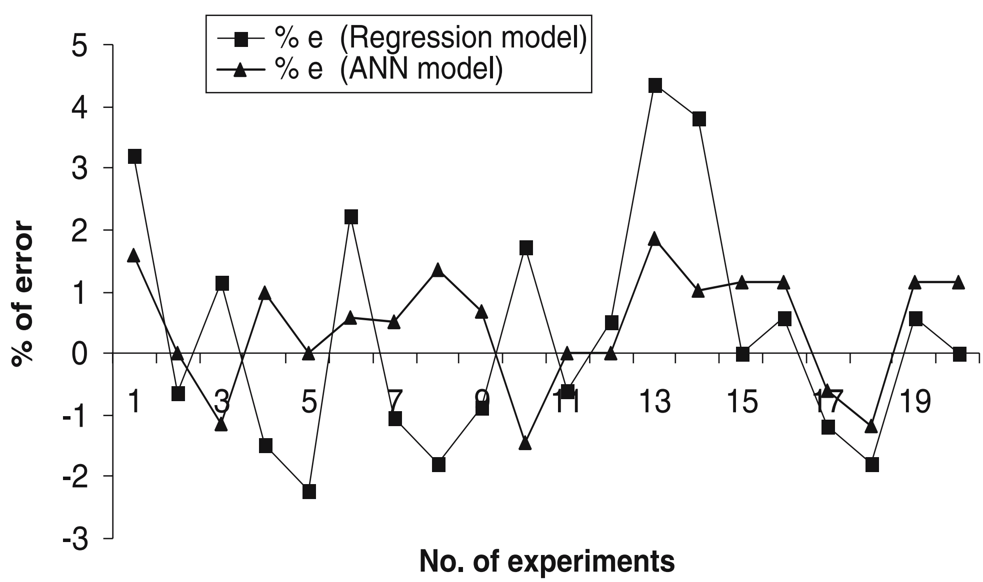


Fig. 9 Comparison of errors in prediction of flank wear

w_{ho}. In the training phase, the values of weights must be initially randomly preset in a chosen range; in this case, from 0 to 0.1. There are 20 training patterns considered for prediction of tool wear. Each neuron is a processing element, which performs a weighed sum of all input variables that feed it. Depending on the value of weighted sum of the variables, the neuron gives a signal to the neurons in the adjacent layer through a non-linear transfer function (sigmoid function in this case). The tool wear of training samples is treated as the desired and target output. The algorithm used for the neural network learning is 'the backward propagation algorithm'. So, the learning has an adaptive nature that means vector pairs from the training model are mapped, respectively, to reinforce the weights until deviation between the training output and the desired output of each training vector sample converges to a negligible error of 0.01 in this application. After the training is completed, the actual weight values are stored in a separate file. The weight values are generated using random function. The neural network described in this paper, after successful training, will be used to predict the level of vibration through the acquisition of process value.

Number of input nodes	3
Number of hidden nodes (feed forward)	5
Number of output nodes	1
Type of learning method	Supervised learning
Algorithm	Back propagation
Learning rule	Gradient descent rule
Number of learning patterns used	20
The leaning parameter used	0.5
Number of epochs	1000

The accuracy of the model depends upon the number of neurons in the hidden layer. The accuracy of the model increases as the number of neurons in the hidden layer is increased. The number of neurons in the hidden layer is initially chosen as one, adding neurons to the hidden layer incrementally. The addition of hidden neurons continues until there is no further improvement in network performance. The final optimum architecture/topology is obtained when the number of neurons is five in the hidden layer. The ANN training graph of tool wear for five neurons is given in Fig. 8. The predicted values of tool wear by the ANN model are given in Table 3. The predicted values of response by both the models (i.e. regression and ANN model) are compared with the experimental values for the validation set of experiments. This comparison has been depicted in terms of % error in Fig. 9 for validation of the set of experiments. In predicting tool wear the average error by the regression model is less than 5%, whereas it is less than 2% with the ANN model. It is found that the predictive ANN model is found to be capable of better predictions of tool flank wear than the regression model if they had been trained within the range.

4 Conclusions

This paper has described the use of Design of Experiments (DOE) for conducting experiments. Two innovative models, regression and artificial neural network (ANN), for predicting tool wear in end milling are presented in this paper. Experiments have been performed to ascertain tool wear in a CNC milling trainer for machining AISI 1020 steel using a carbide cutter based on the DOE technique. The experimental values have been used to develop a regression model and feed forward back propagation artificial neural network model for the prediction of tool wear with different numbers of nodes in the hidden layer. The experimentally determined tool wear values are compared with predicted values obtained from the regression and ANN models. The predictive ANN model is found to be capable of better predictions of tool flank wear within the range that they had been trained. The results of the ANN model indicate it to be much more robust and accurate in estimating the values of tool wear when compared with the regression model; it can be used for process modelling for any manufacturing process. The proposed tool wear prediction methods demonstrate how the usage of the tool can be extended by adjusting machining parameters within the constraints for specific machining conditions. This study provides a better position in continuing the tool monitoring system to enable an automated machining process for more efficient manufacturing in the future.

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