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Predictions of Tool Wear in Hard Turning of AISI4140 Steel through Artificial Neural Network, Fuzzy Logic and Regression Models

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ABSTRACT

Over the past few decades machining of hardened components has become a reality by means of hard turning. The cheaper coated carbide tool is seen as a substitute for cubic boron nitride (CBN) inserts in the hard turning; however, the tool flank wear is an unavoidable phenomenon when using coated carbide tools during hard turning. In this investigation, the cutting tool wear estimation in coated carbide tools using regression analysis, fuzzy logic and Artificial Neural Network (A–NN) is proposed. Work piece taken into consideration is AISI4140 steel (47 HRC). Experimentation is based on response surface methodology (RSM) as per design of experiments. The cutting speed (V), feed (f) and depth of cut (d) are taken as the inputs and the tool flank wear is the output. Results reveal that ANN provides better accuracy when compared to regression analysis and Fuzzy logic.

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1. INTRODUCTION[1]

Recently, hard turning has arisen as a new methodology in the machining arena due to its time and cost efficiency. Hard turning has been depicted as a replacement for cylindrical grinding. Hard turning can be defined as the turning process associated with hard steels for values greater than 45 HRC [1]. The advantages of this process include better material removal rate, less absence of harmful cutting fluids, work cycle time, both hard and soft turning can be done on the same machine [2]. Nowadays CBN tools are widely used for hard turning which is not cost effective. Thus a replacement of the CBN with carbide inserts is required for reducing the machining cost [3].

But tool wear is a major problem in carbide inserts and the wear rate is higher in hard turning. Tool failure causes roughly 20% of the downtime. The budget for cutting tool replacement amounts to 3–12% of the total production costs [4]. For finding the optimum conditions in hard turning the estimation of the wear in terms of the machining conditions (cutting speed, feed and depth of cut) are important.

Many authors have done research, in prediction of tool wear during hard turning [5, 6]. Since the process is quite complex the developing of an analytical model is difficult. The empirical model which is based on the experimental data is well suited in such situations. Regression models which estimate the tool wear as function of cutting conditions have been developed by many authors.

Multiple regression equation for surface roughness estimation have been developed and evaluated by Zhang and Chen[7]. They have used the cutting parameters and cutting forces as inputs. The regression equation for estimating tool wear and roughness during machining of AISI4140 steel using ceramic inserts were also derived by Aslan et al. [8]. The optimal cutting conditions for minimizing the wear are also found. Another regression equation to find the roughness and force components

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during hard turning of X38CrM0V5-1 steel was found by Aouichi et al. [9] the cutting tool that is used is CBN tool. The optimal conditions to reduce the wear were also found out. Sahin [10] used Taguchi method to compare the tool life between CBN and ceramics cutting tools during hard turning of bearing steels by means of empirical relations. The result shows that cutting speed has significant impact on tool life. The CBN cutting tool outperforms ceramic-based cutting tools.

Fuzzy modelling has the capability to model complex system behaviour with realistic approximation [11]. Akkus and Asilturk[12] have modelled roughness using fuzzy, regression and ANN with process parameter as inputs. The Mean square error for each model was calculated and they found that fuzzy gave better results.

Artificial Neural Networks (ANN) are widely implemented to model the non-linear dependencies between sensor signals and tool wear status. The advantage of ANN being independent of the mechanism involved, depends only on, the mapping of data between the input and the output. Ozel and Karpat [13] have developed an ANN model to predict tool wear and surface roughness.Algorithm used for training is Bayesian regularization with Levenberg–Marquardt training Algorithm. They found that ANN with a single output gave better results compared with ANN with multiple outputs.

Scheffer et al. [14] used ANN for estimation of flank wear during hard turning using CBN tools. Features to be used for the model development are crucial as the selected feature should have good correlation with the wear and roughness. Rajeev et al. [15] have developed an ANN based estimator for tool wear estimation during hard turning using coated carbide tool. The process parameters, cutting forces and vibrations signals are used as inputs for model developments. The experiments were carried out based on full factorial design.Wang et al. [16] have used a fully forward connected neural network (FFCNN) to develop a tool wear estimator for CBN tools during hard turning. Extended Kalman filter (EKF) algorithm was used for training.

Based on literature, there are many tool wear prediction algorithms available, based on hard turning. Algorithm based on variation of tool wear for different levels of process parameters which is required for online optimization and adaptive control is very much limited. In this work the tool wearwhen using coated carbide tool, is predicted based on regression and ANN, during the hard turning operation. The input parameters used to create the model are the process parameters. Comparison of predicted values with the measured values is also made.

2. MATERIALS AND METHODS

In this study, hardened AISI 4140 steel (47 HRC) is taken as the work piece. The work piece dimension is 80mm diameter and 250mm length. The hard turning experiments are carried out using industrial type lathe of 2.2 KW (Kirloskar make) in dry cutting conditions. AISI4140 alloy steel heat treated to 47 ± 1 HRC is the workpiece material. The ISO designate CNMG120408 coated carbide tool (CVD coated Ti(C,N)+Al_2O_3) manufactured by SECO is the cutting tool. The Tool holder used is PCL NR2525 M12 type. Tool wear values are measured after a machining length of 200mm. The details are shown in Figures 1and 2. The regression equations are developed using Design Expert Version 7software. The Fuzzy logic and ANN are developed using MATLAB.

3. EXPERIMENTAL PPROCEDURE

The experimental designs are scientifically designed, based on the response surface methodology. The Box-Behnken approach is followed. A total of 17 experiments were carried out as per the requirement, the number of experiments required, is less, when compared to full factorial design The design of the experiments carried out is by having three levels of input parameters as shown in Table1. The flank wear is the response value measured. The details of the experiments are shown in Table 2.

4. REGRESSION BASED MODEL

The regression builds a relation between the input and output parameters. It is formulated as given in the equation given below:

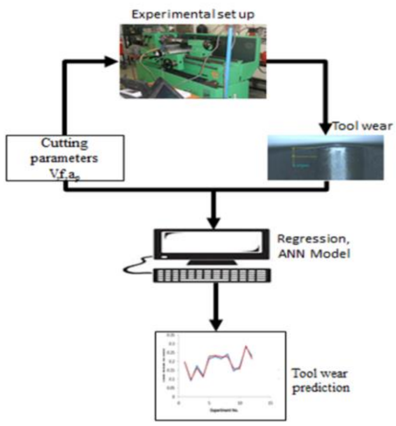

Figure 1. Operational block diagram

Figure 2. Experimental setup

TABLE 1. Levels of Process parameters

Level	V(m/min)	f(mm/rev)	d(mm)
1	70	0.08	0.3
2	120	0.1	0.45
3	170	0.12	0.6

It is a nonlinear quadratic polynomial equation.

$$Y= c_0+\sum_{i=1}^{k} c_i X_i+\sum_{i,j}^{k} c_{ij} X_i X_j +\sum_{i=1}^{k} c_{ii} X_i^2 \quad (1)$$

where c_0, c_1, c_{12}, c_{11}….. are the coefficients, Y is the output and X_i, X_j are the inputs.
Regression equation formulated based on theexperimental data in Table 2 is given below.

$$V_b = 0.12+0.033* V+0.012* f+0.023 * d-6.500E-003* V * d-1.500E-003* f * d+2.500E-003* f^2+4.000E-003* d^2 \quad (2)$$

The tool flank wear values are represented in terms of the cutting parameters. The R^2 value determines the prediction ability of the model. For the above model, the Pred. R^2 value of above model is 95.28%, the Adj.$R^2$is 99.33% and Adeq Precision is 59.084.The regression equation is validated based on the cutting conditions shown in Table 3.

TABLE 2. Experimental values

	Machining parameter			Response factor
Run No	V(m/min)	f(mm/rev)	d(mm)	V_b(mm)
1	170	0.08	0.45	0.145
2	70	0.10	0.30	0.065
3	120	0.10	0.45	0.120
4	120	0.10	0.45	0.120
5	170	0.10	0.60	0.170
6	120	0.12	0.30	0.116
7	70	0.10	0.60	0.121
8	120	0.10	0.45	0.120
9	120	0.12	0.60	0.160
10	70	0.08	0.45	0.075
11	70	0.12	0.45	0.100
12	120	0.10	0.45	0.120
13	120	0.10	0.45	0.120
14	120	0.08	0.60	0.140
15	120	0.08	0.30	0.090
16	170	0.10	0.30	0.140
17	170	0.12	0.45	0.170

5. FUZZY BASED MODEL

A non-linear Fuzzy based model is generated which take in to account the machining parameters as input and flank wear as output parameter as shown in Figure 3. The fuzzy logic tool box of MATLAB is used frames the rules. The membership functions used for defuzzification are based on input values obtained during machining. For tool wear state; the following range is followed for framing the membership function.

TABLE 3. Validation data and Predicted values

	Input parameters			ExperimentalV$_b$(mm)	Predicted V_b(mm)		
Sl.No	V(m/min)	f(mm)	d(mm)		Regression	Fuzzy	ANN
1	70	0.1	0.45	0.09	0.0870	0.0922	0.0891
2	70	0.08	0.3	0.06	0.0510	0.0537	0.0616
3	120	0.08	0.45	0.116	0.1105	0.1126	0.1138
4	120	0.1	0.3	0.101	0.1015	0.1023	0.1031
5	170	0.08	0.3	0.131	0.1300	0.1291	0.1314
6	170	0.12	0.6	0.176	0.1861	0.1820	0.1706

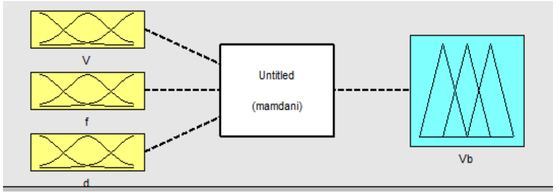

Figure 3. The Fuzzy Inference system

The fuzzy output is validated based on the cutting conditions shown in Table 3.

6. ANN BASED MODEL

Artificial neural networks (ANN) are widely used whenever the relation between the inputs and outputs are nonlinear in nature. ANN works are based on the mapping of input and output data. It is advantageous, in the sense that the complex process during machining is not taken into account during model formation. The widely used model is feed forward neural network topology which consists of three layers as shown in Figure 4.The output from the network is continuously updated till it matches the targeted output. This process is known as training. The training is halted when the mean square error reaches the minimum value or the maximum number of iterations (epoch) are reached. The flow chart for training is represented in Figure 5. The widely used algorithm for training is Levenberg-Marquardt (LM) back propagation algorithm. The MSE is given by the following relation.

$$MSE = 1/N \sum_{i=1}^{k} e(k)^2 \quad (3)$$

where, N=Total number of epochs (iterations), i=epoch number, e(k)=Error between the network output and the target output.

In this work the input taken is cutting speed, feed and depth of cut. The flank wear is the output. After the training using LM algorithm, the network finalized is 3-5-1based on trial and error method. The details are given in Table 4.

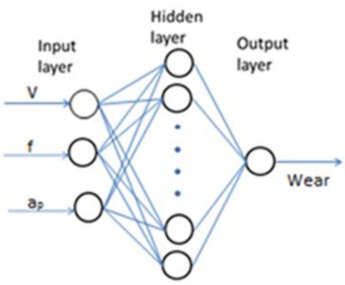

Figure 4. ANN tool wear estimator

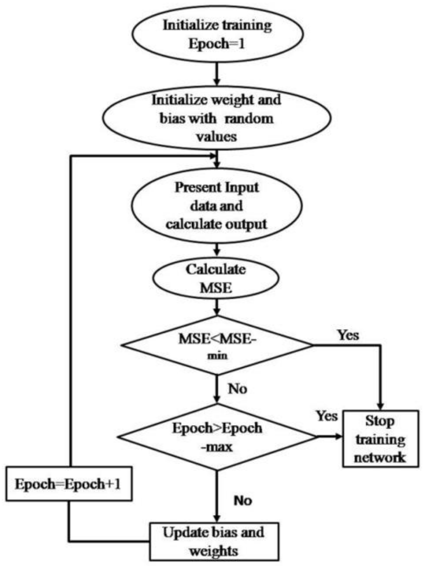

Figure 5. The ANN training process

TABLE 4. Neural Network selection

Structure No	Structure	MSE-
1	3-3-1	5.5673e-4
2	3-4-1	7.81832e-5
3	**3-5-1***	**1.9442e-06**
4	8-6-1	8.19510e-4
5	8-7-1	9.9915e-4

3-5-1*-Selected Network

The training is halted based on the minimum value of MSE. The MSE plot is shown in Figure 6. The MSE value is 1.9442e-6.The overall regression plot is shown in Figure 7. The network is validated based condition given in Table 4.

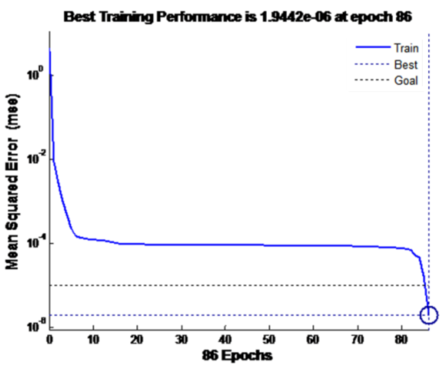

Figure 6. MSE plot of selected network

7. RESULTS AND DISCUSSION

The validation of the models generated by Regression, Fuzzy and ANN are done using data drawn cutting conditions within the range used for formulating the model; the error is calculated based on the comparison with measured values. The average error of regression model is 4.99%, the error percentage of Fuzzy model is 3.66% and for ANN model it is 1.83% predictions ability is higher for all models with the range considered. The ANN model is comparatively better. The details of comparison are shown in Figure 8. The error is calculated based on the relation given in Equation (4). The details are tabulated in Table 5.

$$\% \text{ Error} = \frac{Wear_{experimental} - Wear_{predicted}}{Wear_{experimental}} \text{x}100 \tag{4}$$

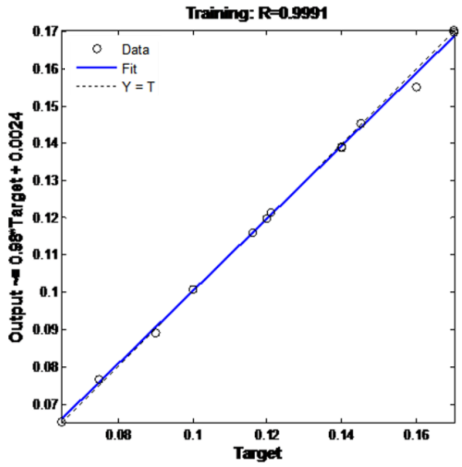

Figure 7. Overall Regression plot

8. CONCLUSION

In this investigation, the Tool flank wear prediction model has been formulated using Regression, Fuzzy and ANN techniques. Data obtained during hard turning of AISI4140 are used to develop the model. The prediction ability of the models are validated with data drawn from cutting condition within the range used for machining. Even though the models give reasonably good results within the range of data considered, The ANN is comparatively better than fuzzy and regression models. As the prediction models are based on cutting conditions, it will pay the way for online optimization and adaptive control of cutting parameters, during real time machining.

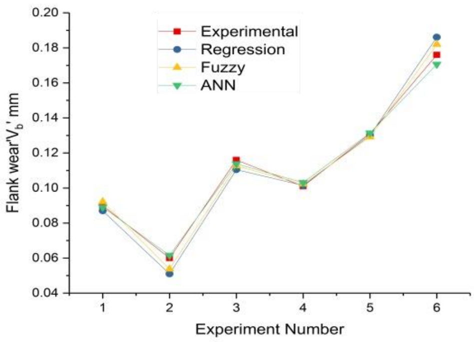

Figure8. Predicted Vs Measured Plot

TABLE 5. Comparison based on error

	Input parameters			Error (%)		
Sl.No	**V(m/min)**	**f(mm)**	**d(mm)**	**Regression**	**Fuzzy**	**ANN**
1	120	0.08	0.3	3.31	2.44	1.00
2	70	0.1	0.3	14.97	10.5	2.66
3	170	0.1	0.3	4.71	2.93	1.89
4	70	0.08	0.45	0.51	1.28	2.07
5	120	0.08	0.45	0.73	1.45	0.31
6	170	0.08	0.45	5.72	3.41	3.06
			Average Error	4.99	3.66	1.83

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چکیده

در چند دهه گذشته ماشین کاری با آلیاژ سخت به واقعیت انجامید. از ابزار پوشش یافته کاربیدی که جایگزین تیغه های سخت مکعبی نیتریتی است استفاده گردید. بهرحال ابزار کاری با آلیاژهای سخت پدیده احتناب ناپذیربوده است. در این تحقیق تخمین برش با استفاده از ابزار پوشش یافته کاربیدی بروش ریگراسیون و روش فازی لوجیک و شبکه عصبی مئرد بررسی قرار گرفت. کار با قطعات آلیاژ استیل **AISI4140(47 HRC)** مورد بررسی قرار گرفت. تجربیات بدست آمده با برش قطعات و با پردازش دادده های ورودی و خروجی شبکه نتایج نشان میدهد آنالیز داده های شبکه عصبی دقت بهتری در مقایسه با روش های ریگراسیون و فازی لوجیک دارد.

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