Middle-East Journal of Scientific Research 24 (7): 2289-2293, 2016
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2016.24.07.23748

Prediction of Tool Wear in Hard Turning of AISI4140 Steel Through Artificial Neural Network and Regression Models

[1]D. Rajeev, [2]D. Dinakaran, [3]N. Kanthavelkumaran and [4]N. Austin

[1]Research Scholar, Hindustan University, Chennai-603103, India
[2]Professor & Group Lead, Centre for Automation and Robotics, Hindustan University, Chennai, India
[3]Mechanical Engineering, Arunachala College of Engineering for Women, Kanyakumari, Tamilnadu, India
[4]Mechanical Engineering, Mar Ephraem College of Engineering and Technology, Elavuvilai, Tamil Nadu

Abstract: The tool wear is an unavoidable phenomenon when using coated carbide tools during hard turning of hardened steels. This work focuses on the prediction of tool wear using regression analysis and artificial neural network (ANN). The work piece taken into consideration is AISI4140 steel hardened to 47 HRC. The models are developed from the results of experiments, which are carried out based on Design of experiments (Response surface methodology). The cutting speed (V), feed (f) and depth of cut (a_p)are taken as the inputs and the wear (V_b) is the output. The results reveal that the ANN provides better accuracy when compared to Regression analysis.

Key words: AISI4140 · ANN · Hard Turning · Regression

INTRODUCTION

In a modern industrial scenario, the hard turning is slowly replacing grinding process in the finishing operation of hard steels. The Cubic Boron Nitride (CBN) inserts are widely used for hard turning [1,2]. Various researches have been carried out to find the effectiveness of less expensive coated carbide tool for hard turning [3, 4]. But tool wear is a major problem in carbide inserts and the wear rate is higher in hard Turing. The wear will lead to a decreased surface quality and machine downtime, which in turn amounts to an increase in production costs [5]. For finding the optimum conditions in hard turning the estimation of the wear in terms of the machining input conditions (cutting speed, feed and depth of cut) are important. Many authors have done research, in the prediction of tool wear during hard turning. 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[6]. Regression models which estimate the tool wear as function of cutting conditions have been developed by many authors. Zhang *et al*. [7] uses the cutting parameters and cutting force to develop a multi regression technique for finding surface roughness. Two sub systems for surface roughness evaluation and control have been developed and evaluated.

E.Aslanet.al [8] have developed regression equation for estimating tool wear and roughness during machining of AISI4140 steel using ceramic inserts. The optimal cutting conditions for minimizing the wear were also derived. H.Aouichi et.al [9] has developed regression equation to find the roughness and force components during hard turning of X38CrM0V5-1 steel. The cutting tool that is used is CBN tool. The optimal conditions to reduce the wear were also found out. Y.Sahin [10] has developed an empirical equation to compare the tool life between the CBN and ceramic inserts, during machining of hardened AISI 52100 bearing steel. CBN tools showed better performance. The artificial neural networks are widely employed whenever the input and output relations are nonlinear [11]. 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 have developed an ANN model to predict tool wear and surface roughness [12].Experimental results were used for training. Algorithm used for training is Bayesian regularization with Levenberg–Marquardt

Corresponding Author: N. Kanthavelkumaran, Mechanical Engineering, Arunachala College of Engineering for Women, Kanyakumari, Tamil Nadu, India.

training Algorithm. The developed model was capable of predicting surface roughness and wear in the range of training. The model was compared with empirical model and it was found to be better. They also observed that ANN with a single output gave better results compared with ANN with multiple outputs. Harun Akkus and IIhanasilturk have modeled 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 [13]. In their study D.E.Dimla Sr and PM Lister [14] have developed a multilayer perception network for predicting wear using force and acceleration as input. The wear states were classified and the scopes of developed tool condition monitoring were also assessed. The material taken in to consideration is AISI4340.

Xiaoyu Wang *et al*. [15] have developed a tool wear estimator for CBN tools based on hard turning. It was a fully forward connected neural network(FFCNN).Training algorithm used being the extended Kalman filter (EKF)algorithm. Based on the literature, there are many tool wear prediction algorithms available, based on hard turning. The algorithm based on the 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 wear when 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.

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 oxide layers are machined and centre holes are drilled before heattreatment. All the experiments are carried out in heavy duty kirloskar lathe. The Ti(C,N) coated carbide of SECO make is used as 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 Figure 1 and 2.

Experimental Pprocedure: The design of the experiments carried out is based on the response surface methodology. The Box-Behnken approach is followed. A total of 17 experiments were carried out as per the requirement, by having three levels of input parameters as shown in table 1. The levels are -1; 0; and+1. The response value measured is flank wear. The details of the experiment and the values of response are shown in table 2. As all the experimental designs are scientifically designed, the number of experiments required, is less, when compared to full factorial design.

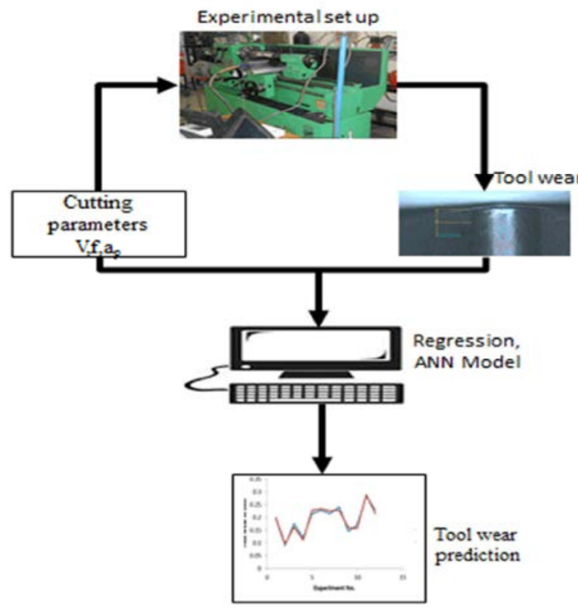

Fig. 1: Operational block diagram

Fig. 2: Experimental setup

Table 1: Levels of Process parameters

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

Table 2: Experimental values

	Machining parameter			Response factors
Run No	V(m/min)	f (mm/rev)	a_p (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

Regression Based Model: The regression builds a relation between the input and output parameters. It is formulated as given in the equation given below. It is a nonlinear quadratic polynomial equation.

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

Wherec_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.

$$Wear = +0.12 + 0.033 \times V + 0.012 \times f + 0.023 \times a_p + 0.000 \times V \times f - 6.500 \times 10^{-3} \times V \times a_p - 1.500 \times 10^{-3} \times f \times a_p + 0.000 \times V^2 + 2.500 \times 10^{-3} \times f^2 + 4.000 \times 10^{-3} \times a_p^2 \tag{2}$$

The tool wear values are represented in terms of the cutting parameters. Within the range of input considered for experimentation, the wear values can be predicted from the above equation. The R^2 value of above model is 95.28%. The R^2 value determines the prediction ability. The regression equation is validated based on the conditions shown in Table 3.

ANN BASED MODEL

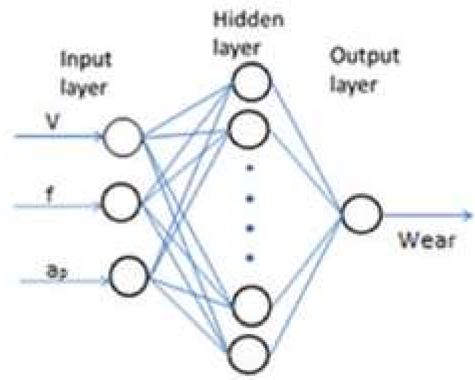

Fig. 3: ANN tool wear estimator

Artificial neural networks (ANN) are widely used whenever the relation between the inputs and outputs are nonlinear in nature. The 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 3. 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 4. The widely used algorithm for training is Levenberg-Marquardt (LM) back propagation algorithm. The MSE is given by the following relation.

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

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 wear is the output. After the training using LM algorithm, the network finalized is 3-5-1.The training is halted based on the minimum value of MSE. The MSE plot is shown in Figure 5. The overall regression plot is shown in Figure 6. The network is validated based condition given in Table 4.

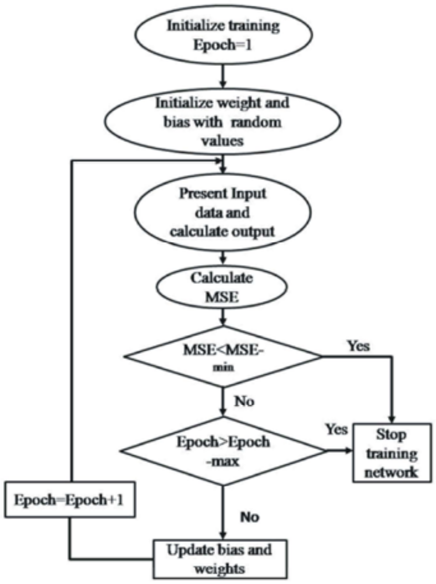

Fig. 4: The ANN training process

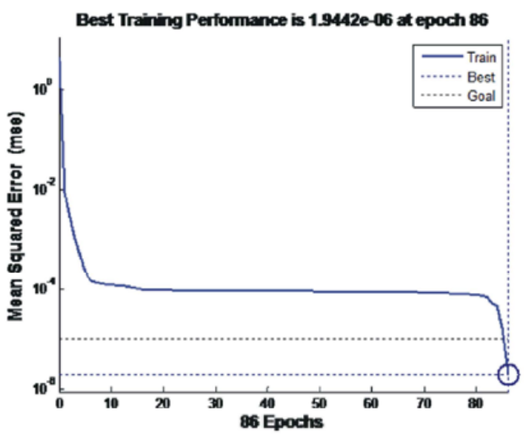

Fig. 5: MSE plot of selected network

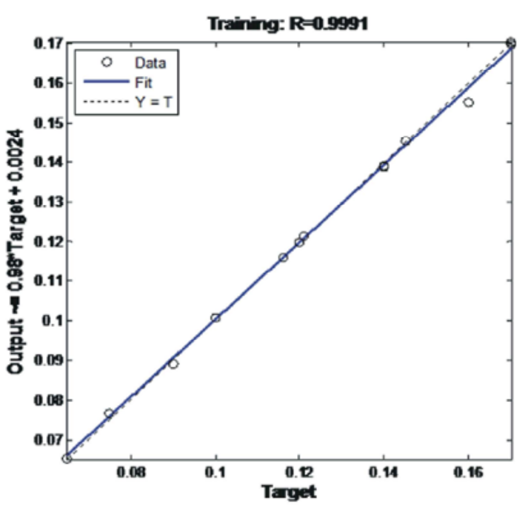

Fig. 6: Overall Regression plot

RESULTS AND DISCUSSIONS

The models generated by Regression and ANN are validated by random cutting conditions; the predicted values from both the models are compared with the experimental values. The average error of regression model is 2.63%, whereas the error percentage of ANN model is as low as 1.468%.The error values of both models are minimal and the prediction ability is higher. The ANN model is comparatively better. The details of comparison are shown in Figure 7. With more data and proper training the results can be improved further. The error is calculated based on the relation

$$\text{Error}\,\% = \frac{\text{Wear}_{\text{experimental}} - \text{Wear}_{\text{predicted}}}{\text{Wear}_{\text{experimental}}} \times 100 \quad (4)$$

Table 3: Validation data and Predicted values-Regression model

	Input parameters			Machinability characteristics		
				Experimental	Predicted	
Sl.No	V(m/min)	f(mm)	d(mm)	V_b(mm)	V_b(mm)	Error(%)
1	120	0.08	0.3	0.09	0.091	1.11
2	70	0.1	0.3	0.065	0.062	4.62
3	170	0.1	0.3	0.14	0.141	0.71
4	70	0.08	0.45	0.075	0.078	4.00
5	120	0.08	0.45	0.116	0.111	4.31
6	170	0.08	0.45	0.145	0.144	0.689
7	120	0.12	0.6	0.16	0.160	0
8	170	0.12	0.6	0.176	0.186	5.68
Average Error						2.63

Table 4: Validation data and Predicted values-ANN model

	Input parameters			Machinability characteristics		
				Experimental	Predicted	
Sl.No	V(m/min)	f(mm)	d(mm)	V_b(mm)	V_b(mm)	Error(%)
1	120	0.08	0.3	0.09	0.0891	1.11
2	70	0.1	0.3	0.065	0.0653	0.46
3	170	0.1	0.3	0.14	0.1390	0.71
4	70	0.08	0.45	0.075	0.0766	2.13
5	120	0.08	0.45	0.116	0.1174	1.21
6	170	0.08	0.45	0.145	0.1451	0.068
7	120	0.12	0.6	0.16	0.1549	3
8	170	0.12	0.6	0.176	0.1706	3.06
Average Error						1.468

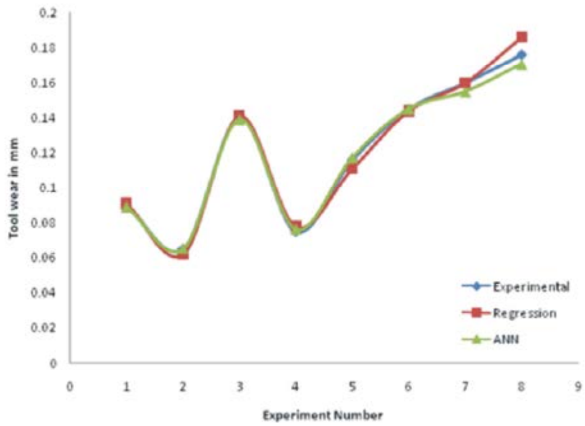

Fig. 7: Predicted Vs Measured Plot

CONCLUSION

In this work, the flank wear prediction model has been formulated based on the data obtained during hard turning of AISI4140.The models generated include multi regression and ANN. The prediction ability of both models are compared to various cutting conditions randomly chosen, Even though both models give reasonably good results within the range of data considered, The ANN is comparatively better. The prediction models based on cutting conditions will pay the way for online optimization and adaptive control of cutting parameters, during real time machining. The accuracy indicates that the models can be considered for industrial use.

REFERENCES

1. Bouacha, K., M.A. Yallese, T. Mabrouki and J.F. Rigal, 2010. Statistical Analysis of Surface Roughness and Cutting Forces using Response Surface Methodology in Hard Turning of AISI 52100 Bearing Steel with CBN tool, Int. J. Refract. Met. H., 28: 349-361.
2. Lin, H.M., Y.S. Liao and C.C. Wei, 2008. Wear Behavior in turning High Hardness Alloy Steel by CBN Tool, Wear, 264: 679-684.
3. Yallese, M.A., K. Chaoui, N. Zeghib, L. Boulanouar and J.F. Rigal, 2009. Hard Machining of Hardened Bearing Steel using Cubic Boron Nitride Tool, J. Mater. Process. Tech., 209: 1092-1094.
4. Çaydas, U., 2009. Machinability Evaluation in Hard Turning of AISI 4340 Steel with Different Cutting Tools using Statistical Techniques, P I MechEng B-J Eng, 224: 1034-1055.
5. Ashok Kumar Sahoo and Bidyadhar Sahoo, 2013. Performance Studies of Multilayer Hard Surface Coatings (TiN/TiCN/Al2O3/TiN) of Indexable Carbide Inserts in Hard Machining: Part-II (RSM, grey relational and techno economical approach), Measurement, 46: 2868-2884.
6. Scheffer, C., H. Kratz, P.S. Heyns and F. Klocke, 2003. Development of a tool wear-monitoring system for hard turning, Int. J. Mach. Tool. Manu., 43: 973-985.
7. Zhang, J. and J. Chen, 2007. The development of an in-process surfaceroughness adaptive control system in end milling operations, Int. J. Adv. Man. Technol., 31: 877-887.
8. Ersan Aslan, Necip Camuscu and Burak Birgoren, 2007. Design Optimization of Cutting Parameters when Turning Hardened AISI 4140 Steel (63 HRC) with Al2O3 + TiCN Mixed Ceramic Tool, Mater Design, 28: 1618-1622.
9. Haouici and M.A Yallese, 2013. Experimental Investigation of Cutting Parameters influence on Surface Roughness and Cutting forces in Hard Turningof X38CrMoV5-1 with CBN Tool, Sadhana, 38: 429-445.
10. Sahin, Y., 2009. Comparison of Tool Life between Ceramic and Cubic Boron Nitride (CBN) Cutting Tools when Machining Hardened Steels, J. Mater Process Tech., 209: 3478-3489.
11. Saeed Zare Chavoshi and Mehdi Tajdari, 2010. Surface roughness modelling in hard turning operationof AISI 4140 using CBN cutting tool, Int. J. Mater Form, 3: 233-239.
12. Tugrul O. Zel and Yigit Karpat, 2005. Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks, Int. J. Mach. Tool. Manu., 45: 467-479.
13. Harun Akkus and Dlhan Asilturk, 2013. Predicting Surface Roughness of AISI 4140 Steel in Hard Turning Process through Artificial Neural Network Fuzzy Logic and Regression Models, Sci. Res. Essays., 6: 2729-2736.
14. Dimla Sr., D.E. and P.M. Lister, 2000. On-line metal cutting tool condition monitoring II: tool-state classification using multi-layer perceptron neural networks, Int. J. Mach. Tool. Manu., 40: 769-778.
15. Xiaoyu Wang, Wen Wang, Yong Huang, Nhan Nguyen and Kalmanje Krishnakumar, 2008. Design of neural network-based estimator for tool wear modelling in hard turning, J. Intell. Manuf., 19: 383-396.