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ARTIFICIAL NEURAL NETWORK ASSISTED SENSOR FUSION MODEL FOR PREDICTING TOOL WEAR ONLINE DURING HARD TURNING

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Abstract: *An attempt was made to use a combination of cutting force and cutting temperature along with cutting velocity and feed rate to predict the tool wear during turning of AISI 4340 steel having a hardness of 46 HRc using a multi coated hard metal insert with a sculptured rack face. An ANN model was developed to fuse the cutting force and cutting temperature signals and to predict flank wear. It was found that the predictions of the ANN model matched well with the experimental results.*
Key words: *Tool wear, Hard turning, ANN, Sensor fusion.*

1. INTRODUCTION

Factors like cutting force, cutting temperature, acoustic emission signals, vibration etc. can be effectively used to predict tool wear. Even though each of these factors are used individually to predict tool wear, a more accurate prediction will be possible if all these factors are considered collectively since each of these factors predict tool wear in their own characteristic fashion. For example temperature responds to flank wear and crater wear in a better way than to fracture type of tool failure, where as cutting force has a better response to fracture type of tool failure. Hence a better prediction of tool wear consisting of different modes is possible by considering the response to these representative factors collectively. Just like a human operator who uses his physical senses to extract details on the state of the cutting operation, in sensor fusion signals obtained from basic sensors are used to extract information on the cutting condition.

A scheme for predicting cutting performance during hard turning with minimal cutting fluid application is reported by (Varadarajan et al., 1998) in which cutting force alone was used as used as an index of tool wear. An in process surface recognition system for end milling based on neural networks is reported by (Yu-Hsuan et al.,1999). (Benardos& Vosniakos ,2002) developed a neural network model for predicting surface roughness during face milling. A neural network based scheme for evaluating wear of carbide inserts was developed by (Dass et al ,1996).But none of the above work reports the fusion of more than one signal to predict cutting performance. In the present work an attempt is made to fuse the cutting force signals with the cutting temperature signals using a neural network model to predict tool wear online.

2. EXPERIMENT

Cutting experiments were conducted in a cutting velocity range of 40 to 120 m/min and feed ranging from 0.05 to 0.14 mm/rev at five levels. The depth of cut was kept at 1.25 mm. The work material was a cylindrical rod of hardened steel (AISI 4340) having a hardness of 46 HRc. Turning was carried out using multi coated hardmetal inserts with sculptured rake face on a HEIDENREICH AND HARBECK high speed lathe. Cutting temperature was measured using an extrapolative cutting temperature measuring technique using Finite Element Analysis reported by (Varadarajan et al.2000) and the main cutting force was measured using a Kistler type tool force dynamometer. The average flank wear was measured using a tool maker's microscope having a least count of 0.01 mm.

3. ARTIFICIAL NEURAL NETWORK MODEL

An appropriate architecture for the artificial neural network was selected through an exhaustive examination of a number of network configurations. This was accomplished by changing the number of neurons in the hidden layer and the number of hidden layers. Normalization of input data was carried out using the equation 1

$$x_i = \frac{x_i}{\sqrt{x_1^2 + x_2^2 + x_3^2 + --- + x_n^2}} \qquad (1)$$

where x_i is the i^{th} input data and the output data were normalized using the relationship

$$x_i = \frac{x_i}{x_{max}} \tag{2}$$

where x_{max} is the maximum value among the output data (Purushothaman and Srinivasa, 1994). A sigmoidal function as shown in Equation 2 was used as transfer function in this model

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

A back propagation algorithm, which adjusts weights according to the gradient descent method, was used to minimize the difference between the desired and actual output of the network. A routine available in (Rao and Rao, 2000)which utilizes a feed forward back propagation algorithm was used in developing this model. Networks with varying architecture were trained for a fixed number of cycles and were tested using a set of input and output parameters. The number of nodes in the hidden layer was assigned on the basis of limiting mean square error when the number of nodes in the hidden layer was increased progressively. Figure1 presents the limiting mean square error as a function of the number of nodes in the hidden layer during dry turning.

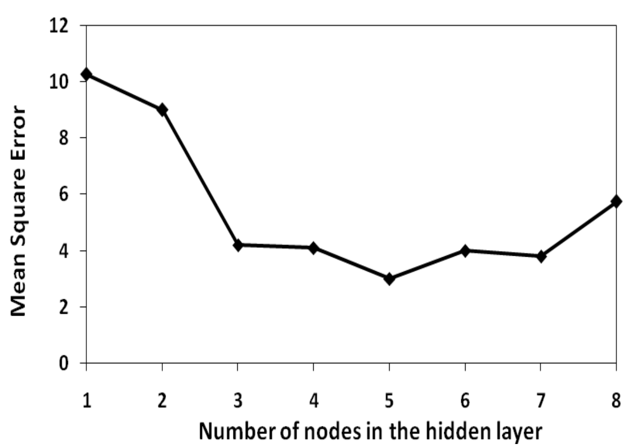

Fig. 1 Variation of limiting mean square error with the number of nodes in the hidden layer during dry turning

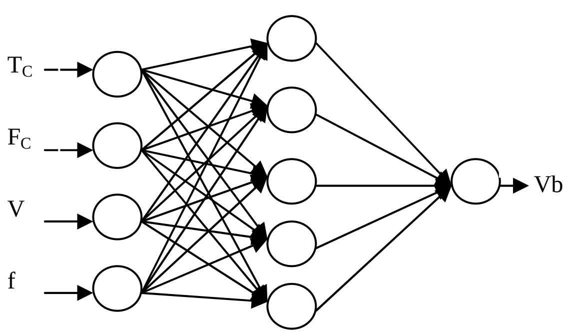

Fig. 2 The 4-5-1 Architecture of the ANN model

It is evident that five neurons can be assigned in the hidden layer to yield minimum mean square error. Accordingly architecture consisting of four neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer was assigned to the model as shown in Figure 2.

An error tolerance of 0.001, learning rate of 0.01 and momentum factor of 0.1 were assigned while training the model. The model was trained using the set of experimental data available in Table 1

4. MODEL VALIDATION

The test patterns used for validating the ANN model during dry turning is shown in Table 2. It is seen that there is good agreement between the predictions by the ANN model and the experimental results. The predictions of the ANN model was compared with the experimental results and the predictions of the regression models during dry turning.

Table 1. Data used for training the ANN model

No	Cutting velocity V(m/min)	Feed f (mm/rev)	Cutting force F_c(N)	Cutting temperature T_c(^{0}C)	Average flank wear (Vb) mm
1	40	0.100	660	827	0.1
2	80	0.100	580	1052	0.135
3	80	0.050	420	939	0.09
4	80	0.063	460	962	0.12
5	80	0.080	480	989	0.13
6	80	0.140	600	1153	0.18

Table 2 The test patterns used for validating the ANN model during dry turning

Cutting condition	Cutting velocity,V (m/min)	Feed (f) (mm/rev)	Cutting force, Fc (N)	Cutting temperature Tc (^{0}C)	Average flank wear V_b mm		% error
					Experimental results	Predictions by (ANN)	
Dry turning	53	0.08	585	910	0.065	0.06	7.6
	91	0.08	530	1130	0.095	0.09	5.2
	120	0.08	465	1200	0.45	0.449	0.2

Linear and non-linear regression models were also developed (Equations 3 and 4) using the same set of data during dry turning and the predictions of the regression models were compared with that of ANN model.

Linear regression model

$$V_b = 0.405+0.0164V+5.567f+0.000574Fc-0.0023Tc. \quad (4)$$

Non-linear regression model

$$V_b = [1.53x10^{17}]\, v^{2.16}\, f^{2.5}\, F_c^{-2.12}\, T_c^{-4.55} \quad (5)$$

A Comparison of average tool wear predicted by ANN model with that predicted by linear and non-linear regression models during dry turning is presented in Table 3

Table 3 Comparison of average tool wear predicted by ANN model with that Predicted by linear and non linear regression models during dry turning

No	Cutting velocity V (m/min)	Feed f (mm/rev)	Cutting force F_c(N)	Cutting temperatureT_c (^{0}C)	Average flank wear, V_b mm			
					Experi-mental results	ANN model	Linear model	Non-linear model
1	40	0.10	660	827	0.100	0.100	0.098	0.080
2	53	0.10	600	930	0.105	0.105	0.041	0.103
3	80	0.10	580	1052	0.135	0.136	0.193	0.154
4	91	0.10	540	1142	0.145	0.145	0.144	0.163
5	120	0.10	480	1221	0.450	0.450	0.405	0.280
6	80	0.05	420	939	0.090	0.091	0.083	0.090
7	80	0.06	460	962	0.120	0.119	0.125	0.119
8	80	0.08	480	989	0.130	0.131	0.169	0.174
9	80	0.14	600	1153	0.180	0.180	0.195	0.219

Table 4 Comparison of standard error on predictions by linear and non-linear regression models and the ANN model

Cutting condition	Average Standard error		
	ANN	Linear	Non-linear
Dry turning	0.00051	0.05324	0.14400

4. INFLUENCE OF CUTTING TEMPERATURE AND CUTTING FORCE ON AVERAGE FLANK WEAR

In order to establish the influence of the cutting force and cutting temperature on average flank wear a regression analysis was performed to correlate cutting velocity, feed, cutting force and cutting temperature with the average flank wear. The coefficient of determination was evaluated during dry turning . A comparison of the coefficient of determination was carried out when cutting force and cutting temperature were considered collectively and individually for developing the regression models. The details are available in Table 5. It is observed that there is considerable improvement in ensor fusion technique may be successfully employed the coefficient of determination when cutting velocity and feed for predicting average flank wear during dry turning.

Table 5 Coefficient of determination during regression analysis when cutting temperature and cutting force were considered individually and collectively during dry turning and minimal application.

Cutting condition	Operating Parameters	Coefficient of determination, R^2
Dry turning	V, f, F_c	0.718
	V, f, T_c	0.871
	V, f, F_c,T_c	0.886

5. RESULTS AND DISCUSSION

In the present analysis cutting force and cutting temperature are considered along with cutting velocity and feed to predict average flank wear. The superiority of the model to predict tool wear when cutting force and cutting temperature were considered collectively along with cutting velocity and feed can be better understood by considering the results of regression analysis presented in Table 6. It is seen that coefficient of determination is 0.718 for a correlation consisting of cutting velocity, feed and cutting force, where as the coefficient of determination is as high as 0.886 when the cutting temperature and cutting force were also considered along with cutting velocity and feed. The coefficient of determination is 0.871 when cutting temperature alone was considered in such a correlation. This clearly indicates that better correlation is possible when cutting force and cutting temperature are considered collectively than when they are considered individually From Table 4 it is observed that the standard error is 0.14400 for non-linear regression model and is equal to 0.05324 for the linear regression model where as it is as low as 0.00051 in the case of ANN model. Hence an ANN model can be considered as a better tool for fusing cutting temperature signals and cutting force signals for predicting tool wear.

6. CONCLUSION

The technique of fusing cutting force and cutting temperature signals appears to be a more efficient method of predicting average flank wear and a sensor fusion model based on artificial neural network can predict tool wear better than similar models based on regression analysis. Artificial neural network assisted develop intelligent cutting tools capable of predicting tool wear online. Fusion models that can fuse cutting force signals, average cutting temperature signals and tool vibration signals can also be attempted for more accurate prediction of tool wear.

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