Online Tool Wear Prediction Models in Minimum Quantity Lubrication

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Abstract

With the problems in usage of cutting fluids, the use of Minimum Quantity Lubrication (MQL) has gained prominence. Though several mathematical models have been postulated in literature on dry cutting, models that deal with cutting fluids are very rare and the models on MQL are seldom found. The present work tries to discuss regression and artificial neural network models postulated on influence of MQL on tool wear, while machining AISI 1040 steel using HSS tool. The proposed models were validated with the experimental results.

Index terms— tool wear; MQL; cutting fluids; regression model; artificial neural networks.

1 INTRODUCTION

iven the current state of manufacturing industry, the ability to develop robust products with the help of cost-effective techniques are necessary to meet the challenges of a dynamic and ever-changing sector. This is particularly true for production processes, where the idle and down times arising from various factors prove to be one of the major impediments in achieving the goal **??**1, **??**].

In terms of the cost factors, machining is considered as one of the most important of the manufacturing processes. The associated machine downtimes are mainly attributed to the frequent replacement of worn tools. Hence, the prime focus for researchers to reduce the downtimes and achieve costeffectiveness resides in the estimation of tool life and the investigation of remedial measures for tool wear.

A key factor that affects the wear rate of tools is the temperature reached during the cutting operation along with the applied forces. Reduction in tool wear can be readily accomplished by using cutting fluids that can act both as lubricants and as coolants while machining. Water miscible oils prove to be the most promising and popular cutting fluids used, owing to the confluence of cooling properties of water and lubricating abilities of oil. Despite numerous advantages, their usage is restricted because of the microbial contamination that poses health hazards to the workers, and associated problems with their disposal. This has given rise to several alternatives including Minimum Quantity Lubrication (MQL).

To assess tool wear online, different methodologies are reported in literature. A majority of the models consider different cutting parameters and predict tool wear either using mathematical models or artificial neural networks.

Mathematical models have been proposed to help evaluation of tool wear under different conditions **??**1, 3 and 4].

Rao **??**5] developed a mathematical formulation to estimate tool flank wear online through the estimation of cutting forces. Relation for predicting radial component of cutting forces from various measured machining parameters was developed.

Theoretical and experimental studies were carried out by Luo et al **??**6] to investigate the intrinsic relationship between tool flank wear and operational conditions in metal cutting processes using carbide cutting inserts. A flank wear rate model, which combines G cutting mechanics simulation and an empirical model, was developed to predict tool flank wear land width. Machining was done under different operational conditions using hard metal coated carbide cutting inserts. The results of the experimental studies indicated that cutting speed had a more dramatic effect, than feed rate, on tool life. The wear constants in the proposed wear rate model were determined by regression analysis using the machining data and simulation results. A close agreement between the predicted and measured tool flank wear land width was reported.

Ozel and Karpat **??**7] studied the predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks. The cutting tool used was cubic boron nitride. In this study, effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and tool wear were experimentally investigated. A four factortwo level fractional factorial design was used. Exponential model for surface roughness and tool flank wear for hard turning of AISI 52100 steel using CBN tools were proposed. The tool wear model was given as:VB= K 2 C a1 V b2 L c3**(1)**

Exponential regression models for surface roughness and tool flank wear were given, respectively, for finish hard turning of AISI H13 steel using CBN tools (Eq.2.2 & 2.3). R a =K 1 H a1 E b1 V c1 f d1 L C e1 (2) VB= K 2 H a1 E b1 V c1 f d1 L C e1 (3) where 'K 1 ' and 'K 2 ' are proportionality constants, 'C' is CBN content of tool in percentage volume, 'V' is cutting speed, 'f' is feed, 'L C ' is cutting length in axial ? ? ? ? direction, 'H' is work material hardness and 'E' is edge radius of CBN tool.

Srikant [8] modeled tool wear in wet machining with cutting fluids of different emulsifier contents. The model was formulated as:VB ? 1.4 t m 0.109 F C 0.623 H 0.669) a 1.6 k 1.3 T C 1.3) (4)

where VB is tool wear, ? is kinematic viscosity of the fluid, t m is machining time, F C is cutting force, H is hardness of the machined surface, R a is the surface roughness, k is thermal conductivity and T C is the cutting temperature. An average Regression coefficient of 0.85 was reported. However, the model was developed only for conventional lubrication and not MQL.

In recent years, the use of artificial neural networks (ANN) for the monitoring of tool wear has proved to be extremely successful. In the conventional system, the operator learns by his experience and tries to take decisions based on his past experiences. This learning is due to the processing of the external data or stimulus by the neurons in the brain to produce the reaction. Artificial neural networks imitate this learning behavior of the human brains. The network learns with the obtained data and takes decisions based on learning data. Many researchers tried Neural Networks to monitor the tool wear and obtained encouraging results.

S.Purushothaman and Srinivasa [9] trained a multi-layer perceptron with back propagation algorithm with 30 patterns of 6 inputs each consisting of speed, feed, depth of cut and the cutting forces in three directions. The outputs were the flank wear, centre line average of the workpiece and maximum depth of the profile as the outputs. The network was trained taking different neurons in the hidden layer as 10, 15 and 20. 15 neurons proved to be optimal. The weights obtained from the training were used for testing with 6 new patterns. Dimla [10] applied independent, descriptive inputs, viz. the three components of cutting force, three components of acceleration describing the vibration. Fusion of signals was emphasised. The results showed a success rate of 73-93% with a single layer perceptron, while the use of a multi layer perceptron scored an accuracy of 81-98%. The error obtained in the network was attributed to the noise in the data. The number of neurons in the hidden layer was fixed based on trial and error method to achieve the minimum error. Srikant [8] developed an ANN model using back propagation neural network for tool wear in wet machining. Better accuracy was reported compared to the built regression model (Eq.2). However, the model was built only for conventional lubrication method.

It is clear from the literature that the regression models and neural networks are employed for tool wear prediction as function of cutting conditions, tool geometry and work material. However, models applied to MQL are seldom found. Hence, there is a need for the development of prediction models as a function of lubricating conditions in MQL.

2 II.

3 MATHEMATICAL REGRESSION MODEL

A mathematical regression model has been built to estimate tool wear on line. AISI 1040 steel was machined using cemented carbide and HSS tools under constant cutting conditions on al 10 HP lathe to estimate several influencing measurable parameters like cutting forces, temperatures, surface roughness of machined samples, hardness of measured samples, etc. The cutting conditions adopted were:

Average cutting speed = 102 m/min Feed range = 0.44 mm/rev Depth of cut = 0.5 mm Water miscible oil with carbon nano tube inclusion levels as 0.5%, 1%, 2%, 3%, 4% and 5% were used as coolant. Flow rate of the coolant was maintained as 100 ml/ hr. Basic properties of the fluids like kinematic viscosity, thermal conductivity, etc. were also measured and used to postulate the model.

In order to reduce the number of variables involved in the model, dimensional analysis is carried out and the following five non-dimensional ?-terms are deduced.? 1 = ? * t m / R a 2 (5) ? 2 = (T * ? * F C) / (R a 2 * k) (6) ? 3 = VB/ R a (7) ? 4 = (R a 2 * H) / F C

where, ? is kinematics viscosity of the fluids in m 2 /s, t m is the machining time in min, R a is surface roughness in m, VB is tool flank wear in m, T is cutting temperature in 0 C, H is hardness of tool is MPa. Since relation between different machining parameters is inherently non-linear, a relationship was assumed as:? 3 = K 1 ? 1 a ? 2 b ? 4 c**(8)**

The relation was converted into a linear relation by taking logarithms of ? terms aslog ? 3 = log K 1 + a * log ? 1 + b* log ? 2 + c * log ? 4 (9)

Multiple linear regression was carried out for the linearized terms using SPSS (a registered product of SPSS Inc., Chicago).

Multiple linear regression postulates a functional dependence between the independent and dependent variables minimizing the modeling error. Experimental data obtained while using conventional cutting fluid, 0.5%, 1%, 2%, 3%, 4% and 5% CNT inclusion levels for HSS and cemented carbide tools was used to build the model, the remaining data was left for validation. A linear function was assumed between the logarithmic terms and the problem reduces to finding the coefficients a, b, c and K 1 . In the present analysis, the above constants were found to be -0.284, 0.111, -0.903 and 139.31 (antilog of (2.144)) respectively. The formulated model may be expressed as:G B B B) 2011 A (ugust © 2011 Global Journals Inc. (US) / (R = 0.277 × (VB=139.31×(? -0.173 t m -0.284 F C 1.014 H -0.903 T C 0.111 R a -0.46 k -0.111) (10)

An average Regression coefficient of 0.91 was obtained.

Eq. 6 has been used to predict the value of tool wear from different parameters.

Analysis of Variance (ANOVA) is a powerful statistical technique often employed confirms the effect of several simultaneously applied factors on the response variable. A null hypothesis, postulating no dependence of the applied factors and response variables is considered and is checked for its validity. Degrees of Freedom (DF) and sum of the squares (SS) are computed for the considered data. F-statistic (variance ratio) is computed as the ratio of sums of squares denoting influence of factors and their interdependence. The computed value of variance ratio (F) is compared with the standard ANOVA table and the hypothesis is accepted or rejected at a particular (1% or 5%) confidence level. If the hypothesis is rejected at 1% confidence level, it also stands rejected at 5% confidence level [9].

In the present work, the degrees of freedom were found to be 3 and 122, F-statistic was obtained as 248.961 from SPSS. The tabulated critical value of F distribution for the obtained degrees of freedom at 1% significance level was 3.78. Hence the proposed null hypothesis advocating no dependence of tool wear on the taken parameters was rejected at 1% significance level. Hence the choice of parameters is justified.

IV.

4 VALIDATION OF PROPOSED MODELS

The proposed models were validated by comparing the predicted results with the experimental results. Results from regression model and neural network model for HSS tool are compared with the experimental results (Figs. 1 & 2). III.

5 ARTIFICIAL NEURAL NETWORKS

Tool wear monitoring in automated industries calls for monitoring systems that can replace human expertise and knowledge. Pioneering researchers realized that if computers are to replace humans then their design should resemble the brain. Artificial neural networks is a science that tries to imitate the mechanism of human brain in solving problems. Several types of artificial neural networks, based on particular computing abilities of the human brain are proposed. Choice of a particular neural network depends on the application [10].

Of the available artificial neural networks, back propagation network has gained importance due to the shortcomings of other available networks [11]. The network is a multi layer network that contains at least one hidden layer in addition to input and output layers.

The number of hidden layer neurons was kept as three and size of the network is fixed as 7-3-1, after testing for the error by trial and error. After fixing the network parameters, the network was trained using experimental data obtained while using 0, 0.5, 2, 4 and 5% CNT inclusions for HSS and cemented carbide tools to obtain stable weight structures. Using these weight structures, the network was tested for remaining data as input patterns. Absolute values of percent errors obtained using regression and neural network models are presented in Table 1 Comparison of predicted tool wear with experimental results in all the tested cases indicate that the error is less than 10% in the prediction of tool wear using regression model and 5% for neural network model, validating both the models (Tables 1 & 2). Higher error in regression model predictions is obtained since some of the factors that contribute to tool wear like condition of the machine tool, inconsistencies in workpiece-tool compositions, etc. were not taken into account and this affects the regression model.

However, since neural network was trained with the experimental data and the influence of all the factors is inherently present in the data, the model is devoid of above limitations. No generalization of the data is done in neural networks, as in case of regression model for finding best-fit curve. Neural network maps the inputs to the outputs in multi-dimensions and takes care of nonlinearity present in the case of study leading to more accurate predictions.

V.

6 CONCLUSIONS

Tool wear prediction models were developed using mathematical regression and neural network. Experimental data of measured tool flank wear was used to develop the models. The models were used to predict tool wear for HSS and cemented carbide tools while using cutting fluids of different CNT content. Predicted tool wear values were compared with the experimental results to validate the developed models. Proposed regression and neural network models to predict tool wear based on several measurable parameters give the values of tool wear within acceptable limits. ANOVA justifies the parameters considered in the model. Neural network predicts tool wear with higher accuracy.

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Comparison of predicted and experimental values while using cemented carbide tool and cutting fluid with 1% CNT inclusion Fig. **??** :

Absolute values of percent errors obtained using regression and neural network models are presented in Table 2. It is observed that maximum error is 9.29% for regression model and 4.82% for neural network model. Comparison of predicted tool wear with experimental results in all the tested cases indicate that the error is less than 10% in the prediction of tool wear using regression model and 5% for neural network model, validating both the models (Tables 1 & 2). Higher error in regression model predictions is obtained since some of the factors that contribute to tool wear like condition of the machine tool, inconsistencies in workpiece-tool compositions, etc. were not taken into account and this affects the regression model.

However, since neural network was trained with the experimental data and the influence of all the factors is inherently present in the data, the model is devoid of above limitations. No generalization of the data is done in neural networks, as in case of regression model for finding best-fit curve. Neural network maps the inputs to the outputs in multi-dimensions and takes care of nonlinearity present in the case of study leading to more accurate predictions.

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1

Figure 1: Fig. 1

Figure 2:

1

Figure 3: Fig. 1

1

0.3
0.25
2011 wear, 0.15 Expt
mm 0.2
Flank 0.1 Regression
A ANN
4 16 0.05
Volume XI Issue V Version I Volume XI Issue V Version I 0 0 10 Machining 30 40 Machining time, min 20 Error for 1 % CNT inclusion 50 Error for 3 % CNT inclusion

of Researches in Engineering of Researches in Engineering) B B B) 0.35 time (min) 5 15 25 35 40 Results from regression model and neural Regression ANN Regression ANN 6.18 2.93 6.72 5.7 3.6 6.72 4.29 9.29 4.82 9.02 3.85 7.8 2.02 2.27 2.27 8.5 1.85 1.06 2.98 network model for cemented carbide tool are compared with the experimental results (Figs. 3 & 4). 2.97

Journal Journal Global G Flank wear, mm 0.1 0.15 0.2 0.3 0.25 0.05 0 ANN Expt Regression

0 10 20 30 40 50
Machining time, min

Fig. 3 :

[Note: (ugust © 2011 Global Journals Inc. (US) Comparison of predicted and experimental values while using HSS tool and cutting fluid with 3% CNT inclusion Comparison of predicted and experimental values while using cemented carbide tool and cutting fluid with 1% CNT inclusion]

Figure 4: Table 1 :

2

Figure 5: Table 2 .

2

0.3
0.25
Flank wear, mm 0.1 0.15 0.2

0.05
0
0 10 20 30
Machining time, min

Machining time (min)	Error for 1 % CNT inclusion		Error for 3 % CNT inclusion	
	Regression	ANN	Regression	ANN
5	0.28	3.86	9.05	3.79
15	8.37	2.67	4.80	1.81
25	5.6	3.64	6.26	1.64
35	1.79	1.41	6.48	2.54
40	9.81	4.5	7.8	3.95

Figure 6: Table 2 :

1

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Machining time, min

Fig. 3 :

[Note: (ugust © 2011 Global Journals Inc. (US)]

Figure 7: Table 1 :

2

0.3
0.25
Flank wear, mm 0.1 0.15 0.2
0.05
0
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Machining time, min

Machining time (min)	Error for 1 % CNT inclusion		Error for 3 % CNT inclusion	
	Regression	ANN	Regression	ANN
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Figure 8: Table 2 :

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