TOOL WEAR PREDICTION IN MACHINING AISI 1040 STEEL UNDER MQL

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***Abstract*— Productivity and quality are critical issues in any manufacturing industry. In order to minimize the idle time associated with tool setups, estimation of tool wear is important. Several models are available in literature to estimate and predict tool wear, however, very few papers are available on machining using cutting fluids. In the available literature, flood lubrication is generally considered. In view of stringent environmental restrictions and drive towards green manufacturing, Minimum Quantity Lubrication (MQL) is gaining momentum. But, since the studies are in incubating stage, not much literature can be found on tool wear estimation in MQL. In the present work, AISI 1040 steel was machined and different parameters like cutting forces, surface roughness, temperatures, etc. were recorded. The data was used to build two models, viz., mathematical regression and Artificial Neural Networks (ANN). The models were tested to estimate their efficacy. It was found that ANN model could predict tool wear with less than 8% error.**

***Key words*—machining, Nanofluids, MQL, Neural Networks, Mathematical Regression**

I. INTRODUCTION

The performance of any manufacturing industry is judged by its ability to produce products of the best quality at minimum cost. Apart from the material cost, different elements like labor cost, machining time, idle time, setup time, etc. contribute to the total cost of the product. Setup times are greatly influenced by the frequent interruptions due to changing of cutting tools because of tool wear. This results in increased setup time, in turn, increasing the total cost of the product. Further, tool wear deteriorates the product's surface finish and its quality. Hence, tool wear continues to be one of the critical parameters in machining and is of interest to the researchers.

Several mathematical models were developed to evaluate the cutting tool wear under various conditions. Luo et al. [1] developed a flank wear prediction model which combined cutting mechanics simulation and an empirical model to predict land width of the tool flank wear. The model could predict the value of tool wear close to the experimental results. Mishnaevsky [2] developed a mathematical model on the basis of theory of dynamic systems, redistribution of contact stress in cutting tool wear and changes in cutting tool geometry due to changes in tool wear. Tool wear was found to be closely related to cutting forces. The model was found to predict the values with reasonable accuracy.

With the growth in automation, online tool monitoring has gained prominence and different artificial intelligence techniques like artificial neural networks (ANN) are used to predict tool wear. Ozel and Karpat [3] studied the effect of work piece hardness, cutting tool geometry, feed rate and cutting speed on tool wear and surface roughness in hard turning by cubic boron nitride (CBN) cutting tool using regression and neural networks. It was reported that the ANN model predicted tool wear with high accuracy. Dimla [4] used cutting force and vibration signals to predict tool wear using ANN. The results with a single layer preceptron scored accuracy of 73-93%, while a multi-layer preceptron showed a success rate of 81-98%. Purushothaman and Srinivasa [5] 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 and surface roughness. 30 samples were used for training the model and 6 models were used for testing. The model predicted tool ear with good accuracy. ANN model developed by Ali and Dhar [6] as a function of cutting parameters to predict tool wear and surface roughness while turning medium carbon steel under minimum quantity lubrication with multilayer feed forward network consisting of four inputs, 25 hidden neurons and four outputs were found to be the optimum network.

An expression was derived by Liu and Altints [7] to find flank wear in terms of machining parameters and cutting force ratio. The developed model was tested with the industrial results and close agreement was found with the predicted and actual values of tool flank wear. Using radial basis function neural networks Elanayar and Shin [8] developed a model that approximates flank and crater wear propagation and their effects on cutting force. The model was tested under different cutting conditions and accurate predictions were obtained. Employing recurrent neural network during turning operation, Ghasempoor et al [9] developed an ANN model on tool wear classification and continuous monitoring. Both crater wear and flank wear were predicted. It was reported that flank wear was more accurately predictable than crater wear, as crater wear is effected by different parameters and is more complex. Choudhury and Bartarya [10] used DOE and neural networks to predict surface finish, flank wear and cutting zone temperature in turning. The models predicted values with good accuracy. While DOE model had maximum error of about 6.87%, ANN model had maximum error of 5.66%.

Though several models are found in literature that predict tool wear, they generally deal with dry machining. However, it is common to use cutting fluids in the industry to curtail friction and high temperatures. Water miscible oils, also known as soluble oils are commonly used as cutting fluids. These fluids are mixtures of oil and water blended with emulsifiers. Due to blending of oil and water, these oils offer good cooling and lubrication properties and give better corrosion protection by forming an oil film on the metal surface [11]. These oils offer adequate wetting abilities due to low viscosity and are non-flammable. Despite several advantages offered, use of cutting fluids leads to several safety and health hazards. Handling and disposal are complex and expensive. The manufacturing units are required to pay attention on handling of used cutting fluids. The stringent environmental laws demand effective treatment and safe disposal of the fluids [12].

In view of problems associated with the cutting fluids, there is focus on minimizing the use of cutting fluids. This led to evolution of Minimum Quantity Lubrication (MQL) wherein a bare minimum quantity of the cutting fluid is employed. To achieve the required cooling, it is evident that the fluids being used in MQL should possess superior properties compared to conventional fluids. With development of material science, nanofluids have emerged as a promising solution to this problem. Nanofluids possess superior cooling & lubricating properties compared to conventional fluids and are more suitable for Minimum Quantity Lubrication (MQL) [13]. Thus, there is a gap between the situations studied in tool wear models and the actual/effective application. Though few tool wear prediction models can be found on flood application of cutting fluids, models that deal with MQL application, especially with nanofluids, are not found in literature. The present work is an attempt in this direction.

II. MATERIALS AND METHODS

In the present work AISI 1040 steel (C: 0.36-0.45%, Mn: 0.6-1%, Si: 0.2-0.3%, S: 0.025% and P: 0.015%) was machined with an uncoated carbide tool (Make: Widia, Designation- CNMG120408 TTS) on a PSG 124 (10 hp) lathe under constant cutting conditions as shown below:

Speed: 105m/min

Feed:0.14 mm/rev

Depth of cut: 1.0 mm

Cutting forces were measured using a piezo-electric dynamometer (Kistler-9272) and cutting temperatures were measured using a K-type thermocouple with the embedded thermocouple technique. Conventional cutting fluid and nano cutting fluid with 0.1%, 0.3% and 0.5% wt of nano graphite inclusions was supplied drop by drop at three different flow rates as: 5ml/min, 10 ml/min and 15 ml/min. Tool wear and surface roughness were measured at regular intervals. The basic properties of the fluids like thermal conductivity and viscosity were evaluated using the regular procedures.

III. REGRESSION MODEL

In the present work, in order to estimate the cutting tool wear online, a mathematical regression model was postulated. Different parameters like cutting forces, temperatures, surface roughness, machining time, flow rate, dynamic viscosity and thermal conductivity of machined etc. that have been measured, were used to postulate the model. In addition, the properties of tools were also included, giving scope for the model to be extended for other tools as well. Dimensional analysis was carried out to reduce the number of variables in this model and derived the following non-dimensional Π-terms.

$\Pi_1 = VB^3/q \times t_m$ (1)

$\Pi_2 = R_a^3/ q \times t_m$ (2)

$\Pi_3 = F_C^3 \times t_m/ \mu^3 \times q^2$ (3)

$\Pi_4 = (T_C \times k \times t_m{}^{4/3}) / q^{2/3} \times \mu$ (4)

$\Pi_5 = Y \times t_m/ \mu$ (5)

$\Pi_6 = (H \times \varphi)$ (6)

where VB is flank wear,
t_m is machining time,
q is flow rate,
R_a is surface roughness,
F_c is resultant cutting force,
T_c is nodal temperature,
φ is wt% of nanoparticle inclusion,
μ is dynamic viscosity of cutting fluid,
k is thermal conductivity of cutting oil,
Y is Young's modulus of tool material
H is Rockwell hardness of cutting tool.

A non-linear relationship was assumed as

$\Pi_1 = K_1 \Pi_2^a \Pi_3^b \Pi_4^c \Pi_5^d \Pi_6^e$ (7)

The non-linear relationship (7) is converted into a linear relation by taking logarithms of Π terms as

$\log \Pi_1 = \log K_1 + a \times \log \Pi_2 + b \times \log \Pi_3 + c \times \log \Pi_4 + d \times \log \Pi_5 + e \times \log \Pi_6$ (8)

Linear multiple regression is carried out for Eq.(8) using Minitab 15 and obtained following regression equation

$\log \Pi_1 = 17.78 - 0.411 \log \Pi_1 + 1.01 \log \Pi_2 + 1.22 \log \Pi_3 - 4.65 \log \Pi_4 + 0.527 \log \Pi_5$ (9)

Taking antilog of equation (9)

$\Pi_1 = 6\times10^{17} \; \Pi_2^{-0.411} \; \Pi_3^{1.10} \; \Pi_4^{1.22} \; \Pi_5^{-4.65} \; \Pi_6^{0.527}$ (10)

Substituting the Π terms from equations (1) to (6) in equation (10) and keeping only VB on left hand side, gave equation (11) which can be used to predict tool wear. The model postulates a functional dependence between the independent and dependent variables minimizing the modeling error.
The formulated model may be expressed as:

105□□1.008× □□0.406× □0.1756× □0.406× □0.1342× □0.1756□0.476× □□□0.418× □□□0.205□1.55* ----- (11)

An average regression coefficient of 0.91 was obtained for all the cases..

Experimental data obtained while using conventional cutting fluid without suspending any graphite nanoparticles, 0.1%, and 0.5% nano graphite inclusion levels for both HSS and carbide tools was used to build the model, 0.3% nano graphite inclusion data was left for validation.

The developed model was tested for adequacy using Analysis of variance (ANOVA) technique that is employed to confirm the effect of input variables on the response variable. Degrees of Freedom (DF) and sum of the squares (SS) are computed for the data. F-statistic (variance ratio) is calculated as the ratio of sums of squares. F-static denotes the 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 particular (1% or 5%) confidence level.

In the present work, the degrees of freedom were found to be 5 and 263, F-statistic was obtained as 104.2 from Minitab. The tabulated critical value of F distribution for the obtained degrees of freedom at 1% significance level was 3.08 [14]. Hence, the proposed null hypothesis proposing no dependence of tool wear on the input parameters was rejected at 1% significance level. Hence the choice of parameters is justified. If the hypothesis is rejected at 1% confidence level, it also stands rejected at 5% confidence level. Table I summarizes the results from ANOVA analysis. P value denotes the probability of null hypothesis to be wrongly rejected. R^2 value was obtained as 0.91 and P-value is zero. This shows that the model has a good fit.

TABLE I. ANOVA ANALYSIS

Source	**DF**	**SS**	**Mean Square**	**F**	**P**
Regression	5	783.07	156.61	104.20	0.000
RE	263	395.31	1.50		
Total	268	1178.38			

IV ARTIFICIAL NEURAL NETWORK MODEL

In the present work back propagation neural network (BPNN) has chosen and C++ program was used to implement BPNN. Heuristic optimisation method (momentum method) is used in the network to optimise the weights. Momentum rate in the present network was fixed as 0.75 and learning rate as 0.45. Cutting force, cutting temperature, hardness of the cutting tool, thermal conductivity of the cutting fluid, viscosity of the cutting fluid, wt% of nano graphite, flow rate of the cutting fluid, surface roughness of machined work piece, machining time, and Young's modulus of the tool were taken as inputs to predict tool wear. The input and output data of ANN model to predict the tool wear in a MQL environment is illustrated in Figure 1.

Normalised input patterns were presented to the network for training and the size of the network was optimised by trial and error. Initially, the number of hidden layers was determined. Figure 2 shows the variation of normalised error with the number of hidden layer neurons for a single and two hidden layers. It can be observed that the error is consistently less for a single hidden layer. Further, four neurons gave the least error. Hence, a network with a single hidden layer and four hidden layer neurons was chosen in the present work. The size of the network was fixed as 10-4-1.

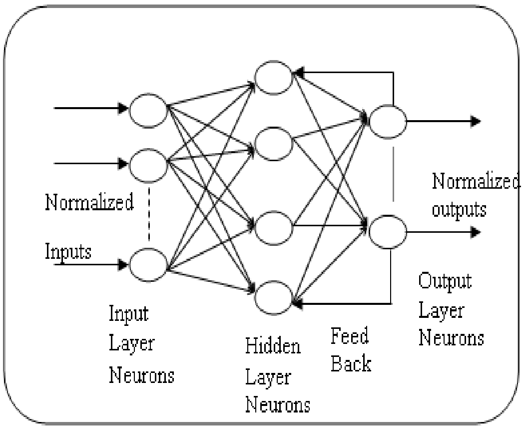

FIGURE 1 REPRESENTATION OF ANN

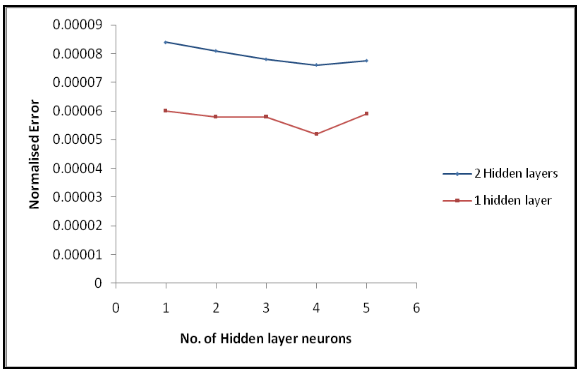

FIGURE 2 OPTIMIZATION OF NUMBER OF HIDDEN LAYERS IN NEURAL NETWORKS

The network was trained with the experimental data and the variation in error is observed for different number of iterations. Figure 3 shows the variation of error with the number of iterations. It can be observed that the error is almost stable beyond 4,000 iterations. Hence, to minimise the processor time, the number of iterations was taken as 4,000. After fixing the network parameters, the network was trained using experimental data obtained while using 0%, 0.1%, and 0.5% nano graphite inclusions for both HSS and carbide tools to obtain stable weight structures. Using these weight structures, the network was tested for remaining data as input patterns.

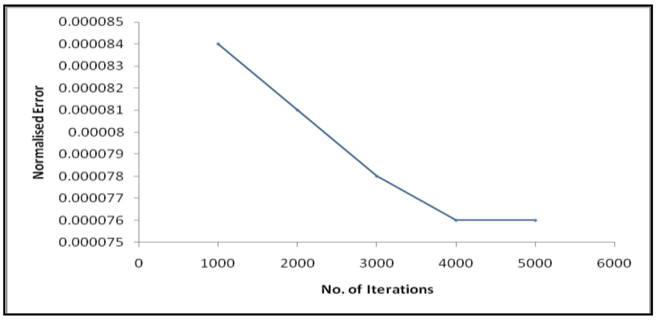

FIGURE 3 OPTIMISATION OF NO. OF ITERATIONS

V. VALIDATION OF MODELS

Experimental data obtained from experimentation for 0%, 0.1% and 0.5% nano graphite conditions were used to build the models. An independent set of data obtained during machining with HSS and cemented carbide tools with the cutting fluid containing 0.3% nano graphite was used for validating the models. The proposed models were validated by comparing the predicted results with the experimental results. Results from regression model and neural network model are compared with the experimental results in Figure 4.

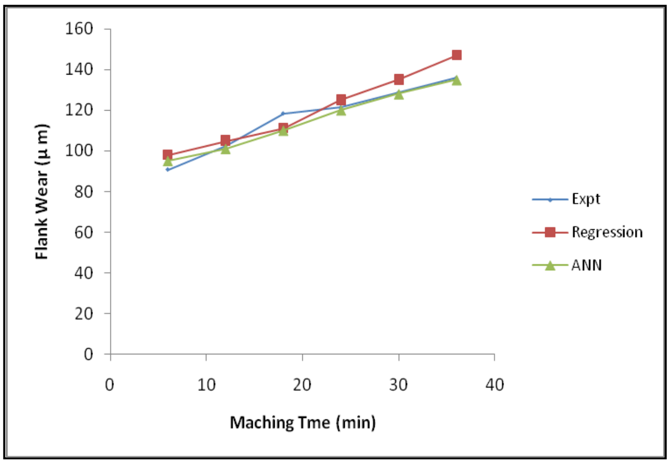

FIGURE 4 VALIDATION OF MODEL

Absolute values of percent errors obtained using regression (R) and artificial neural network models are presented in Table 2. It can be observed that maximum error for regression model is 13.2 % and 7.90 % for neural network model. Both the models gave values within acceptable limit of error, they stand validated. However, there is smoothening and approximation in case of regression models which is not present in the ANN model. This leads to better accuracy in ANN models.

TABLE 2. ABSOLUTE ERROR OF PREDICTION (%)

Time (min)	**5 ml/min**		**10 ml/min**		**15 ml/min**	
	R	**ANN**	**R**	**ANN**	**R**	**ANN**
5	8.04	4.74	5.30	2.31	13.2	3.45
15	2.33	1.55	12.17	7.69	9.54	3.45
25	6.25	7.09	12.69	7.90	8.95	4.45
35	3.05	1.07	7.69	3.84	7.89	2.65
40	4.89	0.54	5.32	2.147	6.78	1.98

VI. CONCLUSIONS

Proposed regression and neural network models predicted tool wear based on several input parameters. The results were obtained within acceptable limits. ANOVA justified the choice of input parameters for the model. The model predicted tool wear with error less than 13.5%, whereas, neural network model predicted tool wear with higher accuracy of error less than 8%. ANN could predict the experimental values more accurately than regression model.

The work can be extended by using different other parameters like vibrations, acoustic emissions, etc. Different nano particles, levels of inclusions and flow rates can also be tried.

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