International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:4, No:2, 2010

Tool Wear and Surface Roughness Prediction using an Artificial Neural Network (ANN) in Turning Steel under Minimum Quantity Lubrication (MQL)

S. M. Ali, and N. R. Dhar

***Abstract*—**Tool wear and surface roughness prediction plays a significant role in machining industry for proper planning and control of machining parameters and optimization of cutting conditions. This paper deals with developing an artificial neural network (ANN) model as a function of cutting parameters in turning steel under minimum quantity lubrication (MQL). A feed-forward backpropagation network with twenty five hidden neurons has been selected as the optimum network. The co-efficient of determination (R^2) between model predictions and experimental values are 0.9915, 0.9906, 0.9761 and 0.9627 in terms of VB, VM, VS and R_a respectively. The results imply that the model can be used easily to forecast tool wear and surface roughness in response to cutting parameters.

***Keywords*—**ANN, MQL, Surface Roughness, Tool Wear.

I. Introduction

THE quality of machined components is evaluated in respect of how closely they adhere to set product specifications for length, width, diameter, surface finish, and reflective properties. Dimensional accuracy, tool wear and quality of surface finish are three factors that manufacturers must be able to control at the machining operations to ensure better performance and service life of engineering component. In the leading edge of manufacturing, manufacturers are facing the challenges of higher productivity, quality and overall economy in the field of manufacturing by machining. To meet the above challenges in a global environment, there is an increasing demand for high material removal rate (MRR) and also longer life and stability of the cutting tool But high production machining with high cutting speed, feed and depth of cut generates large amount of heat and temperature at the chip-tool interface which ultimately reduces dimensional accuracy, tool life and surface integrity of the machined component. This temperature needs to be controlled at an optimum level to achieve better surface finish and ensure overall machining economy.

The conventional types and methods of application of cutting fluid have been found to become less effective with the increase in cutting velocity and feed when the cutting fluid cannot properly enter into the chip-tool interface to cool and lubricate the interface due to bulk plastic contact of the chip with the tool rake surface. The more serious concern by the use of cutting fluid, particularly oil-based type is the pollution of the working environment, water pollution, soil contamination and possible damage of the machine tool slide ways by corrosion [1].

The modern industries are therefore looking for possible means of dry (near dry), clean, neat and pollution free machining and grinding. Minimum Quantity Lubrication (MQL) refers to the use of cutting fluids of only a minute amount-typically of a flow rate of 50-500 ml/hour-which is about three to four orders of magnitude lower than the amount commonly used in flood cooling, where for example, up to 10 liters of fluid can be dispensed per minute. The concept of minimum quantity lubrication (MQL), sometimes referred to as 'near dry lubrication' [2] or 'micro lubrication' [3]. Machining under minimum quantity lubrication (MQL) condition is perceived to yield favorable machining performance over dry or flood cooling condition.

Tool wear and surface roughness prediction plays an important role in machining industry for gaining higher productivity, product quality, manufacturing process planning and also in computer aided process planning. Average principal flank wear (VB) of cutting tools is often selected as the tool life criterion as it determines the diametric accuracy of machining, its stability and reliability. The productivity of a machining system and machining cost, as well as quality, the integrity of the machined surface and profit strongly depend on tool wear and tool life. Sudden failure of cutting tools leads to loss of productivity, rejection of parts and consequential economic losses. Flank wear occurs on the relief face of the tool and is mainly attributed to the rubbing action of the tool on the machined surface during turning operation During turning operation the average principal flank wear (VB)

S. M. Ali is an Assistant Professor in the Department of Industrial and Production Engineering, Bangladesh University of Engineering and Technology (BUET), Dhaka 1000, Bangladesh (e-mail: mithun@ipe.buet.ac.bd)

N. R. Dhar is a Professor in the Department of Industrial and Production Engineering, Bangladesh University of Engineering and Technology (BUET), Dhaka 1000, Bangladesh (e-mail: nrdhar@ipe. buet.ac.bd)

predominantly occurs in cutting tool, so the life of a particular tool used in the machining process depends upon the amount of average principal flank wear. The maximum principal flank wear (VM) and average auxiliary flank wear (VS) also take place during turning and can't be neglected due to their significant impact on surface integrity and dimensional inaccuracy of machined component. The surface finish of the machined component primarily depends upon the amount of average principal flank wear (VB). An increase in the amount of average principal flank wear (VB) leads to reduction in nose radius of the cutting insert which in turn reduces the surface quality along the job axis. The maximum utilization of cutting tool is one of the ways for an industry to reduce its manufacturing cost. Hence tool wear has to be controlled and should be kept within the desired limits for any marching process. Tool wear mainly depends upon the machining parameters for turning a particular work piece material. In order to maximize productivity and overall economy from a manufacturing process, an accurate process model must be constructed for turning operation in a MQL environment.

This paper aims to develop an artificial neural network (ANN) model for the analysis and prediction of the relationship between cutting and process parameters during turning of medium carbon steel by uncoated SNMG insert. The input parameters of the Artificial Neural Networks (ANN) model are the machining parameters: speed, feed, depth of cut and cutting time. The output parameters of the model are four process parameters measured during the machining trials, namely principal flank wear (VB), maximum principal flank wear (VM), auxiliary flank wear (VS) and surface roughness (R_a). Experimental studies have been conducted to establish and validate the proposed model.

Artificial Neural Networks (ANNs) have been widely used for modeling complex manufacturing process due to their learning and generalization capabilities, accommodation of non-linear variables, adaptivity to changing environments and resistance to missing data. ANNs have been widely applied in modeling many metal cutting operations, such as turning, milling and drilling [4]. There is an extensive research interest in the application of ANNs in modeling and monitoring of machining operations [5, 6]. Applications of neural networks in computer-integrated production are adaptive control of cutting process, prediction of surface roughness, cutting forces, vibrations, prediction of tool wear and tool failure, solving of optimization problems [7-9]. Elanayar and Shin [10] proposed a model, which approximates flank and crater wear propagation and their effects on cutting force by using radial basis function neural networks. Ghasempoor et al. [11] proposed a tool wear classification and continuous monitoring neural network system for turning by employing recurrent neural network. Liu and Altintas [12] derived an expression to calculate flank wear in terms of cutting force ratio and other machining parameters. The calculated flank wear, force ratio, feed rate and cutting speed are used as an input to a neural network to predict the flank wear. . Sick [5] demonstrated a new hybrid technique, which combines a physical model describing the influence of cutting conditions on measured force signals with neural model describing the relationship between normalized force signals and the wear of the tool. Time-delay neural networks were used in his studies. Azouzi and Guillot [13] examined the feasibility of neural network based sensor fusion technique to estimate the surface roughness and dimensional deviations during machining. This study concludes that depth of cut, feed rate, radial and z-axis cutting forces are the required information that should be fed into neural network models to predict the surface roughness successfully. In addition to those parameters, Risbood et al. [14] added the radial vibrations of the tool holder as additional parameter to predict the surface roughness. Bisht et al. [15] developed a back propagation neural network model for the prediction of flank wear in turning operations. Process parametric conditions including cutting speed, feed-rate, depth of cut, and the measured parameters such as cutting force, chip thickness and vibration signals are used as inputs to the neural network model. Jang et al. [16] applied ANN in surface roughness study and correlate surface roughness with cutting vibrations. Grzesik [17] used the minimum un-deformed chip thickness to predict surface roughness in turning. Polynomial networks were considered in the work of Lee et al [18] to construct the relationships between the cutting parameters (cutting speed, feed rate, depth of cut) and cutting performance (tool life, surface roughness and cutting force). Li et al. [19] developed a hybrid machining model that integrated analytical models and neural network models for predicting all of the machining characteristic factors. Matsumura et al [20] adopted an approach that could evaluate the influence of machine tool characteristics on cutting processes using adaptive prediction was presented. The network for predicting surface roughness had as inputs the cutting speed, the affinity between cutting tool and workpiece, the chip discontinuity (evaluated by the chip strain), the built-up-edge formation (evaluated by average temperature around the cutting edge), the width of flank wear and the theoretical roughness considering tool wear. An adaptive neuro-fuzzy inference system (ANFIS) and computer vision were used to predict surface roughness by Ho et al. [21] in turning. The computer vision system, comprising a digital camera connected to a PC and the appropriate light sources, provided surface images that were analyzed to calculate the arithmetic average of gray levels (number of shades of gray). This information as well as the cutting parameters was given, for a total of four inputs, to the ANFIS and the roughness value could then be obtained.

A review of the literature on prediction of tool wear and surface roughness reveals that no ANN model has been still developed to predict tool wear and surface roughness while machining medium carbon steel under minimum quantity lubrication (MQL) Condition with uncoated carbide insert designated as SNMG 120408 and Considering the four cutting parameters -cutting speed, feed rate, depth of cut and marching time as input to neural network. No ANN model is still found which determines the surface roughness and three

process parameters (VB, VM, VS) related to tool wear and tool life friendly. This paper deals with developing an ANN model that can be used to predict tool wear and surface roughness and for optimization of machining parameters while performing turning operations under minimum quantity lubrication (MQL) environment.

II. Experimental Procedure and Conditions

The concept of minimum quantity lubrication (MQL) may be considered as a rigorous solution in achieving reduced tool wear and improved surface finish while maintaining cutting forces or power at reasonable levels, if the MQL system can be properly designed. MQL technique not only provides reduction in tool wear or increase in tool life and improvement in surface roughness but also reduces the consumption of cutting fluid. The machining tests have been carried out by straight turning of medium carbon steel on a lathe (7.5 kW) by a standard uncoated carbide insert with ISO designation-SNMG 120408 at different speed-feed combinations. MQL machining has been considered to be an effective semidry application because MQL offers positive part on environment friendliness as well as techno-economical benefit.

The conditions under which the machining tests have been carried out are briefly given in Table I. All these parameters have been selected as per tool manufacturer's recommendation as well as industrial practices for machining medium carbon steel with uncoated carbide insert. Effectiveness of cooling and the related benefits entirely depends on how closely the MQL jet can reach the chip-tool and the work-tool interfaces where, apart from the primary shear zone, heat is generated. The tool geometry is reasonably expected to play significant role on such cooling effectiveness. Keeping this view tool configuration namely SNMG-120408 has been undertaken for this work. The insert was clamped in a PSBNR-2525 M12 type tool holder.

TABLE I
Experimental Conditions

Machine tool	: Lathe Machine(China), 7.5 kW
Work materials	: Medium Carbon Steel
Cutting tool	: Uncoated Carbide, (p-30 grade), Sandvik
Geometry	: -6°,-6°,6°,15°,75°,0.8 mm
Tool holder	: PSBNR 2525 M12 (ISO specification), Widia
Cutting parameters	
Cutting velocity, V	: 66 and 258 m/min
Feed rate, f	: 0.10 and 0.20 mm/rev
Depth of cut, d	: 1.0 and 1.5 mm
MQL supply	: Flow Rate 150 ml/hr, Air Pressure 23 bar, Oil Pressure 25 bar
Environment	: MQL (VG-68 Cutting oil)

The photographic view of the experimental set-up is shown in Fig. 1. A cylindrical bar of medium carbon steel of 167 mm diameter was selected for straight turning. During machining, the cutting insert was withdrawn at regular intervals and then VB, VM, VS were measured under metallurgical microscope (Carl Zesis, 351396, Germany) fitted with micrometer of least count 1μm. Surface roughness was measured respectively by a Talysurf (Surtronic 3+ Roughness checker, Taylor Hobson, UK) using a sampling length of 4.00 mm. The photographic view of the surface roughness measuring technique is shown in Fig. 2.

Fig.1 Photographic view of experimental set-up

An MQL system using cutting fluid and compressed air essentially consists of a compressor for delivering and compressing and delivering compressed air at desired pressure, mixing chamber for mixing cutting fluid and compressed air, suitable nozzle to impinge MQL to the cutting zone, pressure and flow control valves for effective economical use of cutting fluid.

Fig.2 Photographic view of surface roughness measuring technique

III. ANN Model Formulation

Before developing an ANN model to predict tool wear and surface roughness, it is very much important to identify the input and output parameters of the network. The forecasting capability or interpolation capability of an artificial neural network (ANN) model strongly depends on the appropriate selection of input-output parameters. In our proposed model, the input parameters that have been considered are machining variables and machining time. The machining variables or set up variables, which include cutting speed (V), feed rate (f) and depth of cut (d). These parameters can be set up in advance. It means that these parameters are controllable and

can be selected prior to perform machining operation. Machining time (t_c) influences the process performance to a great extent. As machining time increases, tool wear also increases and so significantly influence the surface quality. Considering this, machining time has also been considered as one of input parameters of the model. The optimization of machining process can be achieved by proper selection of these parameters.

Productivity and economy of manufacturing by machining are significantly affected by life of the cutting tools. The need for accurate assessment of tool wear has increased considerably in order to produce the required end products so that a new tool may be introduced at the instant at which the existing tool has worn out, thus preventing any hazards occurring to the machine or deterioration of the product surface finish. The importance of maximizing a tool's working time and doing the utmost is to keep tools from breaking is directly related with cutting-process optimization. Tool wear sensing has been one of the primary objectives in order to produce the products with desired surface finish and accuracy in an automated industry so that a new tool may be introduced at the instant at which the existing tool has worn out.

With the progress of machining, the cutting tools attain crater wear at the rake surface and flank wear at the clearance surfaces due to continuous interaction and rubbing with the chips and the work surfaces respectively. The principal flank wear is the most important because it raises the cutting forces and related problems. Again the life of the tools, which ultimately fail by the systematic gradual wear, is generally assessed by the average value of the principal flank wear (VB), which aggravates cutting forces and temperature and may induce vibration with progress of machining. Wear may grow at a relatively faster rate at certain locations within the zones of flank wear apart from notching.

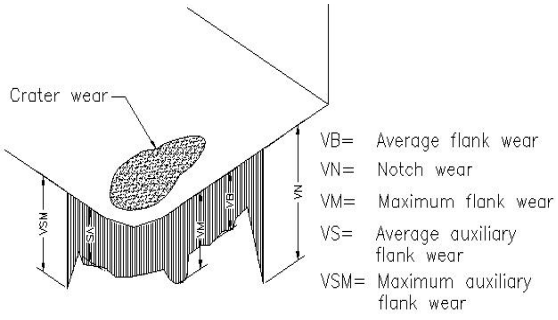


Fig. 3 Schematic view of general pattern of wear

Schematic view of general pattern of wear is shown in Fig. 3. The width of such excessive wear are expressed by VM (maximum flank wear), VS (average auxiliary flank wear) and VSM (maximum auxiliary flank wear). The pattern and extent of the auxiliary flank wear (VS) affects surface finish and dimensional deviation of the machined parts. In this ANN mode, three important tool wear indices namely VB, VM and VS and one universally applied surface roughness index namely, average surface roughness, R_a have been considered as output parameters of the network. The average roughness is the area between the roughness profile and its center line, or the integral of the absolute value of the roughness profile height over the evaluation length. Therefore, R_a is specified by the following equation:

$$R_a = \frac{1}{L}\int_0^L |Y(x)|\,dx, \quad (1)$$

When R_a is evaluated from digital data, the integral is normally approximated by a trapezoidal rule:

$$R_a = \frac{1}{n}\sum_{i=1}^{n} |Y_i| \quad (2)$$

Where, R_a is the arithmetic average deviation from the mean line (μm), L is the sampling length, and Y is the ordinate of the profile curve. Graphically, the average roughness is the area (Fig. 4) between the roughness profile and its center line divided by the evaluation length.

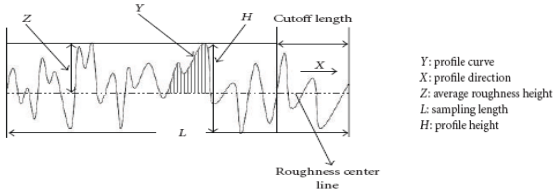


Fig. 4 Arithmetic Average value of roughness (R_a) [22]

The input parameters of the neural network are the cutting conditions, namely cutting speed (V), feed rate (f), depth of cut (d) and cutting time (t_c). The output parameters of the model are four process parameters measured during the machining trials, namely principal flank wear (VB), maximum principal flank wear (VM), auxiliary flank wear (VS) and surface roughness (R_a). The input/output dataset of the ANN model that we are to going to be formulated to predict tool wear and surface roughness in a MQL environment is illustrated schematically in Fig.5. Experimental studies have been conducted under MQL environment to establish and validate the proposed ANN model.

In this work, four basic steps have been adopted in the development of the model: collection of input-output dataset; pre-processing of the input-output dataset; designing and training of the neural network and finally performance evaluation of the designed neural network. The optimal network architecture was determined after several simulation trials by MATLAB 7.1 software.

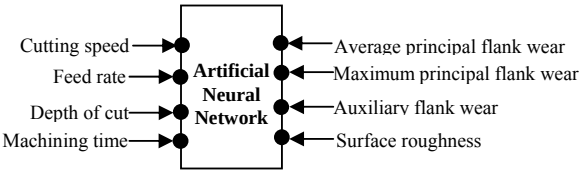


Fig. 5 Schematic diagram of ANN for tool wear and surface roughness

A. Collection of Input-Output Dataset

The machining tests have been carried out by straight turning of medium carbon steel on a lathe by a standard uncoated carbide insert with ISO designation-SNMG 120408 at different cutting speeds (V), feed rates (f), depth of cuts (d) and machining time (t_c) under MQL (VG-68 cutting oil) condition. During machining trials, the cutting insert was withdrawn at regular intervals to examine the pattern and extent of wear under a metallurgical microscope. After each trial, the average surface roughness value was also measured by a Talysurf. Thus several pairs of output variables in response to the different combinations of machining/input parameters have been obtained.

B. Pre-processing of Input-Output Dataset

The capability of the artificial neural network (ANN) model to generalize regarding unseen data dependents on several factors such as appropriate selection of input-output parameters of the system, the distribution of the input-output dataset, the format of the presentation of the input-output dataset to the neural network. For our ANN model, the input parameters used are the four main machining parameters (cutting speed, feed rate, depth of cut, marching time), while the output dataset are the four process parameters (average principal flank wear, maximum principal flank wear, average auxiliary flank wear, average surface roughness).

$$P_i = \begin{bmatrix} \text{Cutting speed, V} \\ \text{Feed rate, f} \\ \text{Depth of cut, d} \\ \text{Machining time, } t_c \end{bmatrix} \quad T_i = \begin{bmatrix} \text{Average principal flank wear, VB} \\ \text{Maximum principal flank wear, VM} \\ \text{Average auxiliary flank wear, VS} \\ \text{Average surface roughnes, } R_a \end{bmatrix}$$

In this study, several machining tests were carried out and thus 38 pairs of input-output dataset were obtained during the machining trials. Before training the ANN by feeding the dataset to the network and the input-output mapping, one significant task is to process the experimental data into patterns. Training and testing pattern vectors are formed before input-output dataset are fed to network. Each pattern is formed with an input condition vector (P_i) and the corresponding target vector (T_i), which is shown in the matrix. Before training the network, the input-output dataset were normalized within the range of -1 to +1 using the Matlab command **'**premnmx'.

C. Neural Network Design and Training

The network architecture/ topology or features such as number of neurons and layers are very important factors that determine the functionality and generalization capability of the network [23]. The selection of the activation function and training algorithm also play a significant role to obtain better forecast of response variable. In this work, standard multilayer feed-forward back-propagation hierarchical neural network has been considered for the prediction of tool wear and surface roughness in turning medium carbon steel in MQL environment. The neural network has been deigned with MATLAB 7.1 software. The back propagation algorithm is a gradient decent error-correcting algorithm which updates the weights in such a way that network output error is minimized [24]. The feed forward backpropagation network usually consists of an input layer (where the inputs of the problems are received, the inputs are the activity of collecting data from the relevant sources. These data are fed to the neural network), one hidden layer (where the relationship between the inputs and outputs are established represented by synaptic weights) and an output layer which emits the outputs of the network. The number of hidden layer may vary depending on the nature, complexity and non-linearity of the data at hand, but single hidden layer is sufficient to deal with most of the practical case.

In this work, the input layer has four neurons corresponding to each of the four cutting parameters and four neurons in the output layer corresponding to each of the four response parameter (Fig. 5). In order to find out the best network architecture, different networks with different number of hidden layers and neurons in the hidden layer were designed and verified; different training algorithm were used; transfer function in the hidden layer and output layer were changed and observed the generalization capability of the different networks and finally the optimal network was selected to predict tool wear and surface roughness. The issue of determining the optimum number of hidden nodes is a crucial and complicated one in neuronal model. In general, network with smaller number of hidden neurons are preferable as they usually have better generalizations ability and less over fitting problems. But network with too few hidden neurons may not have enough power to model, store and learn the data. The most common approach in determining the number of hidden neurons (nodes) is via trial and error. Several rule of thumbs have also been proposed, such as, the number of hidden nodes depends on the number of input patterns and each weight should have at least ten input patterns (sample size). In the case of one hidden layer network, several practical guidelines exist. These include 2n+1, 2n, n\2 where n is the number of input nodes. Lawrence and Fredrick [25] suggested that the number of hidden neuron = (n_1+n_2), where n_1 and n_2 are the number of input and output nodes respectively.

For the optimal network architecture, tangent of sigmoid (sigmoid function is of the form $f(x) = (1/1+e^{-x})$) transfer function 'tansig' has been used in the hidden layer and linear (linear function is of the form $f(x) = x$)) transfer function 'purelin' has been used in the output layer**.** The ANN configuration is represented as 4-25-4 that is input layer consists of four input neurons; the hidden layer consists of twenty five neurons and the output layer consisting of four output neurons. The number of neurons in the hidden layer is determined by trial and error method after designing and investigating many networks which vary in their structure, transfer function, training algorithm etc. As mentioned above, there is no fixed rule for determining the number of neurons in the hidden layer. The number of neurons in this layer must be large enough to provide non-linear evaluation space in the network.

Training of an ANN plays a significant role in designing the direct ANN-based prediction. The accuracy of the prediction depends on how well it has been trained. The training of the neural network using a feed-forward back propagation algorithm has been carried out in the work. The network performs two phases of data flow. First the input information is propagated from the input layer to the output layer and, as a result it produces an output. Then the error signals resulting from the difference between the networks predicted values and the actual values are back propagated from the output layer to the previous layers for them to update their weights accordingly. The update of weights continues until the network error goal is reached.

The number of neurons in the hidden layer is intentionally chosen to start with five neuron and hidden neurons are added to the hidden layer incrementally. The addition of hidden neurons continues until there is no significant progress in network performance. The performance of the network was evaluated by mean squared error (MSE) between the experimental and the predicted values for every output nodes in respect of training the network. The feedback from that processing is called the "average error" or "performance". Once the average error is below the required goal or reaches the required goal, the neural network stops training and is, therefore, ready to be verified.

MATLAB 7.1 has been used for training the network architecture which has been developed for prediction of tool wear and surface roughness in MQL environment. The training performance of the optimal network (consisting of twenty five hidden neurons) architecture is shown in Fig. 7.

A computer program was performed under this MATLAB version. The input-output dataset consisting of 38 patterns was divided randomly into two categories: training dataset consist of 75% of the data and test dataset which consist 25% the data. There are 28 training patterns considered for ANN modeling of tool wear and surface roughness. After the training, the weights are frozen and the model is tested for validation. In this work, the network is validated in terms of agreement with experimental results.

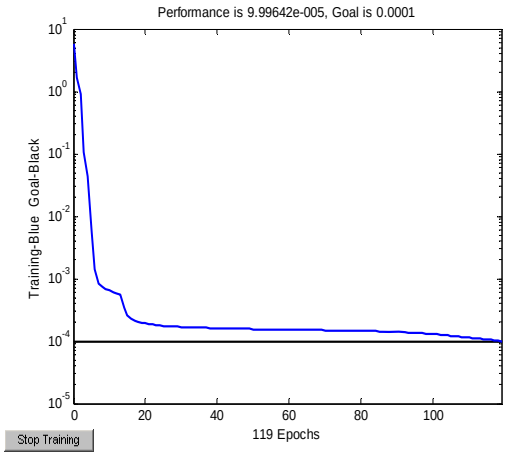


Fig. 6 ANN training performance

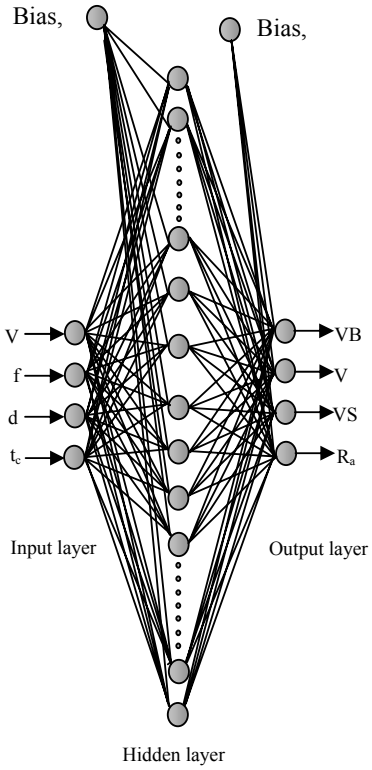


Fig. 7 Proposed ANN architecture

For this purpose, the input parameters to the network are sets of values (in this case 10 pairs of dataset which have been shown in Table II) that have not been used for training the network (raw untrained data) but are in the same range as those used for training. This enables to test the network with regard to its capability for interpolation regarding unseen data.

When a feed-forward network is developed under MATLAB, it generates initial weight and bias values for a layer with the help of Nguyen-Widrow algorithm. This reduces training time by setting the initial weights in such a way that the active region of the layers neuron will be distributed approximately evenly over the input space. The advantage of this over completely random initialization is that once the training starts the weights movements are smaller and settle quickly, since the majority of weight movements were eliminated by the method of initialization [26].

Each neuron in the network acts as a processing element which performs a weighed sum of all input variables that are fed to it. Depending on the value of weighted sum of the variables, the neuron gives a signal to the neurons in the adjacent layer through a non-linear transfer function (sigmoid function in this case). The tool wear and surface roughness values of training samples are treated as the desired and target output. The algorithm used for the neural network learning is 'the backward propagation algorithm' with Levenberg-Marquardt (LM) version. This training algorithm offers higher accuracy in function approximation. It also facilitates faster training. The neural network learning is adaptive in nature that

means vector pairs from the training model are mapped respectively to reinforce the weights until deviation between the training output and the desired output of each training vector sample converges to a negligible error of 0.0001 in this application.

The optimum ANN architecture is shown in Fig. 7. For clarity, not all of the connections between input-hidden neurons and hidden-output neurons are shown in Fig. 7. The momentum constant and learning rate used in this model is 0.5 and 0.1 respectively. The maximum number of training epochs that was set is 10,000 and the training error goal was 0.0001. After the training is completed, the actual weight values are stored in a separate file. The value of R^2 and MAPE values between the network predictions and the experimental values using training and test dataset for different network architecture have been shown in Table III. The summary of the proposed model (Fig. 7) is given in Table IV.

D. Performance Evaluation of the Designed Network

Training and testing performance of the optimum network architecture can be evaluated by the following measures:

$$\mathrm{RMSE} = \left(\left(\frac{1}{p} \right) \sum_j \left| t_j - o_j \right|^2 \right)^{1/2} \quad (3)$$

$$\mathrm{MEP} = \frac{\sum_j \left(\left(\left(t_j - o_j \right) / t_j \right) \times 100 \right)}{p} \quad (4)$$

$$R^2 = 1 - \left(\frac{\sum_j \left(t_j - o_j \right)^2}{\sum_j \left(o_j \right)^2} \right) \quad (5)$$

$$\mathrm{APE}(\%) = \left| \frac{\text{Model prediction values} - \text{Experimental values}}{\text{Experimental values}} \right| \times 100\% \quad (6)$$

where,

t : Target value
O : Output value
RMSE : Root mean squared error
MEP : Mean error percentage
APE : Absolute percentage of error
R^2 : Coefficient of determination/ absolute fraction of variance
P : Number of patterns
j : Processing elements

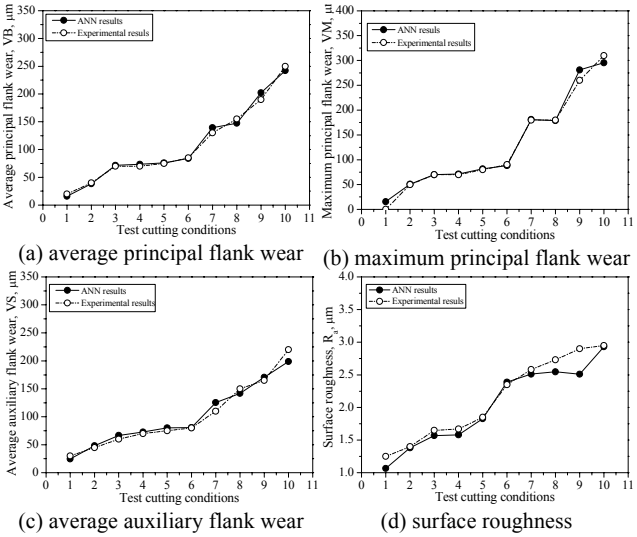
After post processing the network predicted values by using the MATLAB command 'postmnmx', regression analysis was adopted to find the coefficient of determination value (R^2) for both training and testing phases to judge performance of each network. Another index termed as mean absolute percentage of error (MAPE) is also used in this analysis to judge the training and testing performance. The coefficient of determination (R^2) and mean absolute percentage of error (MAPE) values for different network architecture have been presented in Table III. For clarity not all of the hidden neurons that were considered during designing and developing the ANNs model are shown in Table III.

It is shown from the Table II that network with 1 hidden layer and 25 neurons in the hidden layer with 'tansigmoid' and 'purelin' transfer function in the hidden and output layer respectively and trained with Levenberg-Marquardt algorithm provides the best result**.** It can also been seen from Table II that increasing the number of neurons from 25 to 30 has no significant improvement on the performance of the network. So**,** 4-25-4 network architecture was selected as the optimum ANN model.

Fig. 8 shows the ANN prediction values and observed values for four response variables namely average principal flank wear (VB), maximum principal flank wear (VM), average auxiliary flank wear (VS), and average surface roughness (R_a) respectively for different test cutting conditions. The test cutting conditions have been shown in Table III. From the graphs, it is clear that the proposed model can predict values which are nearly very close to experimental observations for each of the output parameters. The results show that the ANN model can be used easily for prediction of tool wear and surface roughness and hence help in optimum selection of cutting parameters (V, f, d, t_c) for the purpose of manufacturing process planning and optimization of machining parameters in turning medium carbon steel by uncoated SNMG insert.

TABLE II
TEST CUTTING CONDITIONS

Test cutting conditions	[V (m/min), f (mm/rev), d (mm), t_c (min)]
1	[66, 0.10, 1.5, 0.5]
2	[66, 0.10, 1.00, 1.0]
3	[66, 0.10, 1.50, 5]
4	[258, 0.20, 1.00, 2.0]
5	[258, 0.20, 1.50, 1.50]
6	[66, 0.10, 1.00, 8.0]
7	[66, 0.10, 1.00, 22]
8	[66, 0.10, 1.50, 24]
9	[258, 0.20, 1.00, 11]
10	[258, 0.20, 1.50, 10,]



(a) average principal flank wear (b) maximum principal flank wear

(c) average auxiliary flank wear (d) surface roughness

Fig. 8 Experimental vs. ANN prediction (a) average principal flank wear, (b) maximum principal flank wear, (c) average auxiliary flank wear and (d) surface roughness for 10 testing cases

TABLE III
R^2 AND MAPE VALUES BETWEEN THE NETWORK PREDICTIONS AND THE EXPERIMENTAL VALUES

	Training performance			**Testing performance**		
Hidden layer	1	**1**	1	1	**1**	1
Hidden neurons	20	**25**	30	20	**25**	30
VB (Average principal flank wear)						
R^2	0.9998	0.9998	0.9998	0.9643	0.9915	0.9907
MAPE	0.0029	0.0061	0.0138	2.4635	0.3633	4.7226
VM (Maximum principal flank wear)						
R^2	0.9999	0.9999	0.9999	0.9815	0.9906	0.9855
MAPE	0.0044	0.0051	0.0036	0.0348	0.3812	3.5843
VS (Average auxiliary flank wear)						
R^2	0.9994	0.9995	0.9994	0.9528	0.9761	0.9745
MAPE	0.0118	0.0096	0.0087	2.5265	1.6331	1.9135
R_a (Average surface roughness)						
R^2	0.9996	0.9996	0.9996	0.8901	0.9627	0.8691
MAPE	0.0044	0.0037	0.0082	4.3964	4.8069	3.6261

TABLE IV
SUMMARY OF ANN MODEL

Object model	:	Tool wear and surface roughness
Input neuron	:	V, f, d, t_c
Output neuron	:	VB, VM, VS, R_a
Network structure		
Network type	:	**Feed-forward backpropagation**
Transfer function	:	Tansig/ Purelin
Training function	:	Trainlm
Learning function	:	Learngdm
Learning conditions		
Learning scheme	:	Supervised learning
Learning rule	:	Gradient descent rule
Input neuron	:	Four
Output neuron	:	Four
Sample pattern vector	:	28 (for training), 10 (for testing)
Number of hidden layer	:	1 (one)
Neurons in hidden layer	:	25
Learning rate, α	:	0.1
Momentum constant, β	:	0.5
Performance goal/Error goal	:	0.0001
Maximum epochs (cycles) set	:	10,000
MSE at the end of training	:	9.99642E-05

IV. RESULTS AND DISCUSSIONS

Artificial neural networks are one of the most widely used computer modeling techniques to develop robust approach for prediction of tool wear and surface roughness in machining steel for different combinations of material properties, cutting tool geometries and cutting conditions. The schematic diagram of artificial neural network for the prediction of tool wear and surface roughness is shown in Fig. 5. The figure reflects the input and output of the network that has been developed. The selection of the neuron number, hidden layers, activation function and training algorithm play much significant roles in obtaining the best result. In this study, an artificial neural network (ANN) with feed-forward back-propagation algorithm was trained and the training epoch (cycles) set for each network is 10,000. The purpose of the training is to minimize the mean squared error (MSE). The training performance of the proposed ANN architecture has been shown in Fig.6. From Fig.6 it is seen that the network error goal is met at 119 epochs. The proposed ANN model is shown in Fig. 7. It consists of 25 hidden neurons. The performance of the ANN model has been highlighted in Fig. 8 for four response variables namely average principal flank wear (VB), maximum principal flank wear (VM), average auxiliary flank wear (VS), and average surface roughness (R_a) respectively. As shown in the figures, it is clear that the values predicted by ANN are very close to experimental values.

To find the best network, different training algorithms were tested. Transfer functions in the hidden and output layer and weight and bias learning function have also been changed and tested during design phase of the network. Finally, tangent of sigmoid function ('tansigmoid') and purely linear function ('purelin') were used as the transfer function in the hidden and output layer respectively. Training of the network was performed using Levenberg-Marquardt (LM) feed forward back propagation algorithm. The weight or bias learning algorithm used here is 'learngdm' that is gradient decent with momentum. The numbers of neurons in the hidden layer were found by trial and error method and finally 25 hidden neurons were chosen for the suggested network. The proposed network can be represented as 4-25-4. To find the optimal network architecture, coefficient of determination (R^2) and mean absolute percentage of error (MAPE) between the network prediction and experimental values were calculated for every network for both training and testing phases. The coefficient of determination (R^2) represents the percent of data that is closest to the line of best fit. The value of R^2 varies between 0 to 1. If correlation coefficient, R=0.922 then R^2=0.850, which means that 85% of the total variation in network prediction can be explained by the linear relationship between experimental values and network predicted values. The other 15% of the total variation in network prediction remains unexplained. The coefficient of determination (R^2) and mean absolute percentage of error (MAPE) for different network topography have been shown in Table III. From Table III, it is shown that the value of R^2 increases up to hidden neuron 25. Then it starts to decrease mainly in terms of testing cases. The network architecture consisting of 1 hidden layer and 25 hidden neurons shows best values of R^2 for both training and testing stages of the network. So, the network consisting of 25 hidden neurons was selected as the optimum one in this research work. The summary of the proposed network architecture has been presented in Table IV. As, the input and output vectors were supplied to the network, it was a supervised learning scheme. The back-propagation learning algorithm with LM versions was used at the training stage of the network. Gradient decent learning rule is used in this study. The learning rate and momentum constant used here are 0.1 and 0.5 respectively. The co-efficient of determination (R^2) obtained corresponding to VB, VM, VS and R_a is 0.9915, 0.9906, 0.9761 and 0.9627 respectively for testing. Regarding

training, these values become 0.9998, 0.9999, 0.9995 and 0.9996. The MAPEs between the experimental and the predicted values are 0.3633% for VB, 0.3812% for VM, 1.6331% for VS and 4.8069% for R_a. The result shows that, the model can be successfully used to forecast tool wear and surface roughness in response to the cutting parameters for which the model has been constructed.

V. Conclusion

One of the primary objectives in machining operation is to produce product with low cost and high quality. In order to achieve such an objective, machining economics can be a significant consideration. Machining economics involves the optimum selection of machining parameters, e.g. cutting speed, feed rate, depth of cut and machining time. The machining parameters directly affect the cost, productivity and quality of products. A better predictive model can help as to choose the optimum machining parameters before performing machining operations. The objective of this work was to develop an ANN model to predict tool wear and surface roughness while turning medium carbon steel under MQL environment.

An ANN model has been developed for prediction of tool wear and surface roughness as a function of cutting parameters. The model has been proved to be successful in terms of agreement with experimental results. The proposed model can be used in optimization of cutting process for efficient and economic production by forecasting the tool wear and surface roughness in turning operations.

The multilayer feed forward network consisting of four inputs, 25 hidden neurons (tangent sigmoid neurons) and four outputs (network architecture represented as 4-25-4) was found to be the optimum network for the model developed in this study. The back propagation learning algorithm has been used in the developed feed forward single hidden layer network. A good performance of the neural network has been achieved with coefficient of determination (R^2) between the model prediction and experimental values are 0.9915, 0.9906, 0.9761, and 0.9627 in terms of VB, VM, VS and R_a respectively The MAPE values for those variables are 0.3633, 0.3812, 1.6331 and 4.8069 respectively. These results show that the ANN model can be used easily for prediction of tool wear and surface roughness in turning medium carbon steel by SNMG insert under minimum quantity lubrication environment. After adopting the Artificial Neural Network (ANN) model, the MQL system can enable significant improvement in productivity, product quality and overall machining economy even after covering the additional cost of designing and implementing MQL system.

ANN models have emerged as a new promising method for estimating tool wear and surface roughness in an intelligent manufacturing system (IMS). These techniques can easily capture the complex relationship between various process parameters and can be easily integrated into an existing manufacturing environment. These techniques has opened up new avenues for parameter estimation, optimization and on-line control of manufacturing system and can assist a lot in computer aided process planning (CAPP).

In this work, input parameters that have been considered to develop the ANN model are cutting speed, feed rate, depth of cut and machining time. The work can be further extended considering more input parameters such as tool-chip interface temperature, machine vibration, cutting tool geometry, workpiece composition, workpiece hardness etc. Then the ANN model to predict tool wear and surface roughness will be more robust and universally applicable.

Acknowledgment

This research work has been conducted in the department of Industrial and production Engineering (IPE) in Bangladesh University of Engineering and Technology (BUET). The authors would like to acknowledge BUET for providing the research facilities and funding to carry out the research work successfully.

References

[1] R.B. Aronson, “Why Dry Machining”, Manufacturing Engineering, Vol. 114, pp. 33-36, 1995.
[2] F. Klocke, and G. Eisenblaetter, "Dry Cutting", Annals of CIRP Manufacturing Technology, Vol. 46(2), pp. 519-526. 1997.
[3] T.F. MaClure, R. Adams, and M.D. Gugger, “Comparison of Flood vs. Micro- Lubrication on Machining Performance”, Website: http://www. Unist.com/techsolve.html, 2001.
[4] E.O. Ezugwua, D.A Fadera, J. Bonneya, R.B. Da silvaa and W.F. Salesa, “Modeling the Correlation between Cutting and Process Parameters in High Speed Machining of Inconel 718 Alloy Using An Artificial Neural Network”, International. Journal. of Machine Tools and Manufacture, Vol.45, pp.1375-1385, 2005.
[5] B. Sick,, “On-Line and Indirect Tool Wear Monitoring in Turning with Artificial Neural Networks: A Review of More Than A Decade of Research”, Mechanical Systems and Signal Processing, Vol.16, pp.487–546, 2002.
[6] D. E. Dimla, P.M. Lister and N.J. leightont, “Neural Network Solutions to the Tool Condition Monitoring Problem in Metal Cutting- A Critical Review Of Methods”, International Journal of Machine Tools and Manufacture, Vol.39, pp.1219-1241, 1997
[7] Y. Liu and C. Wang, “Neural Network Based Adaptive Control and Optimization in the Milling Process”, International Journal of Advanced Manufacturing and Technology, Vol.15, pp.791–795, 1999
[8] V. Karri,, “Performance in Oblique Cutting Using Conventional Methods and Neural Networks”, Neural Comput. Appl., Vol.8, pp.196–205, 1999
[9] X. Li,, S. Dong and P.K. Venuvinod, “Hybrid Learning for Tool Wear Monitoring”, International Journal of Advanced Manufacturing and Technology, Vol.16, pp.303–307, 2000
[10] S. Elanayar and Y.C. Shin, “Robust Tool Wear Estimation with Radial Basis Function Neural Networks”, ASME Journal of Dynamic Systems, Measurement and Control, Vol.117, pp.459–467, 1995
[11] A. Ghasempoor, J. Jeswiet and T.N. Moore, “Real Time Implementation of on-Line Tool Condition Monitoring in Turning”, Int. Journal of Machine Tools and Manufacture, Vol.39, pp.1883–1902, 1999
[12] Q. Liu and Y. Altintas., “On-Line Monitoring of Flank Wear in Turning with Multilayered Feed-Forward Neural Network”, Int. Journal of Machine Tools and Manufacture, Vol.39, pp.1945–1959, 1999
[13] R. Azouzi and M. Guillot, “On-Line Prediction of Surface Finish and Dimensional Deviation in Turning Using Neural Network Based Sensor Fusion”, International Journal of Machine Tools and Manufacture, Vol. 37 (9), pp.1201–1217, 1997
[14] K.A. Risbood, U.S. Dixit and A.D. Sahasrabudhe, “Prediction of Surface Roughness and Dimensional Deviation by Measuring Cutting Forces

and Vibrations in Turning Process", Journal of Materials Processing Technology, Vol.132, pp.203–214., 2003.
[15] H. Bisht, J. Gupta, S.K. Pal and D. Chakraborty, "Artificial Neural Network Based Prediction of Flank Wear in Turning", International Journal of Materials and Product Technology, Vol. 22(4), pp. 328-338, 2005
[16] D.Y. Jang, Y.G. Choi, H.G. Kim and A. Hsiao," Study of the Correlation between Surface Roughness and Cutting Vibrations to Develop An on-Line Roughness Measuring Technique In Hard Turning", International Journal of Machine Tools and Manufacture , Vol. 36, pp.453–464, 1996.
[17] W. Grzesik, "A Revised Model for Predicting Surface Roughness in Turning", Wear, Vol. 194 pp. 143–148, 1996
[18] B.Y. Lee, Y.S. Tarng, H.R. Lii,, "An Investigation of Modeling of the Machining Database in Turning Operations", Journal of Materials Processing Technology, Vol. 105 pp. 1–6, 2000.
[19] X.P. Li, K. Iynkaran and A.Y.C. Nee, "A Hybrid Machining Simulator Based on Predictive Machining Theory and Neural Network Modeling", Journal of Material Processing Technology, Vol.89/90, pp.224–230, 1999
[20] W Matsumura, T., Sekiguchi, H and E. Usui, "An Evaluation Approach of Machine Tool Characteristics with Adaptive Prediction", Journal of Materials Processing Technology, Vol. 62, pp. 440–447, 1996.
[21] S.-Y. Ho, K.-C. Lee, S.-S. Chen and S.-J. Ho, "Accurate Modeling and Prediction of Surface Roughness by Computer Vision in Turning Operations Using An Adaptive Neuro-Fuzzy Inference System", International Journal of machine Tools and Manufacture, Vol. 4, pp. 1441–1446, 2002
[22] ISO 4287, "Geometrical Product Specifications (GPS)-Surface Texture: Profile Method-Terms, Definitions and Surface Texture Parameters", 1997
[23] E.O. Ezugwua, D.A. Fadera, J. Bonneya, R.B. Da silvaa and W.F. Salesa, "Modeling the Correlation between Cutting and Process Parameters in High Speed Machining of Inconel 718 Alloy Using An Artificial Neural Network", International. Journal. of Machine Tools and Manufacture, Vol.45, pp.1375-1385, 2005.
[24] G. Baskar and N.V. Ramamoorthy "Artificial Neural Network: an Efficient Tool to Simulate the Profitability of State Transport Undertakings", Indian J Transport Manage, Vol. 28(2), pp. 243–257, 2004
[25] M. Lawrence and J. Fredrickson, BrainMaker User's Guide and Reference Manual, 7th Edition. California Scientific Software Press, Nevada City, CA, 1998.
[26] B. Nguyen and B. Widrow, "Improving the Learning Speed of 2-Layer Neural Networks by Choosing Initial Values of the Adaptive Weights", Proceedings of the International Joint Conference on Neural Networks, Vol. 3, pp. 21-26, 1990.

S. M. Ali is an Assistant Professor in the Department of Industrial and Production Engineering in Bangladesh University of Engineering & Technology (BUET), Dhaka, Bangladesh. He has obtained both Bachelor of Science and Masters of Science degree in industrial and production engineering (IPE) from Bangladesh University of Engineering and Technology (BUET) in 2007 and 2009 respectively. His research interest includes modeling by Artificial Neural Network (ANN), process capability and optimization.

N. R. Dhar is Professor of Manufacturing Engineering in the Department of Industrial & Production Engineering, Bangladesh University of Engineering & Technology (BUET), Dhaka, Bangladesh. He earned his PhD in Mechanical Engineering from Indian Institute of Technology (IIT), Kharagpur, India. He teaches undergraduate and postgraduate courses in Production Process, Machine Tools, and Machine Tools Mechanism & Vibration. His research areas of interest include Manufacturing with special interest in machining and grinding, Finite Element Method (FEM) and its application in manufacturing, Robotics and its applications, Environmental conscious manufacturing. He has published more than 120 papers in refereed journals and conference proceedings.