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International Journal Of Modern Engineering Research (IJMER)

ANN Based Prediction Model as a Condition Monitoring Tool for Machine Tools

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Abstract: *In today's world of manufacturing, a machine tool has an important role to produce best quality and quantity in phase with the demand. Machine tool in good working condition enhances the productivity and provides an opportunity for the overall development of the industry. Several parameters such as vibration of a machine tool structure, temperature at cutting zones, machined surface roughness, noise levels in the moving parts etc. provide the information of its working condition which is related to its productivity. Surface roughness of the machined part is one of the parameters to indicate machine tool condition. In the recent trends, soft computing tools have emerged as an aid for the condition monitoring of machine tools. In the present work, experiments have been conducted based on Taguchi technique for turning operation with different process input parameters using carbide cutting tool insert and the surface roughness of the turned parts were measured as output characteristic. Relation between input and output was established and a prediction model for surface roughness was built by using artificial neural network (ANN) backpropagation learning algorithm. The predicted values of surface roughness from the prediction model in comparison with the experimental values are found to be in close agreement. This establishes the use of ANN in developing prediction models for better monitoring of the condition of a machine tool for enhancing the productivity.*

Keywords: *Artificial neural network , Condition monitoring, Productivity.*

I. Introduction

Various soft computing techniques are being used in the study of condition monitoring for prediction of health of a machine tool. Surface roughness is one of the parameters that can be used to indicate the condition of a machine tool which also depends on process parameters such as cutting speed, depth of cut, feed rate and tool overhang .The combination of these process parameters result in an optimized machine tool condition for an enhanced productivity and quality of product and also indicating its condition.

Several experimental studies have been conducted to analyze the surface finish under different cutting conditions. A study on EN8 material during face turning operation with a coated ceramic cutting tool under the influence of process parameters such as depth of cut, feed rate and cutting speed revealed that the effect of increase of feed rate is more on the surface roughness than the cutting speed [1]. Further, an experimental study was carried out on AISI 1045 steel material to investigate the effect of cutting speed, depth of cut, feed rate and tool geometry on surface roughness in a turning operation and predict the optimal process parameters. Number of trials were decided based on the Taguchi orthogonal array L25 and the optimal input parameters were investigated with the help of ANOVA technique with 95% confidence level. The study revealed the effect of each of the optimal parameters on surface roughness [2].An experimental work carried out to analyze the surface finish and temperature variation in the cutting tool for a turning operation revealed the quality of surface finish of the work piece with different machining condition [3]. Similarly, an experimental study conducted to analyze the influence of variation of cutting speed, depth of cut, feed rate and cutting tool overhang on surface roughness revealed that the better surface finish is achieved with less feed rate and smaller tool overhang [4]. Focusing the effect of other parameters which affect the machining condition such as vibration, an experiment was carried out to investigate the influence of machine tool vibration on surface roughness with input variables as constant cutting speed and depth cut, along with variable feed rate and cutting tool insert nose radius and the study revealed that the larger insert nose radius with lower feed rate produces better surface finish [5].

II. Ann Based Prediction Model

The focus of present study was to develop an ANN based prediction model which establishes a relationship between input and output parameters. The prediction model was developed by using backpropagation ANN training algorithm. The backpropagation algorithm is generally referred as feed forward, multilayered network with number of hidden layers.

The multilayer feed forward networks consists of a set of sensory units or source nodes that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, layer-by-layer basis and these neural networks are commonly referred to as multilayer perception (MLPs). Multilayer perceptron utilizes the backpropagation algorithm for training the network [6].

The error back-propagation learning consists of two passes, a forward pass and a backward pass. In the forward pass an activity pattern is applied to the sensory nodes of the network, and its effect propagates through the network, layer by layer. Finally a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule. Specifically, the actual response of the network is subtracted from a target response to produce an error-signal. This error signal is then propagated backward through the network, against the direction of synaptic connections. The synaptic weights are adjusted to make the actual response of the network move closer to the desired response in a statistical sense.

Following are the steps of the backpropagation algorithm [7]

Step1 – Initialize the weights.

Initializes the weights and bias to small random numbers, like -1.0 to +1.0 or -0.5 to +0.5

Step2 – Propagate the inputs forward.

Input is fed to the input layers of the network. The input will remain small in the input layers, i.e., for an input unit k, its output O_k is equal to its input value I_k. The net input to a unit in the hidden or output layers is computed as a linear combination of its inputs. Given a unit k in a hidden or output layer, the net input I_k, to unit k is

$$I_k = \sum_i w_{ik} O_i + \theta_k$$

Where w_{ik} is the weight of the connection from unit i in the previous layers to unit k, Oi is the output of unit i from the previous layer and θ_k is the bias of the unit. The bias acts as a threshold in that it serves to vary the activity of the unit.

Given the net input I_k to unit k, then O_k, the output of the unit k, is computed as

$$O_k = \frac{1}{1 + e^{-I_k}}$$

The above function is also called as a squashing function because it maps a large input domain into smaller range of 0 to 1.

Step3 – Back propagate the error.

For a unit k in the output layer, the error Err_k is computed by

$$Err_k = O_k(1 - O_k)(T_k - O_k)$$

Where, O_k is the actual output of unit k and T_k is the known target value of the given input.

Error of a hidden layer unit k is

$$Err_k = O_k(1 - O_k) \sum_j Err_j w_{kj}$$

Where, w_{kj} is the weight of the connection from unit k to a unit j in the next higher layer and Err_j is the error of unit j.

The weights and bias are updated to reflect the propagated errors.

Weights are updated by the following equation, where Δw_{ik} is the change in weight w_{ik}.

$$\Delta w_{ik} = (l) Err_k \, O_i$$
$$w_{ik} = w_{ik} + \Delta w_{ik}$$

l is the learning rate, a constant having a value between 0.0 to 1.0.

Biases are updated by the following equation, where $\Delta\theta_j$ is the change in bias θ_j.

$$\Delta\theta_j = (l) Err_j$$
$$\theta_j = \theta_j + \Delta\theta_j$$

Here the weights of biases are updated after the presentation of each input which is known as case updating. Alternatively the weights and bias increments could be accumulated in variables, so that the weights and biases are updated after all of the training inputs have been presented. This strategy is called epoch updating, where one iteration through the training set is an epoch.

Step4 – Termination conditions.

The training terminates, when:

- All the Δw_{ij} in the previous epoch were so small so as to be below some specified threshold
- The percentage of tuples misclassified in the previous epoch is below some threshold
- A pre-specified number of epochs have expired.

Machine tool condition monitoring has been also carried out with several soft skill techniques. ANN has emerged a popular tool as it can relate several input parameters with an output without much mathematical complexities. ANN is a computational model used to predict a function that depends on large number of unknown inputs. It is a system of interconnected neurons which computes and predicts the values from inputs and has the capability of machining learning and pattern recognition. This tool is generally used to solve the wide variety of problems which are difficult to solve with the help of ordinary rule based programming.

There are number of ANN applications in condition monitoring. A study conducted and discussed the maintenance and system health management with the use of methods and techniques from the field of Artificial Intelligence (AI), particularly experience-based diagnosis and condition-based maintenance and the study revealed that the development of CBM systems is directed towards the ability to diagnose any abnormalities and to calculate the remaining useful life (RUL) using Artificial Intelligence (AI) techniques. AI encompasses the application of Neural Networks (NN), Case Based Reasoning (CBR), and Fuzzy Logic tools and techniques which are ideally suited to efficiently handle the large amounts of data generated through the processes [8]. An experimental study conducted by considering cutting speed, depth of cut and feed rate as process variables, with and without the application of damping material between the cutting tool and tool holder. A 3k factorial design is used to select the machining parameters and ANOVA to analyze the effect of parameters on performance. Regression equations and a multi layer artificial neural network (ANN) are developed for tangential and axial vibration levels and compared with the experimental findings, which are found to be satisfactory and to be used as alternate technique to predict the vibration level [9]. Considering the development of computer applications in the field of condition monitoring, an experimental investigation has been carried out to develop software allowing the cutting conditions optimization and the process monitoring to prevent any trouble during machining operations. The micro movement of the tool is measured using eddy current sensor during the machining operation with different process parameters and the stability of the tests was confirmed against the surface finish. Determination of stable and unstable condition of the process due to vibration generated in the space region for different width of cut and cutting speed is carried out by using fuzzy classification method based on fuzzy rules [10].

III. Experimental Setup

The experimental study has been carried out on the prediction of surface roughness under various conditions of machining parameters such as cutting speed, depth of cut and feed rate for a plane dry turning operation on lathe. Machining of mild steel specimens under different machining conditions was carried out and the surface roughness was measured. Using this data an ANN model was obtained for predicting the surface roughness for several other machining conditions and experimental values were compared with ANN predicted values which were found to be in good agreement.

Number of trials with selected process parameters of cutting speed (A), feed rate (B) and depth of cut (C) were designed by using L9 Taguchi orthogonal array. Taguchi orthogonal array is an effective technique which has the capability of checking the interaction among the selected parameters. The design of experimental work for the present study resulted in nine trials. Tables 1 and 2 provide the selected parameters and parameters set for each trial respectively.

Table 1 Process parameters for experiments

Range	Cutting speed (A)	Feed rate (B)	depth of cut (C)
	m/min	mm/rev	mm
1	250	0.05	0.50
2	420	0.11	0.75
3	710	0.22	1.00

Table 2: Number of trials for the experimental work as per Taguchi L9 orthogonal array

Trial No.	A	B	C
1	250	0.05	0.50
2	250	0.11	0.75
3	250	0.22	1.00
4	420	0.05	0.75
5	420	0.11	1.00
6	420	0.22	0.50
7	710	0.05	1.00
8	710	0.11	0.50
9	710	0.22	0.75

The experimental work was carried on HMTLT-20 engine lathe with dry run condition using a carbide cutting tool insert for mild steel material. Figure 1 shows the experimental setup.

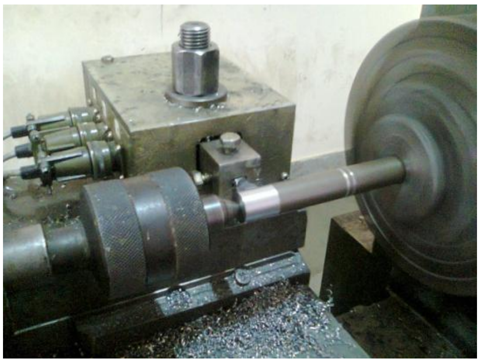

Fig 1: Details of experimental setup

A 20mm diameter mild steel specimen was turned for a length of 40mm in each trial. Surface roughness of turned portion of the work piece was measured using SURFCOM 130A instrument. Table 3gives the measured surface roughness value for each trial.

Table 3: Surface roughness determined experimentally

Trial No.	Surface roughness Microns
1	2.06
2	4.03
3	6.44
4	3.66
5	6.78
6	4.63
7	5.14
8	3.05
9	4.95

IV. Training And Testing Of Ann Model

The experiments were carried out as discussed in the previous section. The set of data from the Tables 2 and 3 were used to train the ANN network. Further, using the same experimental setup, three more trials were conducted for the conditions as in Table 4 for obtaining data to be compared with ANN based prediction of surface roughness

Table 4: Input process parameters for testing trials

Test trial No.	Cutting speed m/min	Feed rate mm/rev	depth of cut mm
1	250	0.22	0.50
2	420	0.11	0.75
3	710	0.11	1.00

The neural network used for obtaining the prediction model consists of three layers, namely input layer, hidden layer and output layer. The number of neurons in the input layer has been set to three depending on number of input process parameters, cutting speed, feed rate and depth of cut. Two neurons were used in the hidden layer by considering the minimum error in the prediction and one neuron was used in the output layer as there is only one output parameter, surface roughness.

V. Results And Discussion

The ANN model network for the present work has been developed with the help of ANN based WEKA machine learning tool. The architecture of the network is as shown in the figure 2. It consists of three inputs, cutting speed, feed rate and depth of cut and one output, surface roughness.

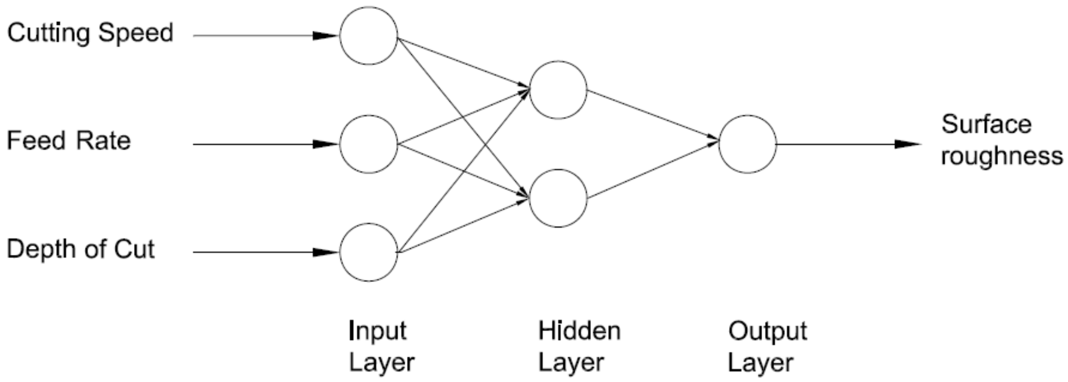

Figure 2: ANN prediction model for surface roughness

The developed ANN prediction model was successfully used to predict the surface roughness for the trials as per Table 4.The surface roughness for the test trials were also measured physically with the help of SURFCOM 130A instrument. Table 5 gives the results in terms of predicted value, measured value and percentage of error for the surface roughness of the specimens.

Table 5: Comparison of measured value and predicted value

Test trial No.	Measured Surface Roughness	Predicted Surface Roughness	Absolute Prediction error(APE)	Accuracy in %	Percentage of Error
	Microns	Microns			
1	3.86	3.65	5.44	94.55	5
2	4.5	4.82	7.11	92.88	-7
3	4.93	5.62	13.99	86	-14

The Absolute Prediction Error is calculated used the below equation,

$$\text{Absolute Prediction Error (APF)} = \frac{\text{Measured Value} - \text{ANN predicted value}}{\text{Measured value}} \text{ X100}$$

Accuracy is used to check the closeness of the predicted and measured value. The accuracy is calculated using below equation.

Accuracy = (1-APE) X 100

VI. Conclusions

The present study of predicting surface roughness using ANN establishes the use of ANN as prediction tool in condition monitoring process as surface roughness is a good indicator of machine health. The development of ANN based prediction models are sure to help industries in establishing a better and efficient method of condition monitoring of machine tools leading to enhancement of its productivity. The present work can extended to include more number of process parameters covering a wider range of machining conditions.

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