PREDICTION OF WORK PIECE HARDNESS USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT:

In a machining operation, the productivity depends on the work-tool combination, speed, feed and depth of cut *etc.* Among the properties of the work-tool materials combination, hardness plays a crucial role in machining. To select the appropriate parameters including the tool material to meet the above objectives, the hardness of the workpiece is to be known. In small and medium scale machining industries the job orders will be of different materials with varying hardness values. This demands an online hardness measuring system. The methodology proposed in this paper is to measure the feed motor current using a current sensor and relate it with the hardness of the material to be machined. This is achieved using a tool with high hardness as a pilot machining tool with standard speed, feed and depth of cut. An artificial neural network (ANN) model has been built to predict hardness using spindle motor current. The ANN has been optimized to predict best possible values and the result of the same has been compared with that of regression analysis.

Key words: Hardness measurement, Cutting parameters, Tool selection, ANN, regression analysis

1.0 INTRODUCTION

The main objective of any manufacturing company includes increase in productivity which can be achieved by reducing machining cost, optimizing machining parameters and by reducing cycle time. To achieve these objectives, a good process planning for machining is rather complex task that requires selection of many different parameters. Once the suitable machining operation and sequence of machining operation is selected, the cutting tool and cutting condition for each of the operation have to be chosen.

The decision parameters for machining operation includes speed, feed, depth of cut, tool geometry, work piece and tool material property. An analysis of any machining process, the tool selection is mainly based on the hardness of the material. Hence the hardness of the material is taken as the important parameter. The hardness of the work differs from component to component for various reasons such as, the method of heat treatment process and presence of hard spots during casting process.

There are instances the operator does not know the exact material for which hardness value cannot be chosen from the database. This demands an online hardness – monitoring unit integrated with the decision support system. Online monitoring of hardness can be effectively done, by measuring feed motor current. As the hardness of the work piece increases, cutting force required for machining is also increases. This cutting force in turn influence the feed motor to draw more current from the supply to maintain its feed rate at a constant rate. This excess current that the feed motor draw from the supply can be calibrated in terms of hardness of the work and a relation can be established between the feed motor current and work piece hardness.

In today's modern manufacturing environment there is an ever increasing demand for cutting tools used in the final stages of manufacturing operations to perform under cost effective cutting conditions and provide high process reliability. This is because any failure due to premature tool breakdown or tool wear can place in jeopardy the already large investment cost in design, labor and materials. The existing tool life improvement methods are discussed below.

Flank wear of the tool is measured and corresponding tool life equation parameters are estimated and optimized for low production cost by utilizing the *Least Square Method* [1]. SUMIBORON PCBN tools are widely used to productivity growth and cost reduction for metalworking. Therefore, the demand for PCBN cutting tools with higher precision performance and longer tool life has increased [2].

The cryogenically treated tool life is higher than the untreated tools at various cutting speeds. [3]. The use of cutting fluid causes economy of tools and it becomes easier to keep tight tolerances and to maintain work piece surface properties without damages. Due to these problems, some of these alternatives are dry machining and machining with minimum quantity lubrication (MQL) [4]. The study of tool life in turning process using the experimental design method is to optimize the various machining parameters by full factorial design, Analysis of variance and Regression analysis [5].

Preheating helps in substantially increasing tool life during end milling Ti-6Al-4V using polycrystalline diamond inserts. Preheating helps in appreciable lowering down the cutting force values during cutting and reducing acceleration amplitude of vibration. [6].

The TiAlN coated drills managed to perform at higher speeds than the TiN coated drills for drilling a type 304 stainless steel work piece material. The TiAlN coated drills showed higher drill life than the TiN coated drills. The tool life for the PVD coated tools was minimum for TiN and maximum for multilayer of TiAlN. Moreover, the thin ~1 micron coating of TiAlN showed significant reduction in tool life compared with thicker TiAlN and multilayer coating. [7].

The proposed research aims to study the feasibility of on-line hardness measurement using current drawing by the machine tool motor after establishing a relation between work piece hardness and current. Later this relation is used to measure the work piece hardness and choose the right tool based on the hardness of the work piece in the chuck. The hardness-current relation for a given cutting condition may be established for commonly used work piece materials like mild steel and cast iron.

2. FEED CURRENT MEASUREMENT

Feed mechanism in a lathe is performed with the help of permanent magnet AC synchronous motor. To sense the feed motor current (I_{rms}), a sensing system is integrated with the turning center. This sensing system consists of three current sensors, which are connected parallel to each phase of the line. The three phase feed motor current I_u , I_v and I_w are measured by three current sensors and passed through a low pass filter. As the used servomotor is AC drive, the AC current is converted into equivalent DC current by finding its root mean square value.

3. EXPERIMENTAL SETUP

The experiment setup consists of feed motor, current sensors and a processor. Current to feed motor is sensed, filtered and converted to equivalent voltage signal. This is to send it to Analog to Digital Converter (ADC), which can read the voltage signal easily. This digital signal is taken as input for hardness measurement.

Figure 1 Digital Clamp Meter

4. PROCEDURE

The standard work-piece is mounted on the machine. Then a single point cutting tool is selected. This single point cutting tool will have a very high hardness capable of machining harder work pieces. This tool is kept as a reference tool for the cutting operation. After the cutting tool is selected, various parameters like feed, speed, depth of

cut are fixed constant and the machining is done. As the tool touches the work, there is a change in current (I_{rms}) value of the feed motor. Then, a pilot cut is given until the current sensor gives a steady signal. This I_{rms} is the induced current during pilot cut using the reference tool. Let, I_o be the air cutting current (*i.e.* current consumed when there is no cutting operation). Now the difference between the two current values is taken as ΔI ($\Delta I = I_{rms} - I_o$). This current is calibrated in terms of hardness of the work piece.

5. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) is modeled on biological neurons and nervous systems. They have the ability to learn, and has the processing elements known as neurons which perform their operations in parallel. ANN's are characterized by their topology, weight vector and activation functions. They have three layers namely an input layer, which receives signals from the external world, a hidden layer, which does the processing of the signals and an output layer, which gives the result back to the external world. Various neural network structures are available.

5.1 Multi-Layer Perceptron (MLP)

This is an important class of neural networks, namely the feed forward networks. Typically, the network consists of a set of input parameters 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 on a layer- by-layer basis.

MLPs have been applied to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. Each neuron in the hidden and output layer consists of an activation function, which is generally a non-linear function like the logistic function, which is given by

$$f(x) = \frac{1}{1 + e^{-x}}, \quad (1)$$

Where $f(x)$ is differentiable and

$$x = \sum_{i=1} W_{ij} \xi_i + \theta_j \quad (2)$$

Where, W_{ij} is the weight vector connecting the i^{th} neuron of the input layer to the j^{th} neuron of the hidden layer, ξ_I is the input vector and θ_j is the threshold of the j^{th} neuron of the hidden layer. Similarly, W_{ij} is the weight vector connecting j^{th} neuron of the hidden layer with the k^{th} neuron of the output layer. i – represents the input layer, j - represents the hidden layer and k -represents the output layer. The weights that are important in predicting the process are unknown. The weights of the network to be trained are initialized to small random values. The choice of value selected obviously affects the rate of convergence. The weights are updated through an iterative learning process known as ‘Error Back Propagation (BP) algorithm’. Error Back Propagation process consists of two passes through the different layers of the network; a forward pass in which input patterns are presented to the input layer 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 if the networks are all fixed. The error value is then calculated, which is the mean square error (MSE) given by

$$E_{tot} = \frac{1}{n} \sum_{n=1}^m E_n \quad (3)$$

$$\text{Where, } E_n = \frac{1}{2} \sum_{k=1}^m (\zeta_k^n - O_k^n)^2$$

Where, m is the number of neurons in the output layer,

ζ_k^n is the k^{th} component of the desired or target output vector and

O_k^n is the k^{th} component of the output vector.

The weights in the links connecting the output and the hidden layer W_{jk} are modified as follows: $\Delta W_{jk} = \eta(-\partial E / \partial W_{jk}) = \eta \delta_j y_j$, where η is the learning rate. Considering the momentum term (α) $\Delta W_{jk} = \alpha \eta \delta_j y_j$ and $W_{jk}^{new} = W_{jk}^{old} + \Delta W_{jk}$. Similarly

the weights in the links connecting the hidden and input layer W_{ji} are modified as follows:

$$\Delta W_{ji} = \alpha \eta \delta_j \xi_i, \quad (4)$$

$$\text{Where, } \delta_j = y_j (1 - y_j) \sum_{k=1}^m \delta_k W_{jk}.$$

$$W_{ij}^{new} = W_{ij}^{old} + \Delta W_{ij} \quad (5)$$

$$\delta_k = (\xi_k - O_k) O_k (1 - O_k) \quad \text{For output neurons and} \quad (6)$$

$$\delta_j = y_j (1 - y_j) \sum_{k=1}^m \delta_k W_{jk} \quad \text{For hidden neurons.} \quad (7)$$

The training process is carried out until the total error reaches an acceptable level (threshold). If $E_{tot} < E_{min}$ the training process is stopped and the final weights are stored, which is used in the testing phase for determining the performance of the developed network. The training mode adopted was ‘batch mode’, where weight updating was performed after the presentation of all training examples that constitutes an epoch [8, 9, and 10].

6. LINEAR REGRESSION ANALYSIS

Linear regression analysis is a statistical technique that identifies the relationship between two or more quantitative variables: a dependent variable, whose value is to be predicted, and an independent or explanatory variable (or variables), about which knowledge is available. The technique is used to find the equation that represents the relationship between the variables. A simple linear regression analysis can show that the relation between an independent variable X and a dependent variable Y is linear, using the simple linear regression equation $Y = a + bX$ (where a and b are constants). Multiple regression will provide an equation that predicts one variable from two or more independent variables, $Y = a + bX_1 + cX_2 + dX_3$.

Linear regression analysis is used to understand the statistical dependence of one variable on other variables. The technique can show what proportion of variance between variables is due to the dependent variable, and what proportion is due to the independent variables. The relation between the variables can be illustrated graphically, or more usually using an equation.

This statistical technique is most commonly used in programme evaluation to estimate effects. The net effects of the programme under evaluation can be assessed using regression analysis, by attributing part of the changes observed to explanatory variables, while the remaining effects are attributed to the programme. For this reason, regression analysis is useful in ex-post evaluation, to determine the net impact of the

programme. However, this technique can also be applied in forecasting and ex-ante evaluation.

6.1 Main steps involved

The application of a linear regression analysis is rooted in an initial credible explanatory model. A sound model can only be applied where the effects of the intervention are well identified and where the production process of the effects is understood.

The main steps involved in performing a linear regression analysis are reviewed in

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Box 1: Main steps involved in performing a linear regression analysis

Step 1 Construction of the causal model

The construction of an explanatory model is a crucial step in the linear regression analysis. It must be defined with reference to the action theory of the intervention. It is

likely that several kinds of variable exist. In some cases, they may be specially created, for example to take account of the fact that an individual has benefited from support or not (a dummy variable, taking values 0 or 1). A variable may also represent an observable characteristic or an unobservable one. The model may presume that a particular variable evolves in a linear, logarithmic, exponential or other way. All the explanatory models are constructed on the basis of a model, such as the following, for linear regression:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon, \text{ where}$$

Y is the change that the programme is mainly supposed to produce

X_{1-k} are independent variables likely to explain the change.

β_{0-k} are constants, and

ε is the error term

Step 2 Construction of a sample

To apply multiple regressions, a large sample is usually required. Note that for time series data, much less is needed. The numbers of samples depend on the complexity of the problem.

Step 3 Data collection

Reliable data must be collected, either from a monitoring system, from a questionnaire survey or from a combination of both. Here, the current data are collected from monitoring system.

Step 4 Calculation of coefficients

Coefficients can be calculated relatively easily, using statistical software that is both affordable and accessible to PC users. In this study, MS – Excel Add – on and Weka are used for analyzing the data.

Step 5 Test of the model

The model aims to explain as much of the variability of the observed changes as possible. To check how useful a linear regression equation is, tests can be performed on the square of the correlation coefficient ' r '. This tells us what percentage of the variability in the y variable can be explained by the x variable. A correlation coefficient of 0.9 would show that 81% of the variability in Y is captured by the variables X_{1-k} used

in the equation. The part that remains unexplained represents the residue (ε). Thus, the smaller the residue, the better the quality of the model and its adjustment. The analysis of residues is a very important step: it is at this stage that one sees the degree to which the model has been adapted to the phenomena one wants to explain. It is the residue analysis that also enables one to tell whether the tool has made it possible to estimate the effects in a plausible way or not. If significant anomalies are detected, the linear regression model should not be used to estimate effects, and the original causal model should be re-examined, to see if further predictive variables can be introduced.

Step 6: Generalization to the total population

The purpose of this last phase is to generalize the coefficients of the model to the population as a whole. It is therefore used to produce an estimation of the effects [11, 12, 13 and 14].

7. RESULTS AND DISCUSSION

The experiments were conducted on lathe. First, work pieces of different hardness were taken. Then, a tool of higher hardness was selected for pilot cut. Parameters like, feed (0.5mm/rev), cutting speed (480rpm) and the depth of cut (1mm) were constantly maintained. To the three-phase supply a current sensor was attached. Then a pilot cut was given and the change in current was measured and tabulated. This procedure was repeated for the various hardness material and corresponding readings were tabulated and current vs hardness graph was plotted in Figure 6.

For training the ANN motor feed current was taken as input value and the corresponding hardness value of the work piece was taken as target. The ANN was first trained with one hidden layer and the number of neurons was varied from 1 to 10 by keeping all other network parameters at their default values. Fortunately the ANN converged in one hidden layer itself. When the number of neurons in the hidden layer is five as shown in Figure 2 the RMS error is minimum. Hence the number of neurons in the hidden layer was taken as five. This value was maintained constant for rest of the training process.

Next, Learning rate was fixed as follows. The learning was varied from '1' to '0' in steps of point one and the RMS error and number of epochs were noted down. The

variation of RMS error and number of epochs with respect to learning rate was shown in Figure 3 & 4. Referring to these figures, one has to choose learning rate such that the RMS error and the number of epochs are minimum. This condition happens when the learning rate is at '1'. Hence, the learning rate is chosen as '1' and for the rest of the study it is maintained constant.

Figure 3 Learning rate Vs RMS error

Figure 4 Learning rate Vs Training Epochs

Figure 5 Moment Vs RMS Error

Figure 6 Moment Vs Training epochs

Next, momentum was fixed as follows. The momentum was varied from '1' to '0' in steps of point one and the RMS error and number of epochs were noted down. The variation of RMS error and number of epochs with respect to momentum was shown in Figure 5 & 6. Referring to these figures, one has to choose momentum such that the RMS

error and the number of epochs are minimum. This condition happens when the momentum is at '1'. Hence, the momentum is chosen as '1' and for the rest of the study it is maintained constant. Thus, The neural network model definitions and model architecture is as follows:

Network type	: Feed Forward Back Propagation
Transfer function	: Sigmoid transfer function
No. of nodes in input layer	3
No. of hidden layers	1
No. of neurons in hidden layer	5
No. of neurons in Output layer	1
Training rule	: Back propagation
Training tolerance	: 0.1
Learning rule	: Momentum learning method
Momentum learning step size	: 0.1
Momentum learning rate	: 0.9
No. of epochs	187
RMS Error	: 0.0352
Training termination	: Minimum mean square error

With the available exprement data, a regression model was built for predicting the hardness value for a given motor feed current. The regression equation is given under

$$Current = 0.0098xRC + 1.1824$$

The results of regression analysis were sumeraised and shown in table 1. Please note that the RMS error of regression analysis was 0.0208. Comparing this to that of ANN RMS error values, one may be tempted to think that linear regression analysis method is superior. However, the ANN model predics the hardness value much better than the linear regression analysis method. This is because of the inherrunt truth that the relationship between the hardness and the feed motor current is non-linear and the ANN models non-linear phenomina better. It is evident from the Figure 8 that the current Vs hardness graph for ANN model is non-linear and that of regression analysis was linear. The result is further reinforced by the predicted values of ANN model.

Table 1

Paraeters	Linear regression analysis method
Correlation coefficient	0.958
Mean absolute error	0.0151
Root mean squared error	0.0208
Relative absolute error	22.5573 %
Root elative squared error	25.1159 %
Total number of instances	8

Figure 7 Hardness Vs Current

Figure 8 Current Vs Hardness by Regression Analysis and ANN Model

8. CONCLUSION

A real time hardness measurement system is proposed, using feed motor current sensing system. The functional dependence of feed cutting current on hardness of the material has been analyzed and expressed in the form of calibrated graph which relates the feed motor current to hardness of the material. By comparing feed motor current with hardness, the measurement is taken. A Neural network model and regression model were built and the results were compared. From the results and discussion above, one can confidently conclude that ANN is better suited for prediction of hardness using motor feed current. This method is, in principle capable of being adapted for wide range of cutting condition, work piece and tool material.

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