PRODUCTION OF CUTTING TOOL VIBRATION IN TURNING USING ARTIFICIAL NEURAL NETWORK

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Abstract: - The cutting parameters like cutting speed, feed, and depth of cut can affect the tool life. Also, the vibration of the tool can affect the tool life. The aim of this study is to predict the cutting tool vibration to enhance the tool life. In this paper, vibration of tool is studied with HSS tool (high speed steel) while turning mild steel. The tool vibration is measured using X Viber vibration meter. The experimental data are tabulated and imported to artificial neural network (ANN). A multilayer perceptron model is trained with back-propagation algorithm using the experimental data. The rake angle, cutting speed, and feed are considered as input parameters for training the ANN. The trained ANN is used to predict tool vibration for different conditions. The predicted values are compared for the specific range to justify the tool change.

Keywords: Machine learning, vibration, neural network

1. Introduction
Tool life is the volume of material removed by a machining tool during its total usage span. The volume may be in cubic mm or cubic cm measured at a standard cutting speed. The most dominant factors affecting tool life are work material, tool material, cutting speed and tool shape chosen for a particular machining operation. But the other machining parameters have also been found to have a secondary effect on the tool life. During the process of shearing the metal, high temperatures are generated at the tool cutting edge region, and these temperatures are found to have a controlling influence on the rate of wear of the cutting tool and on the friction between the chip and tool. Tooling cost is an important factor which should be reduced in order to keep the manufacturing cost to bare minimum. Tool failure can be identified by observing the following factors namely, higher power consumption, poor surface finish, dimensional inaccuracy of the machined material, appearance of a burnishing band on machined surface, tool or work piece vibration, among others. The vibration of machine tools during cutting, affects certain parameters such as surface finish of the workpiece, life of the cutting tool, positioning accuracy of slides, life of machine tool parts particularly transmission elements, removal rate of the material, appearance of chatter marks and errors in dimension and form. The vibration occurring in a machine tool may be classified as follows
I. Free vibration induced by a sudden variation in the cutting force due to change in feed or depth of cut (resulting from variation in machining allowance, blow holes, hard spot or entry of tool into the work piece).
II. Self-excited vibration or chatter due to the interaction of cutting process and machine tool dynamics.
III. Stick-slip motion of the sideways at low sliding speeds.
IV. Forced vibrations due to the periodic forces caused by cutting process, unbalance or defects in transmission system elements like, motor rotors, gears, pulleys, bearings, work pieces and rotating fixtures, etc.

2. Literature review
Anurag Naidu and Sanjay Asati [1], reported a remedial idea to increase production rate by improving the tool life. They developed a system to measure the accuracy and surface finish of the work part. The system could also measure the vibrations generated due to variations in cutting parameters using...
the intelligent systems. Balla Srinivasa Prasad, et.al [2], reported that the tool vibration and wear condition had a direct effect on the tool failure and decreased the life of tool. So, they found a relationship between the tool vibrations and wear properties of tool by using laser Doppler vibrometer. The tool was provided with carbide coatings so that it could improve its wear resistant properties. Chang Tseng [3], explained that during milling process, the work piece and surface roughness was affected by the tool vibration and its wearing properties. The vibration was measured by four accelerometers joined to the tool and the parameter used to derive a relationship with surface roughness was the MSE of the signal. The tool was provided with carbide coatings to improve its wear resistant properties. Future research would be directed towards active control for decreasing vibration in the process. Filippov, et.al [4], had stated that the tool life was affected by the tool vibration. So, they measured the tool vibration using acoustic emission monitoring system to choose the perfect tool material according to the machining materials. Gouarir, et.al [5], had investigated that the tool wear could account directly for tool life failure. So, they devised a tool wear prediction system, which used a force sensor and machine learning (ML) algorithm to monitor the progression of the tool flank wear. More specifically, a convolutional Neural Network (CNN) was used as a method to predict tool wear. By controlling the tool wear, tool life was improved and this could further be enhanced by selecting proper cutting tool parameters. Krishna kumara, et.al [6], reported that the tool wear affects the tool life. During the machining process, vibration signals were monitored continuously using an accelerometer. The features from the signal were extracted and a set of prominent features were selected using Dimensionality Reduction Technique. Experimental observations indicated that the tool life would decrease with cutting speed, feed rate, depth of cut and material hardness. Using the right tool in the right cutting condition in order to reduce tool wear and fracture, increase machining accuracy and to increase tool life and productivity was very significantly evident. Marcelo Mendes de Aguiar, et.al [7], delineated a problem that the surface finish of the workpiece was affected by the tool vibration and tool wear properties. So, they intended to enhance the surface finish of the work piece by reducing the tool vibration. Milling operations were performed on AISI materials with different hardnesses and the cutting parameters were measured using FRF setup (Frequency Response Function). The workpiece surface finish was determined by cutting parameters namely tool vibration, depth of cut, feed, etc. Nexhat Qehaja, et.al [8], have promulgated that the tool life was dependent on the cutting parameters. So, they constructed a prediction model for a first order tool during turning of hardened 42CrMo4 steel at different levels of hardnesses. Experimental observations indicated that tool life will decrease with feed rate, depth of cut cutting speed, and material hardness. Outeiro, et.al [9], outlined that the tool vibration enhances with increase in temperature. So, they measured the residual stress produced by the tool vibration using neutron diffraction. Controlling the tool vibration disguisedly meant controlling the temperature of the machining process. Sam Paul, et.al [10], had asserted that the presence tool vibrations lead to a poor surface finish, which ultimately resulted in a damaged cutting tool and the production of an irritable and unacceptable noise. Experimental observations indicated that the tool life would decrease with cutting speed, feed rate, depth of cut and material hardness. Siamak Ghorban, et.al [11], had deduced a relationship between tool vibration and tool life. Static and dynamic characteristics of cutting tools at different machining conditions were analyzed for different cutting tools. Changes in cutting parameters would drastically improve the cutting tool life. Venkata Rao, et.al [12], proved that tool wear affects the tool life. The tool wear and work piece vibrations were recorded by means of a laser vibrometer and surface roughness of work piece was also monitored. The tool will be changed when the particular wear condition occurs, which was found by the neural network software. Xu Chuangwen, et.al [13], had identified that tool wear and milling depth significantly affected the cutting force and vibration. So, they recorded the cutting force and vibration acceleration signals with which the wear depth on the flank face of the tool was measured. This study observed a tool wear morphology using a scanning electron microscope and investigated the distributions of surface elements on the damaged tools by energy spectrum analysis. The tool and workpiece surfaces were affected by the cutting parameters and this could be considerably avoided by providing proper coating on the tool surface.

The above studies help to conclude that artificial neural network had been used to predict the tool life or tool wear only with respect to machining parameters. The perdition of tool vibration with respect to tool geometry and machining parameter is not addressed. Thus, this paper considers the different
combination of cutting speed, feed, and depth of cut, rake angle and its tool vibration. The aim of this study is to predict the optimal cutting tool vibration at different cutting parameter combinations to enhance the tool life.

The rest of the paper is structured as follows: Section 2 describes the experimental setup, experimental procedure and our observation. Section 3 gives a description of the ANN’s structure, results obtained from ANN and the actual vibration values. Section 4 discusses about the validation of the ANN. Finally, the conclusion is discussed in the last section.

3. Experimental details
The single point ¼ inch cutting tool material is grinded to various rake angles such as 7°, 8°, 9°, 10° and 11°s. The other tool nomenclatures are side rake angle 8°, end clearance angle 6°, side clearance angle 6°, end cutting edge angle 6°, side cutting edge angle 8° and nose radius 1 mm. The machining parameter cutting speed 30 m/min and feed 0.275 mm is selected. The mild steel round rod specimen having 25 mm diameter workpiece is loaded on to the lathe machine. The transducer of X-viber is placed above the tool post and tool vibrations were analyzed for all the above rake angles. Then the experimental data is collected and imported to the neural network to predict the tool vibration error for turning operation with mild steel as the work piece and high-speed steel as the tool material. Then, the results are analyzed and concluded. Figure 1 and 2 shows the tool before machining and after machining and Figure 3 depicts the tools with various rake angles.

4. Results
The tool vibrations are analysed for tools with different rake angles and at constant a depth of 0.25mm. Tables 1 to 5 gives us the vibration values for tools with rake angles 7, 8, 9, 10 and 11 respectively.
4.1 Artificial neural network
Artificial neural networks are also known as neural nets, artificial neural system, parallel distributed processing system and connectionist system. The network is commonly referred to as a directed graph having a set of nodes (vertices) and a set of connections (edges/links/arcs) between nodes.

Each node contributes functions like simple computation and each connection transfers information or signal between nodes. The connections between two nodes are labeled with a number called as connection strength or weight. The weight represents, to what extent the signal is to be amplified or diminished by the connection. A network with single or fewer numbers of nodes cannot solve all the problems. Henceforth, networks which are constructed with large numbers of nodes are used to solve complex problems. Some types of the neural networks are fully connected networks, layered networks, acyclic networks, feed forward networks and modular networks. Figure 4 and 5 shows the architecture of an artificial neural network.

4.2 Actual tool vibration
The X-viber apparatus was used to measure the exact tool vibration of the cutting tools with different rake angles, cutting speeds and feeds. Table 1 gives the values of actual tool vibration values at rake angle 7° at different cutting speeds and feeds.

| Rake Angle (°) | Cutting Speed (m/min) | Feed (mm/rev) | Tool Vibration (mm/sec) |
|---------------|-----------------------|--------------|------------------------|
| 7             | 15.7                  | 0.336        | 1.701                  |
|               | 23.5                  | 0.319        | 1.233                  |
|               | 37.6                  | 0.290        | 1.345                  |
|               | 56.5                  | 0.227        | 1.684                  |
Table 2 gives the values of actual tool vibration values at rake angle 8° at different cutting speeds and feeds.

Table 2. Tool vibration values at 8° rake angle

| Rake Angle (°) | Cutting Speed (m/min) | Feed (mm/rev) | Tool Vibration (mm/sec) |
|---------------|------------------------|---------------|-------------------------|
| 8             | 15.7                   | 0.336         | 1.047                   |
|               | 23.5                   | 0.319         | 1.585                   |
|               | 37.6                   | 0.290         | 1.706                   |
|               | 56.5                   | 0.227         | 1.606                   |

Table 3 gives the values of actual tool vibration values at rake angle 9° at different cutting speeds and feeds.

Table 3. Tool vibration values at 9° rake angle

| Rake Angle (°) | Cutting Speed (m/min) | Feed (mm/rev) | Tool Vibration (mm/sec) |
|---------------|------------------------|---------------|-------------------------|
| 9             | 15.7                   | 0.336         | 1.114                   |
|               | 23.5                   | 0.319         | 1.631                   |
|               | 37.6                   | 0.290         | 1.788                   |
|               | 56.5                   | 0.227         | 1.746                   |

Table 4 gives the values of actual tool vibration values at rake angle 10° at different cutting speeds and feeds.

Table 4. Tool vibration values at 10° rake angle

| Rake Angle (°) | Cutting Speed (m/min) | Feed (mm/rev) | Tool Vibration (mm/sec) |
|---------------|------------------------|---------------|-------------------------|
| 10            | 15.7                   | 0.336         | 1.023                   |
|               | 23.5                   | 0.319         | 1.232                   |
|               | 37.6                   | 0.290         | 1.562                   |
|               | 56.5                   | 0.227         | 1.458                   |

Table 5 gives the values of actual tool vibration values at rake angle 11° at different cutting speeds and feeds.

Table 5. Tool vibration values at 11° rake angle

| Rake Angle (°) | Cutting Speed (m/min) | Feed (mm/rev) | Tool Vibration (mm/sec) |
|---------------|------------------------|---------------|-------------------------|
| 11            | 15.7                   | 0.336         | 1.154                   |
|               | 23.5                   | 0.319         | 1.212                   |
|               | 37.6                   | 0.290         | 1.380                   |
|               | 56.5                   | 0.227         | 1.554                   |

4.3 Predicted tool vibration

The neural network model was used to predict the tool vibration values. Table 6 delineates the values of tool vibration at different rake angles, speeds and feeds. It can be observed that the predicted values closely match with the actual vibration values in most cases.
Table 6. Predicted Values For 7° 8° 9° 10° and 11° rake angles

| Rake Angle (°) | Cutting Speed (m/min) | Feed (mm/rev) | Predicted Tool Vibration (mm/sec) |
|----------------|-----------------------|---------------|-----------------------------------|
| 7              | 15.7                  | 0.336         | 1.5063                            |
| 8              | 23.5                  | 0.319         | 1.0721                            |
| 9              | 37.6                  | 0.290         | 1.3477                            |
| 10             | 56.5                  | 0.227         | 1.6842                            |
| 11             |                       |               |                                   |
|                |                       |               | 1.0481                            |
|                |                       |               | 1.5655                            |
|                |                       |               | 1.7064                            |
|                |                       |               | 1.5642                            |
|                |                       |               | 1.6458                            |

5. Discussion

A feed-forward four layered neural networks is constructed. The network is constructed with four layers namely input layer, output layer and two hidden layers. Each hidden layer consists of 5 nodes. The ANN with one hidden layer gives errors significantly high. Hence two-layer network is considered. The input neurons are cutting speed, feed and rake angle and output neuron is tool vibration. Neurons in the hidden layers are determined by examining different neural networks. MATLAB software is used for training on this network and the ANN is trained using front propagation algorithm.

The neural network is trained with 14 samples, validated for 3 samples and tested for 3 samples. Percentage of error between experimental values and predicted values for the tool vibration is calculated. Mean error percentage is found as 3.454% for amplitude of tool vibration. From the results, it can be inferred that the proposed network model is capable of predicting the values of tool vibration. It also helps in the selection of cutting parameters to achieve good surface quality and also predicts the correct time for tool change.

5.1 Validation of ANN for prediction of tool vibration

The validation of ANN is done with rake angle 6° which is not a trained value. Table 7 shows the experimental and predicted values for rake angle 6°. Here the ANN gives a predicted tool vibration for particular rake angle (6°), cutting speed and feed. The experimental value for this rake angle is close to the predicted values and which is shown in Figure 6. The mean error percentage was calculated.

Table 7. Predicted Value For 6°

| Rake Angle (°) | Cutting Speed (m/min) | Feed (mm/rev) | Tool Vibration (mm/sec) | Predicted Tool Vibration (mm/sec) | Error |
|----------------|-----------------------|---------------|-------------------------|-----------------------------------|-------|
| 6              | 15.7                  | 0.33          | 1.201                   | 1.108                             | 0.077 |
|                | 23.5                  | 0.31          | 1.633                   | 1.741                             | 0.066 |
|                | 37.6                  | 0.29          | 1.541                   | 1.640                             | 0.062 |
|                | 56.5                  | 0.22          | 1.871                   | 1.781                             | 0.048 |
|                |                       |               |                         | Error                              | 0.064 |
6. Conclusion

In this work, five experiments were conducted according to a proposed experiment with four levels of cutting parameters such as cutting speed, feed etc., A neural network (3-5-5-1) was used to learn the collected experimental data. The ANN is trained with 14 examples, validated with 3 examples and then tested with 3 examples.

The trained ANN is used to predict the tool vibration. It was found that there is an agreement between experimental data and predicted values for tool vibration (3.454% of error). In that case, it is possible to change the cutting tool at the correct time in order to get a good quality of products. This neural network could help us to predict tool vibration and reduce surface roughness of the work piece.

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