A simple online tool condition monitoring system using artificial neural networks

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Abstract. During machining occurrence of tool wear is a common phenomenon. As tool wear increases, rubbing of flank surface and workpiece also gets increased. Then, the desired quality of workpiece is not possible to achieve. To minimize this loss of quality, a cutting tool should be changed or ground after reaching certain amount of average flank wear (0.3 mm for uniform and 0.6 mm or non-uniform flank wear). For the detection of worn out state of a cutting tool, condition monitoring is required. During past decades, a lot of research works had been done on both offline and online monitoring of cutting tool. Most of the researchers used high cost setups and sensors for wear detection purpose. In this work, tool wear is detected using spindle speed as the wear detection parameter. Artificial Neural Networks is used as data analysing tool. Back propagation algorithm is used as learning algorithm. Results show that proposed methodology is capable to detect tool wear satisfactorily.

Keywords: machining, turning, online, tool condition monitoring, tool wear, spindle speed, artificial neural networks, ANN, NN.

1. Introduction

In a conventional machining process, there is a physical contact between a workpiece and a cutting tool. Due to this contact, cutting tools have to withstand rubbing action, high stresses and high temperature gradient at the work-tool interface. As a result, wearing of cutting edges occurs, or, there may be a chance of catastrophic failure of cutting tool. If cutting tool wear exceeds a limit during production of job, there will be a chance of degradation in quality of product. That is why tool condition needs be monitored. Another reason of monitoring the condition of tool is that the Risk Priority Number (RPN) of cutting tool is high comparatively to other component of a typical machining setup [1]. RPN = O x S x D, where O = Occurrence of failure, S = Severity of failure, D = Detectability. According to Failure Modes, Effects and Criticality Analysis (FMECA), tool condition should be monitored [2] continuously. Tool condition can be monitored in two ways, either online, or offline. Online monitoring consumes more time, but in online monitoring, real time values of tool wear can be obtained. In offline monitoring, usually direct measurement of tool wear is done. Reduction in dimensions of tool after being worn out is considered. For this, premature failure of cutting edge cannot be detected. To reduce these limitations, online monitoring systems, commonly using some indirect techniques, are developed. Researchers, however, reported [3] direct methods to be more accurate than indirect ones. While gathering online data or signals, there may be disturbances which can distort original signals though there were many filters used for minimizing those disturbances.

According to literature [4], some parameters like cutting force, acoustic emission, machine tool vibration, motor current and spindle power had taken a lion’s share in online tool wear detection. Ghani et al. [5] used a strain gauge type dynamometer for measuring of triaxial cutting forces. This work seemed to be very effective because the error in real time value from measured value varied from 5.91 to 16
percent only. A neural networks based monitoring of coated carbide tool was tried by Daset al. [6, 7] during turning of medium carbon steel using the strategy of sensor fusion. A three-axis cutting force dynamometer and a piezoelectric accelerometer were used for measuring of cutting forces and vibration signals coming out from machine tool while machining. Authors used back propagation neural networks to detect tool wear. Bhuiyan et al. developed [8] a monitoring system to detect plastic deformation during occurring of tool wear. For this, authors used an acoustic emission sensor and collected signals during machining of different frequencies to find out the characteristic signal corresponding to tool wearing. A case study [9] for detection of tool wear had been done by Shen et al. by sensing power signal of spindle and extracted the characteristic feature. Hilbert-Huang transformation tool was used to process the data taken from experiments. On the other hand, a monitoring system to detect tool wear in end milling cutter was developed by Karandikar et al. [10]. Cutting forces at different rotations of spindle were taken as extracted features. Rao et al. [11] reported nose radius to play a significant role during regression analysis of experimental data, and it had a correlation coefficient of 0.4581 against tool wear value. Axinte et al. developed a system using input spindle power signal. Experiments were done by both intermittent, i.e. milling, and continuous cutting operation such as drilling and turning. Das et al. used the Analytical Hierarchy Process (AHP) [12,13] to identify the states of tool condition in a simple way. According to Swain et al., adaptive system [14] is quite helpful as industries are dependent on mostly automated systems. For this type of system, authors mentioned sensors to have played a key role. Cai et al. did experiments on hybrid model [15] based on long short-term memory-based network for tool wear detection, which resulted in ‘outstanding’ performance, especially when operating conditions were varying. In a review, Ostasevicius [16] stated that during industrial revolution (IR 4.0), wireless sensor communication along with internet of things (IOT) made condition monitoring easy comparatively. Denkena et al. [17] reported about non sensitive feature selection for risk minimization in condition monitoring.

From literature, it can be said that, established methods for tool condition monitoring till date are quite costly in general. So, aim of this project is to explore online monitoring of tool wear by different means with a low-cost setup. Using low cost sensors and software with a graphical user interface (GUI), a monitoring system is tried to be developed in this work. Tool wear value can be determined as real time value by sensing rotational speed of spindle as the parameter to detect wear.

2. Cause of choosing RPM as wear detection parameter

Machine tool used in this work is an NH22 HMT lathe. Main power drive of this machine tool relates to a three-phase induction motor. In this motor, slip percentage, $S = \frac{100(N_s-N_R)}{N_s}$, where $N_s$ = Synchronous speed, $N_R$ = Rotor speed. According to Figure 1, as torque changes there is a change in slip percentage. For all rotating machines, synchronous speed is almost constant. So, slip changes because of change in rotor speed. If rotor speed increases, slip will decrease and vice-versa. It can be stated that if torque changes, there should be a change in rotational speed of the machine. If load changes, torque is also changed. During turning, when there is large value of tool wear, load on the motor will be increased. Thus, there will be an increase in torque as well as slip of motor. If slip changes, RPM of rotor fluctuates. So, using the values of fluctuated rotational speed (RPM), tool wear can be detected. That is why RPM is selected as a parameter to detect wear by online condition monitoring.

![Figure 1. Torque-slip characteristics of a three-phase induction motor [18]](image-url)
3. Experimental procedure

Experiments are performed on turning on AISI 1045 alloy steel rod as the workpiece and uncoated single carbide (SNUN 120408- P30) as the cutting tool. Total twenty-four experiments are performed on HMT lathe (NH22). RPM values are measured using infrared (IR) sensors and Arduino board. Also, an Arduino based data acquisition system is developed using LABVIEW software to get the real time values of RPM in excel sheet. Skewness values are extracted from each set of data. Before and after each experiment, tool wear values are taken. Gradual increment of tool wear is shown in Figure 2, 3 and 4 respectively.

During the trial tests of this work, long cylindrical bar has been taken. However, fluctuation of rpm has not been detected well. This is likely to be due to lack of stiffness along the cylindrical bar. A cylindrical bar is quite stiff at the headstock end and stiffness becomes the least in the middle portion of the bar close to the tailstock. Hence, variation of torque due to stiffness is considered to be a problem to the measurement of rpm. For this, short length of bar of 130 mm is taken for the experiment.

After getting tool wear values, those are processed through Neural Networks toolbox in MATLAB. Back propagation algorithm is used to train the data set. Feed forward algorithm is used to change the weights of the network to get the desired output. This process is continued until error between network output and original output becomes too less. At the end of this process, the final neural network is obtained. Using the obtained neural networks, tool wear can well be estimated. After training, some inputs other than training data set are given and the neural networks gives estimation of tool wear value. Error is calculated between NN output and the measured tool wear value. In this way, the proposed method is found working satisfactorily.

4. Experimental data and results

Input and output parameters are written in tabular form. \( V_c \) = Cutting velocity in m/min, \( S_o \) = Feed in mm/rev, \( t \) = Depth of cut in mm, \( W_a \) = Average auxiliary flank wear value in micron, \( W_p \) = Average flank wear value in micron, where \( V_c \), \( S_o \), \( t \) and skewness are the input parameters to the network. \( W_a \) and \( W_p \) are the output of the network whose structure is 4-32-16-2. Tan sigmoid function has been used as the activation function. Total 58 iterations were done to reach minimum error.

After this, this data is organised in three sections as low wear section, medium wear section and high wear section. Table 1 contains data for low wear section for constructing the network. After training the neural network with this set of data, NN estimated Output becomes equal to 0.99 * Target + 0.15, when Target is the measured wear value. During testing stage, NN estimated Output becomes 1.8 * Target - 44. On the whole, NN Output = 1.1 * Target - 3.7 considering both training and testing datasets.

Bar diagram (Figure 5) has been made with few experimental wear values (auxiliary flank wear (column 1 and 2) and principal flank wear (column 3 and 4) of the last two data sets) to compare them with NN output. In the legend, Series1 denotes the NN estimates and Series 2 indicates measured values of average flank wear during experiment.

| \( V_c \) | 95 | 95 | 92 | 89 | 89 | 89 | 86 | 84 | 84 |
| \( S_o \) | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| \( t \) | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |

Table 1. Data for low wear section
| Skewness       | -0.1801 | -0.1801 | 0.0153 | 0.0152 | 0.0525 | 0.2726 | 0.3572 | 0.1178 | -0.3382 | 0.0741 | -0.0078 | 0.0398 | -0.1292 |
|---------------|---------|---------|--------|--------|--------|--------|--------|--------|---------|--------|---------|--------|---------|
| $W_a$         | 95.112  | 27.67   | 28.22  | 35.343 | 36.39  | 37.2   | 44.67  | 51.427 | 59.087  |        |         |        |         |
| $W_p$         | 38.267  | 42.37   | 27     | 52.7167| 55.429 | 60.4067| 62     | 62.25  | 76.7    |        |         |        |         |

Table 2. Data for medium wear section

| $V_c$         | 95      | 95      | 92     | 89     | 86     | 84    |
| $S_o$         | 0.04    | 0.04    | 0.04   | 0.04   | 0.04   | 0.04  |
| $t$           | 2       | 2       | 2      | 2      | 2      | 2    |
| Skewness      | -0.1801 | -0.1801 | 0.0087 | -0.0844 | -0.0486 | 0.1485 |
| $W_a$         | 76.15   | 76.15   | 82.467 | 87.34  | 90.52  | 108   |
| $W_p$         | 86.86   | 86.86   | 100.8  | 129.61 | 131.33 | 132.67 |

Table 3. Data for high wear section

| $V_c$         | 95      | 95      | 95     | 92     | 89     | 86     | 86     | 84     | 84     |
| $S_o$         | 0.04    | 0.04    | 0.04   | 0.04   | 0.04   | 0.04   | 0.04   | 0.04   | 0.04   |
| $t$           | 2       | 2       | 2      | 2      | 2      | 2      | 2      | 2      | 2      |
| Skewness      | 0.0153  | 0.0152  | 0.0525 | 0.2726 | 0.3572 | 0.1178 | -0.3382 | 0.0741 | -0.0078 | 0.0398 | -0.1292 |
| $W_a$         | 113.811 | 113.81  | 157.01 | 114.76 | 119.36 | 183   | 137    | 193.153| 146.79 |
| $W_p$         | 143.52  | 143.52  | 206.86 | 146.69 | 215.83 | 147.51 | 238.83 | 156.51 | 273.183|

Figure 5. Bar diagram of comparison of low wear test

Table 2 shows data for medium wear section. Regression equation of the neural network corresponding to all the training and testing data sets is: Output = 1*Target - 8.2*10^{-15}. Figure 6 shows the typical comparison between experimentally measured wear values and NN predicted values of few data (auxiliary flank wear (column 1 and 2) and principal flank wear (column 3 and 4) of the last two data sets). In the legend, Series1 denotes the predicted values by NN networks and Series2 gives measured values of wear during experimentation.

Figure 6. Bar diagram of comparison of medium wear test

Table 3 shows the data set for high wear section to form the neural networks. For training, NN estimated Output = (1*Target + 0.66). With the testing data, the NN Output becomes (0.8*Target + 1.9). Overall, with training and testing stage data, neural networks estimated Output = 0.96*Target + 1.7. Figure 7 shows comparison between two sets of experimental wear (auxiliary flank wear and principal flank wear of 1st and 3rd column data given in Table 3) values and NN estimated values. In the legend, Series1 denotes the NN output and Series2 denotes measured values of average flank wear during experiment.
As the results show, deviation in estimated value by neural networks from the measured value increases in high wear cases. This may be due to some causes to explain. As flank wear is increasing, contact of tool with work piece will get increased. So, variation of torque is not the same as occurred for low wear sections. This may be an important cause for high fluctuation at high wear region. Kaya et al. [19] reported the variation of torque and force to be higher with high tool wear. This was concluded for a milling process where an artificial neural network was employed. As shown in experimented data, depth of cut and feed are constant throughout the experiment. Cutting velocity is not given a wide variety, but one can see that skewness extracted from RPM values has a wide variation. So, this can be a key feature for wear detection, where cutting tool is in rotating condition such as grinding, milling, drilling, etc. Again, this newly designed tool condition monitoring setup costs quite less than the equipment used by previous researchers, and hence, may be employed at any small and medium scale industries.

5. Conclusion

Tool wear is successfully estimated with a low deviation with the proposed system. The setup is of quite low cost compared to that proposed by the previous researchers, and it is easy to connect the setup with a machine tool. Signals coming from the sensor used may have some disturbances that can be filtered out to reduce the error in output. In this work low-cost sensor is used, but one can also use high cost available sensor. At last, it can be stated that the proposed methodology can easily be implemented as the system developed is able to estimate flank wear with quite good accuracy.

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