An approach to determine condition of boring tool using acoustic & vibration signals

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Abstract: The work presented in the paper focuses on an approach for automatic system to determine boring tool condition, using acoustic signatures. This acoustic signal based tool wear prediction system removes the need for manual inspection of the tool cutting edges and minimizes the time used on wear measurement. The tool condition prediction system proposed in this paper for boring operation essentially utilizes acoustic sensor i.e. microphone. In order to understand effects of vibrations generated during boring operation on tool, vibration signals were also recorded and processed to compare it with acoustic signals. The signals were acquired by data acquisition system in LABVIEW environment. The data thus obtained were further processed using Fourier transform and wavelet transform. Using this transforms, 12 number of time domain, frequency domain and time frequency domain features were collected then with soft computing techniques which are learning from data strategy i.e. RBF and MLP, prediction of tool condition was done. The experimental results were analyzed with respect to various depth of cuts, feed rates and cutting speed for EN8, EN-9 and EN-31 steel. This approach is well suited for determining condition of boring tool using acoustic and vibration signals.

1. Introduction

The area of condition monitoring is gaining importance in the various machining operations because of the major concern in the manufacturing industries. Boring operations is one of the most essential machining operations in any manufacturing industry. Although the automated technologies has given great future as a cost effective solution, these systems as a whole could not be implemented full proof until certain prerequisites are met. The requirement of uninterrupted boring operation is one of the major prerequisite to achieve maximum efficiency. However, deteriorating process conditions such as tool wear resulting into bad geometric features for the part often results into the interruption of the machining operation causing increase in the downtime of the machine tool. Therefore, developing an effective tool wear monitoring has become one of the most important aspects in the automation of cutting/semi finishing processes. An effective condition monitoring system[1] must sense the condition of tool at appropriate time, allow for effective tool change strategy when tool becomes dull and maintain proper cutting conditions throughout the process. The monitoring of boring tool condition using acoustic signals is not much explored as a research area. The tool change policy in industry has resulted in many drawbacks like wastage of manufacturing resource if the tool is prematurely changed and hampering the quality of parts produced if the worn out tool is used for a longer time. This work aims to develop an approach to determine the condition of tool in boring operation by analyzing acoustic emissions. [2],[3] To understand the effects of vibrations generated...
during boring operation on tool, vibration signals were also recorded and processed to compare it with acoustic signals.

2. Approach
The proposed approach essentially considers boring as a machining operation to be done on CNC turning centre. In this work, indirect way of tool condition estimation is adopted hence acoustic as well as vibration signals are considered. The input parameters for machining are cutting speed (m/minute), feed (mm/revolution), depth of cut (mm), material hardness (HRC), tool slenderness ratio. The response parameters are surface finish and tool wear in terms of loss of weight. The responses are measured using industrial equipments and sensors. The details of the experiments are given in the next section. The signals acquired for analysis are acoustic emissions [4] and vibration, are intermediate responses from the system. To understand the relationship of the signals with output parameters, there is a need to establish statistical model between them. The result of the analysis and model building are discussed and the validation of the developed model using non linear system is also given in this paper.

3. Experimental Procedure
The experimental set up consists of a machine and sensors, the software systems, tools; raw material used. It also shows the machining parameters and the response parameters considered in the experiments. Figure 1 shows the schematic illustration of the experimental set up.

![Figure 1. Experimental Set up](image)

The experiments were carried out in the Laboratory environment. In this work a CNC Tuning centre (MTAB made, Model MAXTURN CNC Plus +) is utilized. The program of instruction for boring operation is developed for the workpiece. The machine has a Fanuc control system. The program is developed by using G codes and M codes given by the manufacturer. For experimentation purpose, a boring bar of 40 mm diameter. The boring operation is performed on the work pieces by using a CNMG 120408 Insert (CERATIZIT made). The material chosen for the experiments is EN 8, EN 9 and EN31). These are medium to high carbon steels and they are readily machinable in any conditions. The acoustic emissions are captured by means of an acoustic emission sensor and the vibration signals are captured by means of vibration sensor. A ¼ inch free field microphone of GRASS made is utilized to capture the sound signals generated during machining of the workpiece, similarly a PCB made accelerometer is employed to capture the vibration signals during the cutting operations. For this study, NI Cdaq-9191 is used to acquire signals from the sensors. A virtual interface was created in the LABVIEW for acquiring the sound and vibration signals. The ultimate response parameters for the experimentation are tool wear and work piece surface roughness. Tool wear is calculated as a difference weights of the insert before machining and final weight of the insert i.e. the weight after machining. This difference is calculated for every experimental run. The weight of the insert was measured using the analytical balance. The surface roughness of the work pieces bored is measured by
using a MITUTOYO made surface roughness tester, SJ201P. This method of measurement is a direct instrument measurement method. Three readings of the roughness average roughness parameter are taken and their average value is taken as roughness of the work piece. A sequence of experimental runs is generated using MINITAB software. [5] The independent variables [6] utilized in this study are: 3 cutting speeds (SP), 3 feed rates (FR), 3 depths of cut (DC), 3 material harnesses and 3 tool slenderness ratios and signals captured during machining. One insert was utilized for machining and the weight of the insert before and after machining was measured using an analytical balance. The measured values were used as the dependent variables in the statistical analysis, and as the output neuron in the ANN model.

| Trial No. | Purpose            | Input Parameters                      | Intermediate responses                      | Final Response                      |
|----------|--------------------|---------------------------------------|--------------------------------------------|-------------------------------------|
| 1        | For data Collection| 27*3=81 Runs (as per 3 steel materials)| Only acoustic signals                      | Surface Finish, Tool weight loss    |
| 2        |                    |                                       | Only vibration signals                      |                                     |
| 3        |                    | 27 runs only for EN31                 | Acoustic and vibration signals both         |                                     |
| 4        |                    |                                       | Only acoustic signals only for EN31         | Surface Finish, Tool weight loss    |
| 5        | For validation     | Till tool worn out after 39 runs      | Only acoustic emissions                     | Surface Finish, Tool weight loss    |
| 6        |                    | Till tool worn out after 31 runs      | Only vibration signals                      |                                     |

For experimentation purpose, the conventional way of designing experiments was not considered. The main reason was the data required for prediction of tool condition during boring operation must be independent of design of experiments. Hence this scheme given in Table 1 was adopted. Initially, experiments were conducted and initial as well as final response variables were measured. For one trial that is 27 runs, the vibration channel of the data acquisition system was closed and only acoustic emission was recorded. In the 2nd trial, the acoustic sensor’s channel was closed and only vibration data was recorded. During 3rd trial both the signals were read by the data acquisition system to collect the signals. The 4th trial was conducted only on EN31 with variable machining parameters. This was necessary to reproduce industrial scenario for boring operation. In all these four trials, the response variables were measured using the corresponding instruments. The data thus collected was further utilized for development of neural network model and building of a tool condition estimation system. For validation of the developed model, further experimentations were conducted. For this purpose, trial no. 5 and 6 were conducted till the tool insert completely worn out. These trial were conducted only on EN 31 with fixed values of input parameters. The reason behind this was to see the ability of the developed model to predict tool wear and remaining useful life.

4. Signal Processing
To develop a reliable tool condition monitoring system for predicting tool wear and useful remaining life of the tool, an approach of TCM is developed. The outline of the idea is presented in Figure 2. In this approach, the acoustic signals and vibration signals are captured from boring operation. These signals are then acquired through a wireless data acquisition system and are then transferred to computer for further signal processing. Based on the analysis of signals done, the decision making is done to predict the tool wear and remaining useful life of the tool. The response parameters surface finish and weight of the tool are measured and are related to the signals. The validation of the proposed model is done to ensure the viability of the system. So six important steps are developed for the proposed approach i.e. (a) Acquisition of signal data (b) Signal Processing (c) Feature Extraction (d) Feature selection and (e) decision making.

**Figure 2.** Procedure adapted for signal processing and model building for tool condition prediction

Signal preprocessing includes the amplification, de-nosing and conditioning of the acquired raw signal. The raw acoustic and vibration signal data is collected from the experimental runs performed using boring operation. The better the raw signal is de-noised, the more accurate the tool wear is predicted. The signals preprocessing includes signal de-noising using wavelet analysis. The denoising of the raw signal data is done by using wavelet analysis.

**Figure 3.** Comparison of acoustic signal de-noising performance based on different wavelets
The comparison of acoustic signal denosing performance based on different wavelets i.e. Coifflet, Symlet and Daubechis wavelet is shown in the figure. The comparison of vibration signals denoising performance can also be obtained in the similar way. In order to understand the principles of monitoring strategies proposed in this study it is necessary to discuss some of the mathematical details regarding the feature extraction [7] and tool life detection strategies. Furthermore, a self organizing neural network is used for decision making regarding the tool wear and tool remaining useful life. The basic mathematical principle behind each of this aspect in the monitoring strategy is discussed.

4.1. Feature Extraction
The preprocessed signal contains large volume of information that’s needs to be broken into meaningful information. This information so extracted are the features of the signals and are generally processed in time domain to obtain its statistical characteristics, in frequency domain to analyze power of signal distribution over a range of frequencies and in time frequency domain to obtain spectrum of non-stationary signals.

4.2. Feature Selection
The tool life predictions with all the signal features are not the best selection because the irrelevant and redundant features are able to negatively affect the performance of a condition monitoring system and also the prediction model. The volume of the features extracted is very large; therefore, in order to improve the performance of prediction model, the features should be optimized. A numbers of techniques are used for this purpose. Here the techniques such as Pearson’s correlation-based Feature Selection (CFS) method, chi-squared statistics selection method, R squared (R2) statistics selection method are used to optimize the features.

4.3. Model for Tool Life Estimation and Remaining Useful Life
To model TCM for estimating tool wear and remaining useful life of the tool, there was a need to use an information processing paradigm such as Artificial Neural network. ANN is inspired by the biological nervous system. The modeling of tool wear, RUL and surface roughness prediction system using ANN was essential due to highly non-linear relationship between inputs and outputs, over determined nature of the system and large size of data to handle. So two types of the neural network algorithm were used. Multi-layer perceptron neural network (MLP) and Radial basis function (RBF) [10] is utilized to model the tool condition and remaining useful life of the tool in boring operation.

![Figure 4](image)

**Figure 4 .** RBF architecture used for tool condition prediction from acoustic and vibration signals

The experiments are conducted to collect the data of acoustic and vibration signals and corresponding output of weight loss of tool and roughness of the surface machined is recorded. It was found that the tool worn out at experiment no 39. This is found from the fact that there was a reduction of 0.05 gm of total weight of the cutting tool. The Figure 5 represents the tool wear and the tool worn out. It can be observed from the graph that tool worn out took place at 39th experimental run.
As a same insert was used to carry out all the experimental runs, the insert started wearing out after carrying out experimental runs. As a consequence of which the remaining useful life of the cutting tool started reducing. The Figure 6 shows that when the tool wear reduces, the remaining useful life of the tool increases gradually. The red mark in the graph shows that there is a failure of tool at that point.

The experiments are performed to acquire the acoustic signals and vibration signals both from the boring operation performed on CNC turning Centre. The signals data is acquired through a data acquisition system. The raw signals data is processed using advanced signal processing techniques. The acoustic and vibration signal data captured during boring operation is processed using appropriate ANN [1] signal processing technique.

When acoustic and vibration signals were captured during experiments with isolated machining parameters, following observations were made: The data collected from after feature extraction of the acoustic emission signals was used for prediction of tool wear. It is observed that the tool worn out at the end of Experiment no. 39 which exactly matches with the experimental result. However, when same study was conducted with acquired vibration signals, the neural network designed for it predicted Tool worn out at the end of Experiment no. 31 which is 8 experiments prior to actual tool worn out. The correlation coefficient for first case was 0.9812 and for second case 0.8036. This indicates that the vibration signal has some amount of noise remaining after de-noising. Thus acoustic signal becomes more reliable for accurate tool wear prediction under the considered scenario. This issue can be sorted out by further investigation of vibration signals [8]. For this, three components of the vibration signals (i.e. along x, y and z axis) needs to be captured separately.[9] This will help to remove unwanted signal and improve the reliability of vibration sensor. The results obtained from the signal processing techniques clearly give the indication of the applicability of the developed model.
5. Results and Conclusion

When acoustic and vibration signals were captured during experiments with isolated machining parameters, following observations were made: The data collected from after feature extraction of the acoustic emission signals was used for prediction of tool wear, it concluded that tool worn out at the end of Experiment no.39 which exactly matches with the experimental result. However, when same study was conducted with acquired vibration signals, the neural network designed for it predicted Tool worn out at the end of Experiment no. 31 which is 8 experiments prior to actual tool worn out. The correlation coefficient for first case was 0.9812and for second case 0.8037. This indicates that the vibration signal has some amount of noise remaining after de-noising. Thus acoustic signal becomes more reliable for accurate tool wear prediction under the considered scenario. This issue can be sorted out by further investigation of vibration signals. For this, three components of the vibration signals (i.e. along x, y and z axis) needs to be captured separately. This will help to remove unwanted signal and improve the reliability of vibration sensor.

Tool condition monitoring systems are finding vast applications in modern manufacturing industries due to their advantages in the production of quality parts and reducing waste of important manufacturing resources. As a very important part of the proposed TCM system, advanced signal processing technique was used to minimize the disadvantages of indirect monitoring method by proposing a wavelet packet transformation. The artificial neural network used in this work is easy to implement, highly accurate and reliable as compared to analytical methods. The developed systems of AE signal for TCM showed high-accuracy prediction capabilities for early detection of tool condition so the systems can be adopted as in-process tool condition monitoring systems to meet the needs of the cost-effective means to prevent defects and provide optimized tool usage strategy in the metal cutting industry.

6. References

[1] Francis, C., Uros, Z., Real-Time Cutting Tool Condition Monitoring in Milling, Journal of Mechanical Engineering, Volume 57, Issue 2, pp. 142-150, 2011
[2] Li, X., Patri, K.V., Wavelet packet transforms of acoustic emission signals for tool wear monitoring, Journal for Manufacturing Science & Technology, Volume 1, Issue 2, pp. 89-93, 1999
[3] Mathew, M. T., Srinivasa Pai, P. and Rocha, L. A., An Effective Sensor for Tool Wear Monitoring in Face Milling: Acoustic Emission, Sadhana Volume 33, Issue 3, pp. 227–233, June 2008.
[4] Patra, K., Acoustic Emission based Tool Condition Monitoring System in Drilling, Proceedings of the World Congress on Engineering, London, U.K., Volume 3, July 6 - 8, 2011.
[5] Botsaris, P.N., Tsanakas, J.A., Vogiatzi, M.E., Tool Wear Monitoring by Design of Experiments for Drilling, Proceedings of International Congress on condition monitoring and diagnostic engineering, Stavanger, Norway, 30 May -1 June, 2011.
[6] Panda, S.S., Chakraborty, D., Pal, S.K., Monitoring of drill flank wear in the time domain, Proceedings of The Int. Conf. On Artificial Intelligence And Applications, Innsbruck, Austria 2005.
[7] Heinemann, R., Hinduja, S., A New Strategy for Tool Condition Monitoring of Small Diameter Twist Drills in Deep-Hole Drilling, International Journal of Machine Tools and Manufacture, Volume 52, pp 69–76, 2012.
[8] Pettersson, L., Vibration Analysis of a Boring Bar, Research Report, ISSN 1103-1581, Feb. 2002.
[9] Zhang, C., Yao, X., Zhang, J., Jin, H., Tool Condition Monitoring and Remaining Useful Life Prognostic Based on a Wireless Sensor in Dry Milling Operations, Sensors, Volume 16, Issue 6-795, pp 1–20, 2016.
[10] Xu C., Fan X., Luo W., Research of Tool Wear Based on Radical Basic Function Network, Proceedings of the International Multi Conference of Engineers and Computer Scientists 2009 Hong Kong, Volume I, March 18 - 20, pp.1-6, 2009.