

Vibration Based Tool Insert Health Monitoring Using Decision Tree and Fuzzy Logic

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Abstract: The productivity and quality in the turning process can be improved by utilizing the predicted performance of the cutting tools. This research incorporates condition monitoring of a non-carbide tool insert using vibration analysis along with machine learning and fuzzy logic approach. A non-carbide tool insert is considered for the process of cutting operation in a semi-automatic lathe, where the condition of tool is monitored using vibration characteristics. The vibration signals for conditions such as healthy, damaged, thermal and flank were acquired with the help of piezoelectric transducer and data acquisition system. The descriptive statistical features were extracted from the acquired vibration signal using the feature extraction techniques. The extracted statistical features were selected using a feature selection process through J48 decision tree algorithm. The selected features were classified using J48 decision tree and fuzzy to develop the fault diagnosis model for the improved predictive analysis. The decision tree model produced the classification accuracy as 94.78% with five selected features. The developed fuzzy model produced the classification accuracy as 94.02% with five membership functions. Hence, the decision tree has been proposed as a suitable fault diagnosis model for predicting the tool insert health condition under different fault conditions.

Keywords: Statistical features; J48 decision tree algorithm; confusion matrix; fuzzy logic; weka

1 Introduction

Tool wear during metal cutting operation is a cause of major concern in manufacturing industry, as it degrades the quality of product during manufacturing process and would also lead to economic losses for the manufacturing unit. It is important to monitor the condition of tool so as to re compensate the effect of tool wear on the machined components. It is therefore necessary to develop an accurate tool wear predictive models such as monitoring the condition of any tool during machining in order to improve the overall efficiency [1].

The main goal of Condition monitoring is not only decreasing the manufacturing costs by reducing downtime and needless cutting tool changes, but also enhances the product quality by eliminating wear, excessive tool deflection and poor surface finish on its parts. There are two methods normally employed for tool wear sensing: Direct and Indirect methods. Direct method involves measuring the actual wear using optical devices such as radioactive analysis on the tool which is generally a quite difficult process [2]. The direct method is capable of providing higher accuracy only at certain conditions and has not been yet proven to be useful economically as well as technologically. Ryabov et al. used laser displacement sensor for online tool geometry in milling process [3]. Prasad et al. evaluated tool wear by using stereo vision technique [4]. Zuperl reported a real time tool condition monitoring system for milling tool [5]. Indirect method involves the use of single or multiple sensors by measuring the cutting forces, vibration, torques, temperature, acoustic emissions etc. Scheffer et al. reported a wear monitoring system in a turning operation using vibration signature and strain elements [6]. Vibration and acoustic emission (AE)

signals are the most widely used approaches in order to monitor the condition of rotating machines [7]. The faults can be detected by comparing the signals of a machine running in normal and faulty conditions. In this study, the vibration signals are used for the fault categorization. The vibration signals from the semi-automatic lathe will be non-stationary due to the wear and tear occurred during machining [8]. Alonso et al. studied the possibilities of vibration signature for monitoring the tool wear [9] Data modeling using machine learning approach are normally employed to solve such problems.

Machine learning approach is one of the methods considered for obtaining the required features. The aim of machine learning is to give computer systems the ability to make predictions based on training data [10]. Machine learning approach involves three main steps, namely feature extraction, feature selection, and feature classification. There are several types of features such as statistical feature [11], histogram feature [12], wavelet features [13,14] have been successfully studied for the various fault diagnosis application. Balazinski et al. developed an Intelligent techniques for monitoring the tool condition [15] Gangadhar et al. classified the single point cutting tool condition in turning process using statistical features [16]. Sanithya et al. used statistical features for monitoring the single point cutting tool [17]. Madhusudana et al. used histogram features for monitoring the milling tool. Benkedjough et al. predicted the milling tool condition using the continuous wavelet transforms (CWT) [18]. In all the above literature visual basic code was used for extracting the statistical features. In this study, the feature extraction process was carried out using MATLAB. The vibration signals obtained under all fault conditions were processed for extracting features. The following features namely, maximum, minimum, mean, median, standard deviation, kurtosis, skewness, sample variance, mode and standard error were extracted using MATLAB.

After the feature extraction, the feature selection process was carried out. The most important features can be identified using any one of the algorithm such as fuzzy [18], Support vector machine [19], Decision Tree [11] and Principle component analysis [20]. Elangovan et al. used decision tree for selecting statistical features in the surface roughness prediction during turning [21]. Jegadeeshwaran et al. concluded that decision tree is a powerful tool for selecting the contributing features [11]. Many studies have been proved that the decision tree can be chosen as a powerful tool for feature selection. Hence, in this study features were selected using the decision tree algorithm.

The immediate step after selection is feature classification. Feature classification is a process of categorizing the features using some internal calculations. There are many algorithms available for feature classification. The decision tree is one of the algorithm which can be suggested as a hybrid algorithm for both feature selection and feature classification for a bearing fault diagnostics study [22]. In a recent study, the best first tree was proposed as a best fault predicting model for the hydraulic brake system [11]. Support vector machines is one of the important classifiers which were successfully studied for the various applications such as misfire detection in IC engine [23], tool condition monitoring [24] and brake fault diagnosis [25], Navie bayes and bayes net [26]; k star [17]; proximal support vector machines [27] are the few algorithms that were used for various fault diagnosis applications. Among these, fuzzy is one of the technique which can be used for condition monitoring and fault diagnosis. Cuca et al. developed a fuzzy logic based tool condition monitoring for end milling [28]. Ren et al. developed a Type 2 fuzzy system for tool condition monitoring using the AE in micro milling [29]. However, there is a limited study on the tool condition monitoring using machine learning and fuzzy logic. In particular, the research content is almost nil for monitoring the condition of a carbide coated tool inserts using fuzzy. Hence in this study, an effort has been made for monitoring the tool condition using the decision tree and the fuzzy inference engine. The selected features were classified using the decision tree algorithm and the fuzzy model. The decision tree results were then compared with the results of the fuzzy model tool insert health prediction.

The paper has been structured as follows:

- (i) Section 2 shows the experimental study and the experimental procedure for acquiring the vibration signals under good and faulty conditions.

- (ii) Section 3 explains about machine learning approach which includes the feature extraction, feature selection and feature classification process
- (iii) Section 4 demonstrates the result and discussion. Section 5 consists a concluding remarks.

2 Experimental Study

In this study, the vibration analysis has been used for predicting the tool condition using machine learning approach and fuzzy logic through an experimental study. A semi automatic lathe (ESTEEM & ETM356) was chosen for the machining process.

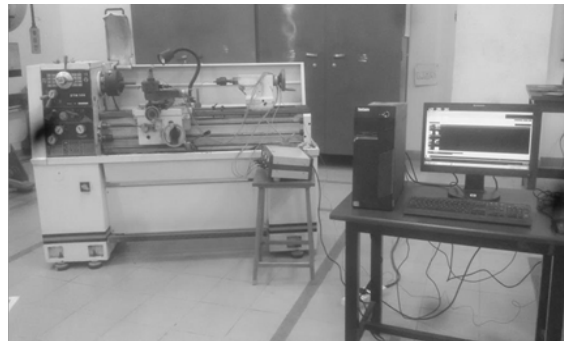


Figure 1 (a): Experimental setup

The carbide coated insert fitted tool was used for the machining process. A piezoelectric accelerometer was attached to the tool post to measure the vibrations produced by the tool for each of the conditions (Good, Bad (Broken), Flank wear and Thermal). Piezoelectric accelerometers are normally used for acquiring vibration signals due to its large frequency response.



Figure 1 (b): Sensor attached to the tool post

The sensor used for the process is a piezoelectric accelerometer. In this study, the piezoelectric accelerometer (3055b1 Low Impedance Voltage mode (LIVM) manufactured by Dytron) was used for acquiring the vibration signals. The piezoelectric accelerometer was then connected to a signal conditioning unit where the signal is manipulated for the next stage for processing. Then these signals are acquired by using the DAQ module NI 9234.



Figure 2: Data Acquisition Hardware-NI9234-4 Channel DAQ

This DAQ card module consists of 4 analog input channels with a sampling rate of 50 kilo samples per second and a resolution of 24-bit). The signals were then processed using a computer with lab view software. These signals are recorded and the corresponding values are stored in excel sheets. Fig. 2 and Fig. 3 show the NI DAQ 9234 used for acquiring the vibration signals and an uni-axial accelerometer respectively.



Figure 3: IEPE type Accelerometer

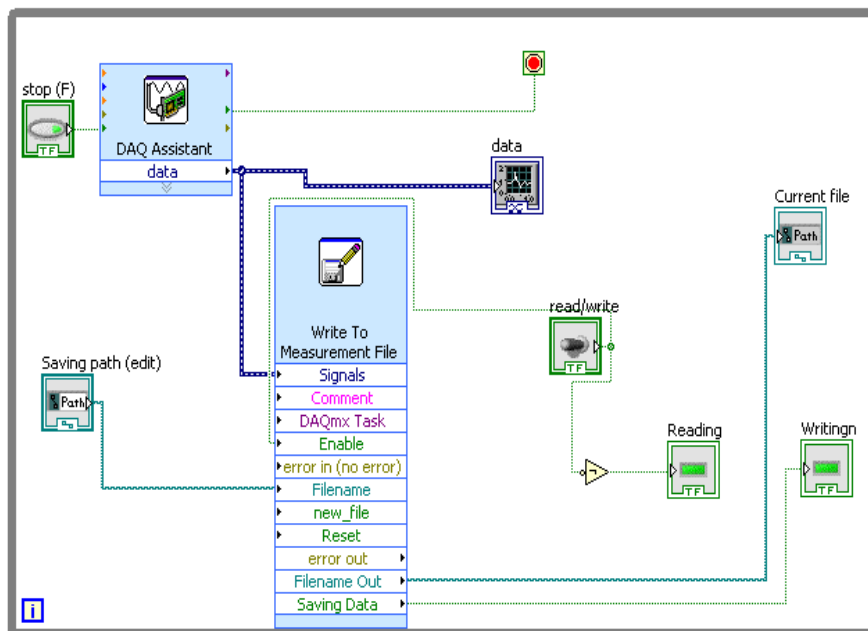


Figure 4: Signal processing with LabVIEW

The following parameters were used for conducting the experiments.

Sample length	:	1024 (Arbitrarily chosen)
Sampling frequency	:	24 kHz (As per Nyquist sampling theorem)
No. of samples	:	67 (Arbitrarily chosen)

The experiment was conducted in two phases. In first phase, the insert was in a good condition. The vibration signals for each parameter were acquired while other two parameters are constant. The corresponding vibration signals were recorded. Under each set of parameters, the predictability of the classifier model was tested. The parameters under which the maximum accuracy was obtained were selected for the fault diagnosis study. In the fault diagnosis study, under each fault conditions, the relevant vibrations signals were acquired with the selected parameters in phase 1. The extracted vibration signal was processed using the machine learning approach.

Fig. 4 shows the sample LabVIEW program used for acquiring the vibration signals. Fig. 5 and Fig. 6 shows the sample vibration signals acquired under good and faulty condition.

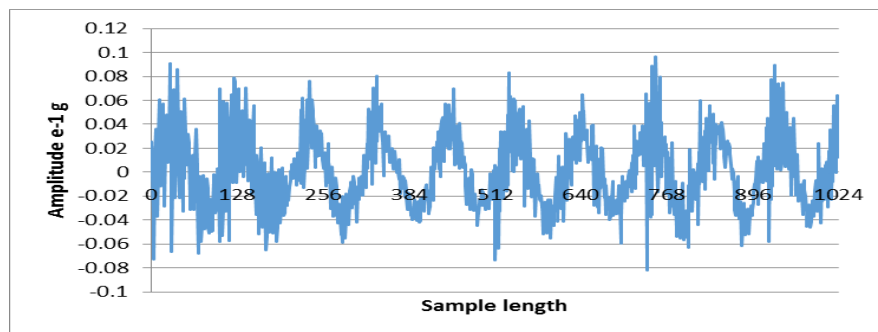


Figure 5: Vibration signal acquired from the setup (S: 770 rpm; F0.135 mm; DOC: 0.8 mm)

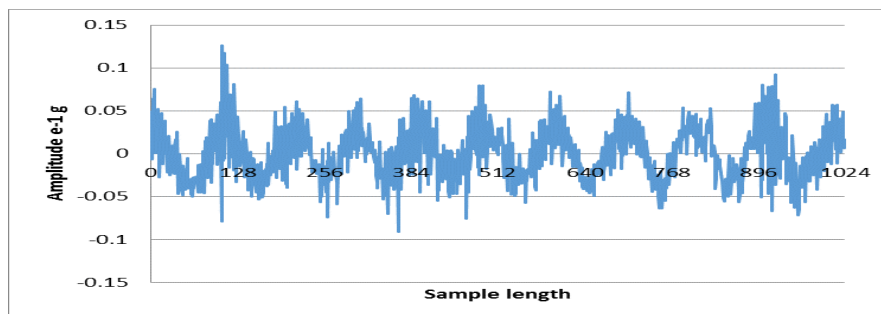


Figure 6: Vibration signal acquired from the setup (S: 770 rpm; F0.214 mm; DOC: 1.2 mm)

The most frequently occurring fault conditions were then studied. They are flank wear, Thermal wear and broken condition [30]

- 1) Flank wear: It occurs as a result of friction between the machined surface of the work piece and the tool flank. Flank wear appears in the form of wear land and is measured by the width of this wear land. Flank wear affects to a great extent due to the mechanics of cutting. If the amount of flank wear exceeds a particular critical value (VB 0.5-0.6 mm), then excess cutting force will lead to tool wear. Fig. 7 shows the flank wear of the tool.



Figure 7: Flank wear

- 2) Thermal cracks: It is the combination of temperature variations and mechanical shock that could possibly lead to thermal mechanical failure. Thermal mechanical failure is most frequently experienced on the edge and sometimes during interrupted-cut turning, facing operations on a large range of components and during operations with irregular fluid flow. Fig. 8 shows the thermal wear of the tool.
- 3) Broken edge: The mechanical fracturing of an insert happens once force overcomes the inherent strength of the leading edge. These kinds of faults are mechanically generated while finishing up the machining operation with high depth of cut. Fig. 9 shows the broken edge of the tool.



Figure 8: Thermal wear

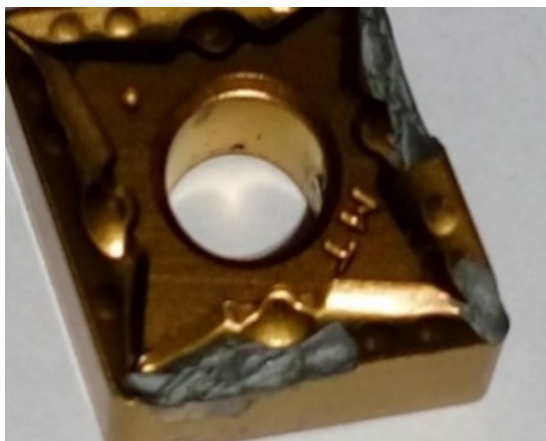


Figure 9: Broken edge

3 Machine Learning Approach

As discussed earlier, machine learning approach consists three basic steps: (i) Feature extraction; (ii) Feature Selection; (iii) Feature classification.

3.1 Feature Extraction and Selection

Feature extraction is a process of extracting informative and non-redundant data from set of large measured values. These features represent the data measured in a more informative way and are helpful in further analyzing of the required information. Certain statistical parameters such as kurtosis, skewness, variance, standard deviation, maximum value and minimum value were extracted from the acquired vibration signals. All the statistical parameters were calculated using the MATLAB code. Tab. 1 shows the formula's used for finding the statistical feature values. Tab. 2 shows the sample features extracted through MATLAB.

Table 1: Statistical features Formula

Name of Statistical Features	Description/ Formula
Standard Error	$\sqrt{\frac{1}{n-2} \left[\sum (y - \bar{y})^2 - \frac{\sum (x - \bar{x})(y - \bar{y})^2}{\sum (x - \bar{x})^2} \right]}$
Standard Deviation	$\frac{\sqrt{n \sum x^2 - \sum(x)^2}}{n(n-1)}$
Sample Variance	$\frac{\sqrt{n \sum x^2 - \sum(x)^2}}{n(n-1)}$
Kurtosis	$\left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{(x_i - \bar{x})^4}{s} \right) \right\} - \frac{3(n-1)}{(n-2)(n-1)}$
Skewness	$\frac{n}{(n-1)(n-2)} \sum \left(\frac{(x - \bar{x})^3}{s} \right)$
Maximum value	Maximum signal point value in a given signal
Minimum value	Minimum signal point value in a given signal
Range	Difference in maximum and minimum signal point values for a given signal
Sum	Sum of all feature values for each sample
Mean	The arithmetic average of a set of values or distribution
Median	Middle value separating the greater and lesser halves of a data set

Table 2: Statistical features

Maximum	Minimum	Standard Deviation	Kurtosis	Skewness	Condition
1.935	0.0096	0.302	336.17	-17.34	Good
1.925	0.0040	0.128	506.51	-21.22	Good
3.754	0.0497	-0.406	-435.90	-7.18	Good
1.599	0.1048	2.146	447.27	-12.48	Flank wear
1.804	0.0816	-0.286	164.93	-14.99	Flank wear
1.984	0.0293	1.285	880.38	-36.36	Flank wear
1.868	0.0186	2.759	425.10	-13.83	Thermal wear
1.698	0.1248	-0.554	161.64	-7.54	Thermal wear
1.844	0.0325	1.040	270.58	-15.03	Thermal wear
1.886	0.0086	0.275	396.02	-18.36	Broken
1.599	0.1048	2.146	447.27	-12.04	Broken
1.868	0.0186	2.759	425.10	-13.83	Broken

Twelve statistical features were extracted from the raw vibration signatures. All the features may not be essential for the classification process. The process of selecting contributing features is called as feature selection. The feature selection process was carried out using J48 decision tree algorithm. Extracted features were the input to the algorithm. The output is a form of a graphical tree known as decision tree. From the decision tree, five features that have contributed for classification were only selected for training and testing. They are: (1) Maximum (2) Standard deviation (3) Minimum value, (4) Kurtosis and (5) Skewness. The selected features were classified using J48 decision tree algorithm and fuzzy classifier.

3.2 Feature Classification

Grouping is allotting the classification to new arrangement of perceptions by contrasting and the effectively settled information set whose class enrollment is known. Order wording is separated into two directed and unsupervised. The unsupervised system is likewise called grouping. A calculation that actualizes the arrangement is called classifier. The J48 decision tree classifier and Fuzzy classifiers have been used here.

3.2.1 Feature Classification Using J48 Decision Tree

A decision tree is a tree based learning representation philosophy used to speak to characterization rules. Choice tree learning is a standout amongst the most prevalent learning approaches in grouping since it is quick and produces models with great execution. For the most part, decision tree algorithm are particularly useful for order learning if the preparation cases have blunders (i.e., loud information) and properties have missing qualities. A decision tree is a game plan of tests on traits in inward nodes and every test prompts to the split of a node. Every terminal node is then appointed an order. A standard tree prompted with c5.0 (or perhaps ID3 or c4.5) comprises of various branches, one root, various nodes and various clears out. One branch is a chain of nodes from root to a leaf; and every node includes one characteristic. The event of a quality in a tree gives the data about the significance of the related. A decision tree is a tree based information representation philosophy used to speak to arrangement rules. J48 algorithm is a broadly utilized one to develop decision trees. The technique of framing the Decision Tree and abusing the same for highlight determination is described by the accompanying:

- (i) The chose set of measurable elements is given as contribution to the algorithm; the yield from the algorithm is the choice tree.

- (ii) The decision tree has leaf nodes which speak to class names and different nodes connected with the classes being characterized.
- (iii) The branches of the tree represents to every conceivable estimation of the element node from which they begin.
- (iv) The decision tree can be utilized to group highlight vectors by beginning at the base of the tree and traveling through it until a leaf node which gives an arrangement of the occasion is recognized.

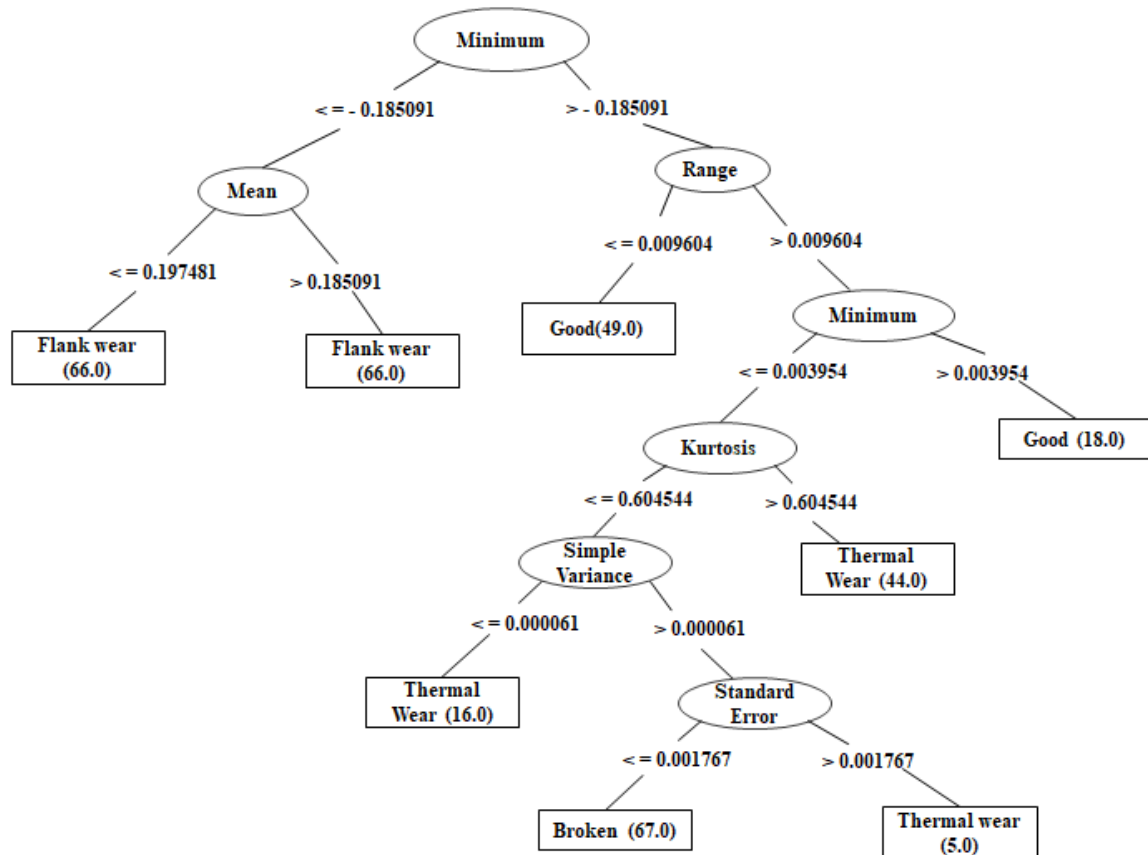


Figure 10: Decision tree

3.2.2 Feature Classification Using Fuzzy Model

Fuzzy classification is the process of grouping the statistical features as input variable and classification accuracy as output variable depending upon range of variables. From the decision tree as shown in Fig. 10, eleven rules were generated.

The membership functions were created for the each contributing features. The trapezoidal membership function was used in the fuzzy tool box. Fig. 11-Fig. 15 show the membership function for the input features minimum, kurtosis, skewness, standard deviation and median respectively. The output variable is the condition and its membership function are also shown in Fig. 16.

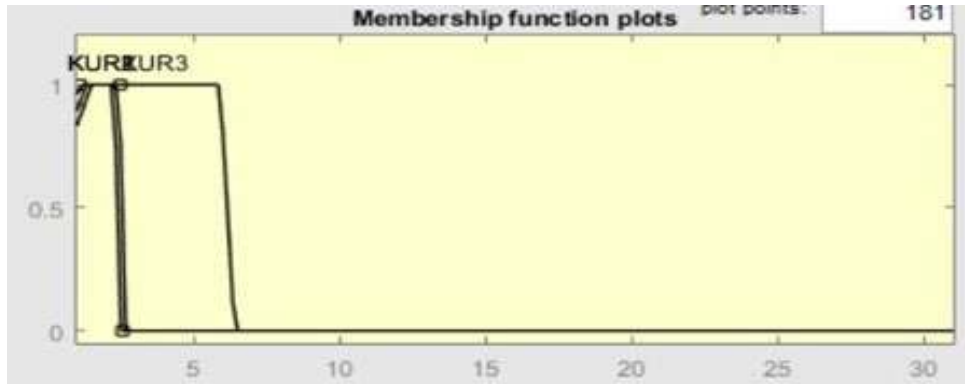


Figure 11: Membership function-Kurtosis

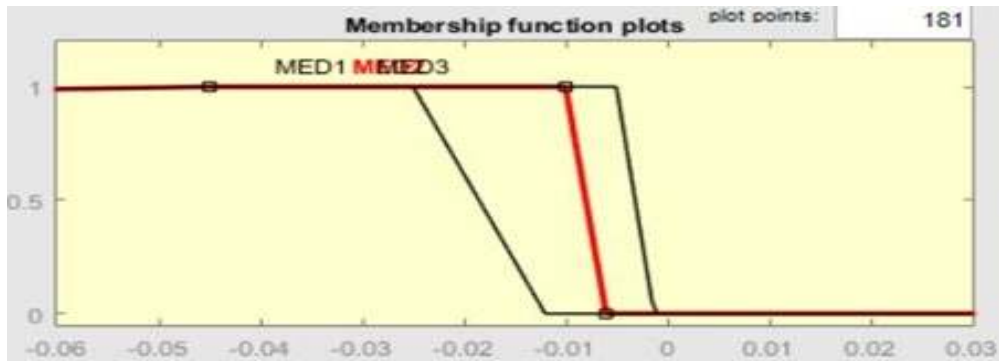


Figure 12: Membership function-Median



Figure 13: Membership function-Minimum

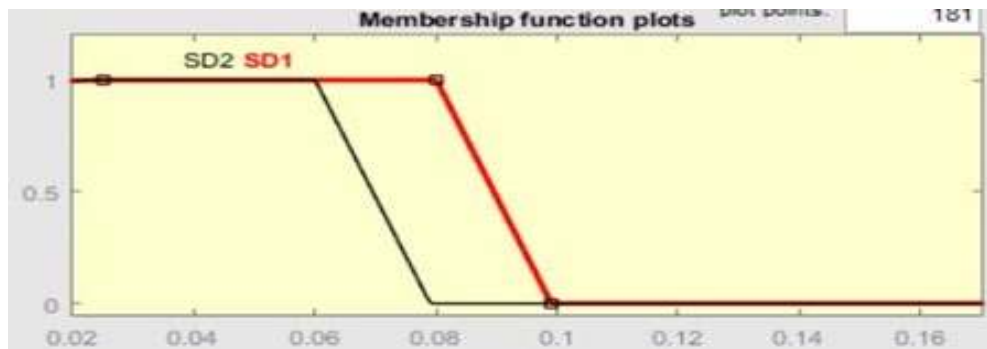


Figure 14: Membership function-Standard Deviation

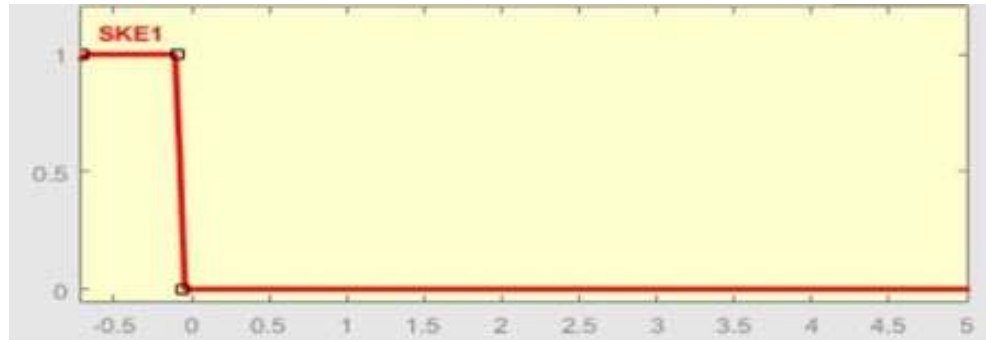


Figure 15: Membership function-Skewness

Output Variables:

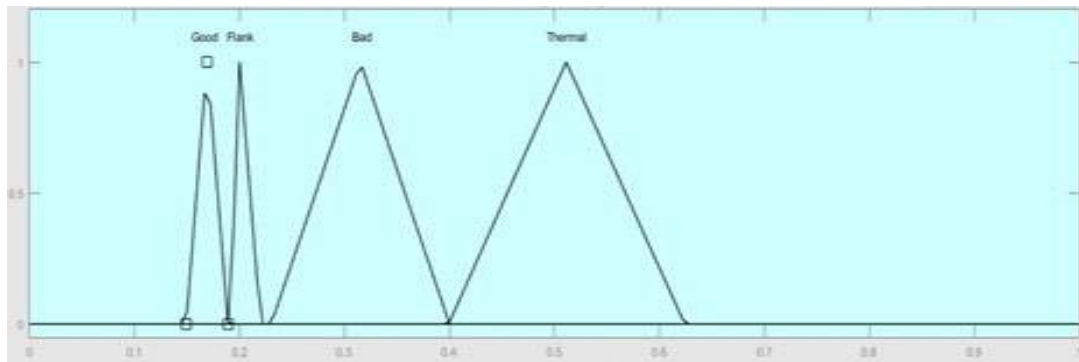


Figure 16: Membership function-Condition of the tool

4 Results and Discussion

In this study, the carbide coated tool insert condition monitoring was carried out. Under different machining conditions, the vibration signals were acquired. Eleven statistical parameters namely standard error, sample variance, kurtosis, skewness, standard deviation, minimum, maximum, mean, median, range and sum were extracted from the acquired vibration signals. All the eleven features may not be needed for the classification. Hence, important features alone were selected using the decision tree algorithm. Five parameters namely, minimum, standard deviation, maximum, kurtosis and skewness were identified as leading contributors amongst the features that were extracted.

4.1 Classification Accuracy Using J48 Decision Tree

The selected features were classified using the decision tree algorithm. The selected features are the input to the algorithm. The output is the classification accuracy. The classification accuracy has been presented in the form confusion matrix as shown in Tab. 3. The confusion matrix is a square matrix in which the summary of the classification accuracy can be found. The diagonal elements in the confusion matrix are the correctly classified data points and the nondiagonal elements are misclassified data points.

In the confusion matrix, first, row represents the data points belong to the good condition. The first element in the first column belongs to its classified state. Out of 67 data points, 66 were correctly classified as Good. One data has been misclassified as Thermal wear. The second row represents Flank. The second element in the second column is a number of data points that are correctly classified. Out of 69 data points, 64 data points were correctly classified. The three data points were misclassified as thermal wear. As discussed above the classification and the misclassification details can be studied using the confusion matrix.

Table 3: Confusion matrix

Prediction/Condition	Good	Thermal	Flank	Bad
Good	66	0	1	0
Flank	0	64	0	3
Thermal	1	2	62	2
Bad	0	1	4	62

Among the 268 data points belong to all fault conditions, 14 data points were misclassified. Referring the confusion matrix, none of the fault conditions have been misclassified as good condition. Hence J48 can be used for the fault related study.

Classification Summary

Total number of data points	: 268
Number of data points that were correctly classified	: 254
No. of data points that were mis classified	: 14
Overall classification accuracy	: 94.78%

4.2 Classification Accuracy Using Fuzzy Classification

Fuzzy classification is the process of grouping elements into a fuzzy set whose membership function is defined by the truth value of a fuzzy propositional function. To be precise, a class is a set that is defined by a certain property, and all objects having that property are elements of that class. This process of classification evaluates for a given set of objects whether they fulfill the classification property, and consequentially are a member of the corresponding class. However, this intuitive concept has some logical subtleties that need clarification. Here for fuzzy classification we will be taking the all the five parameters and making them in to input variables with trapezoidal membership function based on the rules generated from the decision tree. The output variables will be the conditions good, bad (broken), flank and thermal with triangular membership functions. The rules for the fuzzy classification will be framed after analyzing the rules from decision tree.

Table 4: Confusion matrix

Prediction/Condition	Good	Thermal	Flank	Bad
Good	66	0	1	0
Flank	0	63	2	2
Thermal	0	1	62	4
Bad	1	3	2	61

A confusion matrix is a table that is often used to describe the performance of a classification model (classifier) on a set of test data for which the true values are known. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing. For good condition the correctly classified instances are 66 and misclassified is one. For bad condition the correctly classified instances are 61 and misclassified is six. For Flank condition the correctly classified instances are 63 and misclassified is four. For Thermal condition the correctly classified instances are 62 and misclassified is five. Thus, for each condition we get an accuracy of 98.57%, 91.42%, 94.28%, and 92.85%.

Classification Summary

Total number of data points	: 268
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Number of data points that were correctly classified	: 252
No. of data points that were misclassified	: 16
Overall classification accuracy	: 94.02%

By comparing decision tree and fuzzy classifiers, the decision tree produced the maximum classification accuracy as 94.78%. Hence, decision tree outperforms the fuzzy set and it can be suggested for the tool insert health prediction.

5 Conclusions

In this study, the J48 decision tree algorithm and fuzzy logic was used as classifier for classifying the conditions using the statistical features calculated from the vibration signals of the non-carbide tool (Tungsten carbide) used in turning operation. The accuracy of J48 decision tree classifier was found to be 94.78%. Fuzzy logic classifier was used to classify the statistical features further and the accuracy of the classification was found out to be 94.02%. Thus we can see that, although the classification accuracy of the J48 decision tree is similar to fuzzy logic classifier we can see that the decision tree classifier holds a slightly upper hand. This system provides a possible application to improve the accuracy and precision of condition monitoring system. It also informs the machine operator of any faults detected. This will significantly reduce the damage be it major or minor to the machine as well as the tool and thus increasing the overall efficiency.

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