Journal of Engineering Science and Technology
Vol. 10, No.10 (2015) 1310 - 1325

PREDICTION OF TOOL CONDITION DURING TURNING OF ALUMINIUM/ALUMINA/GRAPHITE HYBRID METAL MATRIX COMPOSITES USING MACHINE LEARNING APPROACH

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Abstract

Aluminium/alumina/graphite hybrid metal matrix composites manufactured using stir casting technique was subjected to machining studies to predict tool condition during machining. Fresh tool as well as tools with specific amount of wear deliberately created prior to machining experiments was used. Vibration signals were acquired using an accelerometer for each tool condition. These signals were then processed to extract statistical and histogram features to predict the tool condition during machining. Two classifiers namely, Random Forest and Classification and Regression Tree (CART) were used to classify the tool condition. Results showed that histogram features with Random Forest classifier yielded maximum efficiency in predicting the tool condition. This machine learning approach enables the prediction of tool failure in advance, thereby minimizing the unexpected breakdown of tool and machine.

Keywords: Hybrid composite, Machining, Tool condition, Statistical features, Histogram features, Machine learning, Random forest, Regression tree.

1. Introduction

Metal matrix composites are one of the most widely used materials because of their adaptability to different situations and the relative ease of combination with other materials to serve specific purpose through tailored properties. Substantial progress in the development of light metal matrix composites, particularly aluminium metal matrix composites have been achieved in recent decades, and they have been introduced in several important applications. Reinforcement of many light metals has opened up the possibility of application of these materials in areas where weight reduction is the first priority.

Nomenclatures

a_p	Depth of cut, mm
v_c	Speed, m/min
v_f	Feed, mm/rev

Abbreviations

CART	Classification and Regression Tree
CNC	Computer Numerical Control
Gr	Graphite
HMMCs	Hybrid Metal Matrix Composites
MMC	Metal Matrix Composites
TCM	Tool Condition Monitoring
WEKA	Waikato Environment for Knowledge Analysis

Aluminium matrix composites suitable for automotive and aircraft applications (frames, piston rods, piston pins, brake discs and gear box casing) have high specific strength and stiffness, improved damping capabilities, lightweight design, enhanced fatigue performance and thermal stability at elevated temperatures [1]. There is a growing interest worldwide in manufacturing hybrid metal matrix composites (HMMCs) which possesses combined properties of its reinforcements and exhibit improved physical and mechanical properties [2]. Hard ceramic particles in the matrix improves the properties but make these materials very difficult to machine by blunting the cutting edge as well as by causing excessive wear in conventional tools [3]. To understand the machining characteristics of particulate reinforced hybrid aluminum metal matrix composites, extensive investigations were carried out.

2. Machinability Studies on Metal Matrix Composites

A major problem when machining metal matrix composites is the extensive tool wear caused by the strong ceramic reinforcement. Effective machining of such composite is a challenge to the manufacturing industries and cutting tool wear is a critical phenomenon which influences the quality of the machined part. It has been concluded by Erry YulianT.Adestaet al., [4] that an increase in negative value of rake angles increases the force encountered at the cutting edge which leads to excessive heat generation and consequently faster the tool wear. Tool wear was also found to be significant when zero rake angles were used [5, 6]. Tool condition monitoring can provide valuable information to improve product quality at lowest possible price. Hence machinability studies using machine learning approach has been taken up.

Tool condition monitoring

To meet customers demand for high quality products at the lowest possible price and to compete on a global front, manufacturers today are facing numerous challenges for achieving high dimensional accuracy on their products [7, 8]. To meet these goals, manufacturers are focusing on the technical aspects including achieving uninterrupted automated machining process for longer

duration with least human supervision. Improved information gathering and analysis techniques are needed to achieve those requirements [9]. Cutting tool wear condition monitoring is an important technique that can be useful especially in automated cutting processes to prevent any damage to the machine tool and workpiece. One of the major hurdles in realizing complete automation is the prediction of cutting tool state. Since tool wear is a critical factor in productivity, several tool condition monitoring techniques have been attempted to control the tool wear and surface quality during machining using Computer Numerical Control machines.

Excessive wear on cutting tools give rise to both shape and dimensional changes in manufactured components, some-times leading to scrapping, increasing the production cost. Several research efforts have been made to develop an on-line tool condition monitoring systems. Chelladurai et al., [10] discussed the problem of detection of flank wear in turning operation using vibration and strain measurement methods. Vibration and strain data during the cutting process were recorded using two accelerometers and one strain gauge bridge. Dimla and Lister [11] described an experimental and analytical method for on-line tool condition monitoring involving the use of three mutually perpendicular components of the cutting forces (static and dynamic) and vibration signature measurements. Based on the analysis, it was possible to identify trends in the sensor signals as the tool insert wore. It was also possible to separate and identify changes in the sensor signals originating from changes in cutting conditions. This type of analysis in time and frequency domains showed that more components of the measured signals correlated well with the tool wear.

Abouelatta and Madl [12] found a correlation between surface roughness and cutting vibrations during turning of free cutting steel and derived mathematical models for the predicted roughness parameters based on cutting parameters and machine tool vibrations. A Fast Fourier Transform (FFT) analyser and a Surtronic 3+ based instrument were used to measure tool vibrations in radial and feed directions and surface roughness respectively. Results showed that the predicted models for both cutting parameters and tool vibrations were more accurate than those depending on cutting parameters alone. Satyanarayana Kosaraju et al., [13] discussed the online prediction of tool wear using acoustic emission in turning titanium alloys and revealed that acoustic emission signal in turning titanium alloy can be predicted with a reasonable accuracy within the range of process parameters. Soumen Mandal [14] discussed the applicability of tool condition monitoring methods used for conventional milling in micromilling.

Thomas et al., [15] discussed the analysis of surface roughness and tool vibration data generated by dry turning of mild carbon steel samples at different levels of speed, feed, and depth of cut, tool nose radius, tool length and workpiece length. Literature survey showed only limited sources in the area of machine learning techniques related to machining of metal matrix composites.

In the present study, an attempt has been made to implement machine learning technique to predict the actual tool condition during turning of aluminium hybrid metal matrix composites. Such an approach to cutting tool condition monitoring can help in on-line realization of the tool wear.

3. Experimental Procedure

3.1. Synthesis of composites

Aluminium hybrid metal matrix composites were fabricated using stir casting techniques. It consists of Al-Si10Mg alloy reinforced with 9 weight percent of alumina with an average particle size of 15-20 microns and 3 weight percent of graphite with an average particle size of 50-70 microns. The chemical composition of the matrix alloy is given in Table 1.

Table 1. Composition of Al-Si10Mg Alloy.

Chemical composition	Cu	Mg	Si	Others (Mn,Ni,Zn, Fe, Pb, Sn, Ti)	Al
%	0.1 max	0.3 max	10 max	1.5 max	Balance

Cylindrical bars of length 310 mm and diameter 32 mm were manufactured using stir casting process. The alloy was melted and held at 750 ºC in graphite coated crucible to which preheated reinforcements (9 weight percent of aluminaand 3 weight percent of graphite) at the temperature of 350 ºC were added and mixed using a mechanized stirrer operated at 350 rpm. 1.5 weight percent of magnesium was added to improve wetability between the matrix and reinforcements. The molten metal was then poured in a permanent cast iron mould which was preheated at 250 °C. The cast specimens were taken out after cooling.

3.2. Machining of composites and signal data acquisition

Tools with specific amount of flank wear (0.1 mm, 0.2 mm, 0.3 mm and 0.4 mm) were deliberately created in tool inserts using a tool and cutter grinder and confirmed using Tool Maker's Microscope for accuracy. Figure 1 shows the tool (K10 grade) with flank wear of 0.4 mm created using tool and cutter grinder and measured by Tool Maker's Microscope.

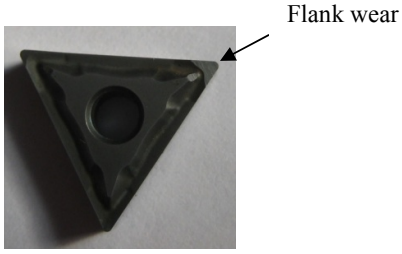


Fig. 1. Tool with Flank Wear of 0.4 mm.

These faults were created to predict the actual tool condition during machining process. Experiments were conducted on a CNC lathe using these four pre-worn out K10 grade carbide tools (0.1 mm, 0.2 mm, 0.3 mm and 0.4 mm worn out tool) along with a new K10 carbide tool. The specimen of the K10 tool was TNMG160404 with nose radius of 0.4 mm and rake angle of 12°. Cutting

conditions employed in the study were: cutting v_c=300m/min, v_f=0.1mm/rev and a_p =0.5mm. Cutting parameters for machinability studies were varied for three levels and optimum cutting conditions were arrived at based on Taguchi's Design of Experiment. The cutting parameters were selected based on the capability of the CNC machine used for the machining process.

The experimental setup is shown in Fig. 2. A piezo electric mono axial accelerometer (Dytran Instruments/3035B1) was mounted on the tool holder to record vibrations during machining. Output of the accelerometer was connected to the signal conditioning unit which converts the signal from Analog to Digital. Digitized vibration signal (in time domain) was stored as multiple text files using proprietary software.

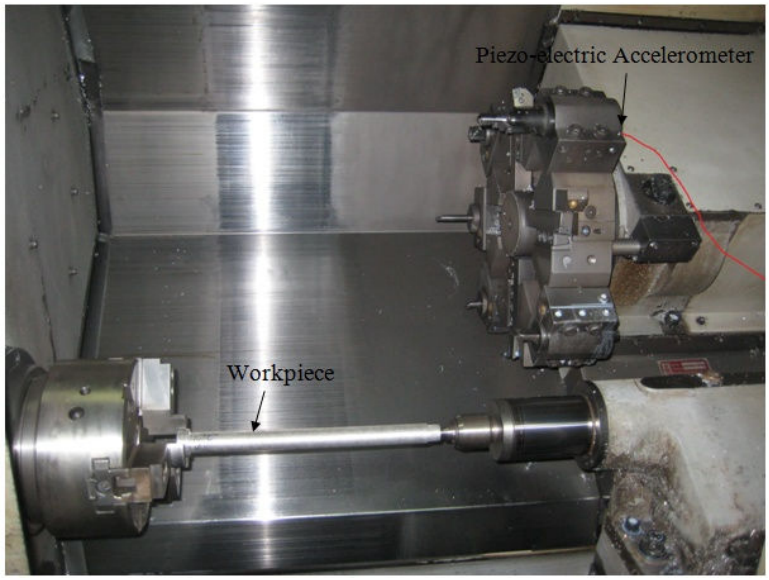
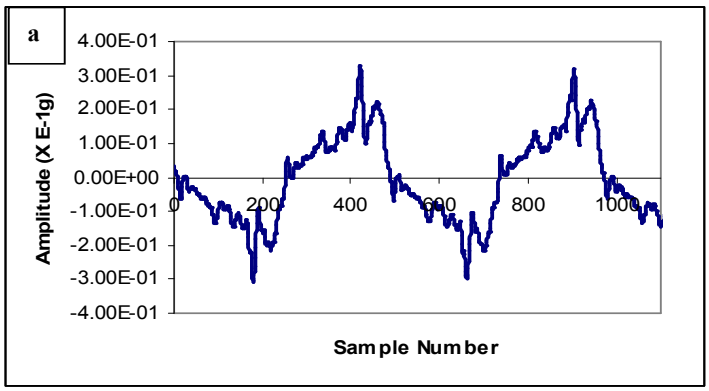


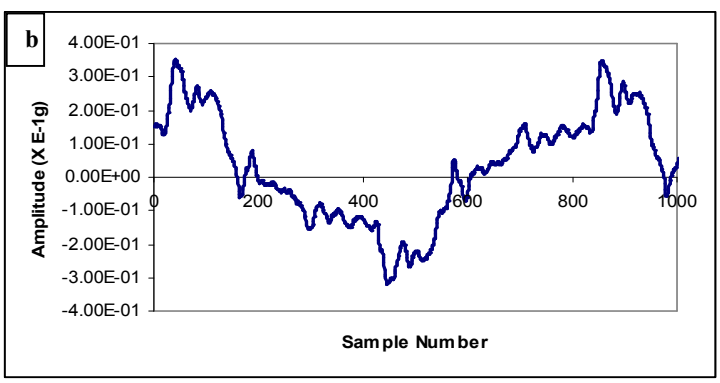
Fig. 2. Experimental Setup.

Cast hybrid aluminium MMC rods (cylindrical workpieces) were initially turned and faced to obtain specimens 30 mm diameter and 300 mm long. Accelerometer was mounted on the tool post using an adhesive mounting. A sampling frequency of 10 KHz and a signal length of 1024 were set based on the Nyquist criterian (frequency should be greater than two times the band width). Desired speed (300 m/min), feed (0.1 mm/rev) and depth of cut (0.5 mm) were programmed into the CNC controller. Machining operation was initiated and the data acquisition system was switched on. The first few signals were ignored purposefully to avoid initial random variation and to allow the process to stabilize. Once the process stabilized, two hundred signals were acquired for each tool condition.

Vibration signals from the machine tool during machining under diverse conditions differ significantly in their pattern and amplitude. This variation can be effectively used to train a machine learning system to detect the tool condition

automatically. A model could be successfully developed by deriving various features of the vibration signature and analysing their information content. Figures 3 (a)-(e) shows the time domain signal plot of vibration acceleration obtained for the new tool and tools with pre-determined amount of wear (0.1 mm, 0.2 mm, 0.3 mm and 0.4 mm average values respectively) during machining of Al/9%Al_2O_3/3%Gr composite. In vibration term, it is a graph of acceleration with respect to time. These figures show only a single signal recorded (sample number) in 1 second during experimentation and 200 such distinct signals were recorded for each tool condition during machining. From these Figures, it can be observed that the '0.4 mm pre-created wear' condition (Fig. 3(e)) has maximum amplitude (6.5E-01g) compared to 'new tool' (3.0E-01g, Fig. (a)). This shows that tool wear above 0.3 mm induces excessive vibrations, which can be easily sensed by the operator without the need for any monitoring device. Conditions with tool wear above 0.4 mm were not simulated due to practical difficulties caused by excessive vibrations as well as due to sparking at tool-workpiece interface. Amplitude values were lowest for the new tool and increased as the amount of pre-created wear in the tool increased.





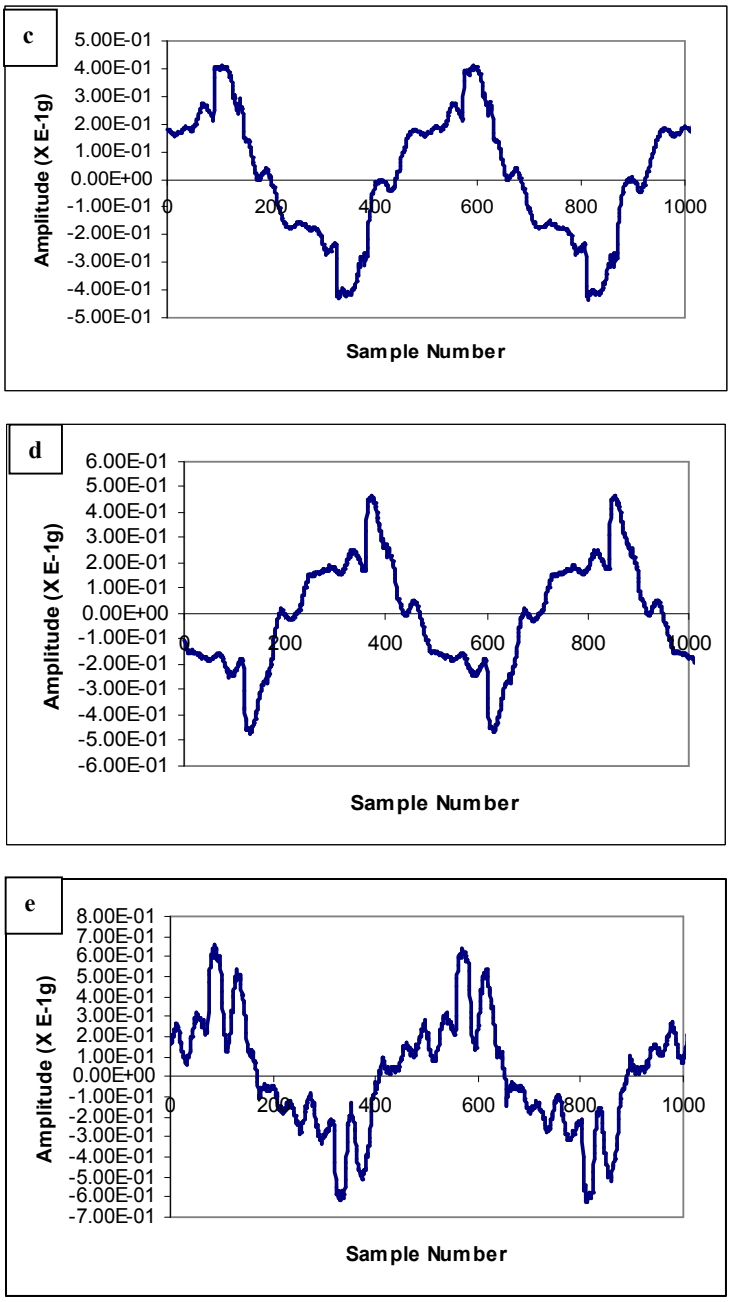


Fig. 3. Time Domain Signal Plot of Vibration Acceleration (a) New Tool (b) Tool with 0.1 mm Pre-Created Wear (c) Tool with 0.2 mm Pre-Created Wear (d) Tool with 0.3 mm Pre-Created Wear (e) Tool with 0.4 mm Pre-Created Wear.

3.3. Machine learning approach

The main aim of this approach is to apply appropriate sensor signal processing and pattern recognition techniques to identify and predict the cutting tool condition, so as to reduce the loss brought about by tool wear or tool failure.

The economic aspect of downtime (production loss during tool replacement) due to tool failure is very important in an automated factory. Therefore, monitoring systems are necessary to detect the progress of tool wear during the cutting operations, so that worn tools can be replaced in time. An effective Tool Condition Monitoring (TCM) system can improve productivity along with workpiece quality and hence has a major influence on machining efficiency. In the present study, data mining was done by processing the vibration signals incurred during the turning operations to predict the cutting tool condition. Waikato Environment for Knowledge Analysis (WEKA) software was used as a tool for data mining and analysis.

3.4. Feature extraction

Process of computing relevant parameters of the signals that reveal the information contained in them is called feature extraction. Main objective was to identify the most effective set of features to arrive at a reliable conclusion on the tool condition. Two sets of features namely, statistical and histogram features were extracted from the time domain vibration signal using MATLAB. Statistical features considered for analysis in this study are: Standard Deviation, Variance, Mode, Mean, Median, Co-Variance, Kurtosis, Skewness, Range, Minimum and Maximum. These statistical features couldextract from the signal and hence were considered for further analysis. Histogram features with a bin size of twenty (h1 to h20) were also extracted from the same set of vibration signals.

3.5. Feature selection using decision tree

To reduce the computational load and increase the accuracy of the model, the number of features used for classification has to be optimized. Feature selection or dimensionality reduction can be used to find the optimum number of features that have to be considered for classification. As there are number of techniques available for feature selection, decision tree algorithm was widely used [16, 17].

In this work, the C 4.5 algorithm (available as J48 in WEKA) was used for dimensionality reduction of both statistical and histogram features. The decision tree thus obtained was used for determining the minimum number of features that have to be used without sacrificing the accuracy of classification. Decision tree algorithm was used only for feature selection. Hence the tree was not pruned. A part of the visualized tree for statistical feature and histogram feature are given in Figs. 4 and 5 respectively.

The decision tree represents features in their order of importance. The top most node (feature) appearing in the tree contains maximum information about the signal. Remaining nodes in the branches gives the order of importance of the features. From Figs. 4 and 5, the order of importance of statistical and histogram features can be noted. Missing features do not have significant information for classification.

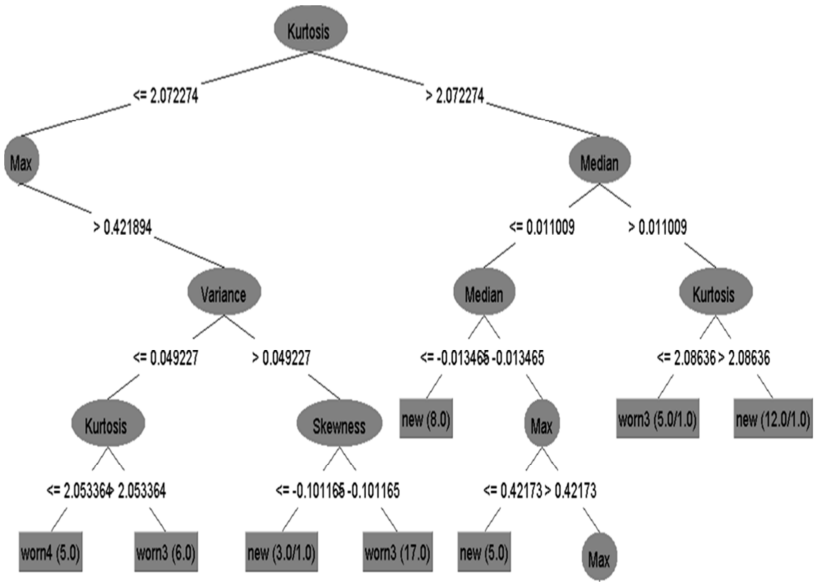


Fig. 4. Part of Decision Tree Used for Statistical Feature Reduction.

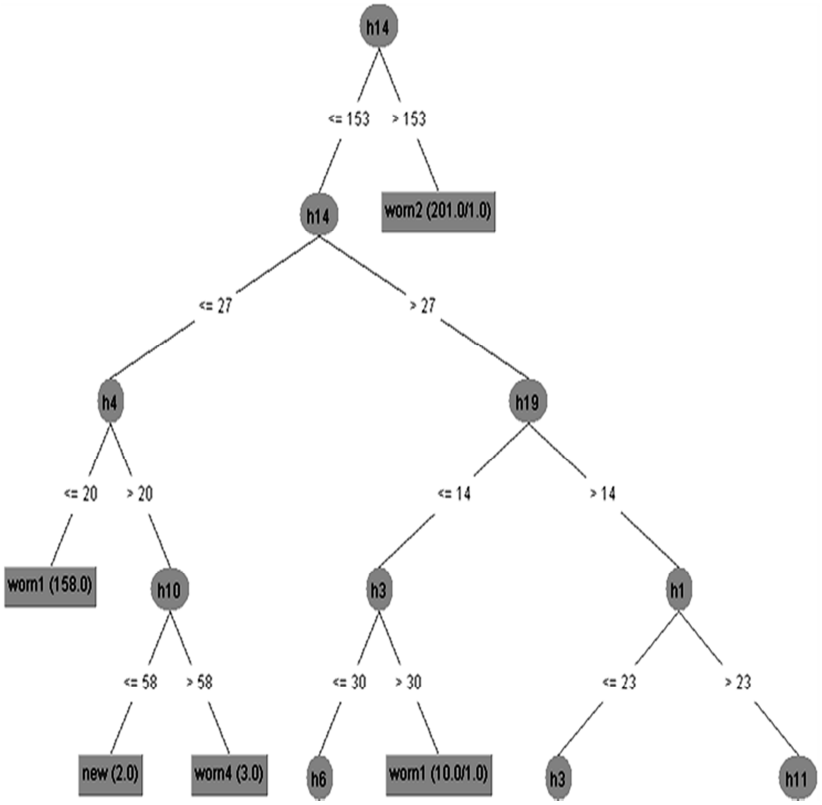


Fig. 5. Decision Tree for Histogram Feature Reduction.

3.6. Dimensionality reduction of features for predicting tool condition

For dimensionality reduction, initially all the features (statistical and histogram) were considered for classification and the classification accuracy was noted. Features which do not appear in the tree were then removed and the classification accuracy was again observed. Similarly, features were removed one by one based on their order of prominence (i.e. least prominent feature was removed followed by the next least prominent feature) and the corresponding classification accuracies were noted. Figures 6 and 7 shows the plot of classification accuracy versus the number of statistical and histogram features respectively.

Classification accuracy of statistical features (Fig. 6), shows that classification accuracy increased as number of features increased from one to three (43.6 to 77.1%) and then dropped to 76.8% when number of features were 4. This drop could be probably due to localized structural inhomogeneity in the specimen (vibration pattern changes due to agglomeration of particles at some location in the sample). Classification accuracy increased thereafter to 81.8%. Maximum classification accuracy of 82.9% was attained when number of features considered was 8 after which the accuracy decreased slightly.

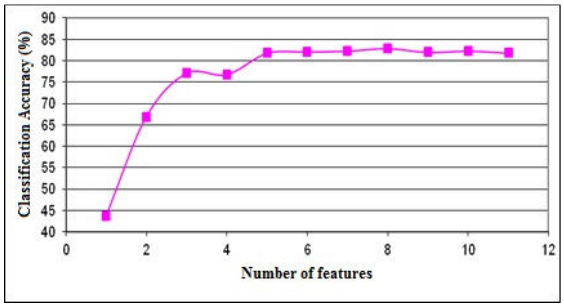


Fig. 6. Classification Accuracy versus the Number of Statistical Features.

From Fig. 7, it can be observed that, classification accuracy gradually increases as number of histogram features increases from one to four (62.3 to 87%). Minor variations were observed in the classification accuracy. Classification accuracy was maximum (88.9%) when the number of features considered was 9. Higher classification accuracy is always desirable and hence the number of features was chosen as 9 from a total of twenty histogram features. This dimensionality reduction (from 20 to 9) led to a significant reduction in computational load.

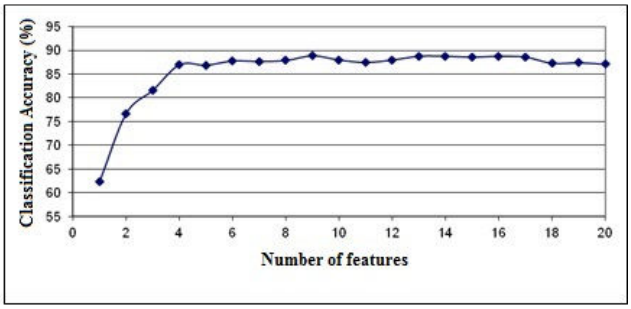


Fig. 7. Classification Accuracy versus the Number of Histogram Features.

4. Evaluation of Classifier

Random Forest classifier and the Classification and Regression Tree (CART) classifier (both of which are tree based classification techniques developed by Leo Breiman [18] were compared in this work to predict the actual condition of the uncoated carbide tipped tool while turning an Aluminium Hybrid Metal Matrix Composite.

Random forest is a tree based classifier consisting of a collection of tree structure, where each tree gives a classification. It uses a number of decision trees in order to improve the classification rate. Hence, the forest consists of using randomly selected inputs or combination of inputs at each node to grow each tree. To improve the accuracy, the randomness injected has to minimize the correlation while maintaining the strength. CART builds classification and regression trees for predicting continuous dependent variables (regression) and categorical predictor variables (classification). It works by recursively splitting the feature space into a set of non-overlapping regions.

After dimensionality reduction, the following features (statistical and histogram) were considered for further study.

i) Statistical features = Standard Deviation, Variance, Mean, Median, Kurtosis, Skewness, Minimum and Maximum.
ii) Histogram features = h14, h15, h19, h4, h1, h3, h10, h11 and h6.

Various features (both statistical and histogram) extracted from the machining vibration signal and the corresponding condition is fed in to the algorithm for training. After the completion of training a set of unseen data was presented to the classifier for classification and the results were observed for consistency in classification accuracy. It is observed that a training set in the sample space leads to a decision tree, which may be too large to be an accurate model; this is due to over-fitting. Such a fully-grown decision tree needs to be pruned by removing the less reliable branches to obtain better classification performance over the whole instance space. Pruning is required only if decision tree is used as a standalone classifier built using a single tree. The post-pruning strategy for the decision tree is not used since the random forest algorithm uses the method of voting using multiple tree models for extracting the final classification results.

4.1. Validation of classifier for the prediction of tool condition

Classifiers (Random Forest and CART) were validated with the help of a confusion matrix. A confusion matrix is a plot used to evaluate the performance of a classifier. It contains information about actual and predicted classifications done by classifier. Interpretation of the confusion matrix is presented in the following sections.

4.2. Confusion matrix for evaluation of statistical feature

Confusion matrix for statistical features shows how data points were classified for the particular tool condition. Worn1, worn2, worn3 and worn4 in the confusion matrices indicates 0.1 mm, 0.2 mm, 0.3 mm and 0.4 mm pre-worn out tool conditions respectively. Referring to the first row of the statistical feature

confusion matrix for Random Forest algorithm, for a new tool (Table 2), the number of correctly classified instances is 190. Three instances have been misclassified as worn 1, three instances have been misclassified as worn 3 and four instances have been misclassified as worn 4 tool conditions respectively. Referring to Table 3, showing statistical feature confusion matrix for simple CART algorithm, first element in the first row has 176 instances which have been correctly classified as new. Twenty four instances have been misclassified in all. The correctly classified instances for worn1, worn 2, worn 3 and worn 4 tool conditions are 182, 192, 136 and 142 respectively. Comparing Table 2 and 3, confusion matrix for statistical features of Random forest and simple CART, the numbers of correctly classified instances were more in Random forest classifier than when simple CART classifier was used.

Table 2. Confusion Matrix for Random Forest-Statistical.

New	Worn1	Worn2	Worn3	Worn4	
190	3	0	3	4	New
1	196	0	3	0	Worn1
0	3	193	2	2	Worn2
4	5	1	143	47	Worn3
3	0	3	51	143	Worn4

Table 3. Confusion Matrix for Simple CART-Statistical.

New	Worn1	Worn2	Worn3	Worn4	
176	6	1	10	7	New
5	182	7	6	0	Worn1
0	3	192	2	3	Worn2
6	10	4	136	44	Worn3
7	1	1	49	142	Worn4

4.3. Confusion matrix for evaluation of histogram feature

Confusion matrix for histogram feature gives the number of data points which have been correctly classified or misclassified for the corresponding tool condition.

Table 4. Confusion Matrix for Random Forest- Histogram Features.

New	Worn1	Worn2	Worn3	Worn4	
199	1	0	0	0	New
2	194	0	2	2	Worn1
0	0	200	0	0	Worn2
0	0	0	158	42	Worn3
1	2	1	36	160	Worn4

Referring to Table 4 (histogram feature for random forest), the first row of the confusion matrix represents the ‘new tool’ condition. First element in first row, i.e. 199 represents the number of data points that belong to this condition and have been classified correctly as ‘new’. Second element in the first row depicts the points which have been misclassified as ‘worn 1’ condition. This misclassification occurs probably when the vibration signals taken for a particular

tool condition during machining looks similar to other tool conditions. Similarly the second row represents the 'worn1' condition. Second element in second row (i.e. 194) represents the correctly classified instances for 'worn 1' condition. First element in the second row depicts the points which have been misclassified as 'new' tool condition, similarly the third, fourth and fifth element in the second row indicates the points which have been misclassified as worn 2, worn 3 and worn 4 conditions respectively. Similar interpretation can be given for all other elements as well. To summarize, the diagonal elements shown in the confusion matrix represents the correctly classified points for the respective experiments and all the non-diagonal elements represent misclassified ones.

Referring to Table 5 (histogram feature analysis using simple CART), the first element in the first row (191), second element in the second row (189), third element in the third row (199), fourth element in the fourth row (148) and fifth element in the fifth row (148) depicts the correctly classified points for the corresponding conditions respectively. Non-diagonal elements indicate the misclassified points for the corresponding conditions, as explained already. The misclassifications (in Worn 3 and Worn 4) can be attributed to high chatter and noise produced at the extreme condition.

Table 5. Confusion matrix for Simple CART-histogram features.

New	Worn1	Worn2	Worn3	Worn4	
191	4	0	0	0	New
2	189	0	4	5	Worn1
1	0	199	0	0	Worn2
0	2	0	148	50	Worn3
7	2	2	41	148	Worn4

Comparing Table 4 and 5, confusion matrix for histogram features of Random forest and simple CART, it was observed that when Random Forest was used as a classifier, the number of correctly classified instances for every tool condition was relatively more compared to classification using simple CART.

5. Discussions on Confusion Matrix for Evaluation of Tool Condition

In all the confusion matrices derived, the number of misclassifications does not vary much for 'new', 'worn1' and 'worn2' conditions. Classification accuracy for each class can be obtained by dividing the correctly classified instances by the total number of instances. For example, the condition 'new' of histogram features using Random Forest algorithm (Table 4), the number correctly classified instance is 199 (first row, first column) out of the total 200 supplied, hence the classification accuracy for this condition is 99.5%.

The classification accuracy for histogram feature, when only these three conditions (new, worn1, worn2) considered were 98.83% for Random Forest and 96.5% for Simple CART. Similarly, the classification accuracy for statistical feature by considering these three conditions was 96.5% for Random forest and 91.66% for simple CART. However at extreme condition of tool wear, that is when the wear is 0.3 mm and 0.4 mm, the classification accuracy decreases significantly due to machine chatter and very high degree of vibration, which will generally not be

encountered during commercial machining process. These extreme conditions were chosen for gathering wide range of data for extracting histogram and statistical features and their further classification. Worn 3 and Worn 4 tool conditions were relatively worse than those compared to rejected tools in an industry and hence these conditions will not be normally preferred. Although the classification efficiency is very low, the misclassifications are mostly between the two extreme conditions. Since these conditions are very rare in practical applications, the model only needs to identify the condition as being extreme. In addition, the number of misclassifications at extreme conditions is almost similar for both the classifiers. Thus at extreme conditions, both Random Forest and CART can be considered to perform at almost the same level for both statistical and histogram features. The classification of the tool condition was purely based on the features (both statistical and histogram) extracted from vibration signals during machining. The overall classification performance is presented in Table 6.

Table 6. Comparison matrix of classifier performance.

Feature type	Random forest	Simple cart
Statistical features	86.5%	82.8%
Histogram features	91.2%	87.5%

Classification accuracy of statistical feature using Random Forests was found to be 86.5% while with Simple CART it was found to be 82.8%. Again, the classification accuracy of histogram features using Random Forests was 91.2% and with Simple CART it was 87.5%. This is due to; in the Random Forest algorithm, the classifier was built with a 10 fold cross validation. Hence Random Forest classifier with twenty bin size of histogram features was well suited for online prediction of tool condition.

6. Conclusions

Vibration Signature Analysis was used for the condition monitoring of uncoated carbide cutting tool while machining Aluminium Hybrid Metal Matrix Composites. Extensive machining experiments were conducted on the composite sample simulating various possible conditions that are likely to be encountered in an industrial set-up. Vibration analysis was done using signal processing techniques to develop a model to predict tool condition during machining. The statistical and histogram features were extracted from the vibration signal and was then classified using two different classifiers. It was observed that a combination of histogram features with Random Forest algorithm was well suited for tool condition monitoring while turning aluminium hybrid metal matrix composites. The overall classification accuracy achieved was 91.20%. The system has the capability to be retrofitted onto any existing machine and can also be integrated into the controller of a CNC machine for monitoring the tool condition during machining.

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