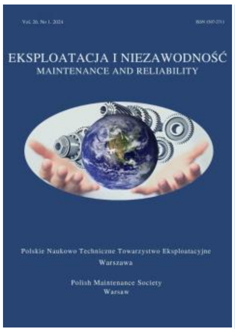

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Milling cutter fault diagnosis using unsupervised learning on small data: A robust and autonomous framework

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Highlights

- Multi-class classification in 6 different classes pertaining to different faults commonly occurring in milling tool cutter.
- Development of methodology based on unsupervised learning with very little training data needed.
- Robustness of methodology shown with testing with blind data set from a different set of tool inserts.
- Sensitivity studies to prove the robustness of the chosen parameters.

Abstract

Tool condition affects the tolerances and the energy consumption and hence needs to be monitored. Artificial intelligence (AI) based data-driven techniques for tool condition determination are proposed. Unfortunately, the data-driven techniques are data-hungry. This paper proposes a methodology for classification based on unsupervised learning using limited unlabeled training data. The work presents a multi-class classification problem for the tool condition monitoring. The principal component analysis (PCA) is employed for dimensionality reduction and the principal components (PCs) are used as input for classification using k-means clustering. New collected data is then projected on the PC space, and classified using the clusters from the training. The methodology has been applied for classification of tool faults in 6 classes in a vertical milling center. The use of limited input parameters from the user makes the method ideal for monitoring a large number of machines with minimal human intervention. Furthermore, due to the small amount of data needed for the training, the method has the potential to be transferable.

Keywords
tool condition monitoring (TCM), milling cutter, PCA, k-means clustering

1. Introduction

Controlled removal of material plays a significant role in subtractive machining which shapes a job into the preferred size. The term 'controlled' implies the coordination of a cutting tool and workpiece through a machine tool either manually or with the aid of computers. Turning, milling and drilling are the predominant machining activities that have been well established in industry and heavily explored in past decades. Among these three, most of the research has been persuaded towards milling owing to its versatile and complex nature. Milling can be operated in multiple degrees of freedom through more than one cutting teeth (edges) – usually called a toothed milling cutter. Any misconduct during machining affects the cutting tool and leads to its in-process failure. Consequently, it also disturbs the workpiece and degrades its surface finish,

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reduces machining accuracy, causes idle time – interruptions, to name a few. Hence, tool condition monitoring (TCM) has gained much consideration and is being profoundly investigated [6, 19, 35]. Considerable work has also been carried out focusing on the milling tool condition monitoring [20, 36, 39]. In spite of the many works, detection of in-process failures continues to be a challenge. TCM is considered to be a part of preventive and corrective maintenance however tending towards predictive and reinforced maintenance as a need of intelligent services anticipated in the fourth industrial revolution. Applying Machine Learning (ML) and artificial intelligence (AI) assists in developing an intelligent framework for TCM to track and avoid tool failures well before they occur. This is mostly considered either as ML-based classification (specific condition as healthy or faulty) or ML based prediction (continuous value) via regression. A lot of ML-based regression algorithms have been established for predicting cutting tool remaining useful lifespan (RUL) and few failures. Different techniques using the entire spectrum of the AI tools such as classification tools [5, 18, 23], decision trees [10, 11, 13, 14], artificial neural networks [12, 21, 31, 40], autoencoders [3, 15, 28, 30]. In summary of the literature review, most of the researchers employed supervised learning methods which yield potential results without any doubt however they limit themselves to classify data as supervised and prone to type II errors in case of lack of feature engineering. Hand crafted features in conventional machine learning requires a good knowledge of signal patterns and corresponding faults and on the other hand, deep learning models are unable to explain reasoning behind decision making. On the whole, training of supervised ML learning algorithms need precise data and deep learning algorithms on the other hand perform well on datasets of high volume.

Some researchers indeed have employed the unsupervised learning approach for tool condition monitoring and classification. Ashfahani et al. [1] used unsupervised continual learning method in tool monitoring systems to detect the tool wear state. Shi et al. [27] used unsupervised learning for monitoring tool breakage. They posed the problem as a binary classification problem for anomaly detection. Torabi et al. [32] applied clustering methodology for fault detection in high speed milling using force and vibration signals. The applicability, fault rate and feasibility of clustering method were discussed within the framework of state of the art studies. Gittler et al. [7] predicted the tool wear condition during milling via unsupervised machine learning approach. The tool condition was predicted with meaningful and accurate values according to the results. Brito et al. [2] worked on the definition of the tool wear condition during turning by utilizing self-organizing map. The authors demonstrated that using vibration acceleration signals, it was possible to estimate the tool wear with 92% accuracy. Rozo et al. [4] used Gaussian mixture model based clustering for the classification. They also provide an excellent overview of the different clustering techniques used for the tool classification. Specifically for milling tool condition monitoring. Yu [38] also proposed an adaptive technique based on Gaussian mixture model for determination of the cutting tool performance. The model developed showed a good performance in terms of indicating the performance characteristics of a cutting tool. Li et al. [16] used the partitioning around medoids, as the clustering technique. They argue that the PAM is inherently more robust in the presence of outliers. They apply the methodology for determining the tool wear state and use 4 classes for determining the degree of wear. The tool wear degree classification problem has also been investigated by Torabi et al. [33]. Liu et al. [17] used the unsupervised learning approach for chatter detection. They employed a combination of Gaussian mixture model and k-means clustering for the detection and binary classification. An excellent review of the machine monitoring system over the last decade has been carried out by Ahmad et al [9]. Tran et al. [34] also reviewed the machine learning based tool condition monitoring systems including cloud migration, shared knowledge databases and custom networks to enlighten the future of tool monitoring systems.

Based on the review of the literature, there is no work that deals with multi-class classification of different kinds of damage in milling tool condition monitoring using unsupervised learning techniques without any feature engineering. This is the main contribution and novelty of the paper. In this study an unsupervised learning approach is developed for a multi-class classification of faults in a milling cutter tool. The principal component analysis (PCA) is used for dimensionality reduction and feature extraction. The first 6 principal components are then used with the k-means clustering approach for the classification.

Once the model is trained using minimal human intervention, new data sets can be projected onto the feature space and the condition can be determined. The problem of multi-class classification for milling tool condition monitoring taking into consideration this wide range of tool faults has not been dealt with in the best knowledge of the authors. In addition, to the multi-class classification, the outlined method is easily transferable to other problems as it requires very little data for training and operator skill for labeling and classification. The unsupervised learning approach has been applied instead of deep neural network in order to ensure that the approach can be used for online-tool monitoring in an industrial scale to monitor tools in a large facility with multiple parallel machining processes as well as ensure that damage may be detected with little training data.

2. Experimentation and data collection

In order to characterize progressive behavior and continuous deterioration of cutting tools in terms of cutting tool vibrations, experiments are planned meticulously. Design of experiments plays a crucial role in authenticating the datasets used for further processing and decision making. To generate data sets, vibration signatures were acquired for in-process damaged and damaged-free configurations of a tipped tool, for face milling. The experimental setup was arranged in an industrial environment 'Axis Metal-cut Technologies' based in Pune, India. In this research, data acquisition has been carried out twice; first by considering a set of machining parameters for training the algorithm and second to validate the results by blind dataset. The experimental arrangement used for both cases is represented in Figure 1. The details are provided in Table 1. It should be noted that the sensor location was chosen at the top of spindle as the rotation of the spindle is considerably higher (1000 – 2500 rpm). At that location a high amplitude signal is observed. Experiments were designed to capture anomalous moments of various in-process faults such as edge fracture, notch and crater wear, flank face and nose radius wear etc. The efficiency and robustness of monitoring systems is fully dependent on the severity of the defective conditions and input factors of machining under which the vibrations data was acquired. For the blind data set, the tool was inspected and the size of each fault was measured using the metallurgical microscope. The size of various faults was determined using the metallurgical microscope and the captured images for the tool are provided in figure 2. The size for each fault are specified in Table 2. The fault-free inserts used in machining were brand new inserts, i.e., never used before as shown in Figure 3. On the other hand, cast out defective inserts (such as edge fracture, notch and crater wear, flank face and nose radius wear etc. as shown in Figure 4) were collected and faulty configurations were considered.

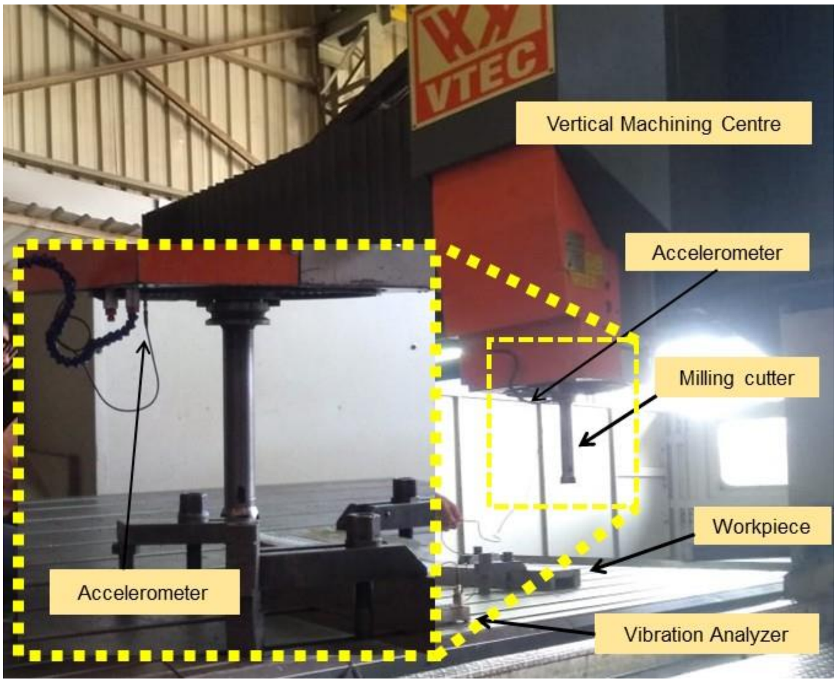
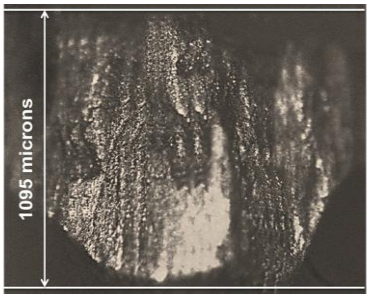


Fig. 1: Experimental Setup.

Table 1. Experimental Setup details.

Sr. No.	Property	Specification
1.	Equipment	Vertical Machining Center (VTEC Model: VF4000 with table travel 4200 mm along X-axis, spindle head travel 2300 mm along Y-Axis and vertical travel 920 mm along Z-Axis equipped with FANUC 18iMB CNC controller)
2.	Sensor	PCB Piezotronics, Model: 352C03 Integrated Circuit-Piezoelectric of sensitivity (±10 %) = 10 mV/g and range of ± 500g_{pk}, frequency (≤5%) = 0.5-10,000 Hz
3.	DAQ system	Dewesoft, Model: DEWE–43A
4.	Work piece	Mild steel hollow cuboid of section ‘C’ (650 250 100 in mm)
5.	Tool	Milling cutter diameter was 63 mm and four inserts with carbide- coated teeth
6.	Microscope	Conation Technologies, Model: SuXma-MOTO, with magnification range 50X to 1000X)

(a)



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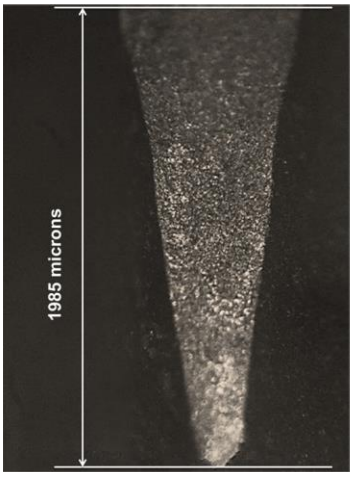


(b)

(d)

(e)

Fig. 2. Verification of different tool faults under metallurgical microscope (a) wear at flank face (b) wear at nose radius (c) notch wear (d) crater wear (e) fracture at cutting edge.

Table 2. Size of various faults.

Sr. No.	Type of fault	Size (μ m)
1	Wear at flank face	1300 – 1500
2	Wear at nose radius	900 – 1000
3	Notch wear	1800 – 2000
4	Crater wear	1500 – 1650
5	Fracture of cutting edge	2400 – 2500
6	Built-up cutting edge	800 – 950

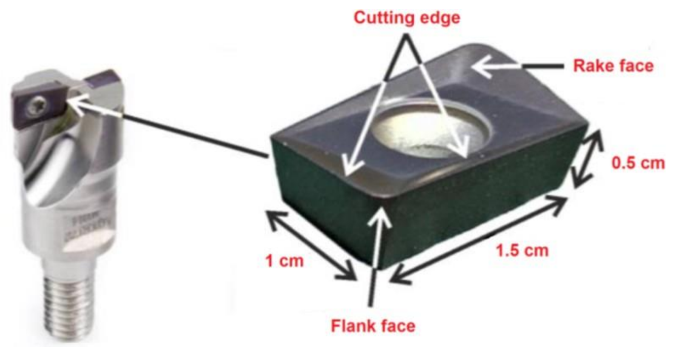


Fig. 3. Defect-free (Normal) insert with the dimensions.

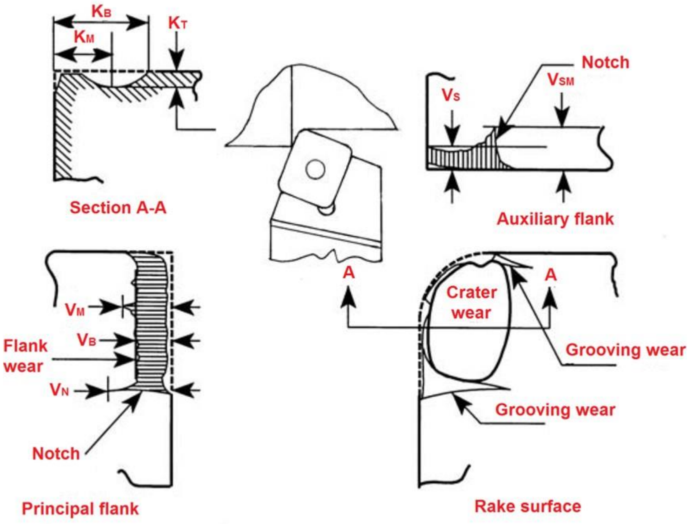


Fig. 4. Defective inserts.

The performance of the cutting tool primarily depends on three factors viz., the speed at which material removal is performed, table feed, and depth of the cutting, thus have been selected for the investigation. The standard machining parameters were chosen referring to the standard Komet catalog and usual formulae and were chosen as, cut depth 0.25 mm, speed 178 m/min, and table feed 1980 mm/min. By considering this machining inputs and tool configuration stated in Table 3, face milling operations were performed 7 times, and change in vibration was collected. To begin with data collection, the primary check was carried out to ensure the machine tool and its components are in a normal state. Initially, some rough cuts were performed to omit unevenness the random vibrations. Measurements were carried out at 20 kHz sampling rate for at least 20 s in each case.

Table 3. Tool Configurations

Sr. No.	1	2	3	4	Class label
1	Normal	Normal	Normal	Normal	T_N
2	Normal	Normal	Normal	Wear at flank face	T*WFC*
3	Normal	Normal	Normal	Wear at nose radius	T*WNSR*
4	Normal	Normal	Normal	Notch wear	T*WNT*
5	Normal	Normal	Normal	Crater wear	T*WCT*
6	Normal	Normal	Normal	Fracture of cutting edge	T*FCE*
7	Normal	Normal	Normal	Built-up cutting edge	T*BUE*

For the data processing, the measured signal was divided into sets with 5000 samples. 15 of those sets were used for training. The unseen data sets were used for testing and validation. In addition to the training data, the blind data set was collected on the same machine with a different tool insert at a different time. As the machine used for the data collection was the same, the underlying vibrations of the machine are maintained. As different tool inserts were used the applicability of the method is much greater albeit at the current time has been tested only for one machine.

3. Methodology

As mentioned before, the unsupervised learning approach is used for classification problem. Unsupervised learning is a class of AI algorithms which use and identify patterns in unlabeled data sets without any human intervention. The application of unsupervised learning ensures that real-time monitoring is possible with minimal training data and at the same time minimal expertise of the operator. Also due to the unsupervised approach, minimal human intervention is needed, thus ensuring a large number of machines can be monitored simultaneously by one operator.

The methodology can be explained in detail based on the figure 5. The methodology has the off-line part which can be viewed as the training of the unsupervised learning approach. The online part is for the real-time monitoring. During the training phase, data from multiple classes without labels is used. The data is pre-processed with de-noising to increase the signal to noise ratio in the measurements, followed by zero padding which allows a better resolution in the frequency domain. These are standard procedures in signal processing. The discrete Fourier transform is then employed to convert the data from the time domain to the frequency domain. Then the PCA is done on the frequency domain data. The PCA is a commonly used feature extraction method which is applied with a view to project a high dimensional data into lower dimension data. PCA ensures that maximum information of the original dataset is retained in the dataset with the reduced no. of dimensions and the corelation between the newly obtained principal components is minimum. The mathematics behind the PCA may be found here [29]. The classification process is then carried out using first 6 PCs for the clustering through the k-means clustering algorithm. The coefficients from the PCA and the cluster means from the k-means clustering are used in the online system for classification. The k-means clustering is an unsupervised algorithm for partitioning the data into clusters. The algorithm works iteratively to yield centroids of k clusters with minimal error. The centroids are treated as the representatives of those clusters. More details of the k-means clustering algorithm may be found [26]. The new data is pre-processed similar to the data in the training phase. The processed data is then projected on the PC space using the PCA coefficients and assigned the classes based on the Euclidean distance from the cluster means. The testing was carried out on unseen test data from the measurements collected in the same campaign as the training dataset as well as with the blind data from a completely new measurement campaign at a different time on the same machine, as explained in the experimentation and data collection section.

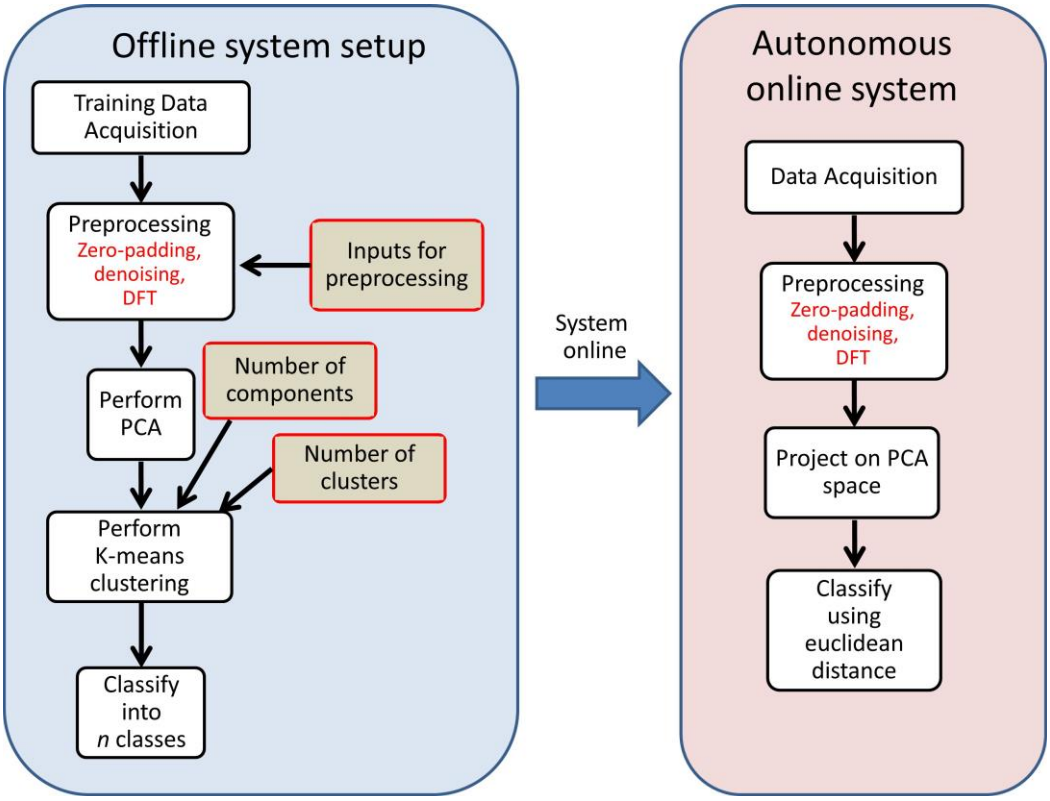


Fig. 5. Methodology flowchart.

It should be noted that, in the offline system, there are just three points of human intervention. In determining the pre-processing, in determining the number of PCs taken for clustering and the number of clusters to be identified. In the pre-processing stage, the DFT is used to convert the data from time to frequency domain. This is done based on the experience from conventional techniques, where spectrograms were used for determining damage in tools. The zero-padding is necessary to improve the resolution in the frequency domain. It improves the feature extraction but might increase the computational effort. The number of PCs to be used for characterization are taken on the basis of their total contribution. The value of 90% is commonly used in the PCA based processing [22, 37]. The number of clusters to be used needs a little operator insight and knowledge of the training data. But once these parameters are established, the online system is completely without any human intervention. This is the key benefit of using unsupervised learning. This technique is easily scalable and needs very limited data for training as compared to the deep neural network techniques. Also, at no point in the offline and online part are the data labels for the data sets needed and hence the methodology is identified as unsupervised learning.

4. Results and Discussion

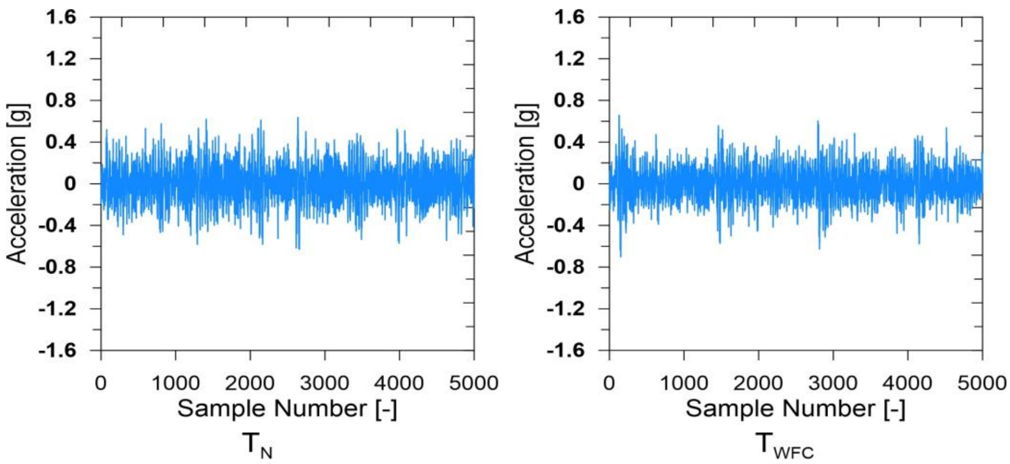
This section discusses the step-by-step results for the methodology employed.

4.1. Offline system setup

The raw data was collected using tools in different conditions. The raw data for all the cases is presented in Figure 6. As can be seen, there is a difference in the time signatures but not a lot of insights may be obtained from the time domain data. So the data was converted to the frequency domain. The frequency spectrum is shown in Figure 7. As can be seen, there are significant differences in the peaks, but the changes are far too many and hence are beyond the capabilities of human comprehension to summarize.

Hence, the PCA was used to reduce the dimensionality of the data. The PCA for the first 6 components are shown in Figure 10. The different colours indicate different tool conditions. It should be noted that the different colors shown in the PCA are for presentation only. The data used for the PCA was not labeled. It can be seen that there is a fairly good clustering of the same tool condition. But at the same time using just 2 PCs might lead to misclassification as the classes are fairly close to each other particularly in PC5 and PC6. The contributions of each of the PCs are shown in Figure 10c. Only the first 6 PCs were used as the total contribution for the 6 PCs exceeds 90% which is taken as a good standard for the depiction of the sensor features and differences [22, 37].

Once the components are known, the k-means clustering algorithm is used for the classification. The input parameter apart from the PCA scores is the number of classes that are to be identified. The definition of the number of classes may be done through sensitivity studies as done in [25] or based on the knowledge of the investigator. The clustering was done using the first 6 PCs but only the first two PCS are shown in the figure 9 for the sake of conciseness. If the number of clusters to be identified is 7, comparing to Figure 10d, we can see that the identified clusters are not in line with PCA results which indicates severe misclassification. On the other hand, if the number of clusters to be identified is given as 6, the clusters related to fracture of cutting edge, and built up cutting edge are grouped together and the other clusters are accurate with the distribution shown in Figure 10d. As the tool damage identified will be still related to cutting edge, thus helping us identify the problem. Hence a clustering approach with 6 clusters will be carried on from here. For the 6 clusters approach the agreement between the identified clusters perfectly matches those obtained from the PCA plot knowing the labels. Again, it needs to be highlighted that the data sets were not labeled but only the total number of different classes was used as the input. These results indicate that the unsupervised learning approach outlined can indeed perform multi-class classification. So, the new data can be used in the online-system setup and used for assessment. The coefficients obtained from the PCA and the cluster centroid coordinates obtained from the k-means clustering are then are then used for the online system. The PCA coefficients allow projection of the new data in the equivalent PC space. While the proximity to the cluster centroids allows classification



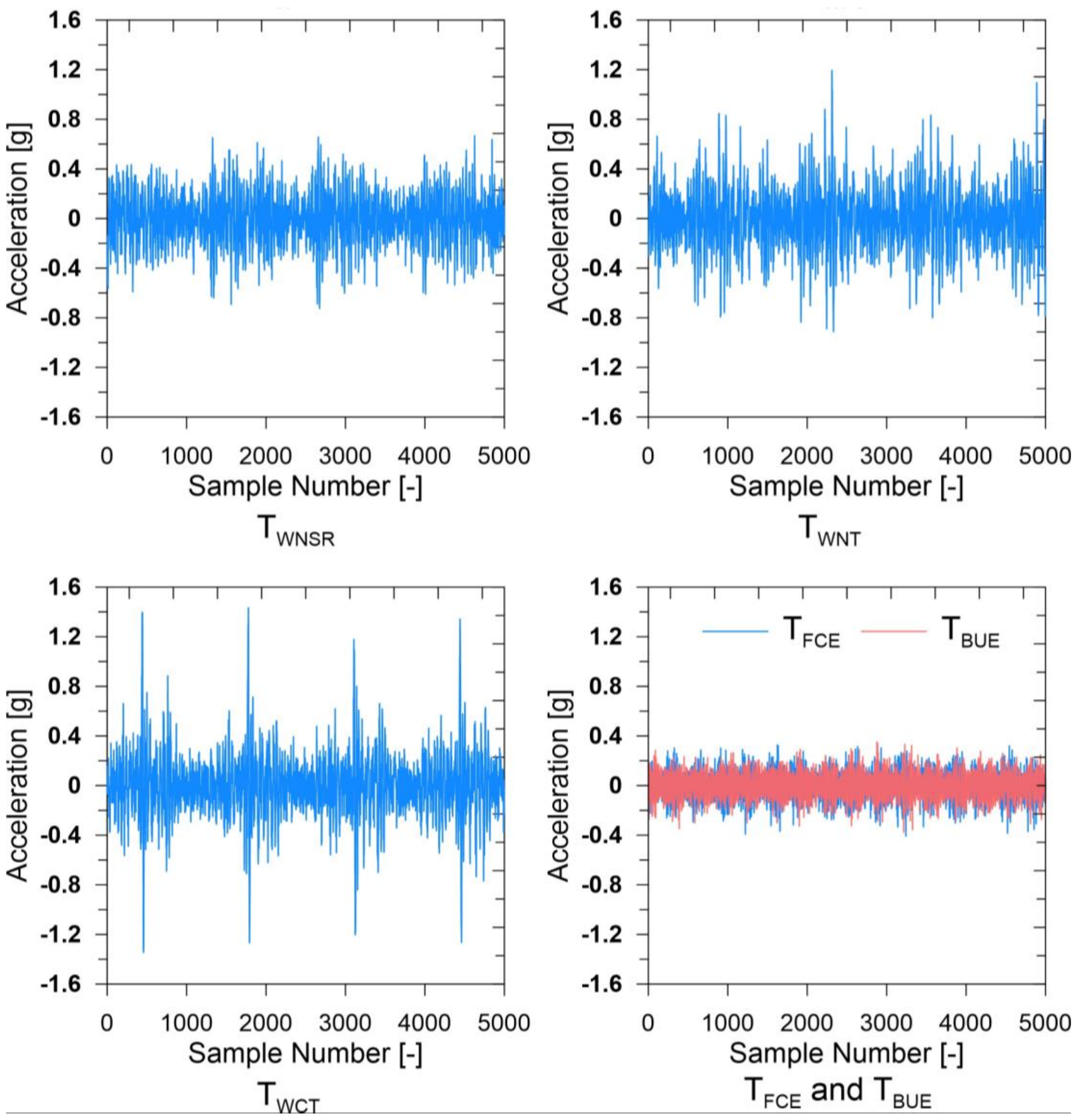


Fig. 6. Comparison of time domain signals in different conditions.

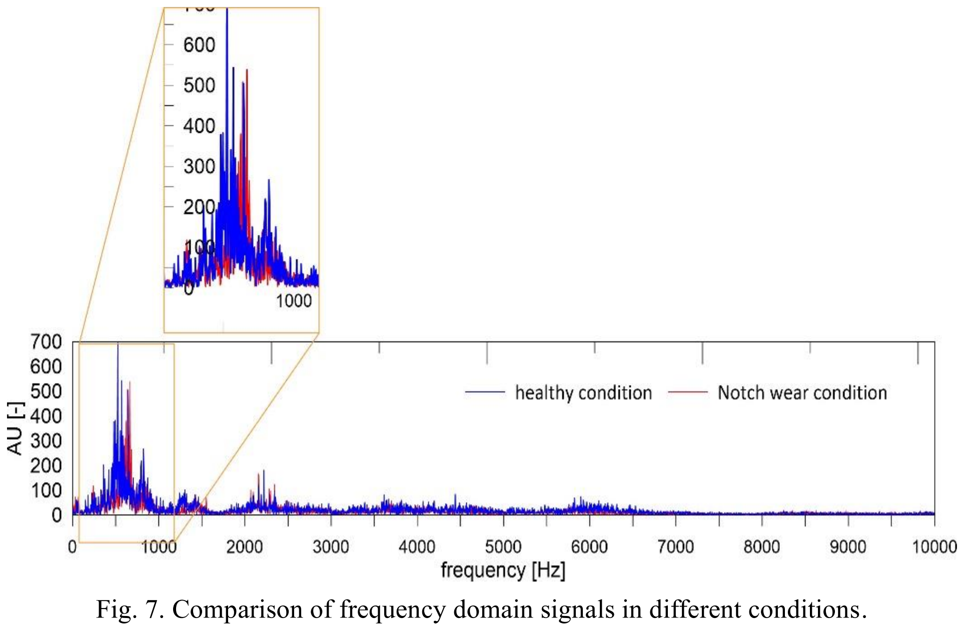


Fig. 7. Comparison of frequency domain signals in different conditions.

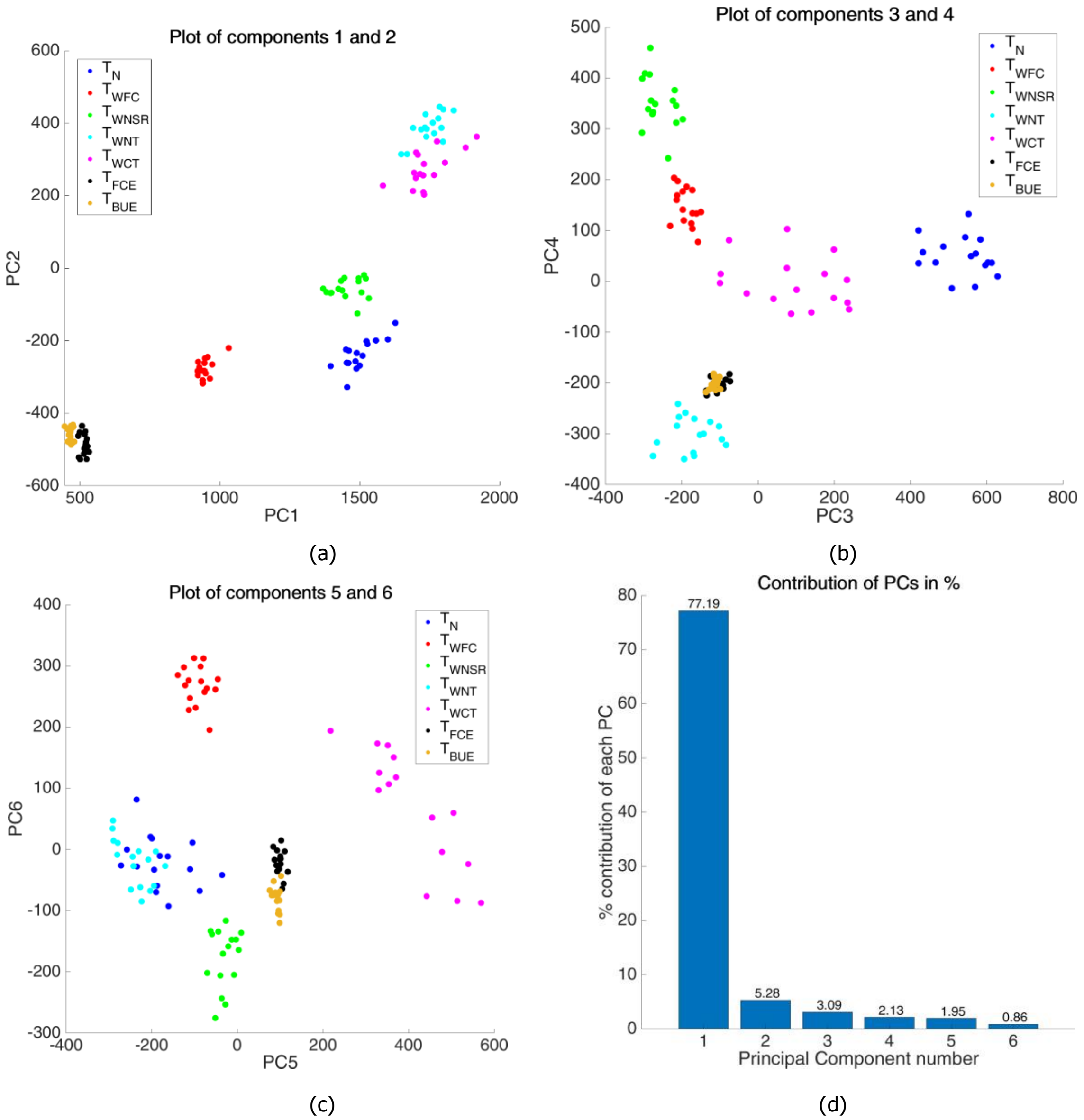


Fig. 8. PCA projections for training data set (a) PC1 v/s PC2 (b) PC3 v/s PC4 (c) PC5 v/s PC6 (d) Contribution of first 6 PCs.

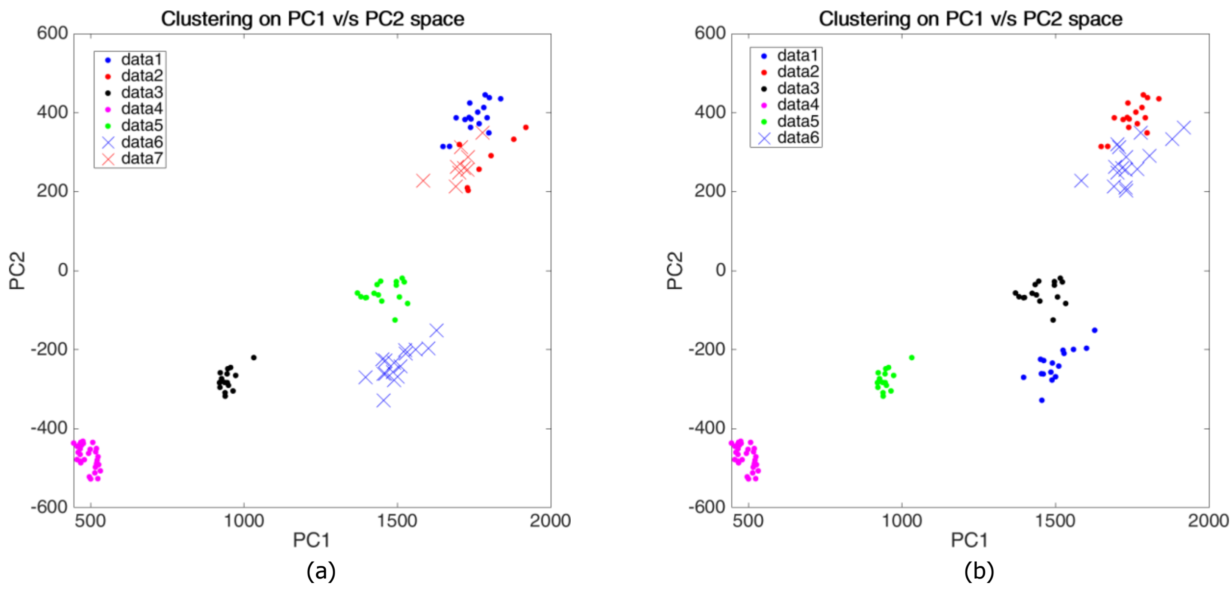


Fig. 9. K-means clustering (a) with 7 classes (b) with 6 classes.

4.2. Online system setup

Once the system is trained and put online, the new data collected can easily be projected into the PC space and using Euclidean distance in 6 dimensional space the cluster number may be identified. The figure 10 shows the projection of two such data sets from unseen test data. The projections are slightly different than the training data, but indeed are projected in the vicinity of the trained data. In order to determine the statistical stability of the method, 100000 random samples from the unseen data were tested for the classification performance. As can be seen a very high accuracy of classification is obtained with maximum misclassification of 0.7%.

The colours used for the same class are kept similar. The projected data is shown with 'diamond' symbol. Based on this the validity of the projections can be ascertained. The cluster is assigned based on the Euclidean distance from the cluster mean obtained from the k-means clustering algorithm. The statistical stability of the approach and the validity to the unseen data set was then determined in the confusion matrix. The accuracy of the classification is excellent, but there are 9 potential false positive classifications which may be of concern. The false positive is the condition where the damage is present and missed by the algorithm. This damage when not detected early may lead to catastrophic failure. In order to avoid this solution, more studies were carried out for the 9 misclassified signals. The 4 preceding 5000 samples and 4 following samples were taken and classified. They are shown in Table 4. As can be seen there is some misclassification, but out of the 9 sets presented, most of the samples will be correctly classified. The largest misclassification was for 10000 samples which at 20 kHz sampling rate lasts 0.5 s. Hence, we can conclude that the false positive misclassification will not lead to a large damage later as it will be caught in a short time.

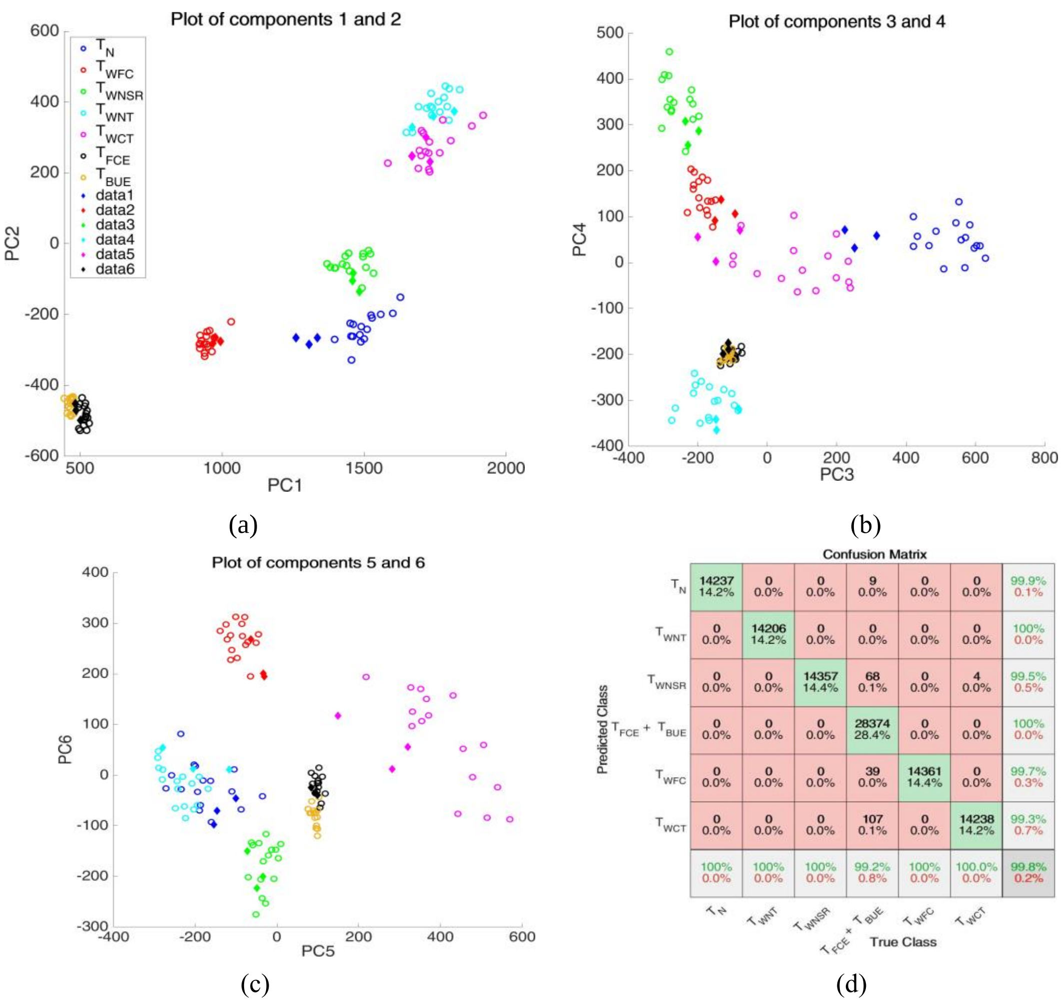


Fig. 10. Results for testing dataset (a) Projection of test data in PC1 v/s PC2 space (b) Projection of test data in PC3 v/s PC4 space (c) Projection of test data in PC5 v/s PC6 space (d) Confusion matrix for statistical testing.

This indeed shows that the proposed methodology has a potential for real time tool condition monitoring, and the risks of false positive classification is well managed. The next section provides some additional studies that show the robustness and stability of the methodology which is another essential characteristic of the proposed technique. Another point to note is that, as the computational effort and the memory needed for the methodology is not high, the methodology can be implemented on a small IC and allow a low cost and easily scalable monitoring system which works in real time is possible.

Table 4. Analysis of False Positive Classification.

Sample numbers	False Positive incident								
	1	2	3	4	5	6	7	8	9
n-4	4	4	4	4	4	4	4	4	4
n-3	4	4	4	4	4	4	4	4	4
n-2	4	4	4	4	4	4	4	4	4
n-1	4	4	4	1	4	4	6	4	4
n	1	1	1	1	1	1	1	1	1
n+1	4	1	4	4	1	4	4	1	4
n+2	4	4	4	4	4	4	4	4	4
n+3	4	4	4	4	4	4	4	4	4
n+4	4	4	4	4	4	4	4	4	4

- n is time signal with false positive
- 4 corresponds to class $T_{F\ CE} + T_{BUE}$
- 1 corresponds to class T_N
- 6 corresponds to class $T_{W\ CT}$

4.3. Sensitivity studies

In order to check the robustness of the methodology developed, some sensitivity studies were carried out. The studies aim at showing the applicability of methodology and its performance under different conditions. The studies covered include, the classification performance using different amounts of training data (training sets), Classification performance for different sample size, classification performance for different number of PCs used for classification. These tests are carried out corresponding to the user inputs provided in the offline system setup stage. They show that the methodology is not overly sensitive to the chosen parameters (small difference in the tuning parameters only results in marginal change in the performance), so a small error in the tuning parameters will not affect the performance of the methodology. For a multi-class classification problem, many performance metrics have been proposed in the literature [8]. For the sake of this study, accuracy and false-positive rate is chosen.

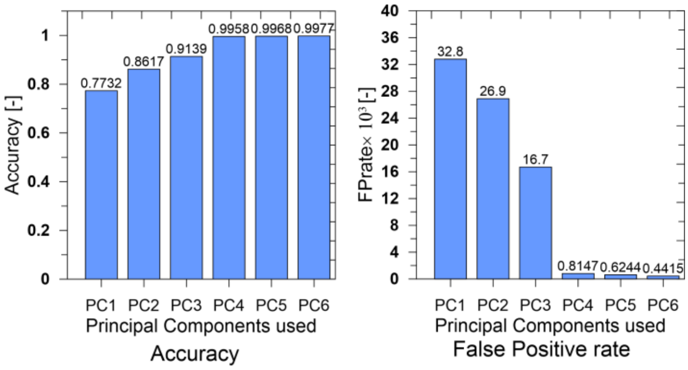


Fig. 11. Sensitivity of methodology to number of PCs used for classification a) Accuracy b) False Positive Rate.

The figure 11 shows the accuracy and false positive rate for using different number of PCs for the classification. As can be expected, as the number of PCs used increases the accuracy as well as the FP rate improve. The improvement, for each PC added goes down which is expected as the contribution of the later PCs to the variation is lower.

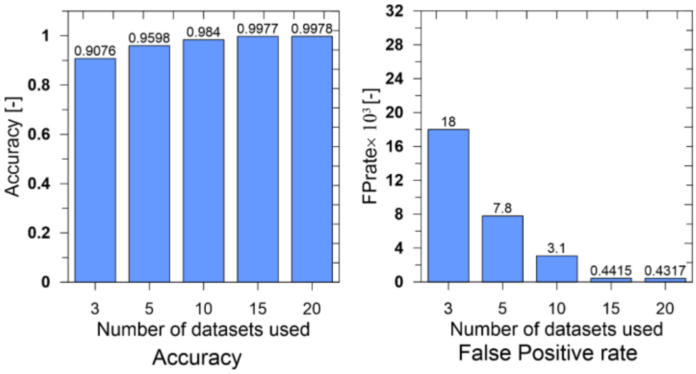


Fig. 12. Sensitivity of methodology to number of datasets used for training a) Accuracy b) False Positive Rate.

The figure 12 shows the performance with increase in the number of training datasets. These results too follow the intuitive trend, as the number of data sets increase the performance improves. The figure 13, presents the performance when different size of samples were used in each dataset. As can be seen, first as the number increases from 1000 to 5000 and improvement is seen. While for the 10000 samples the performance falls. This behavior can be explained based on the fact that, in order to maintain the amount of data used for training, when the size of the data set was increased, the number of training data sets was reduced. Hence, when the sample set size is 10000 samples the number of training sets are fewer leading to increased error in classification. In summary, the proposed technique even after the use of PCA maintain the physical nature of the system and make sense intuitively (eg: more data leads to better classification, more PCs (information) leads to better classification etc.) Hence the technique is considered robust and requiring only limited operator skill for calibration.

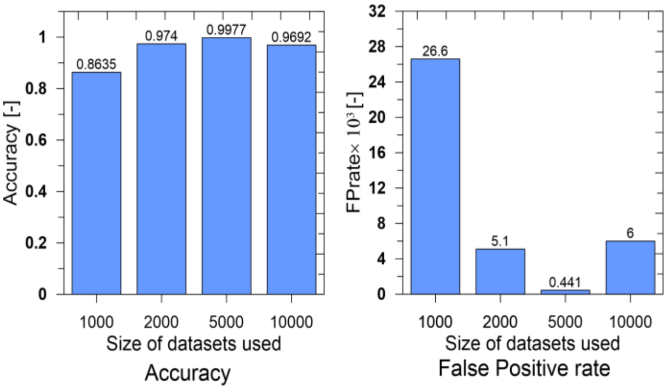


Fig. 13. Sensitivity of methodology to size of datasets used a) Accuracy b) False Positive Rate.

4.4. Comparison with ML based techniques

The same dataset has been used with a range of ML algorithms and has been presented by Patange et al. [24]. The performance of the above technique may be compared to the once presented by Patange et al. [24]. Under similar sample size and training datasets, the unsupervised approach seems to outperform the hand-crafted features. The maximum accuracy obtained with the ML tree algorithms was 96.25% while the proposed technique achieves 97.4%. The accuracy may be further improved with minimal increase in computation time to 99.77%. Furthermore, the proposed unsupervised learning approach needs very little operator input, and expertise, at the same time is found to be computationally very efficient. The projection and classification takes approximately 0.007 s as compared to 0.2 s reported in [24]. A point to note is that the, the ML algorithms were implemented in visual basic (VBA), while the current unsupervised learning approach is implemented in Matlab, the processing time is not directly comparable. But we can indeed conclude, that it is suitable for real time monitoring. A possible reason for the better performance of the methodology over the ML technique, is the choice of the features, the features used by Patange et al. are statistical in nature, and only ascribe the difference in the signals obtained in terms of the change in the statistical parameters. On the other hand, the PCA reduces the dimensionality while maintaining the features which can explain the maximum deviation in the data set. So indeed due to the better and targeted feature extraction strategy, the performance of the methodology is better.

5. Validation on Blind data

The methodology was applied on dataset obtained separately with a different tool insert which is so-called 'blind dataset' (completely unseen by the training). The results are presented in form of a confusion matrix in figure 14.

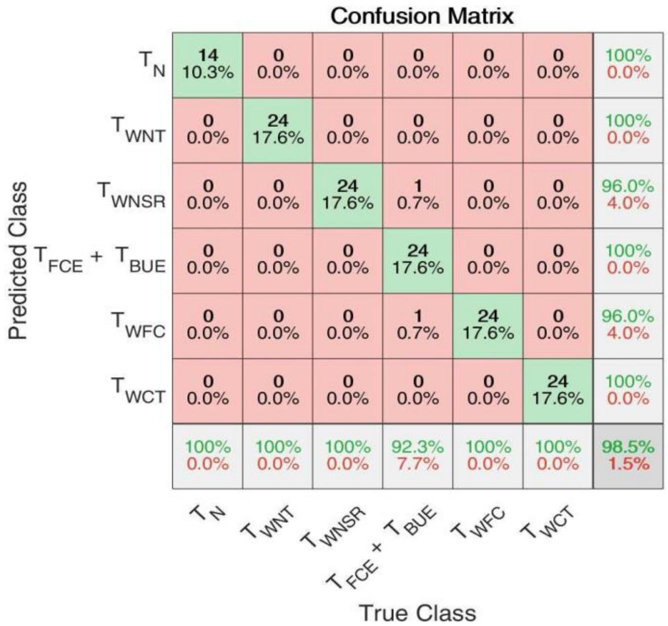


Fig. 14: Confusion matrix for blind dataset.

As the amount of reliable data from the blind tests was limited, the number of runs made are quite small. But the method shows high accuracy (> 98.5%) and there are no false positive incidences. Hence it can be said that the outlined method gives excellent results for the multi-class classification of different faults in the milling tool. In summary, as the training data needed and the operator skill required for the methodology is limited, the calibration step for each machine can be easily conducted separately. Also, as the human intervention is very minimal, multiple machines can be monitored in parallel with individually maintained databases. Thirdly, as the training stage is not time consuming, datasets for the calibration can be regularly updated, in order to take into consideration the change in the machine vibration parameters. Hence the methodology has a huge potential in application on the shop floor with a fleet of machining machines with minimal human supervision.

6. Conclusions and future work

The paper outlines a methodology for multi-class tool condition classification based on unsupervised learning principles. The methodology includes a two-stage approach. The offline stage is the training step carried out using the training data. The PCA is used for feature extraction and dimensionality reduction. The PCs from the PCA are used for classification using the k-means clustering algorithm. For the TCM the collected data in real time is projected on the PC space and then classified based on the Euclidean distance to the median obtained from the k-means clustering approach. The key takeaways from the study on the vertical milling center with tool faults are:

- Multi-class classification is possible (6 classes)
- High accuracy (≈ 97%), and few false positives
- Methodology is robust and works on blind data
- Stable performance, not strongly correlated to the chosen training and signal processing parameters

Although, the methodology works in the given conditions and with blind data, there remain some questions on the cross-applicability of the technique to data from other machines as well as different machining conditions. This is identified as an area of future work. Tackling these problems is identified as the next step of research. Another significant shortcoming of the present study is that the effect of the different cutting conditions on the performance of the methodology has not been studied. This has to be investigated experimentally and is recognized as another area of future work. But as mentioned earlier due to low amount of training data necessary, the training data set can be enlarged to include different conditions. The increase in the data with the increase in the complexity will not be of the same order as is expected in other AI based data-driven techniques. Furthermore, the methodology is not computationally intensive and the small increase in training data will not adversely affect the real-time implementation.

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