CONDITION MONITORING OF FACE MILLING TOOL USING VIBRATION AND SOUND SIGNALS

Thesis

Submitted in partial fulfillment of the requirements for the degree of

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by

MADHUSUDANA C. K.

DEPARTMENT OF MECHANICAL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA,

SURATHKAL, MANGALORE – 575025

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D E C L A R A T I O N

I hereby *declare* that the Research Thesis entitled **"CONDITION MONITORING OF FACE MILLING TOOL USING VIBRATION AND SOUND SIGNALS"** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Department of Mechanical Engineering** is a *bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

Register Number : **138038ME13F15**

Nameof the Research Scholar : **MADHUSUDANA C. K.**

Signature of the Research Scholar :

Departmentof Mechanical Engineering

Place : NITK-Surathkal

Date :

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This is to *certify* that the Research Thesis entitled **"CONDITION MONITORING OF FACE MILLING TOOL USING VIBRATION AND SOUND SIGNALS"** submitted by **Mr. MADHUSUDANA C. K.** (**Register Number: 138038ME13F15**) as the record of the research work carried out by him, is *accepted as the Research Thesis submission* in partial fulfillment of the requirements for the award of degree of **Doctor of Philosophy.**

Research Guide(s)

Dr. Hemantha Kumar
Assistant Professor
Department of Mechanical Engineering
NITK, Surathkal

Prof. Narendranath S.
Professor
Department of Mechanical Engineering
NITK, Surathkal

Chairman-DRPC
Date:

DEDICATION

This thesis is dedicated to:

- ❖ *My parents and my entire family members, who never stop giving of themselves in countless ways,*

- ❖ *My teachers who taught us the purpose of life,*

- ❖ *My friends who encouraged and supported me,*

- ❖ *All the people in my life who touched my heart,*

I dedicate this research work.

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(Madhusudana C. K.)

ABSTRACT

Fault diagnosis of the cutting tool is very essential for improving the quality and maintaining the accurate dimension of the products during machining process. The milling is a multi-toothed metal removing process. In face milling, because of dynamic variation of cutting forces, thermo-mechanical shocks and vibration, which results in catastrophic tool failure along with gradual wear of the tool inserts. Wear development during machining can reach up to unacceptable level, resulting in inaccurate dimension and poor surface finish of the components. Monitoring the condition of the cutting tool during face milling operation is a vital role before the tool causes any damage on the machined surface which becomes highly valuable in order to avoid loss of products, damage to the machine tool and associated loss in productivity. Keeping in view of the automation, it is necessary to choose an effective and efficient method for monitoring the cutting tool condition without affecting the machining setup and the work material.

This study mainly deals with the fault diagnosis of the face milling tool using vibration and sound signals through signal processing techniques and machine learning approach. The face milling is a machining process with an intermittent cutting action. The milling tool will undergo different types of faults such as flank wear, breakage and chipping which occurs predominantly during milling. The vibration and sound signals under these faulty and healthy milling tool conditions are acquired and these signals are further analyzed. Current research work is mainly categorized into two phases.

The first phase is to detect/diagnose the face milling tool conditions by analyzing the vibration and sound signals using signal processing techniques. The signal processing techniques such as time-domain analysis, spectrum analysis, cepstrum analysis and continuous wavelet transform (CWT) method are applied to recognize the face milling tool conditions. The cepstrum analysis has been applied for the first time in fault detection of the face milling tool and has provided the sufficient information about the face milling tool condition using both vibration and sound signals. Generally conventional data processing is computed in time or frequency domain which is not suitable for analyzing non-stationary signals. In order to overcome the lack of a global view on how to develop machining monitoring systems based on artificial intelligent models, machine learning approach is one of the best methods for developing an effective tool condition monitoring (TCM) system.

In the second phase, fault diagnosis studies of the face milling tool using vibration and sound signals based on artificial intelligence techniques are conducted. Fault diagnosis of the different tool conditions based on machine learning technique is basically comprised of three steps; feature extraction, feature selection and feature classification. Different features such as, statistical features, histogram features, discrete wavelet transform (DWT) features and empirical mode decomposition (EMD) features are extracted from the acquired vibration and sound signals. For example, features such as skewness, mode, standard error, maximum, minimum, range, sum, mean, standard deviation, median, sample variance and kurtosis are computed from each acquired vibration and sound signals will serve as statistical features. The important features out of all extracted features are to be selected using induction based on decision tree technique (ID3 algorithm or J48 algorithm). The artificial intelligence techniques such as support vector machine (SVM), Naïve Bayes algorithm, artificial neural network (ANN), decision tree algorithm and K-star algorithm are used to classify the data using selected features. Fault diagnosis analysis with acquired vibration and sound signals are carried out by making use of different combinations of feature extraction methods and different classifiers with selected features based on decision tree technique.

Overall results have shown that the vibration signal based fault diagnosis has given better classification accuracy than the sound signal based fault diagnosis. The current research work has demonstrated that the statistical features served as best features among all other features extracted such as, EMD features, Histogram features and DWT features. It is also found that the Naïve Bayes algorithm provides best classification accuracy in comparison with other classifiers used such as SVM, ANN, decision tree and K-star algorithm. Based on research work, it is proposed that the combination of statistical features and the Naïve Bayes algorithm as classifier is the best feature-classifier pair using vibration signals in tool condition monitoring system for the face milling process.

Keywords: *Fault diagnosis; Face milling; Vibration signal; Sound signal; Signal processing technique; Artificial intelligence technique; Machine learning approach.*

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ABBREVIATIONS

AE	: Acoustic emission
AISI	: American iron and steel institute
ANN	: Artificial neural network
ANFIS	: Adaptive neuro-fuzzy inference system
AR	: Autoregression
ARTMAP	: Adaptive resonance theory mapping
BNC	: Bayonet Neill–Concelman
CCD	: Charge coupled device
CNC	: Computerized numerical control
CWT	: Continuous wavelet transform
DAQ	: Data acquisition system
DFT	: Discrete Fourier transform
DSP	: Digital signal processing
DWT	: Discrete wavelet transform
EEMD	: Ensemble empirical mode decomposition
EMD	: Empirical mode decomposition
FE	: Finite element
FEA	: Finite element analysis
FEM	: Finite element method
FFT	: Fast Fourier transform
FL	: Fuzzy logic
FNN	: Fuzzy neural network
FP	: False positive
FPGA	: Field-programmable gate array
FRF	: Frequency response function
FT	: Fourier transform
GA	: Genetic algorithm
HHT	: Hilbert–Huang transform
HMMs	: Hidden Markov models

HRC	: Rockwell hardness
ICA	: Independent component analysis
IMF	: Intrinsic mode function
IR	: Infra-red
JIS	: Japanese industrial standard
LabVIEW	: Laboratory virtual instrumentation engineering workbench
MATLAB	: Matrix laboratory
MLP	: Multilayer perceptron
NCF	: Normalized cutting force
NI	: National instruments
OM	: Optical microscope
PCA	: Principal component analysis
PSVM	: Proximal support vector machine
RBF	: Radial basis function
RMS	: Root mean square
RQA	: Recurrence quantification analysis
RSS	: Residual sum of square
SAGNN	: Self-adaptive growing neural network
SLP	: Single layer perceptron
SOM	: Self-organizing map
STFT	: Short-time Fourier transforms
SVC	: Support vector classifier
SVM	: Support vector machine
TCM	: Tool condition monitoring
TCMS	: Tool condition monitoring system
TFD	: Torque force distance
TP	: True positive
TPF	: Tooth passing frequency
VI	: Virtual instrumentation
WT	: Wavelet transform

CHAPTER-1

INTRODUCTION

1.1 OVERVIEW

Machining is the most common manufacturing process and widely used to manufacture components that require high accuracy in dimension and good surface quality. The present global market competition has attracted the manufacturer's attention on automation of manufacturing systems via condition monitoring of machine tool and processes results in improving quality of the products, minimizing inspection and enhancing manufacturing productivity. Excessive tool wear and tool breakage are the main reasons for the machine tool downtime. The damaged cutting tool, which results in poor surface finish and inaccurate dimension of the product. Production rate increases significantly by reducing the machine tool downtime. Tool condition monitoring (TCM) is extremely viable in reduction of cutting tool downtime.

In modern manufacturing industries, there is an increasing need for low cost with high quality products. The quality of a product is strongly associated with the condition of the cutting tool during machining. The machined products should have the desired shape with precise dimension and an acceptable surface finish. Besides these factors, tool life also plays a vital role in the manufacturing (Orhan et al. 2007). Uncontrolled variations in cutting conditions influence product quality, resulting in the decrease in productivity due to an increase in rejections based on quality standards, which in turn increases production cost. Therefore, most of the manufacturing industries are aiming to implement strategy based automated manufacturing systems with an effort to improve process control. Also the competitiveness in the global market has encouraged the manufacturers to produce high quality products at higher production rate, which has led to manufacturers demand for advanced methods for online TCM system. There is a constant need for a comprehensive research in developing real-time automated monitoring and diagnostic systems. These systems would continuously monitor the process behaviour and apply corrective action in a timely manner, whenever changes in tool condition occur.

1.2 SIGNIFICANCE OF TOOL WEAR PREDICTION

Automated manufacturing systems provide good quality products at a higher rate of production and less cost in today's competitive world. It becomes necessary to reduce production downtime. Tool wear and chatter are major factors affecting machining process in the form of surface finish and dimension of the products. Therefore it is necessary to assess tool wear regularly. Various techniques have been proposed for tool wear monitoring and chatter detection in the recent past. None of these techniques were universally successful due to the complex nature of tool wear occurrence during the machining process. Tool wear prediction has become an important component of the TCM system. The TCM system is one of the effective tools which will be helpful in sustaining the desired process functions, performance and reducing unscheduled shutdowns.

In machining operations, the most common methods of cutting tool failures are progressive wear and fracture of the cutting edge, which will have detrimental effects on both the dimensions and the surface finish of the final product. Therefore, it is very essential that cutting tools are not permitted to degrade sufficiently to cause damage to the work materials. Hence, it is necessary to recognise/diagnose the tool condition during the process using TCM system. The following section will describe the methods for condition monitoring of the cutting tool.

1.3 TOOL CONDITION MONITORING METHODS

The monitoring of cutting tool wear is a more complex task than expected, because tool wear induces very small changes in a process with a very wide dynamic range. Some important methods for cutting tool monitoring are explained below.

1.3.1 Mathematical model based condition monitoring

Analytical models can be very useful to study the effects of tool geometry on the various machining parameters, but these models are too complex to be of any value in a real-time TCM system. The non-linear, stochastic and time invariant nature of machining processes make modelling very difficult. A transformation between the signal characteristics and the physical law representing the process is necessary to establish such a model. Because of the complexity of the process, modelling of the physical law cannot be performed analytically in most instances (Scheffer, 2006). Traditional assessment of tool life using Taylor's tool life equation does not provide sufficient information about the complete life cycle of the tool. In some situations, it may lead to an overestimation of tool life and in some situations to underestimation of tool life and this will lead to excessive replacements of the tool. It was found from experiments that the Taylor's tool life equation could estimate within ± 35 percent of the actual tool life. As a consequence, precious time and scarce resources will be wasted (Teti et al. 2010).

1.3.2 Signal based condition monitoring

TCM techniques include direct measurement and indirect measurement of tool wear. Direct measurements of cutting edge provides the most accurate information about physical deterioration of the cutting tool in certain conditions only. During machining the cutting fluid surrounds the tool, making online direct measurements difficult. Also the direct measurements have not yet proven to be very attractive either technically or economically. Currently, indirect measurements are more suitable for on-line in process applications. Indirect measurements are based on the relationship between the measuring data of the machining process and the tool conditions. The measuring process data, such as vibration signals, current signals, sound signals, cutting force signals, acoustic emission (AE) signals, etc. are acquired using suitable sensors such as accelerometer, AE sensor, cutting tool dynamometer, Hall effect sensor, etc. can be seen in indirect measurement technique.

1.4 MEASURANDS FOR MACHINING PROCESS

A sensor/transducer is a device which converts one form of energy into another form. It processes a physical quantity of the system to be analysed in such a way that it is generating the signal which can be read easily by an instrument or by an observer. Some energy forms related to machining processes contain radiant energy, thermal energy, electrical energy and mechanical energy. The input quantities or properties that are to be measured by sensors are called measurands. The common measurands for machining process monitoring are as shown in Figure 1.1.

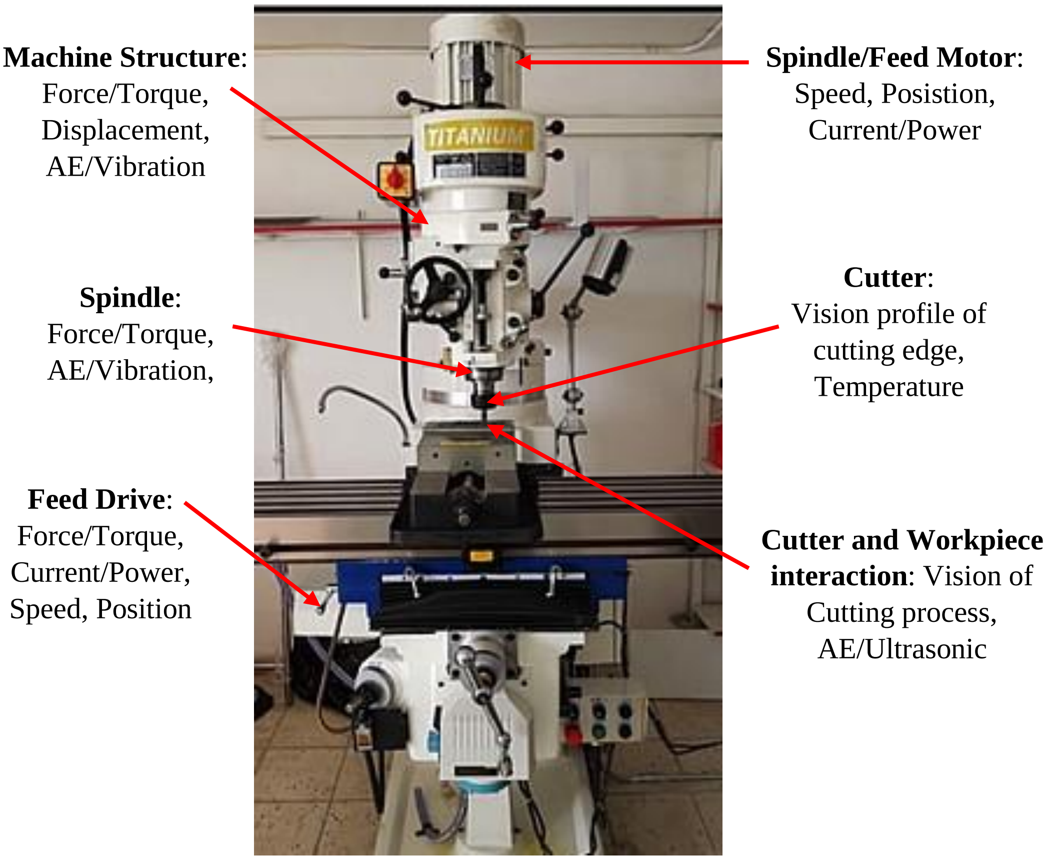


Figure 1.1 Measurands commonly used for machining process monitoring

Figure 1.1 illustrated the commonly used measurands in machining monitoring systems. Mainly, four types of sensor signals are most widely used to monitor the machining process such as vibration signals, cutting force analysis, motor power/current signals and AE signals.

1.4.1 Cutting force analysis

Cutting force is one of the variables, which can be measured during machining process. This variable has some desired characteristics like rapid response and high sensitivity to the changes in tool condition. Cutting force signals are used to investigate the cutting tool /process condition. The cutting force is measured using dynamometers. Strain gauge type or piezoelectric type dynamometers are widely used for cutting force measurement. The analysis of cutting forces by using tool dynamometer in order to examine the cutting tool conditions or process condition can be seen in the literature explained in section 2.4.1.

1.4.2 Acoustic emission (AE) signal analysis

During machining, due to the rapid release of energy from the material surface or from the localised sources in a material, the transient elastic wave is created. This wave is acquired by the device called AE sensor. Chip breakage, impact of the chip at the workpiece, crack formation and propagation, plastic deformation in the shear zone, friction on the flank and the rake face are the major sources of AE in machining process. By using this AE technique, the condition of the cutting tool (wear, tool breakage/chipping) and/or machining process can be easily analysed. The usage of AE sensor in fault diagnosis of cutting tool condition and machine elements will be discussed in section 2.4.2.

1.4.3 Vibration signal analysis

Vibration occurs due to the interaction between the workpiece and the cutting tool during machining. Variation in cutting forces and spindle rotation could also be the reason for vibration. Vibration characteristics such as frequency and amplitude will be varied as the chatter or cutting tool wear occurs. Many failure modes of the machining process can be discovered in the vibration signals. The vibration signal can be easily measured by using accelerometer. The vibration analysis technique has been widely used in machining processes. The literature on machining process using vibration signals will be explained in section 2.4.5 and in the present study.

1.4.4 Motor power/current signal analysis

During machining, by analysing the spindle drive current the status of the cutting tool such as tool wear, breakage, collision, etc. can be detected. Some desired parameters such as, motor power, phase shift, line voltage and current can be assessed from the measurement. This technique has the ability to gain information about the actual power required to drive the machine tool controller without additional sensors. The Hall sensors are used to measure the current during machining process (Li and Chen, 2015).

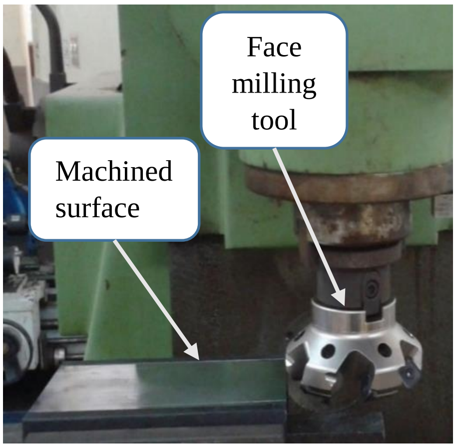
In indirect measurement, signal processing deals with the analysis of acquired signals so that the information contained in signals can be extracted, displayed, analysed, interpreted or converted to another type of signal that may be of use. Specifically, the signal processing method is classified as the time domain, the frequency domain, and time-frequency domain analysis. Then the signal is further analysed by using artificial intelligence approaches and/or machine learning techniques to build a decision making system (Li and Chen, 2015). The details about signal processing techniques and machine learning methods will be explained in Chapter 3. In this thesis, an attempt is made to explain the fault diagnosis of the face milling tool using sound and vibration signals through machine learning technique and also based on conventional signal processing techniques. The following section will explain, briefly the process of face milling and different tool conditions which are considered for the analysis in the present study.

1.5 FACE MILLING PROCESS

Face milling involves the use of multi-toothed, rotating cutters to remove material from the surface of a workpiece. Face milling tool has multiple cutting edges that are unevenly loaded by cutting force despite being engaged in the workpiece at the same time. Figure 1.2 depicts the milling machine and the face milling operation.

In milling, the primary motion (rotational) is provided by the cutting tool, wherein the face of the tool approaches the work material. Normally the primary motion absorbs a majority of the total power required for machining, which is easily seen by the harsh conditions (temperature and pressure). The primary motion is delivered to the work material via a multiple-tooth cutter which intermittently enters, removes a particular amount of the work material and exits. This action produces a helical-continuous chip or discontinuous chips in one revolution, depending on the properties of the material being cut and the condition of the inserts. Normally, face milling is performed with indexable inserts that are mechanically fastened to the cutter body refer Figure 1.3. These inserts provide a deep axial cut and narrow radial cut to the work material.

(a) Milling machine



(b) Face milling tool with workpiece

Figure 1.2 illustrates (a) Milling machine and (b) face milling process

These inserts are normally made from carbide or ceramic materials with tungsten-carbide coatings, depending on the wear resistance required. Such inserts can be used until a given cutting edge is blunt, at that time they are indexed (repositioned) in the cutter body to present a new, sharp cutting edge. Once all the edges of the indexable insert have been fully utilised, the insert is discarded and a new insert replaces the worn out one.

Metal cutting operations such as drilling, planing and turning utilize equivalent material removal mechanisms to those applied in milling. However, the difference in tool geometry and the distinct metal removal features associated with rotating multi-point tools, generate significantly different forces of greater complexity. The forces generated during milling are characterised by four features;

- Rapidly changing forces as a result of interrupted cutting.
- The force fluctuations have a periodicity and deterministic characters.
- Presence of strong deterministic and stochastic components.
- The signals from several inserts in the same cutting tool have great similarities.

Although milling is a common machining operation, the interrupted cutting process is unusual when compared to other metal removal operations. The process of engaging and disengaging the work material is a sequential operation that produces a great variable force signal. The mean value of this force may differ greatly from the instantaneous values, as well; the mean and the maximum values have notably large differences between them. Basically it is found that the operation with minimum number of teeth, results in the greater the difference between the mean and maximum force values.

Machining of metals is frequently accompanied by relative vibration in the machine tool-work material structure. Vibrations are intended to occur in metal cutting operations under certain operating conditions. The face milling process produces vibrations of deterministic character that propagate through the structure of the machine. In addition, there are vibrations generated by other factors inherent to face milling that contribute to the overall complexity of the vibration signals (Shridhar 2012). Measurements are taken from the machine tool-work material structure with different tool conditions which can be seen in the following section.

1.6 CUTTING TOOL FAULTS

Cutting tool wear is the result of load, friction and high temperature between the cutting edge and work-piece. In the metal cutting process the cutting tools suffer different kinds of wear such as crater wear, flank wear, chipping and fracture and notch wear (Latifzada, 2013). Milling is one of the most versatile machining processes used for various metal cutting operation. It is highly effective in producing components with complex profiles with high surface integrity and geometrical accuracy. Milling is a machining process with intermittent cutting action which generates the transient impact force on the cutter. Tool 'chipping' and tip 'breakage' are predominantly occurred due to these impact forces. Baek et al. (2000) investigated the chipping and breakage tool conditions in the milling process. Along with these faults, the ‘flank wear’ is also one of the faults arising during the process. A few researchers Vallejo et al. (2008) and Yan et al. (1999) examined the flank wear during milling operation for online monitoring of the milling tool. Figure 1.3 depicts the milling cutter and tool insert, generally that are used in the milling operation.

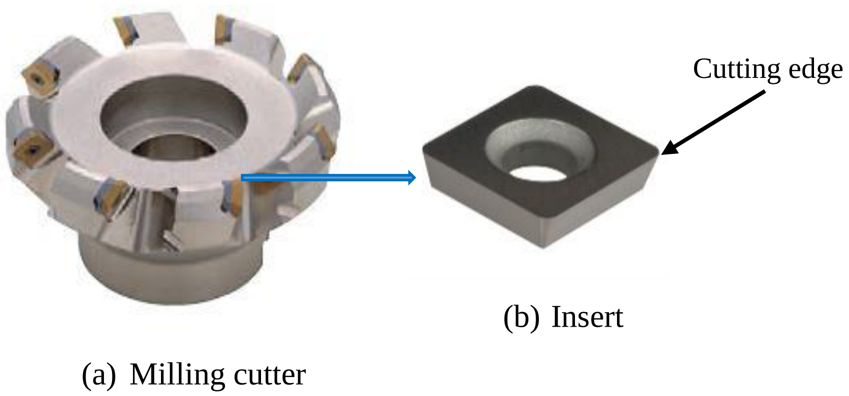


Figure 1.3 Milling cutter with insert

1.6.1 Flank wear and crater wear

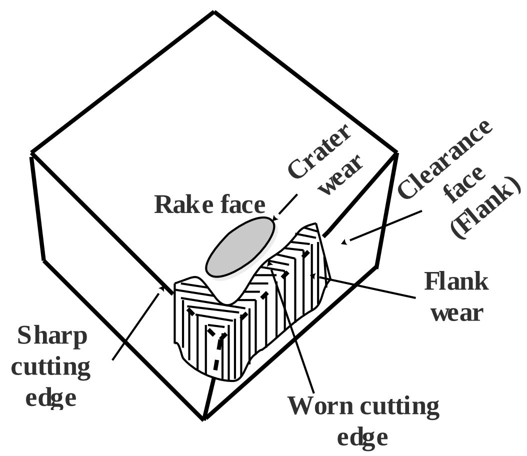
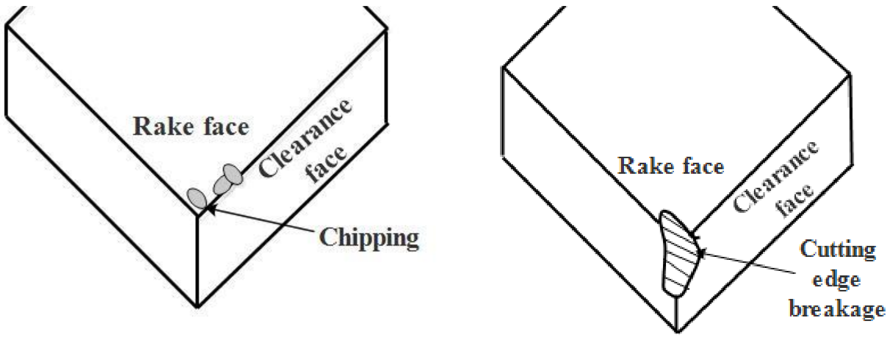


Figure 1.4 Flank wear and crater wear on cutting tool insert

Cutting tool wear on their rake face and clearance (or flank) face occur by the process of attrition. Attrition is defined as a rubbing process that takes away the material, while gradually weakening both the surfaces in contact. The two prominent wear on a cutting tool are crater wear and flank wear. Both these wear decrease the tool life and will change work dimensions. Figure 1.4 shows the milling insert with crater wear and flank wear. The rubbing of the cutting tool along the new work material surface causes flank wear. As the flank wear increases, the dimension of the machined components drift away from acceptable tolerances. Crater wear results from the action of a chip flowing along the tool face. Most often the crater or cavity is formed close to the cutting edge.

1.6.2 Tool chipping and breakage

Figure 1.5 shows the chipping and breakage (or fracture) of the tool edge and they are also other types of common tool failure in milling operations and these faults are affecting the rake and clearance face to varying degrees. Chipping appears when a relatively small amount of tool material is removed, but the variations in geometry of the tool has little effect on the work material surface finish. When fracture occurs, a significant portion of the tool edge is broken off, which imparts substantial changes to the cutting conditions. Also, the tool edge is susceptible to fracture from transient thermal stresses that occur in discontinuous machining.



(a) Chipping on rake face near cutting edge

(b) Breakage of cutting edge

Figure 1.5 Chipping and breakage inserts

The flank wear, chipping and breakage conditions predominantly occur as fault conditions in milling process. Hence these three fault conditions are considered for the analysis. In contrast with turning, milling is a multi-point cutting process with increased complexity, renders greater challenges in condition monitoring and fault diagnosis of the cutting tool.

Byrne et al. (1995) made an in depth study on requirement of TCM system, which is to be used for optimizing the tool usage, reducing the non-productive time, tool breakage detection, improving the process stability, etc. The demands on TCM system in industrial applications and manufacturing research field are summarized as follows;

- High robustness
- Unmanned production
- Little maintenance
- Reduced response time
- Low installation cost, etc.

TCM system is very helpful to improve the quality of the component, production rate and reduction in downtime and to increase the system reliability. In addition, the TCM system is characterised by better performance due to the integration of most powerful hardware and software. It comprises of signal processing and artificial intelligent techniques software, microelectronic components, etc. which provide the relationship between the process and the sensor data. These will make the systems truly knowledge-based, self-learning and adaptive.

1.7 MACHINING PROCESS MONITORING

Process monitoring is signifying the condition of the process with measuring process parameters such as sound signals, cutting force signals, vibration signals, current signals, etc. Process monitoring helps to decrease the cost of machining process by increasing the quality of products and reducing the tool breakage downtime and maintenance cost.

The machine tool operators carry out the monitoring task primarily. They visually identify the broken tools and also chatter condition from the generated sound with the system. The contemporary monitoring methods are automated monitoring algorithms. These algorithms utilise sensor measurements for defining the state of the process.

Complex processes are monitored with the signal processing methods which investigate the acquired signals of the systems. Artificial intelligence methods are most commonly used techniques for process monitoring. They are mostly utilized for pattern recognition and for designing the process monitoring algorithm.

In indirect measurement of cutting tool, an option for analysing the tool condition is to use signal monitoring of various process parameters including cutting force, sound, acoustic emission (AE) signal, current signal, temperature, vibrations, etc. Among this, vibration monitoring is extensively used as a successful technique in identification of fault in machining process. Sound monitoring is a cost effective method in the area of fault diagnosis and condition monitoring. In this research work, sound monitoring is also tried for fault diagnosis study.

1.8 MONITORING METHODS USING VIBRATION AND SOUND SIGNALS

The existing cutting tool monitor methods still cannot satisfy all the practical needs for quick response, reliability, robustness and some other performances. So it is necessary to find some other research techniques to improve the result. This study mainly discusses the analysis of vibration and sound signals to diagnose the face milling tool conditions. Here, there are two parts in the analysis of signals. The first part describes the analysis of sound and vibration signals to recognise the face milling tool conditions through the signal processing techniques. The second part reveals the fault diagnosis of the face milling tool using sound and vibration signals based on machine learning approach.

1.8.1 Fault detection based on signal processing techniques

In milling process, vibration of the machine tool-work material structure is based on the cutting forces. The cutting forces are varied due to tool wear/breakage and correspondingly the vibration pattern will be altered. These variations in the acquired signal can be analysed in such a way that the rate at which the change in dynamic force per unit time (acceleration) is measured and the characteristics of vibrations are derived from the vibration patterns obtained. Each component in the system has its own frequency which can be determined from its dimensions, rotating speed etc. The condition of those components can be analysed through signal processing techniques such as time-domain, spectrum, cepstrum, etc. A brief introduction about the traditional signal processing techniques are as follows.

1.8.1.1 Time-domain analysis

The time-series plot is expressed in terms of amplitude and phase information of the acquired signal. In the present study, the acquired signals such as vibration and sound signals will be analysed through time series plots in order to identify the condition of the face milling tool.

1.8.1.2 Spectrum analysis

Spectral analysis or Fourier transform is a most widely used technique in vibration signal analysis. It converts given signal from time domain to frequency domain by integrating the given function over the entire time period. With the help of components character frequency, faulty conditions can be identified. This type of vibration analysis is called as frequency domain or spectral analysis which relates frequency to its components and is widely used as basic approach. In milling, frequency components such as tooth passing frequency, spindle rotation frequency are considered as key terms in spectrum of acquired signal to recognise the milling tool condition. The detailed analysis of spectra in terms of TPF and spindle rotational frequency using vibration and sound signals will be discussed in Chapter 5.

1.8.1.3 Cepstrum analysis

The Cepsrtum analysis is another kind of signal processing method. The cepstrum was originally referred as the power spectrum of the logarithmic power spectrum. The cepstrum plots provide the information about the condition of the process/cutting tool by investigating the quefrency component in the acquired signal. The detailed study of vibration and sound signals of the face milling tool conditions will be explained in Chapter 5.

But in milling, the generated signal from the process may be non-stationary and non-linear in nature. These conventional methods such as time and frequency domain techniques are not suitable to analyse the non-stationary signals. This leads to the next level of vibration analysis techniques which are highly machine specific. The wavelet transform methods are the advanced vibration analysis techniques which can be used to investigate the non-stationary signals.

1.8.1.4 Wavelet analysis

Conventional data processing is computed in time or frequency domain. Wavelet processing method combines both time and frequency information. Wavelet analysis provides the 'time-frequency' information in a single plot. The continuous wavelet transform method is one of the wavelet analyses and is used to investigate the milling tool condition in the present study. This technique is used to analyse the vibration and sound signals to identify the face milling tool conditions.

1.8.2 Fault diagnosis based on machine learning techniques

Machine learning is a technique which is used to train the model with the help of training dataset. Based on the information available in the training data, it creates some threshold values for classification. Then the trained model does analysis and classify the testing dataset by using these threshold values. In machine learning technique, the monitoring task is performed with classifying the given data. The data is investigated in several consecutive steps. These steps are feature extraction, feature selection and data classification respectively. Figure 1.6 illustrates the steps involved in monitoring algorithm.

Machine learning methods address most of the problems and are proved to be a stronger method. Researchers have reported the capability of many machine learning techniques to perform fault diagnosis. Feature extraction and feature classification are the most important phases in machine learning techniques. The following subsections will give a brief introduction about feature extraction, feature selection and feature classification phases of machine learning approach.

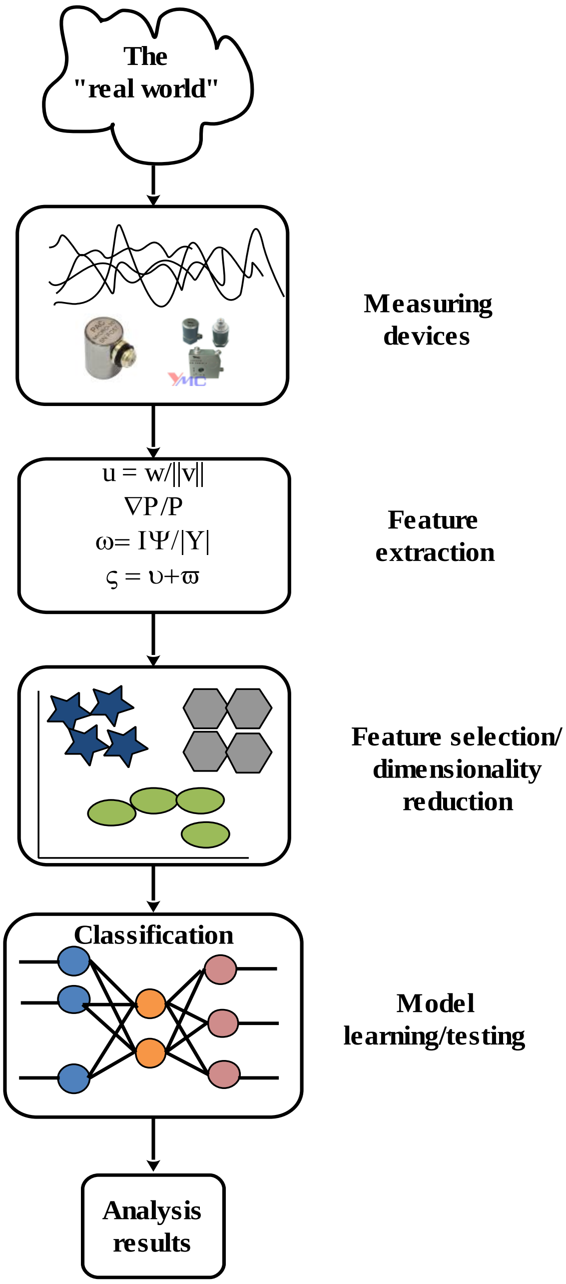


Figure 1.6 Condition monitoring algorithm

1.8.2.1 Feature extraction

After acquiring the signal from the system, extracting the information from the acquired data and reducing the dimension of them, each data will be transformed into a reduced representation called feature vector. This transformation process is called feature extraction. Many features such as, histogram features, statistical features, empirical mode decomposition (EMD) features, etc. can be seen in the area of fault diagnosis and condition monitoring. In the present study, for feature extraction various methods such as statistical, histogram, discrete wavelet transform (DWT) and EMD techniques are applied to vibration and sound signals. The detailed study of extracting the above mentioned features will be discussed in the Chapter 6. After feature extraction, the salient features will be selected using feature selection method. A brief note on feature selection phase is explained in the forthcoming section.

1.8.2.2 Feature selection

In the second step, if still redundant features are available in the feature vector which make the calculations complex and time consuming, the redundant features will be omitted from the feature vector with feature selection approach. Before classifying the conditions of the milling tool, feature selection method is applied to select the salient features. The decision tree, principal component analysis, etc. are the dimensionality reduction methods in fault diagnosis. The decision tree technique is used as a feature selection method in the present study, because the decision tree (J48 algorithm) is the best method for feature selection in the area of condition monitoring (Elangovan et al. 2011). The following section reports a brief explanation on the process of feature classification.

1.8.2.3 Feature classification

Classification methods categorize feature vectors into the determined groups and complete the monitoring process. Artificial intelligence methods are often applied in the classification step and make the monitoring algorithm intelligent (Rooteh and Sadat 2013). The classification of the face milling tool conditions is carried out based on selected features using artificial intelligent techniques such as support vector machine (SVM), artificial neural network (ANN), Naïve Bayes, decision tree and K-star algorithms as classifiers in the present research work.

Very few researchers have reported the vibration and sound signals analyses for fault diagnosis of the face milling process using machine learning techniques. Hence, a detailed study is required in this field. Since sound signal based fault diagnosis can be a cost effective method, it will be very helpful for small and medium scale industries.

In the past decade, advanced signal processing methods are playing a vital role in the area of fault diagnosis and condition monitoring. Also in machine learning approach, the combination of an artificial intelligent technique and the feature extraction method has provided good results in some applications. However those combination cannot be guaranteed the same results to all other applications. So there is a need for identifying the best feature-classifier combination using vibration and sound signals in fault diagnosis of the face milling tool. Machine learning approach based automated fault diagnosis of the face milling process is very essential for automotive, aerospace and industrial applications etc. Hence, in the current research work, our focus is more on these techniques to monitor the health of the face milling tool.

So it is considered worthwhile to investigate the nature of the signals and their dependency on tool wear, specifically for an intermittent machining process, like face milling. This study deals with the fault diagnosis of the face milling tool using signal processing techniques, machine learning techniques using vibration and sound signals.

1.9 ORGANISATION OF THE THESIS

The thesis comprises of eight chapters, each paragraph will give a brief note on each chapter.

Chapter 1 introduces the condition monitoring of the machining process, significance of the cutting tool wear, machining process monitoring techniques, measurands for machining process, face milling process, different tool faults and machining process monitoring. This chapter also brings out the brief introduction about monitoring methods used for vibration and sound signals of face milling process and the outline of the thesis can also be seen.

Chapter 2 presents a detailed literature review on condition monitoring techniques specifically signal processing techniques and machine learning techniques in different fields of applications. It also defines the motivation of the present study, objectives and scope of the research work.

Chapter 3 describes the methodology deployed in fault detection and classification of the face milling tool condition. The detailed explanation about signal processing techniques and machine learning steps such as feature extraction, feature selection and classification methods can be seen in this chapter.

Chapter 4 covers the details about the experimental setup, sensors used, data acquisition system and experimental procedures adopted.

Chapter 5 reveals the results and discussion about fault detection of the face milling tool using signal processing techniques such as time-domain, spectrum analysis, cepstrum analysis and continuous wavelet transform analysis.

Chapter 6 is dedicated for investigation of vibration signals through machine learning techniques i.e. (i) feature extraction methods such as statistical features, histogram features, EMD features and DWT features, (ii) feature selection using decision tree technique and (iii) feature classification using classifiers such as Naïve Bayes algorithm, ANN, SVM, K-star algorithm and decision tree algorithm.

Chapter 7 reveals the results and discussion about the fault diagnosis of the face milling tool using sound signals through machine learning approach.

Chapter 8 concludes the findings from the research work, presents the future scope of this study and provides the key contributions from the study. This section is followed by the references and the list of publications.

CHAPTER-2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter the most recent and significant contributions of the present state of the art related to fault detection and diagnostics of the system/cutting tool are discussed.

The monitoring of machining processes can represent the economy of production by identifying tool wear, surface roughness and anomalies during metal cutting operation. Excessive wear and tool breakage are the main reasons for the cutting tool downtime. The damaged cutting tool can increase its strain level and result in poor surface finish of the product. Production rate increases significantly by reducing the machine tool downtime. Tool condition monitoring (TCM) is extremely viable in reduction of cutting tool downtime. In a TCM system, machining data, such as vibration signal, current signal, sound signal, cutting force signal, acoustic emission (AE) signal, surface finish, temperature, image processing, etc. are acquired with sensors such as accelerometer, AE sensor, charge coupled device (CCD) camera, cutting tool dynamometer, surface profilometer, current sensor, pyrometer, etc. (Teti et al. 2010). The measuring techniques for the monitoring of machining tool have been categorized into two main categories;

- **Direct measurement:** where the actual value of the variable being measured gives a high degree of accuracy. This method has been employed extensively in research laboratories to support the investigations of fundamental measurable phenomena during machining processes.
- **Indirect measurement:** where the actual value is subsequently determined using empirically determined correlations. It is less accurate than the direct method but is relatively simple and more suitable for practical applications.

2.2 DIRECT MEASUREMENT

As the name indicates, these measurements directly assess the condition of the cutting tool. Although this measurement has the advantage of directly determining the states of the cutting tool, in most of the cases it is necessary to interrupt the cutting process to make the required measurements. To minimise the disruption of the machining process, these measurements are normally made between machining cycles. Therefore the advantage of continuous monitoring is removed and detrimental changes in tool condition cannot be recognised until the cycle is complete (Park and Ulsoy, 1993).

Direct measurement of cutting edge provides the most accurate information about physical deterioration of the cutting tool. Park and Ulsoy (1993) adopted direct measurement method using optical sensing techniques with computer vision. LoCasto et al. (1990) used CCD camera for tool wear measurement. Prasad and Ramamoorthy (2001) carried out investigations to predict the tool wear such as crater wear and flank wear using stereo vision method in turning process. Ryabov et al. (1996) used laser displacement sensor for online measurement of tool geometry in the milling process. They evaluated tool geometry failure through intensity and displacement of laser beam simultaneously. Experimental results have shown that the system will not be able to measure the flank wear of dimension less than 40 micron. This is one of the limitations in direct measurement of TCM systems. During machining the cutting fluid surrounds the tool, making it difficult for online direct measurements. These direct measurements provide the advantage of high accuracy in certain conditions only, but they are not yet proven to be very attractive either technically or economically. Currently, indirect measurements are found more suitable for online process applications, while little interest has been shown for improving direct measurement.

2.3 INDIRECT MEASUREMENT

Indirect measurements are based on the relationship between the measured data of the cutting process and the tool condition. Machining process data such as cutting force signals, vibration signals, acoustic emission signals, current/power signals, etc. are acquired through the sensors. Considering a process data like cutting forces present during a machining process are dependent upon the condition of the tool cutting edge. Generally, the tool edge worn out causes increasing in cutting force. Thus the cutting force measurement during machining provides an indication of the tool condition. Increasing cutting forces indicate the increase in tool wear. In reality, the relationship between cutting force and tool wear is more complex. The reason for this complexity lies within the number of unknown and immeasurable parameters (Shridhar 2012).

In indirect tool condition monitoring system, basically there are three principal phases; sensor system, feature extraction and decision making (Prickett and Johns 1999). During machining operation there are a number of energy transfer mechanisms, which are independent upon changes in the condition of the cutting tool. They are manifested by measurable parameters such as sound pressure, vibration, temperature changes etc. in relation to these energy transfer related variables. There are other features of the machining process such as surface finish of the work material, speed fluctuations, etc. that could be used to assess the tool condition. Indirect methods are not limited to continuous machining processes, but can also be applied to discontinuous machining processes. The major advantage inherent to these methods is their non-intrusive feature. Compilation of the indirect methods, which have been highlighted in the literature is presented in Table 2.1. These methods have shown varying degree of success during application in manufacturing environments.

Table 2.1 Indirect sensing methods for tool deterioration (Shridhar 2012)

Process parameters	**Measurement**	**Transducer**
Vibration	Vibration of machine tool-work material structure	Accelerometer
Sound radiation	Acoustic waves	Microphone
Cutting force	Changes of cutting forces	Dynamometer
Power input	Power or current consumption of spindle or feed motor	Ampere meter, Hall effect sensor
Temperature	Variation of cutting temperature on cutting tool	Thermocouple, pyrometer
Roughness of machined surface	Changes in surface roughness of work material	Mechanical stylus, optical transducer
Acoustic emission	Stress wave energy	AE transducer

Considerable research work has been conducted in the area of tool condition monitoring and control due to the fact that tool failure represents about 20% of machine tool down time. Tool wear negatively impacts the work quality in the context of dimensions and surface quality.

2.4 RECORDED SIGNALS

Since past decades, researchers have been working in developing an efficient tool condition monitoring system by acquiring various types of signals during machining. The prominent sensor signals are discussed below.

2.4.1 Cutting force signal

The analysis and prediction of cutting forces are very important in the research of metal cutting processes and the design of cutting tools. Cutting force measurement will also be helpful in thermal analysis, chatter prediction, chip form categorization, surface roughness prediction, monitoring of tool condition, etc. Furthermore a large cutting force means more energy consumption. This has led to the study of the reduction of cutting force through appropriate choices of parameters and tools. During milling the cutting force signals in three different directions namely, *Fr*- radial cutting force, *Ft*- tangential cutting force and *Fx*- axial cutting force are measured using dynamometer as shown in Figure 2.1 (Kuljanic et al. 2009).

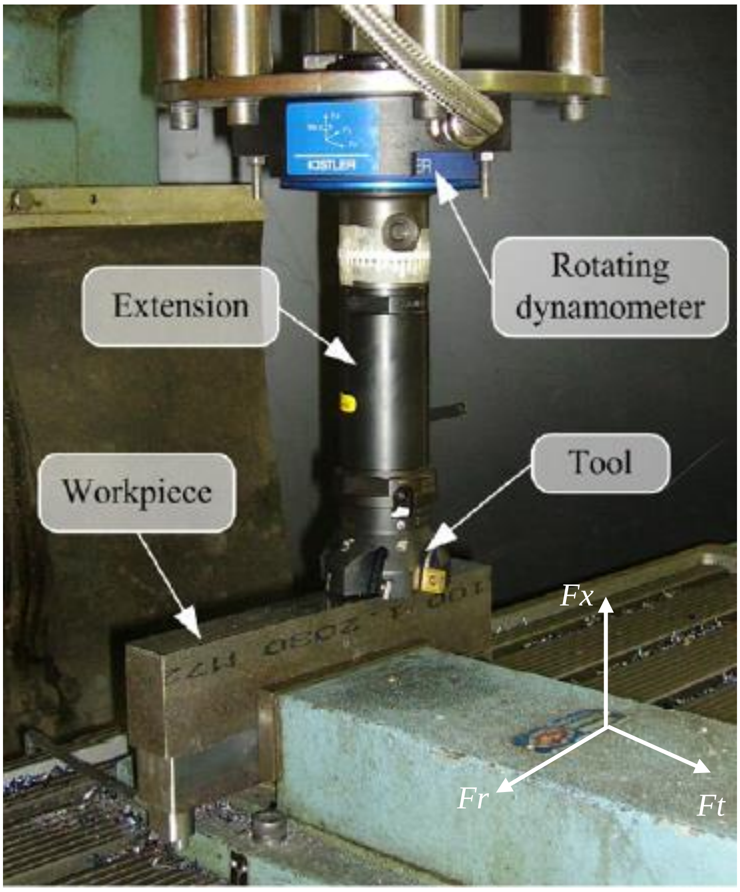


Figure 2.1 Experimental setup using milling tool dynamometer (Kuljanic et al. 2009)

The variations in the cutting forces represent the condition of the cutting tool and many researchers have studied these cutting forces using different techniques in order to diagnose the tool condition. Yan et al. (1999) investigated tool wear in milling process using cutting force signals with development of three kinds of tool wear indices based on statistical and time series techniques namely, maximum amplitude with statistical mean (mean-max), normalized difference of residual sum of square (RSS) standard deviation and first order auto-regression (AR). They reported that these techniques provide an efficient indication of flank wear during machining, however the RSS technique is not so feasible for real time processing. AR approach is computational intensive, but provides relatively missing or low pass alarms, requires suitable multi-DSP (digital signal processing) and hardware implementation for online condition monitoring. Balazinski et al. (2002) estimated the tool wear in turning process using artificial intelligence techniques such as neural network method, fuzzy decision support system and neuro-fuzzy inference system based on cutting force components. Kuljanic and Sortino (2005) proposed tool wear indicators, namely torque force distance (TFD) indicator and normalized cutting force (NCF) indicator in face milling. They reported that the axial component of cutting forces is suitable for determining tool breakage. Further they concluded that TFD indicator is better than NCF, because there is no need to determine the unworn tool cutting force and it is enough to compute the mean cutting force and actual mean torque. Tansel et al. (2005) investigated the performance of a genetic tool monitor system with the measured cutting force in the micro end milling of POCO EDM-C3 soft electrode in order to identify faults during operation. This approach is very conservative to abolish fault alarms during the process and found very accurate within a framed time in the micro end milling process.

Milfelner et al. (2005) optimized the cutting parameters of end milling process using genetic optimization technique. They examined the tool wear and breakage conditions of the milling tool based on cutting force signals. Huang et al. (2007) developed a model to predict the tool wear in CNC (computer numerical control) milling center based on cutting force analysis. They reported that the developed model is suitable for the given workpiece and the cutting tool. Zhu et al. (2008) examined the cutting force signal of micromilling in time and frequency domains using independent component analysis (ICA) method for denoising the acquired signal. They compared the results from ICA method with the wavelet method and observed that the ICA technique is the best method and capable to separate both the Gaussian and non-Gaussian noise sources from the signal than the wavelet method. Chen and Li (2009) correlated the flank wear tool condition to the cutting force signals in end milling of Inconel 817 workpiece material. They reported that the flank wear and edge chipping were two dominating fault conditions and noticed the linear variations in z-direction cutting force with the increase in flank wear. Kaya et al. (2011) studied the development of an online TCM system to estimate tool flank wear by acquiring the three axes cutting forces and torque signals in milling of Inconel 718 superalloy using an artificial neural network (ANN). They have shown a high correlation and low error ratio between the computed and actual values of the flank wear. They observed that the torque is an important signal which is not considered in the literature of development of tool condition monitoring system. Torque signals are the most representative in progression of flank wear when compared with the tangential cutting forces. Subramanian et al. (2013) developed a mathematical model to optimize the machining parameters in order to obtain minimum cutting forces using genetic algorithm and response surface methodology in shoulder milling of Al7075-T6. They validated the predicted values with the experimental results and observed that cutting speed plays a vital role in the models, followed by the feed rate and depth of cut. This study also provided a guideline for researchers to assess cutting performance in design of high speed machining tool. Wang and Cui (2013) studied the tool wear condition in vertical milling machine using cutting force signals through auto associative neural network technique. Huang et al. (2015) developed a monitoring system for detecting the tool breakage condition during end milling process using probability neural network technique through cutting force signals.

2.4.2 Acoustic emission (AE) signal

Acoustic emission is defined as the transient elastic waves which are generated due to the rapid release of energy from localized sources within a material. This AE signal can be found in primary, secondary and tertiary cutting zones. AE signal due to chip formation is primary; due to friction between cutting tool and chip is secondary; due to friction between cutting tool flank and workpiece is tertiary cutting zones. Figure 2.2 depicts the AE signal based fault diagnosis of end milling tool (Marinescu and Axinte 2008). Pai and Rao (2002) used the AE sensor in face milling of En-8 steel material for monitoring the tool breakage, progressive tool wear and chip segmentation and reported that AE signals can be used to identify the tool wear effectively. The usage of AE sensors to monitor machining processes (turning, milling and grinding) is quite effective and detecting malfunctions due to the sensor is very sensitive to the process and also reliable.

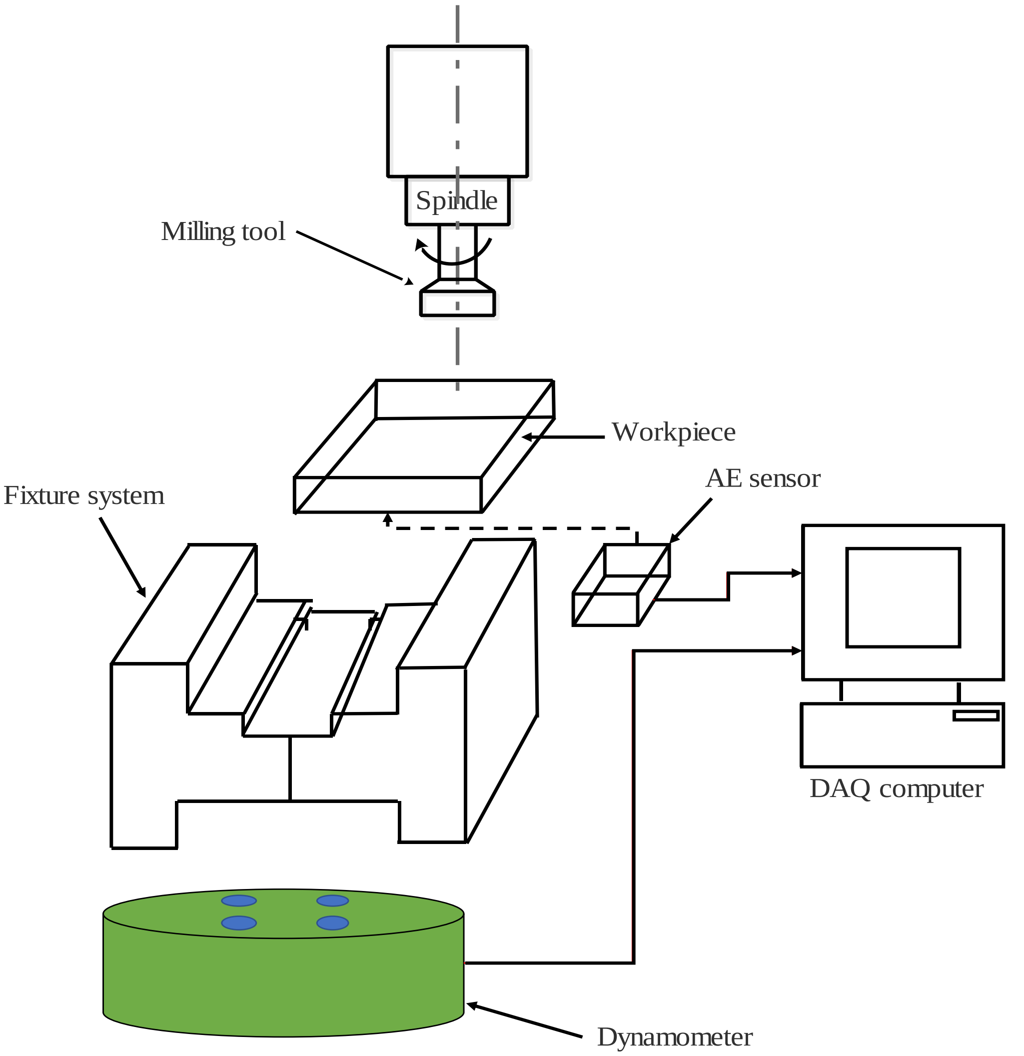


Figure 2.2 Shows the AE sensor based experimental setup (Marinescu and Axinte 2008)

One of the ways to take full advantage of high sensitivity is the fusion with other types of sensors. Jemielniak and Arrazola (2008) studied an application of the combination of AE signals and cutting force signals in micro milling operation. They observed that there was a stronger influence of tool wear on AE signals than on cutting force signals. They also revealed that the AE signal is free from resonance vibrations, which is very important in case of micro machining applications. Integrating these signals in tool condition monitoring minimizes the diagnosis uncertainty, reduction in randomness and provides more reliable tool wear estimation. Marinescu and Axinte (2008) carried out an experiment on determining the malfunctions of both the tool and workpiece (Inconel 718) using cutting force and AE signals in end milling. They reported that the possibility of predicting defects on workpiece surfaces by using AE sensors and also found efficient performance of the combined effects of AE and cutting force signals on tool wear measurement and workpiece surface integrity. Gowid et al. (2015) diagnosed the faults in high speed centrifugal air blower using AE signals. They found that spectral based features is the best tool and AE signals are very informative in fault diagnosis of high speed air blowers.

2.4.3 Current signal

Current signals are measured using Hall effect sensor and Figure 2.3 shows the Hall effect current sensors connected to the three phase line of spindle motor (Li and Guan 2004). Spindle motor current monitoring features have similar characteristics as cutting force signals. This method estimates the cutting force by means of the motor current and then estimated cutting forces are used to predict the condition of the cutting tool.

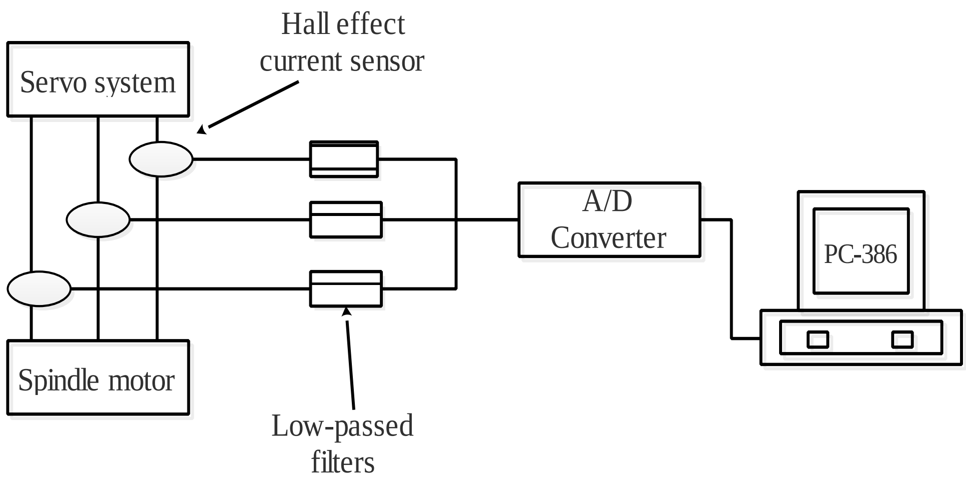


Figure 2.3 Hall effect current sensor for monitoring the cutting tool (Li and Guan 2004)

Lee et al. (1997) identified the tool fracture condition by analysing the motor torque, which is related to induction motor current during end milling process and also carried out experiments with different cutting conditions to find out the effectiveness of the motor torque for recognising the tool condition. Li and Tso (1999) developed a relationship between cutting parameters and current signals under different tool wear conditions using partial experimental design and regression analysis in the drilling process. They also carried out the fault diagnosis studies of drill bit using Fuzzy logic classifier. Li et al. (2000) used the feed motor current and neuro fuzzy technique to predict the feed cutting force and monitor the tool wear in the turning process. O'Donnell et al. (2001) used different sensors to detect tool wear and breakage in drilling, reaming and tapping. The torque signal has the most useful information to monitor the machining processes. However, the use of torque sensor is not always possible. Therefore, they have conducted experimental studies in drilling with multiple sensor types at different locations and acquired power signal, vibration signal and AE signal. They reported that the vibration signals and AE signals are having high levels of noise related to the manufacturing environment. The power signal presented the greatest sensitivity to variations in the tool performance and the least sensitivity to noise.

Rene et al. (2003) estimated the cutting forces from the acquired current signal obtained from servo driver directly to predict sensorless tool breakage in CNC milling machines. Shao et al (2004) observed the inherent fluctuation in measured power signals and compared with the simulated power signals, also estimated tool wear during face milling process. They reported that the developed model is more robust and can be implemented in the applications such as milling process with different cutting conditions. Patra et al. (2007) analysed the motor current signals in drilling process using multi-layer ANN method to assess the flank wear of the drill bit. They compared the results obtained from ANN technique with the regression model. Satti et al. (2009) introduced a novel and practical concept for recognizing catastrophic failure in machine tool in case of large-scale milling machines using average spindle power signals of the machining process. They studied the inherent capacity of the proposed multi-layer detection strategy, which provides useful information about the process variation and failure-induced changes in the acquired power signals. They also reported that this strategy is a cost effective solution to avoid catastrophic failure in large-scale milling processes. Drouillet et al. (2016) employed ANN technique in remaining tool life prediction using machine spindle power in end milling process. They reported that the root mean square power value was very sensitive when tool wear occurs.

2.4.4 Temperature

The cutting zone temperature will change as the tool wear progresses resulting in change in the tool geometry. Therefore the use of temperature was suggested to monitor the tool condition. Figure 2.4 illustrates the temperature measurement test setup during machining (Lin, 1995). IR Pyrometer is used to measure the temperature. During milling the surface radiation is measured by this sensor and the temperature signal is accumulated in a recorder and personal computer.

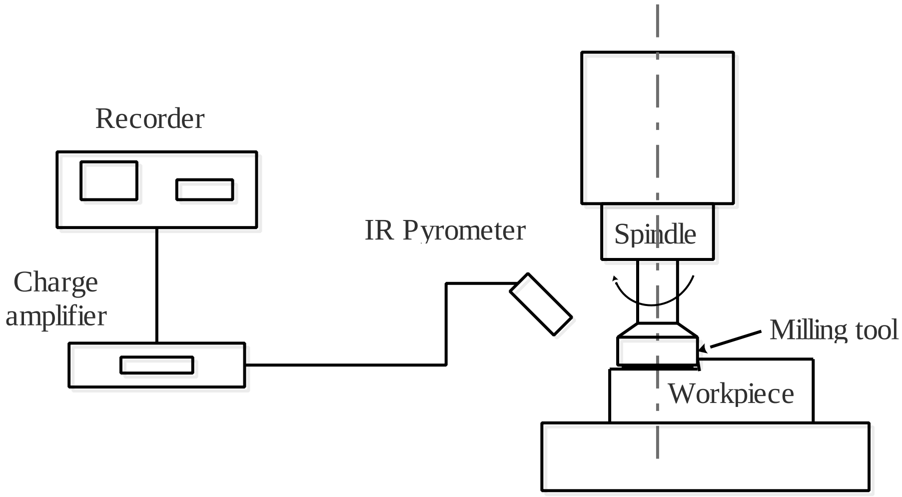


Figure 2.4 Experimental setup of temperature measurement during milling (Lin, 1995)

Lin (1995) studied the tool-workpiece interface temperature using inverse finite element method and infrared pyrometer in end milling process. They reported that the numerical analysis provided a good agreement with experimental investigations in milling of steel and aluminium alloy. Ueda et al. (2001) examined the temperature of the flank face of the cutting tool using the pyrometers in high speed end milling process. They carried out the experiments with different cutting conditions and reported that the abrupt rise in temperature of about 770 ^{0}C occurred at cutting speed of 668 m/min. Choudhury and Bartarya (2003) experimentally correlated the relationship between the flank wear and cutting zone temperature in turning, where the temperature sensor was the natural formed thermocouple between the tool and the workpiece. In this case, only the average temperature in the cutting zone is measured. Another possibility is to measure the temperature by thermal images from the cutting zone. However, in this case the chip which carries out approximately 90% of the energy dissipated during machining will dominate the intensity of radiation. Ming et al. (2003) studied the temperature distribution in tool workpiece interface and heat generation during high speed milling process using Beck's inverse heat conduction theory and infrared thermometer. They validated the numerically computed values of temperature with the experimental results.

2.4.5 Vibration signal

Vibrations are addressed due to the cyclic variations in the dynamic components of the cutting forces. Mechanical vibrations generally result from periodic wave motions. The vibration signal which is coming out during metal cutting process includes facets of free, forced, periodic and random types of vibration. Vibration mode is frequency dependent and it has determining characteristic feature. It is difficult to measure vibration directly. Hence related parameters such as rate at which dynamic forces change per unit time (acceleration) are measured and the characteristics of the vibration are derived from the patterns obtained. The vibration signal is acquired by the sensor called accelerometer. Figure 2.5 illustrates the vibration signal based condition monitoring of the milling tool test setup (Mhalsekar et al. 2010).

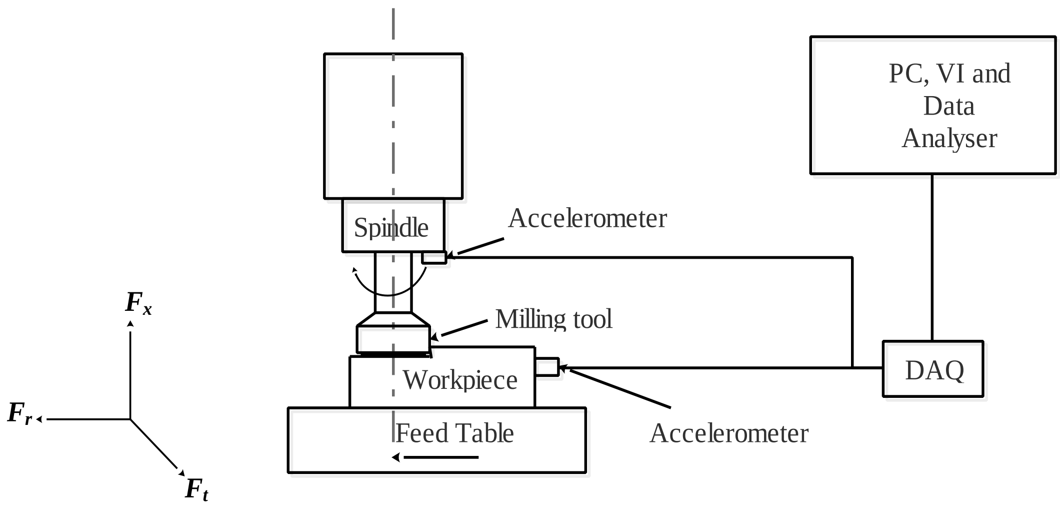


Figure 2.5 Vibration based experimental setup for fault diagnosis of milling tool (Mhalsekar et al. 2010)

Mehta et al. (1983) investigated the tool wear during face milling using vibration signals. They observed increase in the tool wear rate due to vibration which is governed by the stiffness of the machine tool-work material structure. Rotberg et al. (1987) examined the vibration signals during milling for condition monitoring of face milling tool with the different cutting phases such as entry, exit and continuous machining. El-Wardany et al. (1996) investigated the use of vibration signature characteristics in online drill wear monitoring and breakage. They found that the features of vibration signals are sensitive to the tool wear and observed in time and frequency domains. Experimental results showed that in time domain analysis, the kurtosis values increased drastically with drill breakage, while frequency analysis revealed sharp peaks indicating drill breakage. By combining both the techniques it was possible to devise an effective drill monitoring system. Kim and Klamecki (1997) monitored the milling cutter by acquiring the torsional spindle vibration using an optical system and predicted the tool wear by analysing the vibration signals in frequency domain. Dimla (1998) investigated the vibration and cutting force signals during turning of alloy steel using ANN technique to distinguish the different tool conditions such as severe flank wear, broken nose and chipping conditions. They reported that the classification of the turning tool conditions can be achieved in the range from 88% to 96% based on multivariate data analysis using ANN technique. Al-Habaibeh and Gindy (2000) considered combination of signals such as vibration signals, AE signals and cutting force signals to design the TCM system for end milling process using ANN and Fuzzy classifiers.

Abouelatta and Madl (2001) correlated the surface profile of workpiece with the cutting parameters and cutting tool vibrations. Dimla (2002) analysed the vibration signals in time and frequency domains during turning process to correlate the acquired signals with the measured cutting tool wear. They reported that the time-domain characteristics were correlated well with the machining conditions, whereas the frequency domain characteristics were more sensitive to the tool wear. Abu-Mahfouz (2003) studied the drill tool fault diagnosis using vibration signals through the ANN technique. They extracted the features from both time and frequency domains vibration signals and reported that the frequency domain features are more efficient than time domain features in TCM of drilling process. Kuljanic et al. (2009) developed a system to identify the chatter condition of the face milling process using vibration and cutting force signals. Mhalsekar et al. (2010) investigated the vibration signals during face milling using recurrence quantification analysis (RQA) method for monitoring the flank wear of tool insert. They concluded that RQA parameters such as entropy, percent laminarity, trapping time and percent recurrence are useful features for detecting the tool flank wear. Hsieh et al. (2012) studied the micro-milling tool condition monitoring using neural network technique through vibration signals in time and frequency domains. Yesilyurt (2006) found the variations in mean frequency of the scalogram of vibration signals with different feed rates in breakage detection of end milling tool. Fu et al. (2016) investigated the chatter condition of the end milling process using vibration signals based on Hilbert–Huang transform (HHT) method. They concluded that the proposed method is self-adaptive and robust. HHT can be used effectively to distinguish the chatter condition, stable condition of the milling process and also can be identified the transition stage of the process.

2.4.6 Sound signal

Like vibration, machining sound is also a non-stationary signal which carries the information of operating conditions of the process/machine. By hearing the sound of a machine during its running, an experienced operator can even identify and locate any faults in the machine. But the researchers have been giving a little attention to the sound signal analysis for fault diagnosis compared to vibration signal. This is due to the fact that the machine sound is complex with low signal to noise ratio and is contaminated with the industrial noise environment. So it is necessary to filter out the background noise from the raw sound signal with the help of technically advanced signal processing techniques to detect the machine tool faults. The sound based analyser is cheaper, simple to use and portable when compared to a vibration analyser. Microphone sensor is used to acquire the sound signals. Figure 2.6 depicts the experimental setup for condition monitoring of the bearings using sound signals (Kumar et al. 2012).

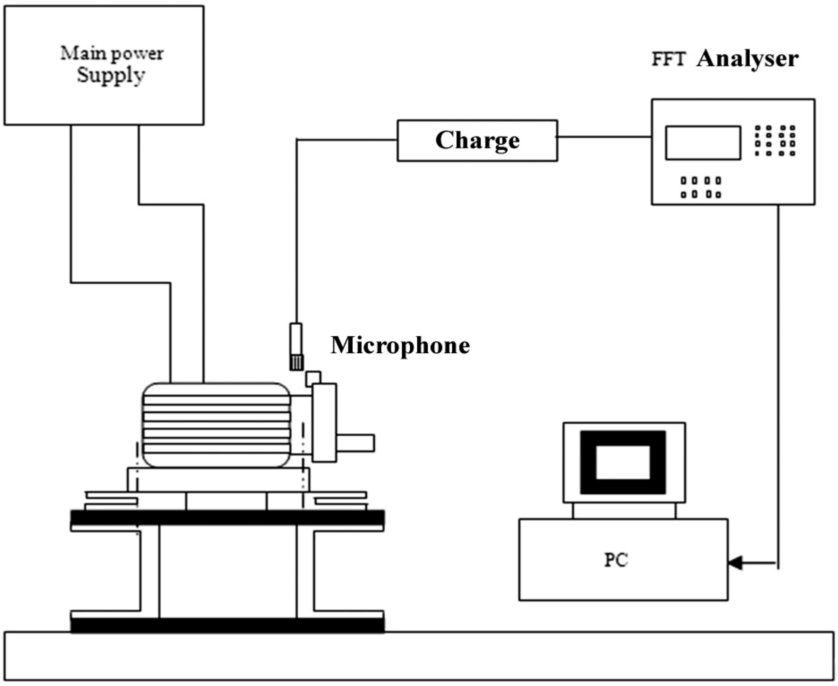


Figure 2.6 Sound signal based fault diagnosis of bearing condition in motor pump (Kumar et al. 2012)

Lu and Asibu (2002; 2004) developed a model which gives relationship between tool wear and sound generation during turning process. They have shown that as the tool wear progresses resulting in variation of the sound pressure distributions. Ghosh et al. (2007) correlated the different signals such as cutting force signal, vibration signal, spindle current signal and sound signal with the tool wear during face milling operation using ANN technique. They validated the proposed method with the laboratory and the experimental results. Salgado and Alonso (2007) estimated tool wear during turning process using feed motor current signal and sound signal through least squares support vector machine and singular spectrum analysis methods. They concluded that the proposed method is fast and reliable for online TCM in turning. Rubio and Teti (2009) developed a monitoring system for analysing the cutting parameters in milling process using graphical analysis and parallel distributed data processing method through sound signals. Kumar et al. (2012) employed the SVM and statistical methods for fault diagnosis of antifriction bearing using sound signals. Lu and Wan (2013) studied the sound signals for micro tool wear monitoring using class mean scattering criteria and the hidden Markov model. They concluded that the signal of frequency above 20 kHz is able to distinguish the healthy and fault conditions of the micro milling tool. Amarnath et al. (2013) extracted the statistical features from the sound signals of the motor pump to identify the condition of the bearing using the decision tree method. They achieved the classification efficiency of about 95% based on sound signals using the decision tree technique.

2.5 SIGNAL PROCESSING TECHNIQUES

In the early days vibration analysis was carried out with the help of time domain signal. The nature or type of the vibration signal is identified with the help of raw time waveform. It is better for analysing impulsive vibration signal to detect faults in components such as bearing, gear, cutting tool, etc. But it is very difficult to identify each of the frequency components which are the most important to identify the faulty component (Saimurugan 2013). Spectrum analysis, cepstrum analysis and wavelet analysis also belong to the signal processing techniques. Many research works using these techniques have been carried out, some of them are discussed in the following sections.

2.5.1 Fault detection through spectrum analysis and cepstrum analysis

Frequency domain analysis is the most widely used conventional technique for fault diagnosis of cutting tool/rotating machine components. The fast Fourier transform (FFT) converts the time domain data into frequency domain data. In case of machining operation, as the tool wear occurs the vibration patterns will change. Due to the tool wear/breakage, the vibration energy is increased at the corresponding rotational frequency. The faulty tool can be identified with the help of increase in amplitude energy level in the frequency plot. Noori-Khajavi and Komanduri (1995) studied the cutting force signals of healthy and faulty drill tool conditions in time and frequency domains. They observed that the frequency domain has provided a good understanding of the tool state than time domain analysis. Orhan et al. (2007) investigated the tool wear in time and frequency domain analyses during end milling of AISI D3 cold work tool steel using vibration signals. They reported that there was no considerable increase in the vibration amplitude until a flank wear reaches 160 µm, above which the vibration amplitude increases significantly. Antonialli et al. (2010) analysed the variations in cutting force during milling of titanium alloy in time and frequency domain analyses. Sivasakthivel et al. (2011) developed a mathematical model with process parameters to analyse the vibration amplitude in high speed end milling of Al 6063 material using spectrum analysis. Huang et al. (2012) investigated the stable and chatter machining processes through spectrum plots of cutting force and vibration signals. Bisu et al. (2012) examined the dynamic behaviour of the milling process to monitor the condition of the cutting tool through spectrum analysis using vibration signals. Huang et al. (2013) analysed the cutting force signal in time-domain, frequency-domain and time-frequency domain in order to find out the range of stability in machining of Titanium alloy. Chen et al. (2012) investigated the relationship between vibration of the tool and workpiece surface roughness in end milling using singular spectrum analysis.

Cepstrum analysis is one of the signal processing techniques which clusters the different frequencies corresponding to components that exists in the rotating machine/system. The cepstrum plots are used to identify the conditions of the system/cutting tool with help of quefrency information in the acquired signals. Sghir et al. (2007) analysed the vibration signals of different condition of the milling tool by using cepstral techniques. They distinguished different tool conditions by computing the power spectral density from the acquired signal. Iturrospe et al. (2005) extracted relevant information for monitoring precision turning operation using AE signals through bicepstral method. Borghesani et al. (2013) carried out fault diagnostic analysis of rolling element bearings using cepstrum analysis. Different bearing damages in various operating conditions were considered in their study. Liang et al. (2013) used power spectrum analysis, cepstrum analysis, higher order spectrum analysis and neural network analysis for induction motor fault diagnosis. They revealed that cepstrum analysis is a very useful tool for detection families of harmonics with uniform spacing or the families of sidebands commonly found in gearbox, bearing and engine vibration fault spectra. Morsy and Achtenova (2014) studied the damage detection in a vehicle gearbox using cepstrum analysis.

Spectrum analysis has its own limitations (Zhu et al., 2009) as it can only be used for stationary signals. Li et al. (2005) revealed that the fast algorithm of wavelet transform is more reliable, sensitive and faster than spectrum analysis in prediction of tool wear condition during turning process.

2.5.2 Wavelet analysis

Wavelet analysis captures both frequency and location information (location in time). The concept of wavelet was first introduced by Morlet in 1982. There are various families of wavelet such as Haar, Morlet, Daubechies, biorthogonal, coifflets, etc. The two major types of wavelet transform are continuous wavelet transform (CWT) and discrete wavelet transform (DWT). Kasashima et al. (1995) conducted an experiment of on-line failure detection in face milling of stainless steel (SUS304) using DWT technique. DWT algorithm is used to predict tool failure such as small chipping and breakage of an insert tip. The result shows that the DWT can extract tool failures with much greater sensitivity than the fast Fourier transform (FFT) even when the amount of chipping is very small. Gong et al. (1997) compared the wavelet transform with the Fourier transform using cutting force signal for monitoring of tool flank wear during turning process and they found that the wavelet analysis is more reliable, sensitive and faster than Fourier analysis. Berger et al. (1998) studied the chatter and non-chatter machining process through wavelet analysis using cutting force signals in turning operation. Mori et al. (1999) analysed the transient responses in cutting force signals during drilling process using DWT. Lee and Tarng (1999) determined milling tool breakage using cutting force signals through DWT technique.

Klocke et al. (2000) computed wavelet parameters for finding variations in cutting force signals of ball end milling under different tool conditions and reported that this technique is reliable for monitoring the ball end milling tool. Li and Guan (2004) analysed the feed motor current signals to predict cutting edge fracture through time-frequency plots in end milling process. Wu and Chen (2006) carried out the fault diagnosis studies on internal combustion (IC) engine and its cooling fan blades using CWT technique through vibration and sound signals. Zarei and Poshtan (2007) applied CWT technique in fault detection of bearing in induction motor using current signals. Yao et al. (2010) applied wavelet transform method for chatter detection and support vector machine (SVM) technique for pattern classification during boring operation using vibration signals. Shao et al. (2011) separated power signal from the mixed signals during milling process based on wavelet transform method and independent component analysis. They conducted experiments with different tool conditions and results showed that the separation strategy is robust and promising for machining process monitoring. Kankar et al. (2011) investigated the vibration signals using CWT technique for fault diagnosis of rolling element bearings and classified the different conditions of the bearing using SVM and ANN classifiers. Vernekar et al. (2014) studied the gear faults in IC engine gearbox using spectrum analysis, CWT analysis and reported that CWT technique is an effective tool for fault diagnosis of the gear.

Lot of research work has been carried out on machinery fault diagnosis using CWT. But CWT takes more computation time, generates large amount of redundant information and requires more memory space. Since DWT does not have these disadvantages, it can be preferred over CWT (Saimurugan 2013). The application of the DWT features in fault diagnosis are discussed in section 2.6.1.3.

2.6 MACHINE LEARNING TECHNIQUES

The pattern recognition technique was first implemented in the year 1989 to automate the fault diagnosis process (Li and Wu 1989). The pattern recognition or machine learning technique classifies the group of objects on the basis of subjective similarity measures. The prominent steps which involved in machine learning approach are feature extraction, feature selection and feature classification.

2.6.1 Feature extraction

The acquired signal in the form of digitized data from the process/system cannot be directly used for machine learning. The required information is extracted from these huge data in the form of features such as statistical features, histogram features, wavelet features, etc. The following subsections will provide the usage of different features in fault diagnosis and condition monitoring.

2.6.1.1 Statistical features

Statistical analysis of acquired signals yields different parameters. These statistical parameters extract the fault information from the large data. Numerous investigations have been carried out in different area of fault detection using a set of statistical parameters as a feature extraction method. The statistical parameters such as mean, standard error, median, mode, standard deviation, variance, kurtosis, skewness, range, minimum, maximum, etc. have been widely used by the researchers on their studies on intelligent fault diagnosis. Sugumaran et al. (2007) used the statistical features of vibration signals for fault diagnosis of roller bearings through decision tree and proximal SVM techniques. Alonso and Salgado (2008) applied the statistical features and some other techniques such as, ANN, singular spectrum analysis and cluster analysis in TCM system for detecting the tool wear in turning process. Elangovan et al. (2010) studied the performances of Naïve Bayes and Bayes net classifiers through histogram and statistical features in turning operation using vibration signals. They concluded that statistical features yield more classification accuracy than using histogram features.

Wang et al. (2013) carried out the classification of different milling tool conditions using distributed Gaussian ARTMAP (adaptive resonance theory mapping) network by extracting the statistical parameters in time and frequency domains from the cutting force signals. Sakthivel et al. (2014) achieved good classification results using the combination of principle component analysis (PCA) and decision tree technique in fault diagnosis of mono block centrifugal pump through the statistical features of vibration signals. Painuli et al. (2014) investigated the different conditions of a single point cutting tool using statistical features of vibration signals. Gangadhar et al. (2015) used the statistical features and decision tree technique for classifying the tool conditions in turning process using vibration signals. Jegadeeshwaran and Sugumaran (2015) employed a clonal selection classification algorithm (CSCA) for condition monitoring of a hydraulic brake system using statistical features of vibration signals.

2.6.1.2 Histogram features

A difference in the range of amplitude for different classes could be viewed when the magnitude of the signals were measured in time domain. Variation in the signal amplitude could be shown by using one of the best methods namely histogram plot. This histogram plot provides some valuable information for classification and this information would serve as histogram features for fault diagnosis of cutting tools and/or a machinery system. Sugumaran and Ramachandran (2011) employed a fuzzy based classifier to diagnose the roller bearing conditions using histogram features and decision tree technique. Sakthivel et al. (2011) investigated the different conditions of the centrifugal pump based on histogram features of vibration signals using decision tree and Naïve Bayes techniques. They reported that the decision tree technique provides the best classification accuracy than the Naïve Bayes technique. Sugumaran and Ramachandran (2011) examined the vibration signals of roller bearing system using SVM and proximal-SVM (PSVM) techniques. They extracted the statistical and histogram features from the vibration signals. They compared the performance of both the classifiers and concluded that histogram-PSVM was the best feature-classifier combination in roller bearing fault diagnosis. Guo and Mao (2015) investigated the cracks in aluminium alloy beam using histogram based technique and ultrasonic IR (infra-red) thermography.

2.6.1.3 Discrete wavelet transform (DWT) features

DWT decomposes the signal into two frequency sub bands such as low frequency band (approximate coefficients) and high frequency band (detailed coefficients) through high pass filters and low pass filters. Then the decomposed low frequency component of the signal will be again decomposed into approximate and detailed coefficients. This iteration will go on and at each step the approximate coefficient is considered as DWT feature. DWT analysis is much more efficient, less computation time and is reliable to identify small changes in AE and current signals of the drilling process for tool breakage detection (Li et al. 1999). Wu et al. (2001) implemented a real time tool condition monitoring in drilling operation based on DWT using current signal. Suh et al. (2002) investigated the milling process based on the DWT analysis to find the stability in the machining process using cutting force signals. Mehrabi and Asibu (2002) found 97 % accuracy in tool state detection for TCM of the turning process based on hidden Markov models and DWT technique using vibration signals. Li and Guan (2004) proposed an algorithm which consisted of wavelet denoising, discrete wavelet analysis and FFT for detection of cutting edge fracture of end milling tool using feed motor current signals. They found that this algorithm is not applicable for light machining operations, because of difficulties in extracting the information from the current signal of low cuts for fault detection. Choi et al. (2004) used the DWT technique and linear regression method for estimating the tool wear in ramp cuts in end milling process. Franco-Gasca et al. (2006) applied the DWT method for tool condition monitoring in a drilling process using driver current signals. Kim et al. (2007) demonstrated that DWT is the most effective technique among various signal processing techniques such as fast Fourier transform, Wigner-Ville distribution and short time-frequency transform in damage detection of rotor system using vibration signals. Barakat et al. (2011) discussed the application of self-adaptive growing neural network (SAGNN) and DWT technique in fault diagnosis of the mechanical machinery system and a chemical plant. They reported that the SAGNN classifier optimizes the number of nodes, minimizes the computation time and creates hidden sub-space for every output class. Kumar and Singh (2013) used the Symlet wavelet (DWT family) and vibration signals for measuring the defect width on the outer race of the roller bearing.

2.6.1.4 Empirical mode decomposition (EMD) features

The assumption behind the development of empirical mode decomposition (EMD) algorithm is that any signal consists of different intrinsic modes of oscillations. EMD algorithm decomposes the signal into a number of IMFs, each resulting IMF component consists of the local characteristic of the signal. For example, an IC engine gearbox is operating with different mechanical faults, the amplitude energy of each IMF are obviously different. Therefore, the amplitude energy feature of each IMF component can be used to identify the different fault of mechanical components of an IC engine gear box. Lei et al. (2008) used an improved distance evaluation technique and adaptive neuro-fuzzy inference system technique in fault diagnosis of rolling element bearing using statistical characteristics and EMD features extracted from the vibration signals.

Kalvoda and Hwang (2010) investigated the performance of end milling of aluminium alloy in frequency and time-frequency domains using Hilbert-Huang transform method based on vibration and cutting force signals. They concluded that cutting force analysis provides a better result in tool state than vibration signals. Cao et al. (2013) used an independent component analysis, EMD and genetic algorithm B-spline network methods for fault diagnosis of cutting tool during turning operation using vibration signals. Shi et al. (2014) employed the EMD method and independent component analysis technique for tool breakage detection in the face milling process. Ali et al. (2015) examined the performance degradation of automatic bearing system based on statistical features using EMD and ANN techniques. Jedlinski and Jonak (2015) used the wavelet transform, ANN and SVM techniques for fault detection of the gear box. They reported that SVM and ANN techniques have provided 90% and 92% classification accuracy respectively. Bakker et al. (2015) analysed the fixture cassette deformation during linear friction weld process using EMD technique. Cao et al. (2015) studied the chatter occurrences during the end milling process through ensemble empirical mode decomposition technique and nonlinear dimensionless indicators using vibration signals.

2.6.1.5 Other feature extraction method

Some other features excluding the above said features (statistical features, histogram features, DWT features and EMD features) were used in the area of condition monitoring. Literature on those features are discussed in this section. Xia et al. (2012) applied the spectral regression based features extraction method to the vibration signals for monitoring the different conditions of the bearing. Aishwarya et al. (2013) used the auto regressive moving average (ARMA) features and electromyogram (EMG) histogram features for different hand movements classification based on EMG signals using ANN technique. Zhang et al. (2015) used the exponential weighted moving average method as a feature extraction technique in fault diagnosis of rolling bearing system using electrostatic signals. Ramalingam et al. (2016) extracted the ARMA features from the electroencephalaogram (EEG) signals for classification of prosthetic limb movements such as, finger open, finger close, wrist clockwise and wrist counter clockwise movements using decision tree technique.

2.6.2 Feature selection

All extracted features from measured data are not required to extract the diagnostic information. Dimensionality reduction techniques remove the redundant information to reduce the original higher dimension for the ease of processing and computation. Recently, the use of feature reduction and feature selection for data preparation before feeding into the classifier has received considerable attention (Cao et al. 2003). The details of the usage of feature selection technique are discussed as follows.

2.6.2.1 Decision tree technique (J48 or C4.5 algorithm)

The decision tree selects a subset of the existing features without any transformation by representing the signal information in the form of tree. The detailed explanation about decision tree method can be seen in the section 3.1.2. The decision tree can also be used as a classifier. Sugumaran et al. (2007) used the decision tree technique for feature selection and proximal SVM technique for classification of faults in roller bearing. Sugumaran and Ramachandran (2007) employed the decision tree technique as a salient feature selection method in fault diagnosis of roller bearing. They also used statistical method for feature extraction and fuzzy algorithm for classification in the study of condition monitoring of roller bearing system. Sugumaran et al. (2008) diagnosed the faults in roller bearing using multi-class SVM technique as a classifier and the decision tree algorithm as a feature selection method based on vibration signals. They also compared the performance of the proposed method to the performance of the binary SVM method. Yang et al. (2009) analysed the vibration and current signals of induction motor to detect the faults using decision tree method for pertinent feature selection and adaptive neuro-fuzzy inference system (ANFIS) method for classification. They achieved the classification accuracy of about 91% and 77% for the vibration and current signals respectively using the ANFIS method. Sakthivel et al. (2010) extracted the statistical features from the vibration signals acquired from the monoblock centrifugal pump under different conditions such as normal, bearing fault, impeller fault, seal fault, combined impeller and bearing fault to classify the different conditions using decision tree technique.

Sugumaran et al. (2013) applied the decision tree algorithm for both feature selection as well as classification to diagnose the faults in the helical gear box system using vibration signals. Muralidharan and Sugumaran (2013) analysed the vibration signals using CWT method and decision tree technique to find out the different conditions of the monoblock centrifugal pump such as, healthy condition, cavitation, bearing fault, impeller fault, combined impeller and bearing fault. Sakthivel et al. (2014) compared the performance of the decision tree technique with the Bayes net, Naïve Bayes and K-nearest neighbour classifiers in fault diagnosis of monoblock centrifugal pump using vibration signals. They concluded that the decision tree has given the best classification efficiency in comparison with other classifiers.

2.6.2.2 Principal component analysis (PCA)

Principal component analysis (PCA) is one of the widely used multi-dimensional features reduction tool. PCA is the preferred choice because it is a simple and non-parametric method of extracting relevant information from complex data sets. The goal of PCA is to reduce the dimensionality of the data while retaining as much as possible of the variation in the original data sets. Malhi and Gao (2004) studied the different bearing conditions using PCA and neural network method through vibration signals. Sun et al. (2007) carried out the fault diagnosis analysis in rotating machinery of Bently rotor kit RK4 based on C4.5 decision tree technique, ANN technique as classifiers and PCA as feature reduction technique. They achieved high classification accuracy using feature selection tool as PCA algorithm with C4.5 decision tree as classifier. Elangovan et al. (2011) used principal component analysis and C4.5 algorithm (decision tree) for tool wear classification. They concluded that the decision tree algorithm is a better method for feature selection than the principal component analysis method in turning process. Ahmed et al. (2012) used the PCA as feature selection method in fault diagnosis of reciprocating compressor using vibration signals. Wang et al. (2015) investigated the fault conditions of the rolling bearing using PCA as feature reduction method and Fuzzy C-means technique as classifier through vibration signals.

There are many techniques available for feature selection. The commonly used technique for selection of feature is decision tree and it provides better results in comparison with other feature selection methods in condition monitoring (Samanta and Al-Balushi 2003).

2.6.3 Feature classification

Feature classification is the last phase of the machine learning approach. In the classification process, the classification algorithm develops a model with the help of training data and the trained model is used to classify the data belonging to various classes of faults. There are various classification techniques to classify the cutting tool conditions. The following subsections provide the details about the use of classification algorithms for online tool wear monitoring.

2.6.3.1 Artificial neural network (ANN)

Artificial neural networks are modelled on the basis of biological neurons and nervous systems. They have the processing elements known as neurons, which perform their operations in parallel. ANN’s are characterized by their topology, weight vector and activation functions. The applications of ANN technique can be seen in condition monitoring and fault diagnosis area, some of them are discussed as follows. Ko et, al. (1995) carried out studies to monitor online tool breakage in face milling using an unsupervised neural network with a combination of adaptive time series modelling algorithm. They found that there is a strong relationship between tool conditions and model parameters which leads to an effective condition monitoring of tool states and this approach is also feasible to classify the various patterns. They suggested that this approach is an effective technique for on-line condition monitoring of milling tool. Tarng et al. (1996) used the unsupervised neural network for tool failure detection through resultant force spectrum analysis in end milling process. This method was able to distinguish the features of the resultant force spectrum with varying cutting conditions and also demonstrated the feasibility of the proposed detection system. Hong et al. (1996) used a neural network technique for condition monitoring of turning tool based on wavelet decomposition. They found that the wavelet features of cutting force signal had a low sensitivity to the changes in machining conditions. Dimla et al. (1998) recognised the tool wear condition of turning operation using multi-layer perceptron

(MLP) neural network through vibration and cutting force signals. Dimla (1999) continued his work with single layer perceptron and MLP, concluded that MLP is an effective tool for analysing the chaotic data and the best suitable for the TCM system of turning process. Dutta et al. (2000) investigated and compared the performance of fuzzy based neural network with the standard back propagation neural network for tool condition monitoring during face milling process using vibration and cutting force signals. They concluded that the proposed method is faster in computational steps and effectively applicable for on-line TCM system. Abu-Zahra and Yu (2003) carried out condition monitoring studies on gradual tool wear in cutting tool inserts during turning process based on DWT method and MLP technique using ultrasound waves. Yu and Junsheng (2006) proposed an algorithm based on EMD method and ANN technique for fault diagnosis of roller bearing system using vibration signals and compared the results of EMD technique to the wavelet analysis. They concluded that the EMD technique is applicable to both stationary and non-stationary signals. Aykut et al. (2007) used ANN for modelling of cutting forces in face milling of work material stallite 6 to investigate the effects of machinability on chip removal cutting parameters. Ghosh et al. (2007) correlated the different signals such as cutting force signal, vibration signal, current signal and sound signal with the tool wear during face milling process using ANN technique. They validated the proposed method with the laboratory and the industrial experiments. The methods using multiple sensors will improve online tool condition monitoring, wear prediction when compared with the single sensor counterparts, but cost effective.

Hsieh et al. (2012) investigated the spindle vibration signals of micro tool under healthy and faulty tool conditions through back-propagation neural network classifier and spectral analysis. The results showed that proper feature extraction for classification gives a better solution than applying all features into the classifier and also reported that the improvement in tool condition monitoring by integrating the different axes of the vibrational signals. Bajic et al. (2012) examined the influence of machining parameters on surface roughness, tool wear and cutting force in face milling of steel as part of the off-line process control by using regression model and neural network model. The results obtained from both the models were compared and showed that both the models were found to be capable of accurate predictions of surface roughness, tool wear and cutting force with a relative prediction error below 10%. Although neural network models gave better relative error 3.35% in comparison with the regression model.

2.6.3.2 Support vector machine (SVM)

SVM is a relatively new computational learning method based on the statistical learning theory (Vapnik 1995). SVM construct an optimal hyperplane which separates the data into two classes. Many researchers discussed the theoretical background of SVM, kernel functions in SVM and its applications. Hsueh and Yang (2008) used the SVM technique in prediction of breakage in face milling cutter using cutting force signals. Hsueh and Yang (2009) employed support vector machine (SVM) method for tool breakage monitoring system in face milling of 7075 aluminium through spindle displacement signals. They have shown that this approach is reliable, highly sensitive, and robust in signal processing and also tool breakage monitoring can be implemented successfully. Cho et al. (2005) used the SVM technique for tool breakage detection in a milling process using cutting force dynamometer and spindle displacement sensor. Widodo and Yang (2007) provided a review of various applications of the SVM technique on fault diagnosis and machine condition monitoring system.

Saimurugan et al. (2011) used statistical features and SVM for fault diagnosis of rotational mechanical system using vibration signals. Kumar et al. (2012) used c-SVM and ν-SVM for fault detection in antifriction bearings under healthy and faulty conditions using sound signals. They found that c- SVM is the best classifier for fault diagnosis of bearings. Muralidharan et al. (2014) studied the different conditions of the centrifugal pump using SVM method, also different families of continuous wavelets and compared the results of different wavelets with SVM as classifier. Vernekar et al. (2014) diagnosed the faults in deep groove ball bearing using SVM technique and wavelet features. Dutta et al. (2016) employed the SVM regression method with Voronoi tessellation technique, gray level co-occurrence matrix technique and DWT technique in prediction of flank wear of cutting tool in turning process based on the machined surface texture. They reported that 4.9% was the maximum estimation error by SVM regression analysis in condition monitoring of the turning tool.

2.6.3.3 K-star algorithm

K-star algorithm works based on “entropy as a distance measure” i.e. the approach is used to compute the distance between two instances is motivated by the information theory. The intuition is that the distance between instances be defined as the complexity of transforming one instance into another. The calculation of the complexity is done in two steps. First, a finite set of transformations, which map instances to instances is defined. A “program” to transform one instance ‘a’ to another ‘b’ is a finite sequence of transformations starting at ‘a’ and terminating at ‘b’. The detailed description about working principle of K-star algorithm is explained in section 3.1.3.4. Painuli et al. (2014) analysed the vibration signals for tool condition monitoring in turning of mild steel using K-star algorithm. They used descriptive statistical features like standard deviation, kurtosis and skewness as salient features from acquired vibration signals of good and faulty tool conditions. K-star algorithm was used to build a model to distinguish tool condition using these selected statistical features. They concluded that the K-star algorithm is able to achieve 78% classification accuracy in turning operation. K-star classifier has achieved appreciable results in some applications such as misfire detection of an IC engine (Bahri et al. 2013).

2.6.3.4 Bayesian network

Bayesian network has played a vital role as fault diagnostic tool in some applications. Abellán et al. (2006) investigated the surface roughness and tool wear condition in CNC milling process using Bayesian network through surface profile measurement system and accelerometer. They achieved 89% and 97% efficiency in surface roughness and tool wear predictions respectively. Addin et al. (2007) employed the Naïve Bayes technique as a classifier in the applications of damage detection of quasi isotopic laminated composites of the AS4/3501-6 graphite/epoxy system and ball bearing of the type 6204 with a steel cage. Chen et al. (2009) classified the multiclass text datasets using Naïve Bayes algorithm. Muralidharan and Sugumaran (2012) analysed the vibration signals obtained from the different conditions of the monoblock centrifugal pump such as, normal, cavitation, bearing fault, impeller fault, combined impeller and bearing fault using Naïve Bayes and Bayes net classifiers based on DWT features. They reported that the Bayes net was the best technique for distinguishing these different states of the pump than the Naïve Bayes classifier. Tobon-Mejia et al. (2012) applied Bayesian networks in diagnosis of remaining useful life of CNC milling tool based on two phases namely, offline and online phases (Figure 2.7). Patil and Sherekar (2013) used Naive Bayes technique and J48 algorithm for classifying the bank dataset. They reported that the J48 technique is the best classifier in comparison with the Naïve Bayes technique.

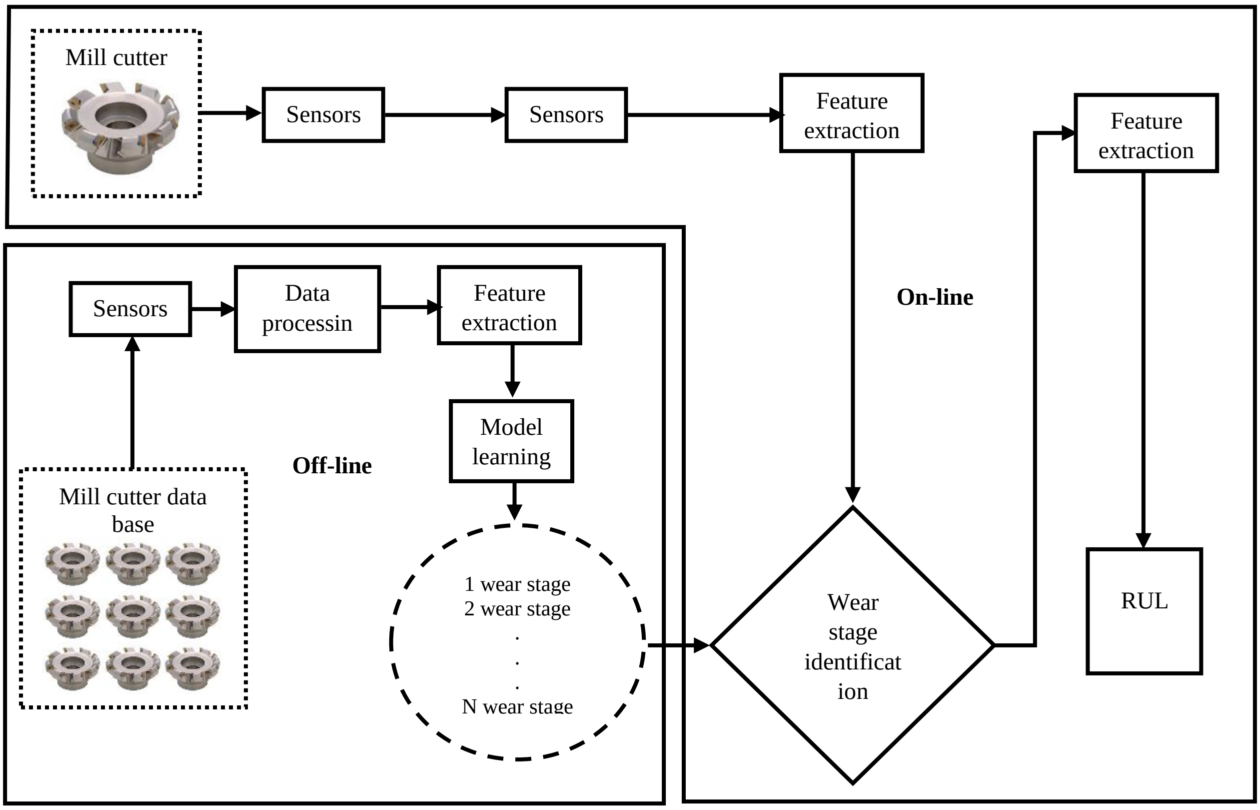


Figure 2.7 Two-phases of tool condition monitoring (Tobon-Mejia et al. (2012)

Karandikar et al. (2013) applied Bayesian inference method to predict the remaining useful tool life in turning of MS309 steel through power signal. They reported that the root mean square time domain power signal is very sensitive for tool wear. Also they showed that, there is a good agreement between the empirically determined true remaining tool life and predicted tool life. Karandikar et al. (2014) used Bayesian inference technique to predict tool life in milling of 1018 steel work material using discrete grid method. They have proposed updated values of the Taylor tool life constants n and C using experimental tool life results. Also they concluded that the predicted distributions agreed with the experimental values of tool life. Kumar et al. (2014) studied the different bearing conditions of the motor pump based on vibration signals using decision tree, Naïve Bayes and Bayes net algorithms. They reported that the Naïve Bayes provided a better classification accuracy of about 90% than the Bayes net classifier.

2.6.3.5 Other classifiers

Some other artificial intelligence techniques which are not highlighted above played a vital role in condition monitoring and the details about the performances of those techniques are reported in the section. Devillez and Dudzinski (2007) developed tool condition monitoring method in turning operation using Fuzzy classifier based on current signals. Liao et al. (2008) investigated the grinding wheel conditions based on AE signals using minimum distance classifier and reported better results in identifying the grinding wheel conditions. Li et al. (2009) used the Fuzzy neural network (FNN) in prediction of tool wear in milling process and compared the performance of the FNN with the different algorithms of ANN technique. They concluded that the FNN technique was superior to the other techniques. Su et al. (2014) diagnosed the fault condition of the gearbox using an adaptive nearest neighbour classifier through vibration signals and achieved a good classification accuracy in condition monitoring of gearbox. Brkovic et al. (2016) carried out the experiments on early fault detection and diagnosis of bearing condition in induction motor using DWT technique and quadratic classifiers based on vibration signals. Patel and Giri (2016) evaluated the performance of the random forest classifier in fault detection of the bearing conditions of the induction motor using statistical features of vibration signals. They compared the results obtained from the random forest classifier with the ANN classifier and reported the best classification efficiency by the random forest technique in condition monitoring of mechanical fault in induction motor. Ramalingam et al. (2016) used the clonal selection classification algorithm as classifier in prosthetic arm condition monitoring using EEG signals based on statistical features and decision tree technique and achieved 80% classification accuracy.

2.7 OTHER METHODS

Other varieties of sensors or techniques have also been employed in various attempts in fault diagnosis and condition monitoring of system/ cutting tool. Baek et al. (2000) developed the digital signal processor board using autoregressive (AR) method and band energy based method for monitoring the breakage and chipping conditions of the face milling tool. They concluded that the developed processor is highly reliable in monitoring the machining process and AR based model is more accurate in fault diagnosis than the band energy based model. Jantunen (2002) presented signal analysis, diagnostic techniques and summary of monitoring methods for tool wear in the drilling process. Cus et al. (2006) developed an intelligent system for on-line monitoring and optimization of cutting conditions based on genetic algorithms (GA) in CNC ball end-milling process. This approach can be used for complex machined parts, which require many machining constraints. They revealed that for the optimization of machining conditions, the proposed genetic algorithm based technique is effective and efficient, and can be implemented for real time intelligent manufacturing system. It lead to reduction in production cost, improvement of product quality and flexibility of machining parameters selection. One drawback of this method was it takes a long time to optimize cutting parameters because of its slow convergence speed. Ritou et al. (2006) presented a study of three-process based TCM indicators which are verified whether they are unaffected by changes in cutting conditions in order to evaluate their relevancy for condition monitoring of small batch manufacturing of industrial parts. They carried out some experiments under various real industrial machining settings and reported that the criteria is unreliable because of misinterpretation of sudden changes in cutting conditions. Therefore they proposed a versatile in process monitoring system to tackle the problem of reliability and to predict the relative radial eccentricity of the cutter. Rubio et al. (2013) developed a system consisting of expert rule based modules for cutting parameter selection to the purpose of multi objectives such as tool life, material removal rate, surface roughness of the workpiece and stability in milling process. Rubio et al. (2013) carried out the analysis of milling force control using fractional order holds method. Researchers have often used the diagnostic tools such as fuzzy logic (Dominik et al. 2013) neural networks (Chiu 2014; Tahmasebi et al. 2013) adaptive neuro fuzzy inference system (Watany 2015) etc. However Sokolowski (2004) noticed a poor classification of tool wear by fuzzy logic. Lauro et al. (2014) provided a review of different monitoring methods and signal processing techniques in machining processes. Teti et al. (2010) reported that the types of sensors used, signal processing methods, decision making techniques and some of the industrial problems raised in the field of machining processes. The main challenge during machining process is to recognise the tool wear/catastrophic failure of the cutting tool without intervention of a human/operator.

Rendering to the above literature review, though many research works have been carried out in the area of condition monitoring/fault diagnosis. Different approaches are identified as being key to the industrial application of operational tool monitoring systems and there are still many unresolved problems in this field of study. Considering these shortages and at the same time by increasing the demand for having reliable, robust, accurate, practical and inexpensive monitoring methods from the industry, the need for doing more research in this field is obvious. This research is going to choose a process monitoring algorithm which comprises of feature extraction method and classifier. Such an objective is to be achieved by investigating and analysing the performance of different combination of monitoring algorithms with using signal processing method and artificial intelligence technique, based on the pattern recognition. The effect of signals acquired from the sensors, the ability of the signal processing methods for working under normal process conditions and for detecting the faulty tool condition during operation will be investigated throughout the rest of the thesis.

2.8 RESEARCH GAP

TCM is essential as to maiantain the surface quality and dimensional accuracy of the workpiece which affect by inevitable tool wear development in addition to that collisions or tool breakage. Abellan and Subiron (2010) reported that the types of sensors used, signal processing methods, decision making techniques and some of the industrial problems raised in the field of machining processes. Many machining monitoring systems based on artificial intelligent process models have been developed in the past for optimising, predicting or controlling machining processes. Many research works present different methodologies without showing clear guidelines or key issues for the development of intelligent machining systems. In order to overcome the lack of a global view on how to develop machining monitoring systems based on artificial intelligent models, this study illustrates a generic methodology which reveals the main parts of a face milling monitoring system through machine learning approach. The principal approach is the vibration analysis which enables to recognize healthy and faulty cutting tool. Conventional vibration analysis has been done in time domain or frequency domain, which can only be able to provide information about the past damage of the cutting tool. This concept can be further extended with a machine learning approach and advanced signal processing techniques for on-line tool condition monitoring studies to identify different tool conditions. Better performance of TCM system depends on the classifier used for diagnosis. Still many investigations are possible in finding the best classifier. Many research works are possible in building on-line fault diagnosis system using combined vibration signal and sound signal with data mining approach. Among the signal processing methods, cepstrum technique has received poor attention in the field of tool condition monitoring. In this thesis fault detection of milling tool by cepstrum method will be examined by analysing the quefrency components in cepstrum plots of acquired signals and the accuracy of the method for recognising the tool states will be analysed. The performance of this method will be compared with the performance of other conventional signal processing methods. Continuous wavelet transform (CWT) is one of the advanced signal processing techniques in fault diagnosis. This study tries to attempt in fault detection of the face milling tool using time-frequency information of the signals.

2.9 OBJECTIVES OF THE RESEARCH WORK

The aim of the study is to develop model-based tool condition monitoring methods for face milling. The methods will combine the feature extraction technique and model-based classifiers to monitor the tool wear in face milling process. The specific objectives are:

1) Fault diagnosis of the face milling tool based on vibration and sound signals using signal processing techniques such as spectrum analysis, cepstrum analysis, empirical mode decomposition (EMD) method and continuous wavelet transform (CWT) method.
2) Fault diagnosis of the face milling tool using vibration and sound signals under healthy and different faulty conditions of the milling tool based on the machine learning approach.
3) To investigate the performances of the different artificial intelligence techniques and to select the best one among them for fault diagnosis of the face milling tool.

2.10 SCOPE OF THE RESEARCH WORK

Manufacturing industries are aiming to produce products in larger volumes with improved quality at a competitive price. Also, the competitiveness within the manufacturing industry compels most companies to search for the most practical solution. These demands are being met with the assistance of automated production centers that include condition monitoring systems. The trend is progressing towards fully-automated manufacturing systems that require little, if any human intervention. Further development of existing monitoring and diagnostic systems will continue as a result of these competitive pressures. The scope of the current research work is drawn as follows;

- This research work concerns with fault diagnosis of the face milling tool using online and offline condition monitoring techniques in conjunction with advanced signal processing techniques.

- To explore the possibilities of using vibration signal analysis and sound signal analysis to improve the fault detection of the face milling tool. The fault information is extracted from the acquired signals in the form of statistical features, histogram features, DWT features and EMD features.
- The signals associated to the face milling process are non-stationary in nature due to its intermittent cutting action. This study utilized wavelet transform and decomposition techniques to analyse the non-stationary signals.
- The main purpose of the study is to select the best tool condition monitoring (TCM) technique that streamlines the machining process by reducing the number of process interruptions created by tool wear. This technique utilizes indirect measurement of signals in a face milling machine.
- By utilizing the developed in-process tool condition monitoring technique, manufacturers can expect a dramatic reduction of machine downtime related with tool changes in milling operations.

2.11 SUMMARY

This chapter reported enlarged review of existing tool condition monitoring techniques. Literature was basically categorized based on direct and indirect measurements for tool condition monitoring, recorded signals, signal processing techniques and machine learning technique. Along with the above, an overview of applications of each method is also discussed citing various researchers who have successfully implemented these techniques for their applications of interest. Also the objectives and scope of the present research work were discussed in this chapter. The methodology involved in this research work and experimental approach are described in Chapter 3.

CHAPTER-3

METHODOLOGY OF THE RESEARCH WORK

This chapter discusses about the methodology for achieving the objectives of the proposed research work. For performing the face milling operation, universal milling machine has been selected. While milling operation under healthy tool and tool with different fault conditions, vibration and sound signals will be acquired. The methodology consists of two stages, namely; (a) On-line monitoring and (b) Off-line monitoring. On-line monitoring is based on machine learning approach and off-line monitoring through signal processing techniques.

3.1 ON-LINE MONITORING

Schematic representation of an online monitoring of the face milling tool is shown in Figure 3.1. The collected signals such as acceleration signals and sound signals will be processed and analysed to diagnose the condition of the face milling tool through machine learning technique.

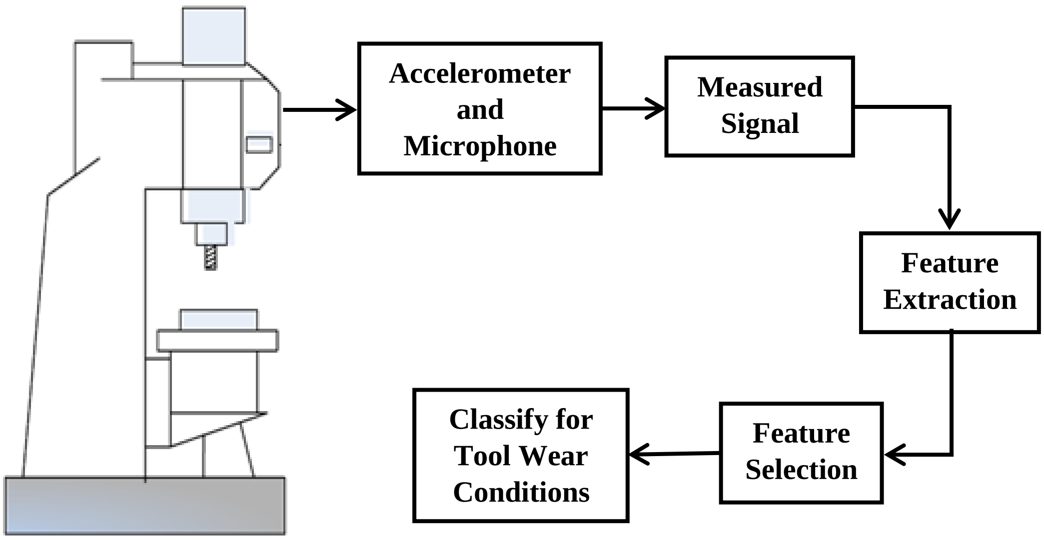


Figure 3.1 Schematic representation of on-line monitoring of the face milling tool

Machine learning technique is a scientific method to examine diagnostically the construction and the study of algorithms that can learn from the data. These algorithms build a model based on inputs and use them to make decisions or predictions, rather than following only explicitly programmed instructions. Machine learning method is used to recognise the signal pattern or the corresponding fault using classification process. Automatic fault diagnosis system can be achieved by the machine learning process. The fault identification using machine learning techniques has three phases. They are feature extraction, feature selection and feature classification.

3.1.1 Feature extraction

The acquired signals are assessed in terms of signal parameters called features which convey useful information about the acquired signal. For example, statistical features, wavelet features, histogram features, etc. can be extracted from the acquired signals. Feature extraction is a process of extracting a set of new features from the acquired signal through some functional mapping (Wyse et al. 1980). In the present study, statistical features, histogram features, DWT features and EMD features extraction methods have been considered for analysis and the details about the methods used for feature extraction are explained in the forthcoming sections.

3.1.1.1 Statistical features

The parameters computed directly from the acquired time domain signals are called time domain features. Statistical features are one set of time domain features and significant ones in fault diagnosis of machine components/cutting tools. Here statistical features will be extracted for fault classification of face milling tool. Statistical features such as skewness, mode, standard error, maximum, minimum, range, sum, mean, standard deviation, median, sample variance and kurtosis are computed to serve as features. Brief descriptions about statistical parameters are displayed as follows.

Standard Error: Standard error is for an individual x in the regression, a measure of the amount of error in the estimation of y, 'n' is the sample size, x and y are the sample means. It can be expressed as,

$$Y = \sqrt{\frac{1}{(n-2)}\left[\sum(y-\bar{y})^2 - \frac{[\sum(x-\bar{x})(y-\bar{y})]^2}{(x-\bar{x})^2}\right]} \tag{3.1}$$

Standard Deviation: This is a measure of power content or effective energy of the signal. The standard deviation (σ) can be expressed as,

$$\sigma = \sqrt{\frac{\sum x^2 - (\sum x)^2}{n(n-1)}} \tag{3.2}$$

Sample Variance: It is variance of the signal points and the following formula is used to compute sample variance.

$$Sample\ Variance = \sigma^2 = \frac{\sum x^2 - (\sum x)^2}{n(n-1)} \tag{3.3}$$

Kurtosis: Kurtosis represents the spikiness or the flatness of the signal. Its value varies with the condition of the tool in such a way that kurtosis value is very low for the unused cutting tool and higher for the fault tool due to the spiky nature of the signal.

$$Kurtosis = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{3.4}$$

where ‘s’ is the sample standard deviation.

Skewness: Skewness characterizes the degree of asymmetry of a distribution around its mean. The following expression can be used to compute skewness.

$$Skewness = \frac{n}{(n-1)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^3 \tag{3.5}$$

Minimum Value: For a given signal, minimum value refers to the minimum signal point value. As the tool gets worn out, the vibration level increases. Therefore, it can be used to predict tool wear condition.

Maximum Value: It refers to the maximum signal point value in a given signal.

Range: It refers to the difference between maximum and minimum signal point values for a given signal.

Sum: It is the totality of all feature values for each sample.

3.1.1.2 Histogram features

Histogram features are another set of time domain features. Histogram is a bar chart, which plots the number of data points that fall within a bin value. The bin range is obtained from the acquired signals pertaining to all conditions of the system/cutting tool being analysed. The amplitude range (maximum value to minimum value of the signals) is divided into a number of sub ranges that are called bins which represent the x-axis of the histogram plot. The number of data points of the signals lie on the corresponding bins are counted and represent the y-axis of the histogram plot. The objective here is to investigate the bins whose data points are the same for a particular class but different from other classes. These values may be very small for a particular class of the cutting tool but may be very large for another class of the cutting tool.

The width of the bin should be fixed such that the height of the bins is varied for different class of the milling tool. It need not be true for all width of bins, but at least a few of them should follow this criteria so that it can be used as a feature for classifying the various conditions (classes). Bin width is a set of limiting values that should be in the ascending order so that the program counts the number of data points between the current bin number and the adjoining higher bin, if any. The bin width need not be constant always; however, in this study a constant bin width is used. Figure 3.2 illustrate the details of bin width and number of bins which can extract the information from the acquired signals. The detailed explanation about the fault diagnosis using bins (histogram features) can be seen in Chapter 6.

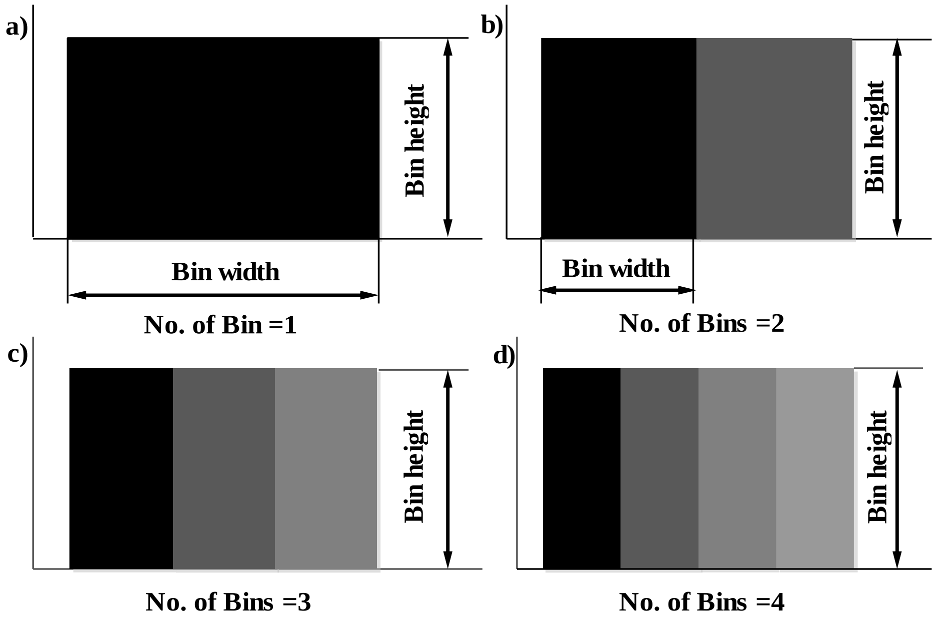


Figure 3.2 Sample histogram of a rectangular distribution

3.1.1.3 Empirical mode decomposition (EMD) features

The acquired signal may contain the different modes of oscillations at a time (nonlinear and/or non-stationary in nature). In order to analyse these coexisting modes, there is a need of an effective approach which pre-processes the given signal. EMD is an adaptive technique which decomposes the arbitrary time series and expresses as a number of intrinsic mode functions (IMF). IMFs represent the each oscillation mode of the signal. Each IMF must satisfy the criteria to define;

- In the whole data set, the number of extremes and the number of zero-crossings must either equal or differ at most by one.
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Let *x(t)* is the acquired signal decomposed into *n* empirical modes and a residue r_n, it can be expressed as,

$$x\,(t) = \sum_{i=1}^{n} c_i(t) + r_n \tag{3.6}$$

Where $c_i(t) = c_1(t), c_2(t), \ldots., c_n(t)$ are IMFs which include different frequency bands ranging from high to low. Each band contains a number of frequency components and they change with the variation of a signal $x(t)$. r_n represent the central tendency of the signal $x(t)$ (Peng, 2006).

EMD decomposes the given signal into a number of IMFs, each resulting IMF represents the local characteristic of that signal. While the system operates with variations in the signal, the amplitude energy of each IMF is different. These variations in the amplitude energy of the IMF can be considered as a feature vector for condition monitoring of the respected system. Based on the principle of EMD, the original signal is a configuration of n number of IMFs and a residue r_n. The total energy E_i' of the pre-n IMFs is computed as;

$$E_i' = \sum_{k=1}^{N} |c_i(t_k)|^2 \tag{3.7}$$

Where E_i' is the amplitude energy of the i^{th} IMFs, $k = 1$ to N represents the discrete data length of the i^{th} IMFs. A feature vector T with the amplitude energy is expressed as;

$$T = [E_1', E_2', \ldots \ldots ., E_n'] \tag{3.8}$$

Where n is the number of IMFs.

Considering that some IMF energy may be very large or low, in order to avoid attributes in greater numeric ranges which dominates in smaller numeric ranges and to reduce numerical difficulties during the calculation, T is regulated by normalizing the feature. For the convenience, the following analysis and processing are considered as,

$$E = \left(\sum_{i=1}^{n} |E_i'|^2 \right)^{\frac{1}{2}} \tag{3.9}$$

Then 'T' becomes,

$$T' = \left[\frac{E_1'}{E}, \frac{E_2'}{E}, \ldots \ldots \ldots, \frac{E_n'}{E} \right] = [E_1, E_2, \ldots \ldots \ldots, E_n] \tag{3.10}$$

Where T' is the normalised vector (Chen et al. 2013). This normalised vector is treated as an input vector to the classifier for the fault diagnosis of the face milling tool.

3.1.1.4 Discrete wavelet transform (DWT) features

The acquired signal can be represented in another form of a signal using basic function, this is called transformation of a signal. It does not change the information which exists in the signal. The wavelet transform is a mathematical tool that transforms a signal into a different form (in the time-scale domain, a series of wavelet coefficients, etc.) using a wavelet function. A wavelet function is a short wave with finite energy characteristics (Yan et al., 2014). Wavelet transform represents the signal in time-frequency domain. Applications of wavelet transform can be seen in various fields such as mathematics, science and engineering as watermarking, image registration, signal denoising, compression, feature extraction, time-frequency analysis, etc. (Zhu et al.,2009). DWT is one of the wavelet transforms and it was evolved by Mallat (1989) with fast algorithm based on the conjugate quadratic filters. The DWT in the mathematical form of a signal *x(t)* is expressed as (Yan et al., 2014);

$$dwt\ (j.k) = \frac{1}{\sqrt{2^j}} \int x(t)\psi^* \left(\frac{t - k2^j}{2^j}\right) dt \tag{3.11}$$

Using the low-pass and high-pass filters, the signal is decomposed into two components. One is low frequency component and another one is high frequency component as,

$$\left.\begin{aligned} a_{j,k} &= \sum_m h(2k-m)a_{j-1,m} \\ d_{j,k} &= \sum_m \mathrm{g}(2k-m)a_{j-1,m} \end{aligned}\right\} \tag{3.12}$$

Where $a_{j,k}$ is ‘approximation’ coefficient and $d_{j,k}$ is ‘detail’ coefficient. Approximation and detail coefficients represent low frequency components and high frequency components of the signal respectively. Approximation and detail coefficients are produced at multiple scales by iterating the process on the approximation coefficients of each scale. The entire process is represented as tree-structure as shown in Figure 3.3.

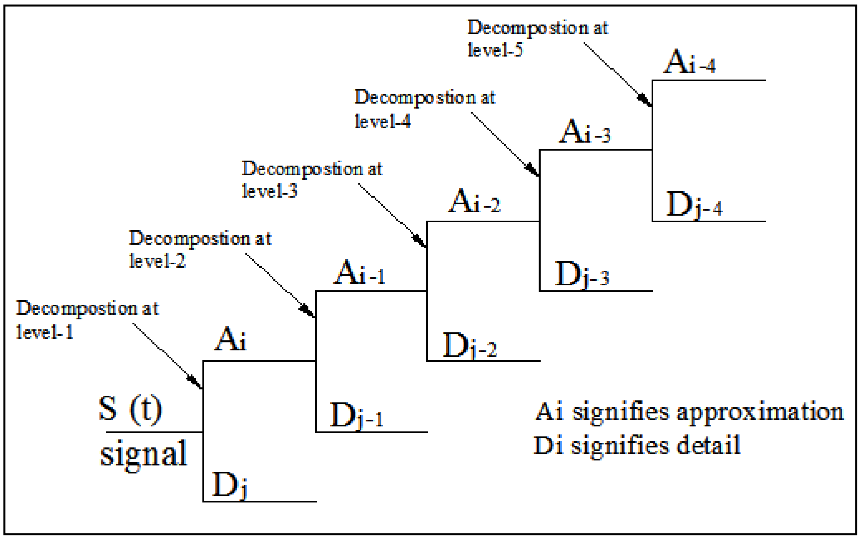


Figure 3.3 Wavelet decomposition tree

These coefficients represent a set of features. Based on the scale and position of the wavelet, the wavelet coefficients represent the characteristics of a signal. The set of such features obtained using DWT termed as feature vector and it is given by (Vernekar et al., 2014).

$$v_i^{dwt} = \{v_1^{dwt}, v_2^{dwt}, \ldots v_{12}^{dwt}\}^T \qquad (3.13)$$

Where v_i^{dwt} component is related to the individual resolutions and can be computed as follows,

$$v_i^{dwt} = \frac{1}{ni}\sum_{j=1}^{ni} W_{i,j}^2 \ ; \ i = 1,2, \ldots .12 \qquad (3.14)$$

Where $n_1=2^{12}$, $n_2=2^{11}$,….. $n_{12}=2^0$,

v_i^{dwt} is the i^{th} feature element in a DWT feature vector, n_i is the number of samples in an individual sub-band. $W_{i,j}^2$ is the j^{th} coefficient of the i^{th} sub-band. v_i gives the mean square value of the decomposed signal at different levels.

3.1.2 Feature selection

The process of feature selection is a difficult task as compared to feature extraction; in this section no new features are generated. It is a process of choosing a subset of '*M*' features from the existing set of '*N*' features ($M<N$), so that feature space is optimally decreased based on certain criterion (Blum and Langley, 1997). The features can be any measure of data points or the signal, but the relevance of them will depend on how well they help in the process of classification. The process of selecting the good features from a pool of features is called 'feature selection'. The good feature will have feature values with minimum variation within a class and maximum variation between the classes. In machine learning system the roles of the feature selection are as follows;

- to decrease the feature space dimensionality,
- to accelerate a learning algorithm,
- to enhance the predictive accuracy of a classification algorithm and
- to improve the understandability of the learning results.

Many techniques are used for feature selection; among them decision tree method is widely used and the best one for feature selection in the area of fault diagnosis (Sugumaran and Ramachandran, 2007; Elangovan et al. 2011).

3.1.2.1 Feature selection using decision tree (J48 algorithm or C4.5 algorithm)

The decision tree technique is used to classify data into discrete ones using tree structured algorithms (Breiman et al., 1984). J48 technique has found immense applications such as medical, engineering, market research statistics, etc. The main purpose of the decision tree is to illustrate the structural information contained in the data. A standard tree represented with J48 algorithm consists of a root node, a number of leaves, nodes and a number of branches. Each branch of a tree represents a chain of nodes from the root to a leaf and each node represents an attribute (or feature). The presence of a feature in a tree gives the information about the prominence of the associated feature. The procedure for making the decision tree and using the same for feature selection is explained below.

- The set of features is treated as an input to the algorithm and the corresponding output is a decision tree.
- It consists of leaf nodes, which indicate class labels and the rest of the nodes related to the classes are being classified.
- The branches of the tree exhibit each predictive value of the generated feature node.
- Feature vectors are classified using decision tree, starting from the root of the tree to the node of the leaf.
- In each decision node in the tree, the most useful feature based on the estimation criteria can be chosen. The useful feature identified based on the criteria which invoke the concepts of information gain and entropy reduction are explained below.

Information Gain and entropy reduction

Information Gain is defined as an expected reduction in entropy by partitioning the samples based on the feature. Entropy is defined as a measure of disorder present in the set of instances. By adding information, it reduces uncertainty. Information Gain compares the entropies of the original system and the system after information added. The Information Gain (S, A) of a feature 'A' to a set of examples 'S' can be expressed as,

$$Gain\ (S, A) = Entropy\ (S) - \sum_{v \in Value\ (A)} \frac{|S_v|}{|S|} Entropy\ (S_v) \qquad (3.15)$$

Where, '*Values (A)*' is the set of all possible values for attribute 'A', 'S_v' is the subset of 'S' of which feature 'A' has a value 'v' (i.e., $S_v = \{s \in S \mid A(s)=v\}$).

Note the first term in the equation (3.15) is the entropy of the original collection 'S' and the second term is the expected value of the entropy after 'S' is partitioned using feature 'A'. The expected entropy described by the second term is the direct sum of the entropies of each subset 'S_v' weighted by the fraction of samples $|S_v|/|S|$ that belong to 'S_v'. *Gain (S, A)* is therefore the expected reduction in entropy caused by knowing the value of a feature 'A'. Entropy is given by,

$$Entropy\ (S) = \sum_{i-1}^{c} -P_i log_2 P_i \quad (3.16)$$

Where, 'c' is the number of classes. 'P_i' is the proportion of 'S' belonging to the class 'i' (Gangadhar et al., 2014).

3.1.3 Feature classification

In machine learning, classification is considered an instance of supervised learning, it means learning where a training set of correctly identified observations is available. In classification, a feature extraction provides a feature vector to assign the data points to a category (Soman et al. 2006). This research work made used of some of the classifiers such as, support vector machine (SVM), artificial neural network (ANN), K-star algorithm, Bayes algorithm and decision tree algorithm to distinguish the face milling tool condition using selected features from the signals. The details about each classifier is explained in the forthcoming sections.

3.1.3.1 Support vector machine (SVM)

Support vector machine is one of the supervised learning methods used for classification. SVM is based on concept of decision planes that defines decision boundaries and it works based on statistical learning method. It classifies the data points by creating a hyper plane or classification plane between the classes. Figure 3.4 shows the classification of two different classes which represent triangles for positive class and circles for negative class. SVM tries to classify these data points (positive and negative classes) by creating an optimal separable hyper-plane. The distance between the two dotted lines (bounding planes) is called margin. The main objective of SVM is to maximize the margin and minimize the generalization error. The data points which are nearer to the bounding planes are called support vectors. These support vectors help to define the margin and contain all the information about classification (Widodo and Yang 2007).

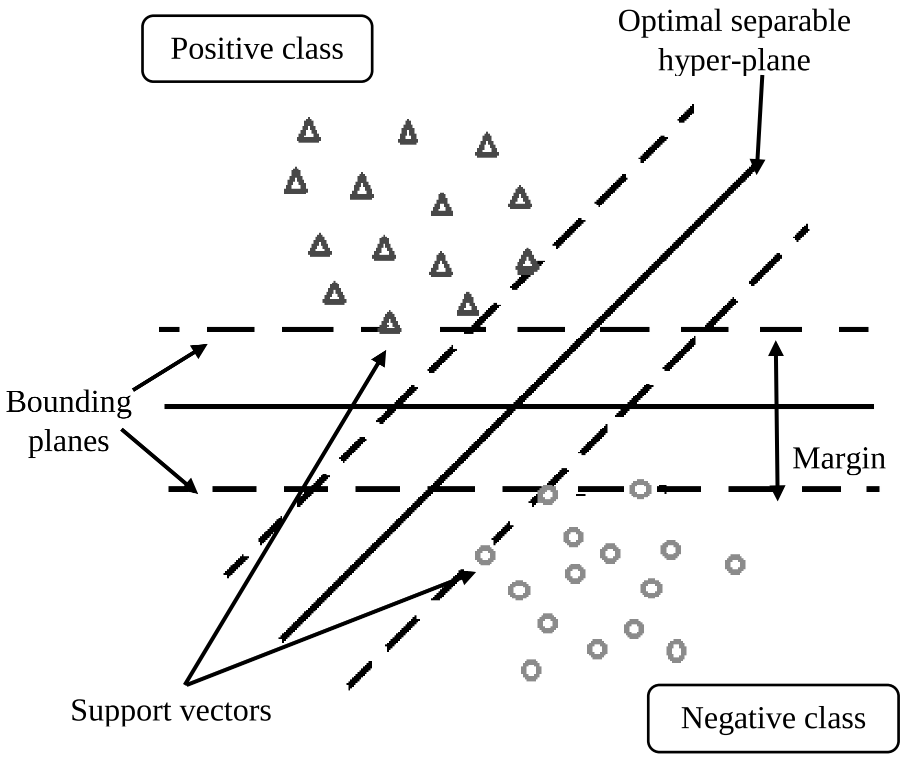


Figure 3.4 Classification of two classes using SVM

Consider a training data set $\{(x_i, y_i)\}$; $i=1$ to L, $x_i \in R^n$, $y_i \in (1,-1)$ where L indicates total number of data points. x_i is the input vector and y_i is the indicator vector. It is required to determine the hyper plane which separates the data points linearly into two classes (triangles and circles). $y_i \in (1,-1)$ is concerned with the two types of classes namely triangles and circles. For the hyper plane $f(x) = 0$ which separates the given data is obtained as a solution to the following optimization problem.

$$Minimize \quad \frac{1}{2}\,||w||^2 + C\sum_{i=1}^{L}\xi_i \tag{3.17}$$

$$Subject\ to \quad \begin{cases} y_i\,(w^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0\,; \qquad i = 1\ to\ L \end{cases} \tag{3.18}$$

Where, 'ξ' is a slack variable which measures the distance between the margin and the examples x_i, 'b' is the bias, $C > 0$ is the constant representing penalty parameter and 'w' is weight vector.

After training, for any new set of features prediction of its class is possible using the decision function. The decision function is a function of 'w' and 'γ', which is given below.

$$f(x) = sign\ (w^T x - \gamma) \tag{3.19}$$

If the value of *f(x)* is positive, then a new set of features belongs to class triangles; otherwise it belongs to class circles (Saimurugan et al. 2011). C-SVC and ν-SVC models (Vernekar et al. 2015) of SVM are used for fault diagnosis of the face milling tool.

3.1.3.2 Bayes algorithm

Bayesian decision making refers to choosing the most likely class given the value of a feature or features. Consider the classification problem with two classes *C1* and *C2* based on a single feature *x*. from the training sets of the two classes, histograms can be prepared and the respective priori probabilities determined. Information extracted from there can be used to carry out classification based on the feature *x*. Figure 3.5 shows a hypothetical case. Class *C1* can be assigned for values of *x* small enough and the alternate class *C2* assigned for sufficiently large values of *x*. This leads to the probability of deciding a classification boundary and a rationale for it. Consider a sample with feature value $x = x_b$ such that,

$$P_{c1}(x_b)dx = P_{c2}(x_b)dx \tag{3.20}$$

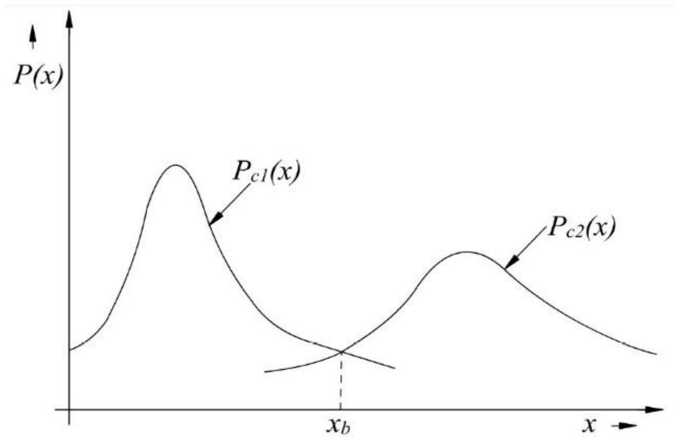


Figure 3.5 Histogram of a hypothetical two-class problem

A sample with feature value $x < x_b$ has $P_{c1}(x_b)\ dx > P_{c2}(x_b)\ dx$. It can be classified as belonging to class *C1*. On the other hand, a sample with feature value $x > x_b$ has $P_{c1}(x_b)\ dx < P_{c2}(x_b)\ dx$. It can be classified as belonging to class *C2*. Thus $x = x_b$ constitutes the classification boundary (Muralidharan, 2012). The procedure has been directly extended to multiple classes and features of Bayes classifier by Hemantha et al. (2014).

3.1.3.3 Artificial neural network (ANN)

An artificial neural network is a paradigm which is built from a number of processing elements called neurons and these neurons are interconnected to each other. The connection between the neurons possesses the associated weight which is being multiplied to the incoming data/signal. ANN uses mathematical formulations to form a model and a neural network is used to learn patterns and relationships in data. Data may be the results of a market research effort or a different operating conditions of a manufacturing process or a set of loan applications given by the loan officer. Regardless of the specifics involved, applying a neural network is substantially different from traditional approaches.

An ANN is denoted by three elements, one is architecture which depicts the connection between neurons. Second is training or learning which determines the weights on the connections and the third one is activation function which is used to compute the output response of a neuron. A typical ANN consists of an input layer, hidden layer and output layer of neurons as shown in Figure 3.6. The Activity of neurons in the input layer represents the raw signal/data, this signal is processed at neurons of hidden layer with the help of weights associated with the connections between input and hidden layers. Similarly the output response of the neurons of the output layer depends on the activity of hidden layer neurons and weights of connection between hidden and output layers (Sivanandam and Deepa, 2006).

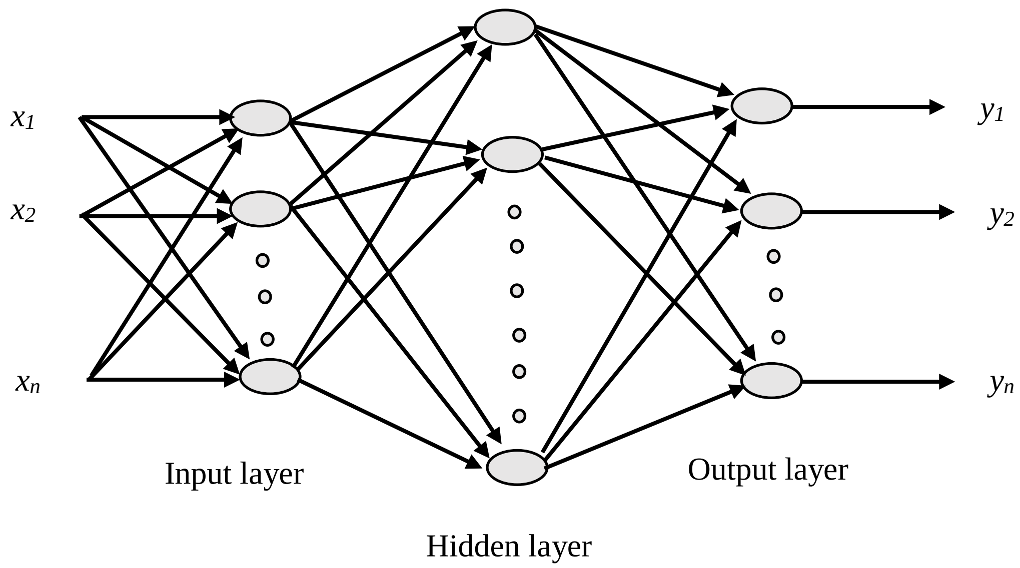


Figure 3.6 Architecture of ANN

In this study, multilayer perceptron (MLP) neural network is used to distinguish the face milling tool conditions, because the single layer perceptron network is only used for linearly separable classification of patterns. The milling tool in fault condition possesses a non-linear/non stationary signals. Hence, the single layer perceptron network is not applicable for this study. MLP is an eminent class of neural networks and it is a unidirectional network with supervised learning and having back propagation algorithm which can be used to update the weights. This comprises of an input layer, one or more hidden layer and an output layer. In MLP networks, there exists a non-linear activation function called logistic sigmoid function which is widely used to perform highly complex tasks.

3.1.3.4 K-star algorithm

The K-star algorithm uses entropic measure based on probability of transforming instance into another by randomly choosing between all possible transformations. Using entropy as appraise of distance has numerous utility. A consistency of approach in real, symbolic, missing value attributes makes it important. An instance based algorithm made for symbolic attributes fail in features of real value thus lacking in incorporated theoretical base. Approaches successful in feature of real values are thus in an ad – hoc fashion are made to handle symbolic attributes. Handling of missing values by classifiers poses similar problems. Usually missing values treated as a separate value, thought as maximally different and substitute for average value. Entropy based classifier is a solution for these issues.

Entropy as a distance measure

Information theory helps in computing distance between instances. The complexity of a transformation of one instance into another is actually the distance between instances. This is achieved in two steps. First define a finite set of transformations they will map one instances to another. Then transform one instance 'a' to another 'b' with the help of 'program' in a finite sequence of transformations starting at 'a' and terminating at 'b'.

*Specification of K**

Given a set of infinite points and set of transformations predefined *T*. Let *t* be a value of set *T*. This t will map t: $I \rightarrow I$. To map instances with itself σ is used in T (σ (a) = a). σ terminates all prefix codes from *T**. Set *T** consists members which define transformation one to one (uniquely) on *I*.

$$t(a) = t_n\big(t_{n-1}(\dots t_1(a) \dots)\big) \; where \; t = t_1, \dots, t_n \tag{3.21}$$

p is a probability function on *T**. Hence properties below are observed:

Step 1: Calculation of total probability of all paths from instance 'a' to an instance *b*. P* in accordance with definition as the probability of all paths from instance 'a' to instance *b*:

$$P * \left(\frac{b}{a}\right) = \sum\nolimits_{t \in p : t(a) = b} P(t) \tag{3.22}$$

The *K**function is:

$$K * \left(\frac{b}{a}\right) = -\log_2 P * \left(\frac{b}{a}\right) \tag{3.23}$$

Please note that K^* is not exactly a distance function. Point to be underscore K^* $(a|a)$ is usually non-zero also is not symmetric function (as emphasized by the notation).

Real numbers

For real number it is found that the probability is given by $P^*(x) = \frac{1}{2x_0} e^{-\frac{x}{x_0} dx.x_0}$ is a scale length. The mean expected value for *x* over the distribution P^*.

Step 2: Category prediction

Category prediction is done by adding probabilities from '*a*' to every instance which constitutes *C*. The probability of each individual instance is calculated and relative probabilities are used as an estimate. Selection of the set exhibiting the largest probability is taken as the classification of the new instance (Painuli et al. 2014).

$$P * (C|a) = \sum_{b \in C} P * (b|a) \tag{3.24}$$

3.2 OFF-LINE MONITORING

Figure 3.7 illustrates the offline monitoring of the face milling tool condition. Analysis of the milling tool will be carried out using vibration and sound signals from the set of experiments. Ultimately, interpret the results obtained from the experiments under different tool conditions will be carried out through signal processing techniques such as spectrum technique, cepstrum technique and continuous wavelet transform (CWT) technique. The brief description about the signal processing techniques are explained in the forthcoming subsections.

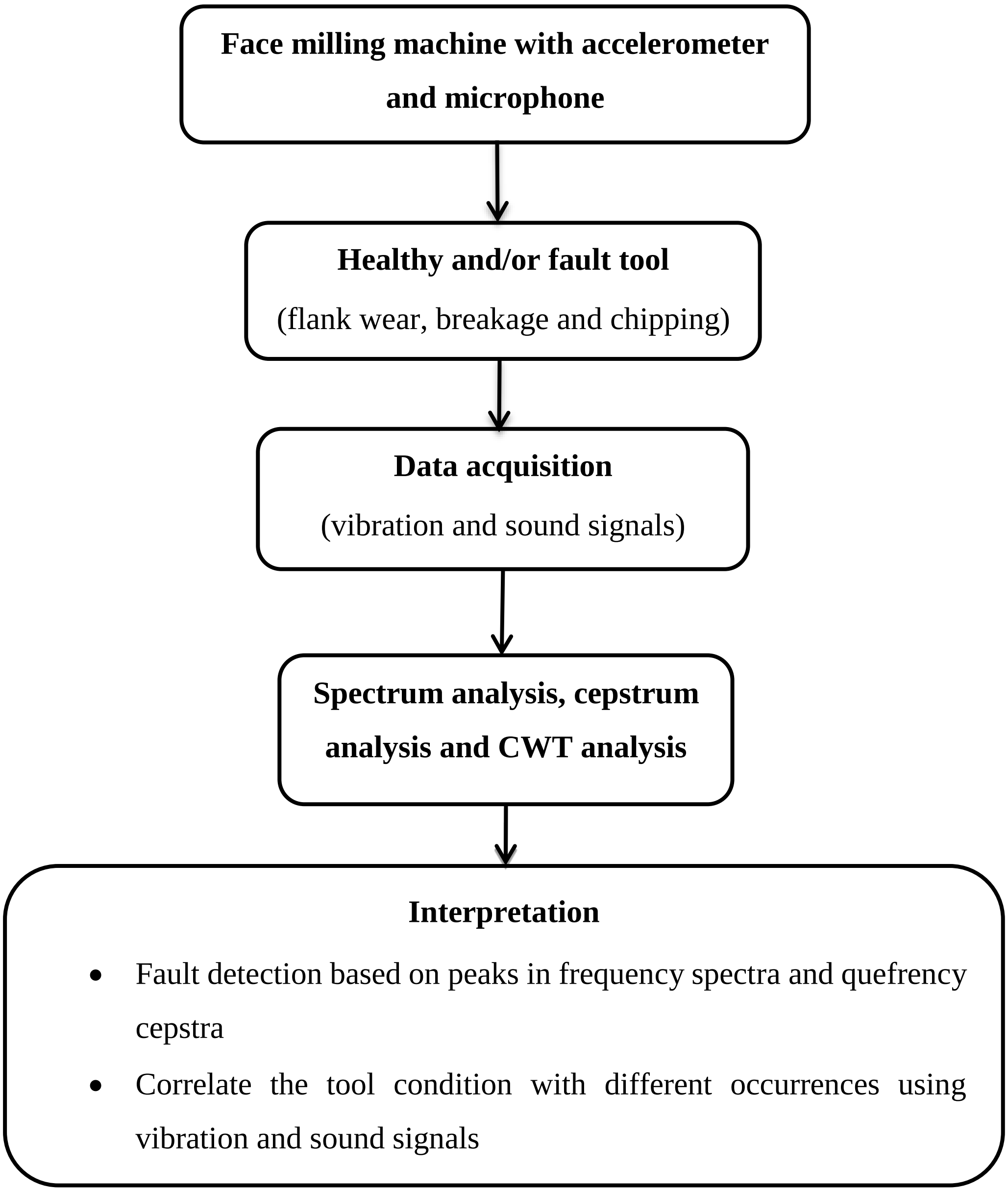


Figure 3.7 Methodology- off-line monitoring of the face milling tool

3.2.1 Time-domain and spectrum analyses

Time domain plot helps to examine the amplitude and phase information of the vibration signal to determine the failure/defect of any rotating machinery system or the process condition. Fault detection using time series response is a difficult task. Fourier transform (FT) is the most widely used technique in vibration signal analysis. It converts the given signal from time domain to frequency domain by integrating the given function over the entire time period. Fourier's approach is based on the assumption that any waveform can be represented as the superposition of a series of sine and cosine waves at different frequencies. A Fourier series is used for representation of continuous-time periodic signals. Fourier transform for the angular frequency $\omega=2\pi f$ and time 't' is given by,

$$X(\omega) = \int_{-\infty}^{+\infty} x(t)\, e^{-j\omega t}\, dt \tag{3.25}$$

Where $X(\omega)$ is the Fourier transform of the signal $x(t)$. FT technique earned much of its importance in processing stationary signal (Vernekar et al., 2015).

3.2.2 Cepstrum analysis

A cepstrum is considered as forward Fourier transformation of the logarithm of a spectrum. It is therefore defined as the spectrum of a spectrum. The cepstrum was originally referred as the power spectrum of the logarithmic power spectrum. Thus, the calculation of cepstrum involves the inverse Fourier transform of the natural logarithm of a spectrum (Randall, 1982). Given a real signal $x(n)$, cepstrum form can be expressed as follows.

The real cepstrum of a signal $x(n)$ (Hasegawa, 2000):

$$c(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} log\left|X\left(e^{j\omega}\right)\right| e^{j\omega n} d\omega \tag{3.26}$$

Where n is cepstral 'lag', if $x(n)$ is real, then $log\left|X\left(e^{j\omega}\right)\right|$ is even. Cepstrum reveals the periodicity in frequency domain usually as results of modulation. Figure 3.8 depicts the relationship between spectrum and cepstrum.

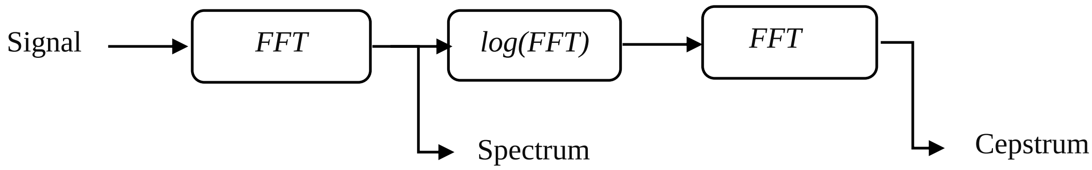


Figure 3.8 The relationship between a spectrum and a cepstrum

3.2.3 Wavelet analysis

The Fourier transform is not suitable for analysing non-stationary signals since it fails to reveal the frequency content of a signal at a particular time. In signal processing, the limitation of FT led to the introduction of new time-frequency analysis called wavelet transform (WT).

Generally, conventional data processing is computed in time or frequency domain. Wavelet processing method combines both time and frequency information. Wavelet analysis is one of the 'time-frequency' analysis. A wavelet is a basis function characterized by two aspects; first is its shape and amplitude, which is chosen by the user, second is its scale (frequency) and time (location) relative to the signal.

The continuous wavelet transform (CWT) can be used to generate spectrograms which show the frequency content of signals as a function of time. A continuous-time wavelet transform of *x(t)* is defined as,

$$CWT\ X_{\psi}(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right) dt,\ \{a, b \in R, a \neq 0\} \tag{3.27}$$

In the above equation (3.27), $\psi(t)$ is a continuous wavelet function in time domain as well as the frequency domain called the mother wavelet and $\psi^*(t)$ indicates complex conjugate of the analysing wavelet $\psi(t)$. The parameter 'a' is termed as scaling parameter and 'b' is the translation parameter. The transformed signal $X_{\psi}(a, b)$ is a function of the translation parameter 'b' and the scale parameter 'a'. In WT, signal energy is normalized by dividing the wavelet coefficients by $\frac{1}{\sqrt{|a|}}$ at each scale.

Morlet wavelet

The Morlet wavelet transform belongs to CWT family. It is one of the most popular wavelet used in practice and its mother wavelet is given by,

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}}\left(e^{jw_0 t} - e^{-\frac{w_0^2}{2}}\right)e^{-\frac{t^2}{2}} \tag{3.28}$$

In the above equation (3.28), w_o refers to central frequency of the mother wavelet. The term $e^{-\frac{w_0^2}{2}}$ involved in the equation is specifically used for correcting the non-zero mean of the complex sinusoid and in most cases, it can be negligible when w_o>5. Therefore, when the central frequency w_o >5, the mother wavelet can be redefined as follows (Vernekar et al., 2014);

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}} e^{jw_0 t} * e^{-\frac{t^2}{2}} \tag{3.29}$$

3.3 SUMMARY

This chapter has discussed about the conceptual overview methodology which comprises of on-line and offline monitoring techniques. The theory portions of the machine learning techniques and signal processing techniques are described. In the subsequent chapter, the experimental outfit required for fault diagnosis of the face milling tool are explained in detail.

CHAPTER-4

EXPERIMENTAL SETUP

4.1 INTRODUCTION

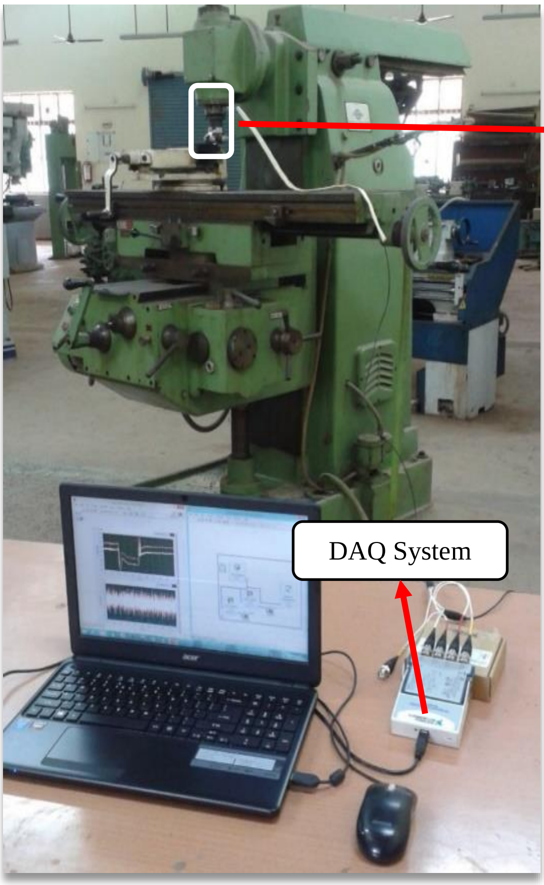
The importance of condition monitoring and methodology involved in fault diagnosis of the milling tool are discussed in the previous chapters. Different faults of the milling tool are considered to select the best signal processing technique and best feature-classifier combination for machine learning based fault prediction. This chapter presents the details of experimental setup and the procedure for conducting the experiments on fault diagnosis of the face milling tool.

4.2 CONDITION MONITORING OF FACE MILLING TOOL TEST RIG

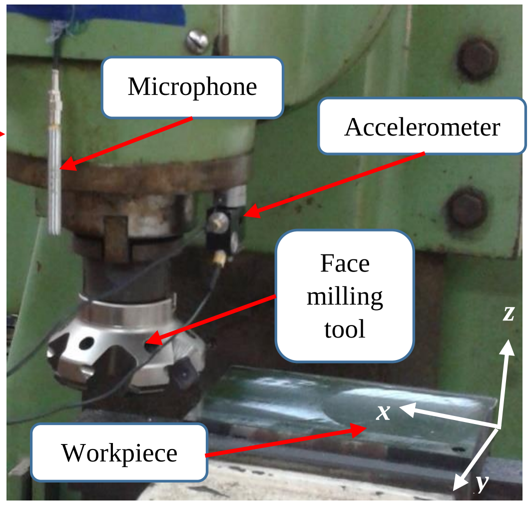
Figure 4.1 shows the experimental setup and instrumentation for vibration and sound signals acquisition during machining. A triaxial accelerometer which is used to acquire the vibration signals is fixed to the spindle housing and the microphone to acquire the sound signals is suspended near the face milling zone. These two sensors are connected to a data acquisition (DAQ) system for processing and analysing the data subsequently. Details of data acquisition system that is the process of sampling sensor signals and converts the resulting samples into digital numeric values that can be stored and retained by a computer is provided in Section 4.5. The accelerometer measures acceleration during machining in *x*, *y* and *z* directions. Only '*x*' direction i.e. feed direction of acceleration signal is considered for the analysis. The corresponding sound signals during milling under healthy tool and different faulty tool conditions are acquired.

The present research work is based on the analysis of vibration and sound signals acquired from the milling machine while performing a face milling operation on the workpiece. All the experiments were conducted under dry milling conditions. A

Universal Milling machine [3M (AU) G all feed automatic] was used with a 3.37 kW motor for the spindle and a 2.24 kW motor for the feed.



(a) Face milling machine with DAQ system



(b) Machine tool – work material structure

Figure 4.1 Experimental setup for condition monitoring of the face milling tool

4.2.1 Test specimen

The commercially available workpiece material of steel alloy 42CrMo4 was used for the current research work. This steel is used for large size parts such as gear, square shaft, sprocket, valve housing, etc. that can be seen in automobile and aerospace applications. They require a good surface finish and therefore one needs to know the state of milling insert at all times. The dimension of machining surface of the workpiece is 100x200 mm^2. The chemical composition of the work material is shown in Table 4.1.

Table 4.1 Chemical composition of the workpiece steel alloy 42CrMo4

C (%)	Si (%)	Mn (%)	P (%)	S (%)	Cr (%)	Mo (%)	Fe (%)
0.38 - 0.45	Max 0.4	0.6 – 0.9	Max 0.025	Max 0.035	0.9 – 1.2	0.15 – 0.3	96.6

The work material was machined on a face milling machine. The dimensions of the workpiece is 200 x 100 x 25 mm^3. The work material was horizontally positioned in the middle of the clamping fixture. This was accomplished by aligning a scribe mark on each end of the work material to the scribe mark of the clamping fixture. Along with vertical positioning of the work material, accurate horizontal positioning was necessary in order to prevent changes in the dynamic structure of the tool-work material.

4.2.2 Specification of milling cutter

The inserts were mounted on a commercially available face milling tool (6 Carbide inserts, Mitsubishi make). The experiments were conducted using six carbide inserts. The specification and dimensions of the face milling tool are given in Table 4.2, Table4.3 and Figure 4.2.

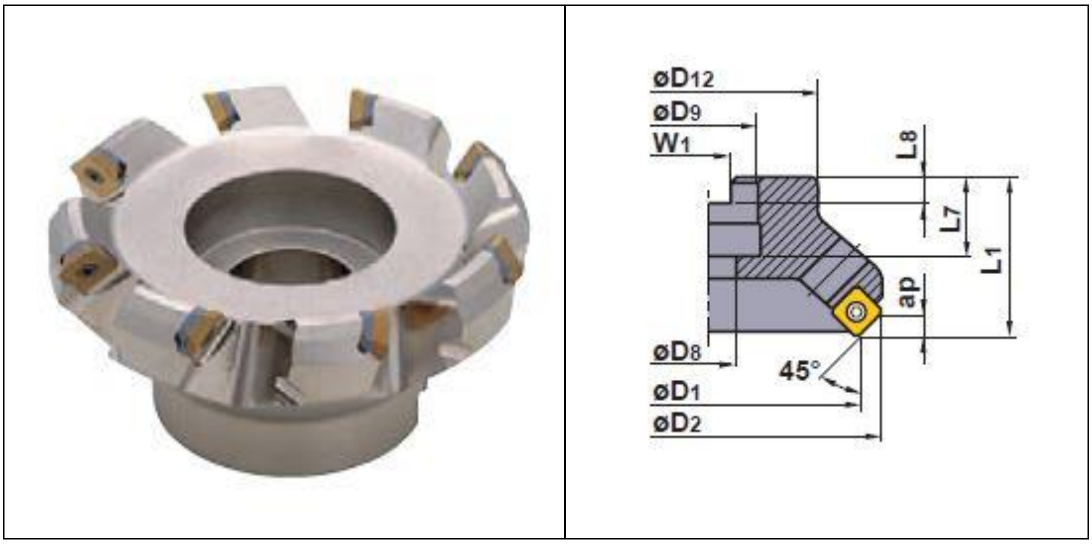


Figure 4.2 Geometry of the face milling tool

Table 4.2 Insert and cutter specification

Face milling tool	SEMT13T3AGSN
Mill Insert	VP15TF
Milling diameter	80 mm

Table 4.3 Dimension of the face milling tool (all dimensions are in ‘mm’)

D_1	D_2	L_1	D_9	L_7	D_8	D_{12}	W_1	L_8	ap
80	93.2	50	27	23	13	56	12.4	7	6

4.3 SENSORS USED

The sensors such as accelerometer and microphone are used in the present study. The details about each sensor and specifications are described in the following sections.

4.3.1 Accelerometer

For acquiring the vibration signals, a triaxial piezoelectric accelerometer (YMC145A100) with response frequency is greater than 15 kHz, measurement range ± 50 g and sensitivity 106.3 mV/g was mounted on bearing housing of the spindle. Figure 4.3 shows the triaxial accelerometer and the specifications of the accelerometer is as shown in Table 4.4.

Figure 4.3 Triaxial accelerometer for measuring the vibration

Table 4.4 Specification of the accelerometer

Make	Integrated electronic piezoelectric
Model	YMC145A100
Sensitivity X axis	97.90 mV/g
Sensitivity Y axis	95.65 mV/g
Sensitivity Z axis	104.6 mV/g
Measuring range	±50 g
Test environment temperature	22^0 C
Temperature range	-41 to 121^0 C
Size	25.4 x 25.4 x 14 mm^3

4.3.2 Microphone

Corresponding sound signals are acquired using microphone (G.R.A.S. 40PH) was fixed near face milling zone. Figure 4.4 shows the microphone and the specifications of the microphone is as shown in Table 4.5.

Figure 4.4 Microphone for measuring the sound signal

Table 4.5 Specification of the microphone

Microphone Type	40PH
Model	G.R.A.S
Test frequency	250 Hz
Measured level	50.13 mV/Pa
Uncertainty	± 0.06 dB

4.4 OPERATING CONDITIONS

During the milling operation, the work material was fed into the cutting tool, while the tool performed an interrupted, bilateral cut. The feed of the mill table was unidirectional. All experiments were carried out under dry conditions and no coolant was used. The selected machining parameters were recommended by the tool producer (M/s Mitsubishi) as to provide optimum cutting performance. The selected machining parameters were used to acquire the signals are as shown in Table 4.6.

Table 4.6 Milling process parameters

Parameter	**Value**
Feed	0.12 mm/tooth
Cutting speed	128 m/min
Depth of cut	0.5 mm
Lubrication	Dry

4.5 HARDWARE-SOFTWARE SETUP USED FOR DATA ACQUISITION

Hardware setup used in the experiments is chosen in a way to have an efficient data acquisition of vibration and sound signals sensed by accelerometer and microphone respectively placed near the machining zone. The following components are used in the hardware setup.

4.5.1 NI USB-9234 DAQ

The NI USB-9234 is shown in Figure 4.5, along with high speed USB carrier (NI USB 9162) is used for acquiring vibration and sound signals. Characteristics of NI USB-9234 are given in Table 4.7. The output of accelerometer and microphone is connected to NI USB-9234 via BNC (Bayonet Neill–Concelman) cables and from here it is connected to the computer. The acquired signals were analysed using LabVIEW software from National Instruments (NI).

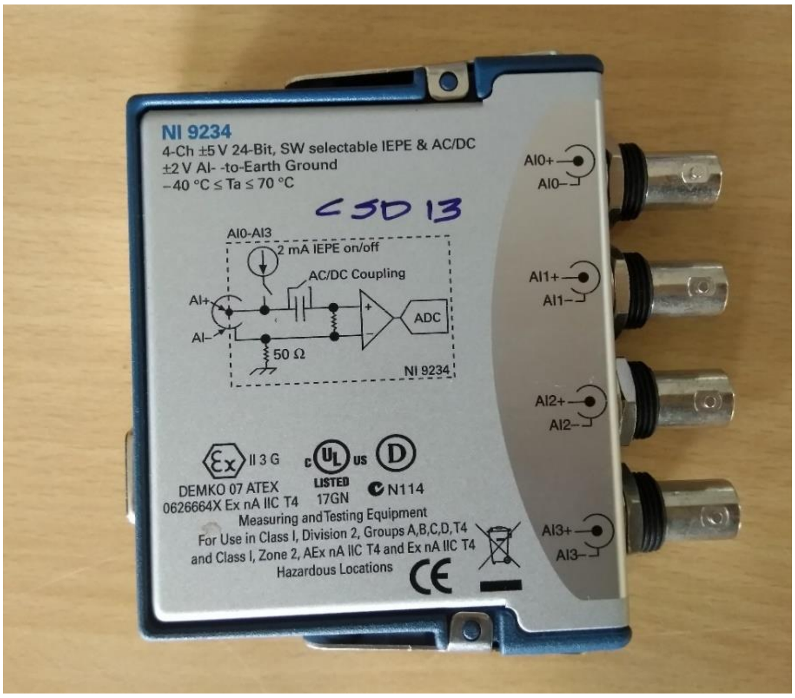


Figure 4.5 NI USB-9234 with NI USB carrier

Table 4.7 Specification of NI USB-9234

Parameter	**Specification**
Number of channels	4 analog input channels
ADC resolution	24 bits
Types of ADC	Delta-Sigma
Sampling mode	Simulations
Sampling frequency	51.2 kS/s/Ch
Input voltage	±5 V
Temperature Range	-40^{0} C to 70^{0} C

To prevent aliasing, the signals are sampled at sampling frequency of 25.6 kHz with 25600 data points per 1 sec time interval under controlled testing conditions.

4.6 SOFTWARE INTERFACE

A virtual instrument (VI) program was developed to acquire and analyse the vibration and sound signals for the present research work. Figure 4.6 and Figure 4.7 depict the block diagram for data acquisition and analysis.

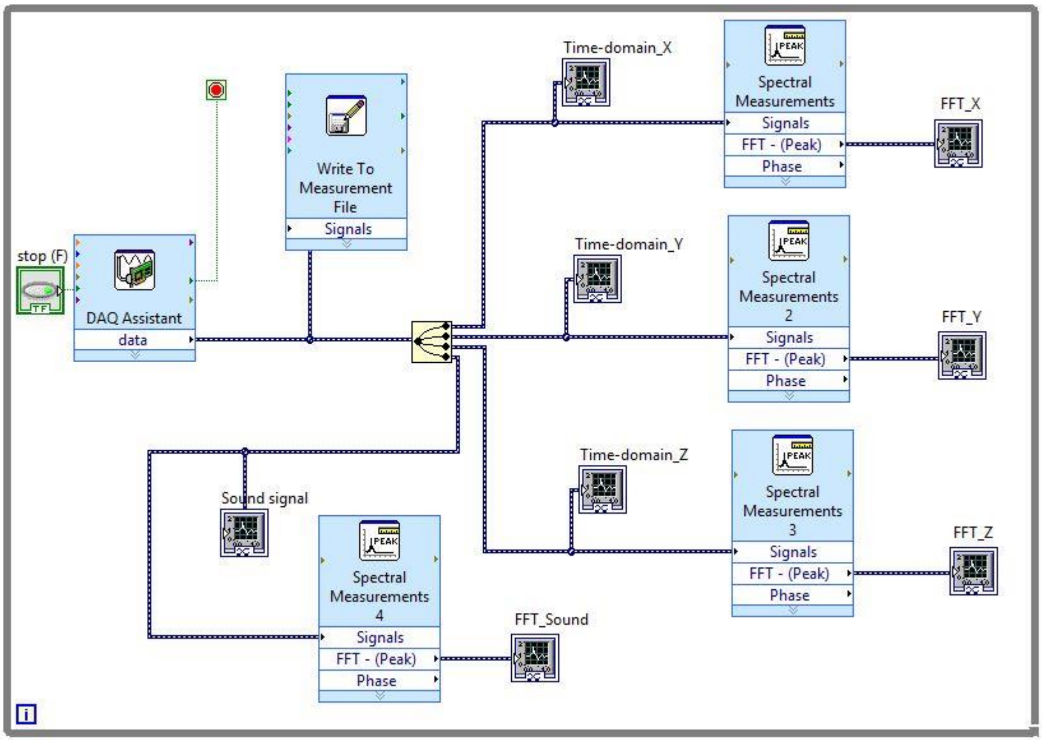


Figure 4.6 VI Block diagram for the data acquisition

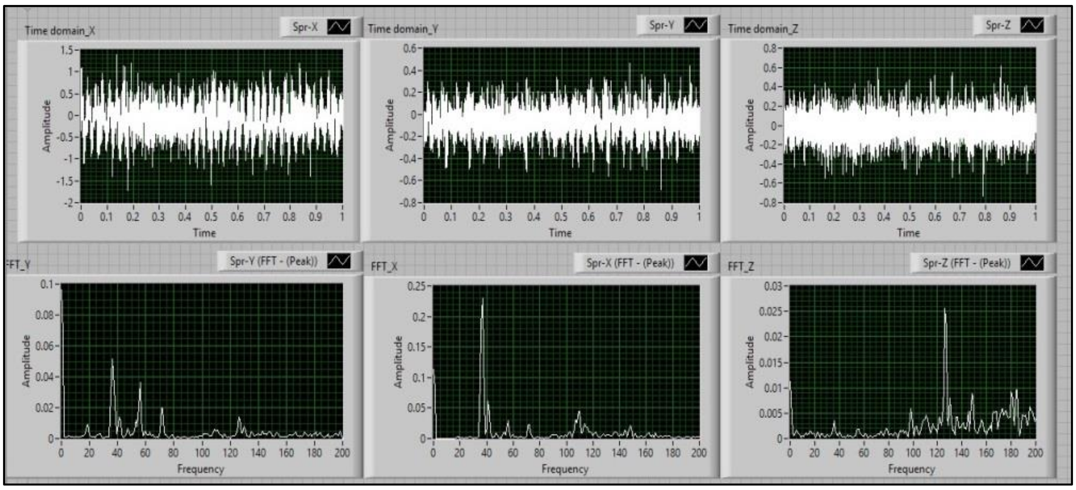


Figure 4.7 Front panel to represent the acquired data

Figure 4.6 shows the graphical block diagram of the VI program. The acquired data are converted into frequency domain by fast Fourier transforms (FFT) in LabVIEW. Figure 4.7 shows the front panel of the VI program. In order to avoid inconsistency in data acquisition, three trials are performed at the set machining parameters and then vibration and sound signals are stored in the data file.

4.7 EXPERIMENTAL PROCEDURE

The following methodology is adopted during face milling operation. The procedure is unchanged during our entire research work. The repeatability of the experiments is also taken care of.

1. Face milling operation will be carried out using universal milling machine [3M (AU) G ALL FEED AUTOMATIC] with commercially available carbide insert (Mitsubishi make: SEMT13T3AGSN-JM VP15TF) and workpiece of steel alloy 42CrMo4.
2. The four different face milling tool conditions considered in the present study are as follows:
    a) Healthy
    b) Flank wear (0.3 mm)
    c) Tip breakage (breakage) and
    d) Chipping on the rake face (chipping).
3. Machining will be carried out with selected machining parameters. They are cutting speed of 128 m/min, feed of 0.12 mm/tooth and depth of cut of 0.5 mm.
4. Acquiring the acceleration and sound signals for healthy and faulty conditions of the face milling tool.

In the healthy condition of the tool, all six inserts are new/unworn inserts (Figure 4.8(a)), whereas in faulty condition, among six inserts one is either flank wear (Figure 4.8 (b)) or breakage (Figure 4.8 (c)) or chipping (Figure 4.8 (d)) and the remaining five are healthy inserts and have been considered for analysis.

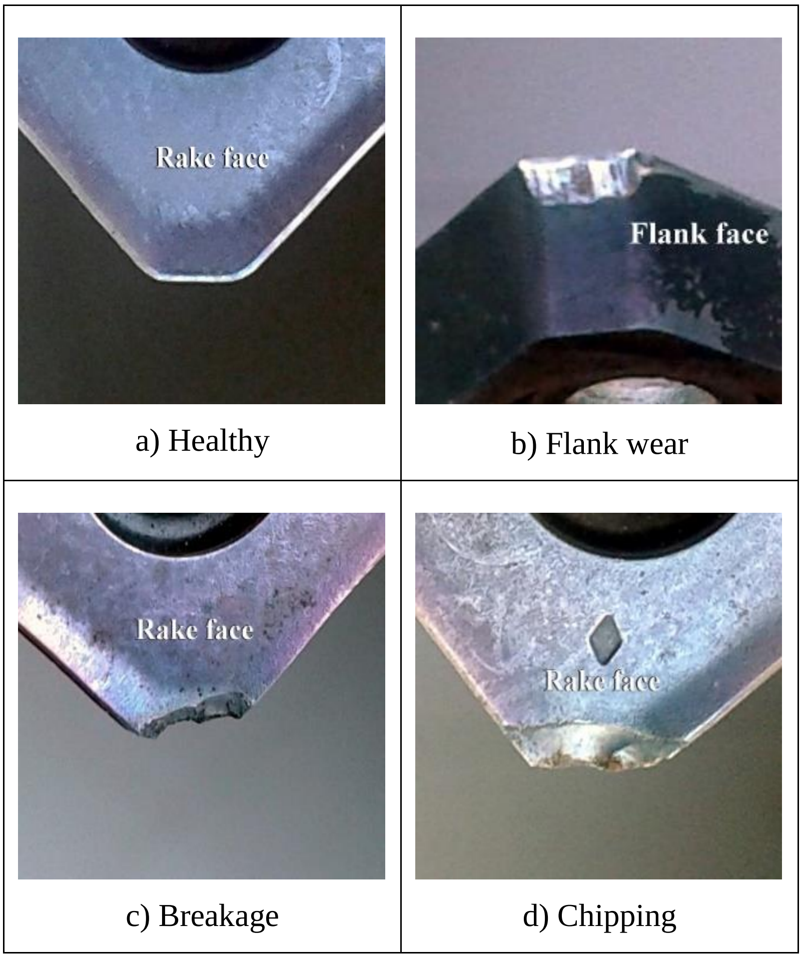


Figure 4.8 Different conditions of face milling tool insert

Different face milling tool insert conditions used in this experiment are as shown in Figure 4.8. Different types of tool wear specified in the research work predominantly appears during milling process. Hence these fault conditions have been considered for current investigation. Fault diagnosis/detection of the milling tool condition will be carried out using signal processing techniques and machine learning technique

4.8 SUMMARY

This chapter has discussed about the experimental setup used for research work which includes the details of the sensors used, data acquisition systems, virtual instrumentation and experimental procedure involved in undertaking the required tests. The subsequent chapter discusses the usage of signal processing techniques based on acquired vibration and sound signals in fault detection of the face milling tool.

CHAPTER-5

FAULT DETECTION USING SIGNAL PROCESSING TECHNIQUES

5.1 INTRODUCTION

In signal processing techniques, the acquired signals are analysed in terms of frequency component, quefrency component and time-frequency components by using spectrum analysis, cepstrum analysis and wavelet analysis respectively. These process parameters are very useful to predict tool condition. In this chapter, some of the signal processing techniques such as time-domain analysis, spectrum analysis, cepstrum analysis and continuous wavelet transform (CWT) analysis are used to investigate the condition of the face milling tool based on the acquired vibration and sound signals during machining.

5.2 MODAL ANALYSIS

Experimental modal analysis deals with the determination of modal parameters such as natural frequencies, damping properties and mode shapes of a structure through experiments. In the experimental modal analysis procedure, modal parameters are to be estimated from the measured frequency response functions (FRFs) i.e. from the output response and the input force data (Sujatha, 2010). The quality of an experimental modal model is only as good as the quality of the FRFs. In the present work, care has been taken in the selection of appropriate transducers and their positioning/mounting as well as aspects related to signal processing. Though the entire process of obtaining the required data is experimental in nature, many mathematical techniques are involved in the computation of FRFs and modal parameters extraction. Figure 5.1 shows the experimental setup for impact test on face milling tool. Figures 5.2-5.4 illustrate the FRF plots of spindle, face milling tool and workpiece. Table 5.1 depicts the frequency response for workpiece-tool system.

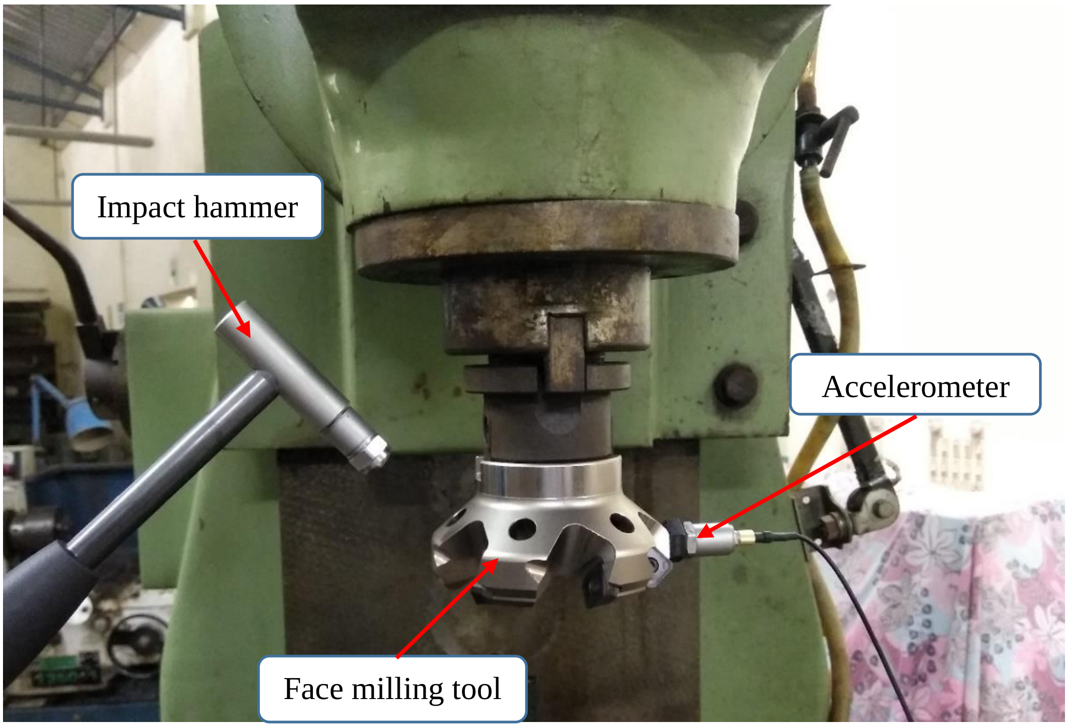


Figure 5.1 Experimental setup for impact test on face milling tool

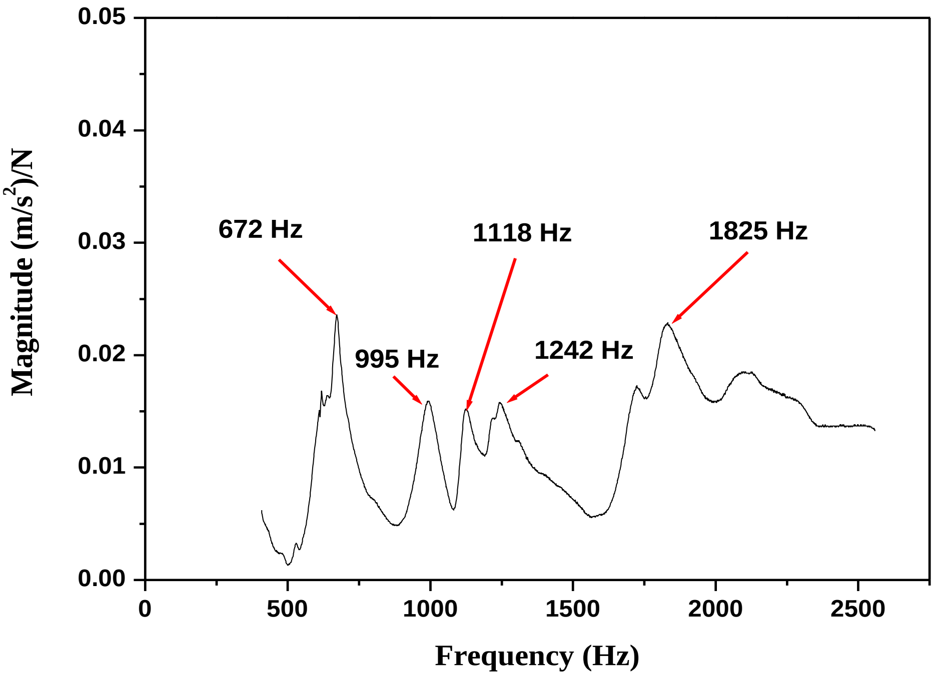


Figure 5.2 FRF of milling setup, accelerometer on the spindle

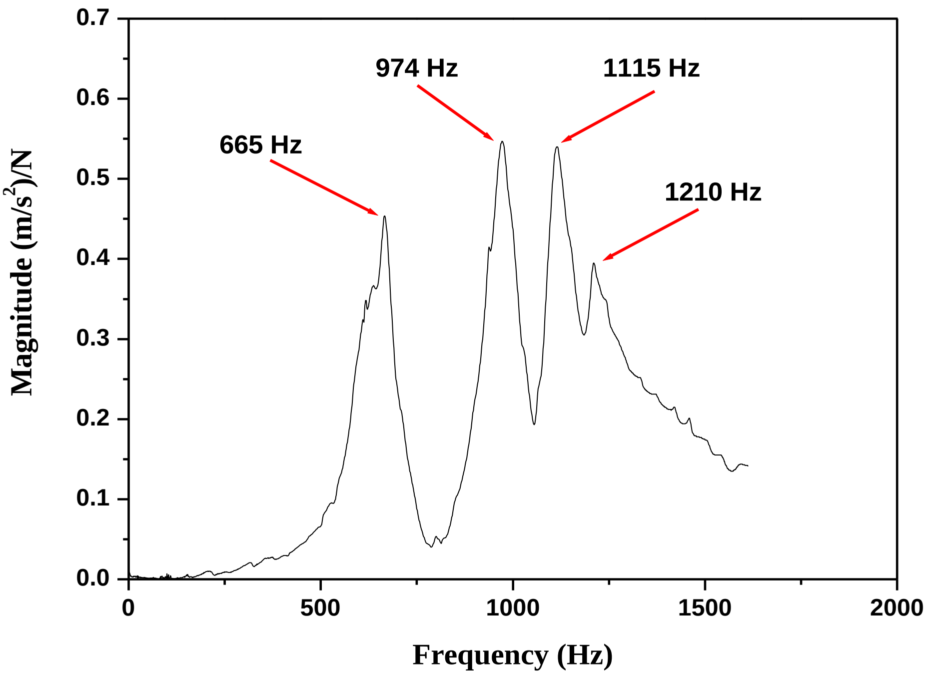


Figure 5.3 FRF of milling setup, accelerometer on the milling cutter

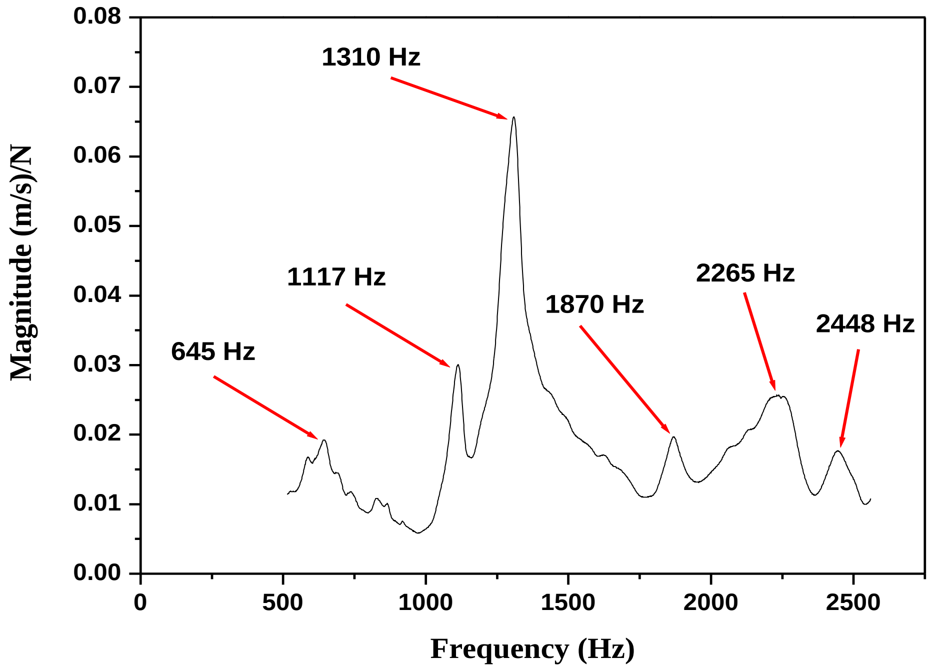


Figure 5.4 FRF of milling setup, accelerometer on the workpiece

Table 5.1 Frequency response for workpiece-tool system

Component/Equipment	**Natural frequencies (Hz)**
Spindle	672, 995, 1118, 1242, 1825
Workpiece and fixture	645, 1117, 1310, 1870, 2265, 2448
Milling tool	665, 974, 1115, 1210

Vibration signals of machine elements always provide the dynamic information about the operating conditions. Vibration monitoring can help fault detection before the significant damage occurs. Changes in the condition of the components of mechanical systems often produce changes in the vibration signature which the system generates. Vibration signals contain information on the natural frequencies of the work piece, fixture, machine tool and spindle which are transformable into various domains to determine signatures of uneven tool wear or possible chipping. The most basic vibration analysis technique transforms the time domain signals to the frequency domain using the fast Fourier transform (FFT) in order to detect the unusual changes in vibration frequencies possibly due to tool wear or breakage (Ramakrishna 2016). Fourier transform (FT) is the most widely used technique in vibration signal analysis. Fast Fourier transform (FFT) is one of the extension of FT (Vernekar et al., 2014).

Impact testing was conducted and the natural frequencies of the milling tool, workpiece and spindle housing were noted and is shown in the aforementioned Table 5.1. The acquired vibration signals for all conditions of the milling tool were analysed using spectrum technique. Figure 5.5 (a-d) illustrate the frequency spectra of vibration signals for all milling tool conditions such as healthy, flank wear, breakage and chipping conditions.

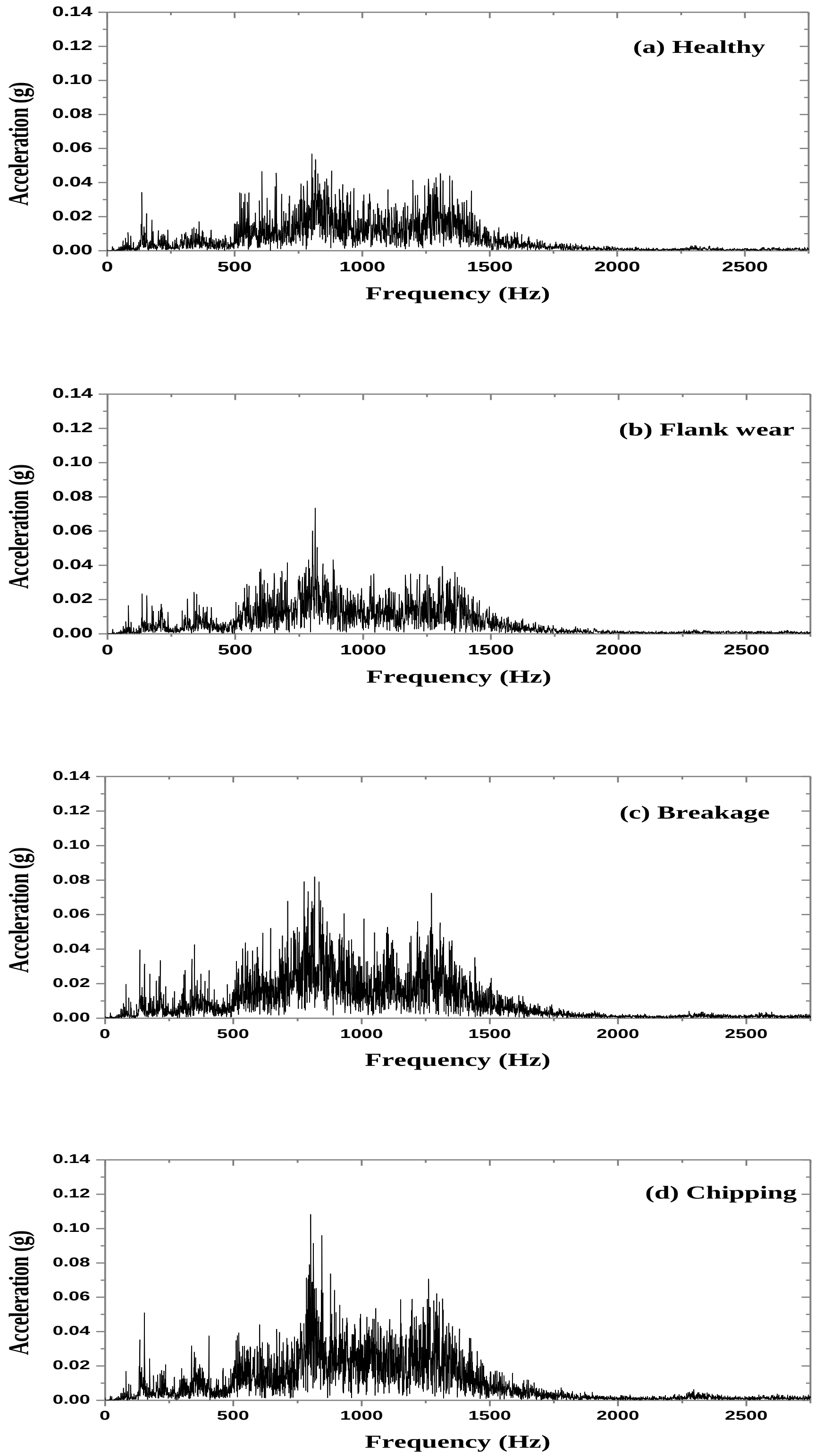


Figure 5.5 Spectrum plots of vibration signals (modal analysis) (a) healthy, (b) flank wear, (c) breakage and (d) chipping

From Figure 5.5 (a-d), it can be clearly observed that for all faulty conditions of the face milling tool, the magnitude of the vibration signals in the frequency ranges of 750Hz to 900 Hz and 1250 Hz to 1350 Hz were varied progressively. The frequency range of 1240 Hz to 1350 Hz depicts the high frequency components of the vibration signals that correspond to one or more of the natural frequencies of the workpiece and spindle housing. Also this information about tool condition is insufficient for fault diagnosis. But in other frequency band of 750 Hz to 900 Hz, none of the natural frequencies correspond to either milling tool or spindle or workpiece were highlighted in the spectra. This shows that other frequency component of the machine tool work material structure has been varied as faults occurred in the milling tool. In order to identify the milling tool condition, further analysis will be carried out by computing the tooth passing frequency (TPF) of the milling tool (section 5.3.1.1).

5.3. TIME AND FREQUENCY DOMAIN (SPECTRUM) ANALYSES

5.3.1 Vibration signals

Time domain plot helps to examine the amplitude and phase information of the acquired signal to determine the failure/defect of any rotating machinery system. The acceleration signals were acquired for healthy and different fault conditions of the face milling tool. Figure 5.6 shows the time-series plots in feed direction for different conditions of the face milling tool such as healthy, flank wear, breakage and chipping tool conditions.

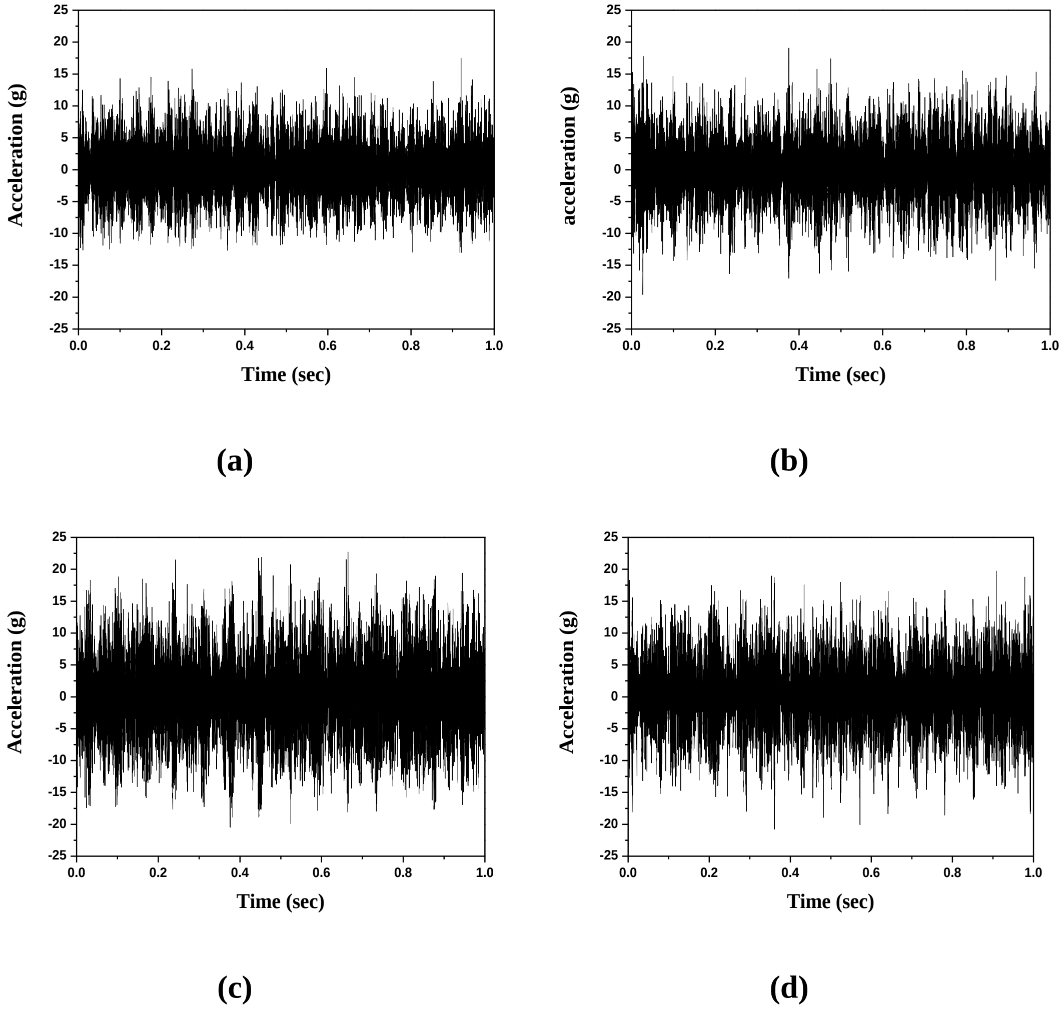


Figure 5.6 Time-series plots of (a) healthy, (b) flank wear, (c) breakage and (d) chipping face milling tool conditions

From Figure 5.6, the acceleration amplitude corresponding to fault condition shows slightly varied as compared to the acceleration of the healthy condition of the milling tool. It is quite difficult to diagnose the faults with the help of time-series plots. Fault diagnosis using time series response is a difficult task. FFT technique is used to detect the face milling tool condition through vibration and sound signals. The following subsection will give the details about fault detection of the face milling tool based on tooth passing frequency analysis.

5.3.1.1 Tooth passing frequency (TPF) analysis of milling tool

In milling process, one of the reasons for vibration of the cutting tool is due to variation in the cutting force. This cutting force signal is periodic and its variation frequency is TPF which depends on spindle rotating frequency (f_s) and number of teeth in the milling tool. Spindle rotating frequency 'f_s' is defined as,

$$f_s = \frac{N}{60} = \frac{1000v}{60\pi D} \tag{5.1}$$

Where D is the diameter of the mill, N is the spindle speed (in revolutions per minute) and v is linear speed (in meters per minute). TPF is defined as,

$$TPF = N_T * f_s = \frac{1000vN_T}{60\pi D} \tag{5.2}$$

Where N_T is the teeth numbers of the cutting tool, while the presence of peaks at additional frequencies represents the chatter. This TPF of milling dynamics is often used for detection of the chatter (Huang et al., 2013).

The spectrum of experimental results for different conditions of the milling tool are shown in Figure 5.7. From spectrum plot, under normal cutting condition in a milling process, the dominant frequency components in the spectrum graph are around the spindle rotating frequency (f_s), tooth passing frequency (TPF) and their harmonics (Orhan et al., 2007).

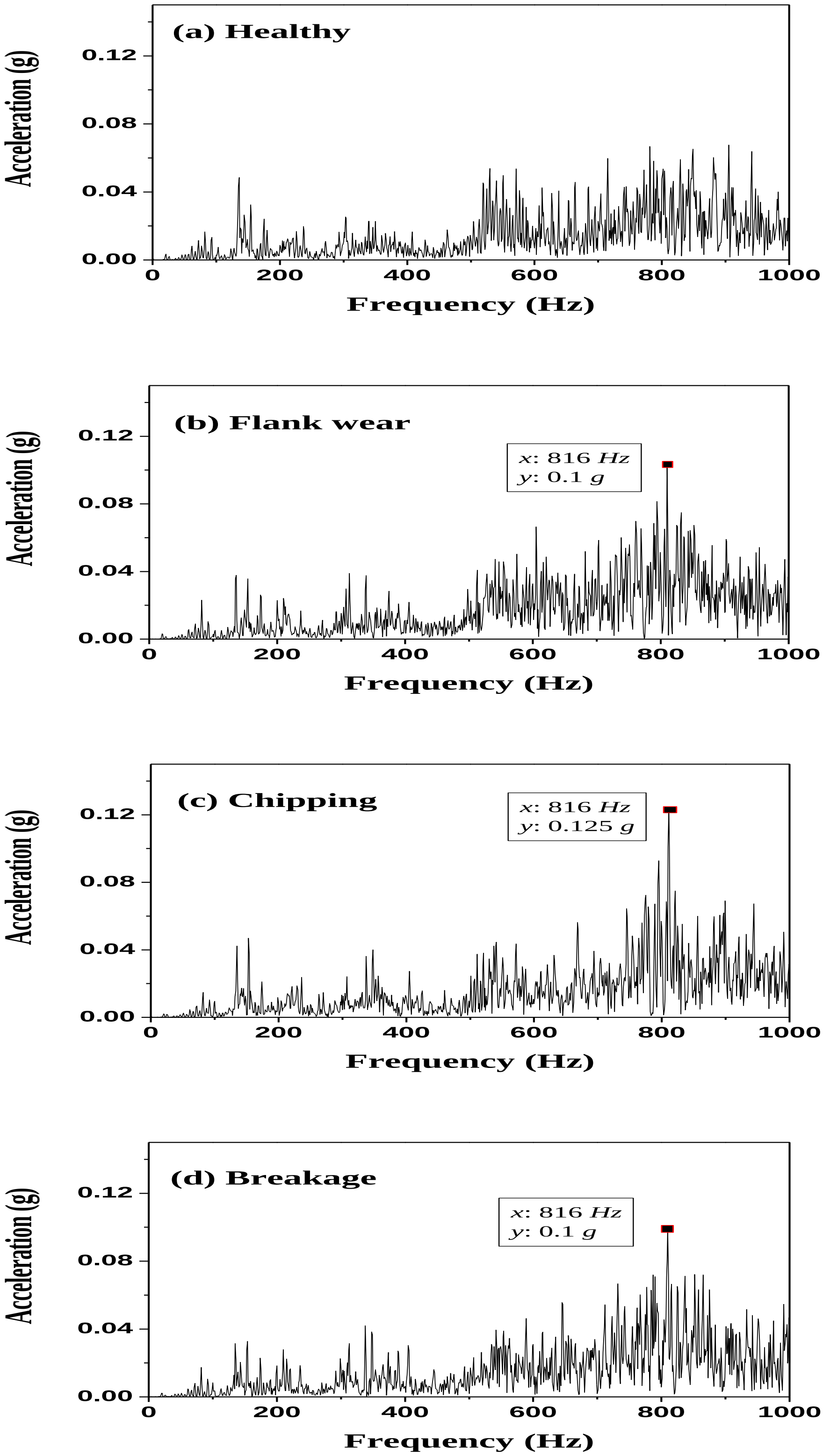


Figure 5.7 Spectrum plots of vibration signals (TPF analysis) (a) healthy, (b) flank wear, (c) chipping and (d) breakage

Table 5.2 Characteristic vibration frequency of spindle speed running at 510 rpm

Parameters	**Value**
Spindle rotating frequency (f_s)	8.5 Hz
Tooth pass frequency (TPF)	51 Hz
Total number of inserts in milling tool	6

Table 5.2 shows the characteristic vibration frequency of milling process with spindle speed running at 510 rpm. TPF for the given spindle speed and the number of tool inserts is about 51 Hz. It can be noticed from spectrum plot that along with tooth pass frequency and its harmonics (1x, 2x, 3x,….etc.), few peaks corresponding to chatter are also present. Figure 5.7 (a) and (b) show the spectra of healthy and flank wear conditions of the face milling tool respectively, 16th multiple of TPF (816 Hz) shows the dominancy among all other harmonics. The corresponding acceleration amplitude of 16th multiple of TPF for the flank wear condition is about 0.1 m/s^2. This signifies the presence of fault in the face milling tool. The increase in the amplitude level of the same frequency (16th multiple of TPF) with increase in severity of fault such as chipping condition can be visualized in spectrum as illustrated in Figure 5.7 (c). The magnitude of acceleration is increased from 0.1 to 0.125 m/s^2, which signifies the increase of fault level in the milling tool. Also for breakage condition, 16th TPF is the dominant frequency among all TPF harmonics. From the overall spectra of vibration signals, it might be evident that 16th multiple of TPF coincides with one of the natural frequencies (816 Hz) of the tool-workpiece material structure.

5.3.2 Sound signals

The sound signal is also another kind of process parameter which has measured during face milling. The sound signals under different tool conditions were acquired. Analysis of sound signals under different face milling tool conditions has been carried out using time-domain analysis, spectrum analysis, cepsrtum analysis and wavelet analysis. Figure 5.8 depicts the time domain sound signals of the face milling tool under different conditions.

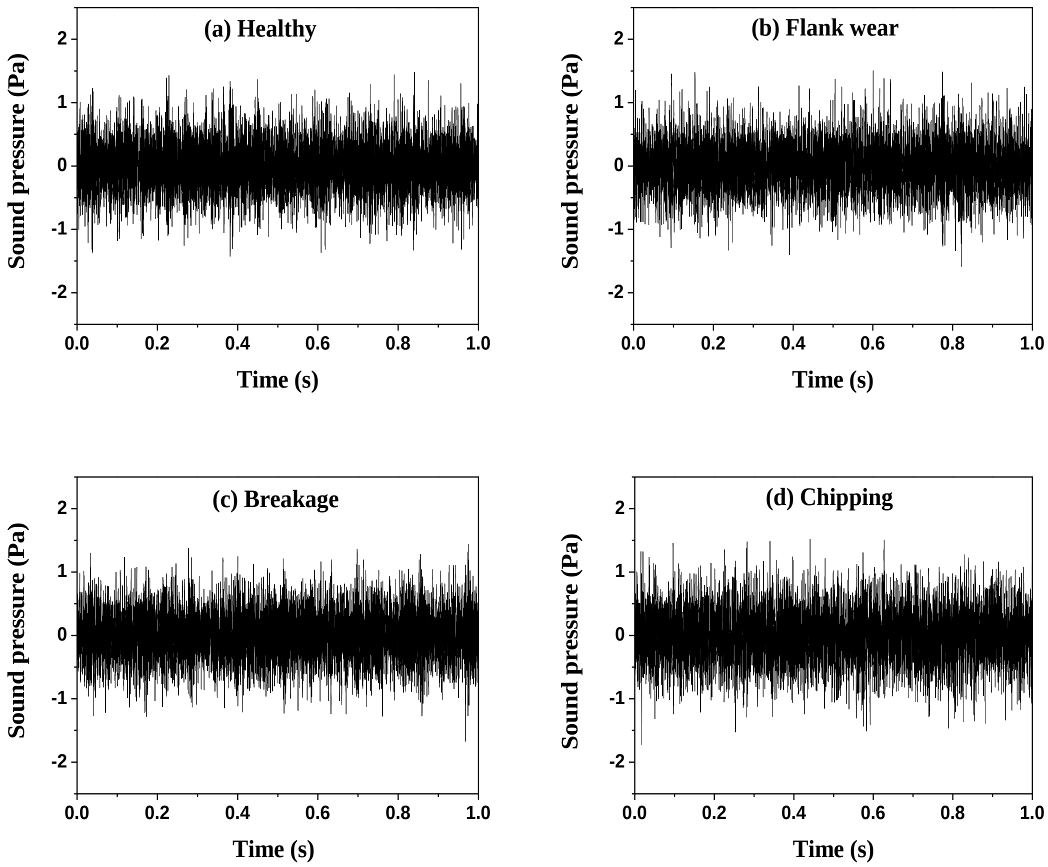


Figure 5.8 Time-series plots of sound signals for different tool conditions (a) healthy, (b) flank wear, (c) breakage and (d) chipping

Figure 5.8 showed the time-series plots of sound signals for different conditions of the face milling tool such as (a) healthy, (b) flank wear, (c) breakage and (d) chipping. It is quite difficult to diagnose the faults with the help of time-series plots. However, as the tool wear/breakage occurs the machining sound becomes tedious and the analysis of healthy tool or broken tool can be detected by identifying the frequency components of the sound signal (Shi et al., 2014). Figure 5.9 illustrates the spectrum plots of sound signal for all conditions (healthy, flank wear, breakage and chipping) of the face milling tool.

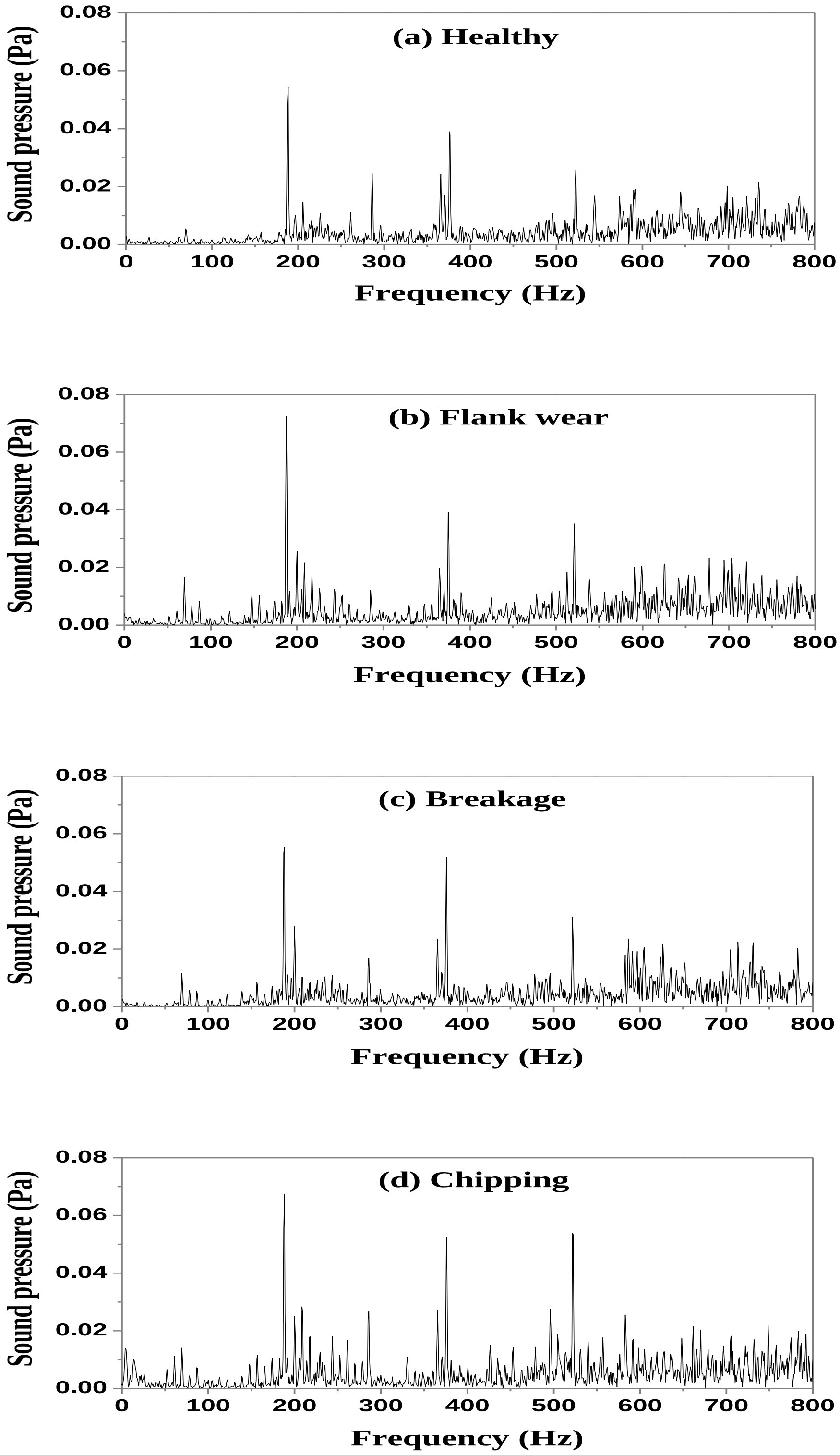


Figure 5.9 Spectrum plots of sound signals for different tool conditions (a) healthy, (b) flank wear, (c) breakage and (d) chipping

From Figure 5.9 (a-d), observation shows that the peak frequencies corresponding to 187 Hz and 374 Hz are the dominant frequencies among all spindle rotating frequency (fs) and their harmonics. When the milling tool is working under fault conditions (flank wear, breakage and chipping), the sound pressure value of these dominant frequencies (187 Hz and 374 Hz) are found to be different in comparison with the healthy condition of the tool.

Further analyses of sound signal has been carried out using cepstrum and CWT techniques in the forthcoming sections. The cepstrum analysis will be carried out in order to recognize the tool conditions and also to validate the results of spectrum analysis.

5.4 CEPSTRUM ANALYSIS

5.4.1 Vibration signals

The cepstrum plots of the face milling tool under different conditions (healthy, flank wear, breakage and chipping) using vibration signals are as shown in Figure 5.10. As discussed in spectrum analysis, the dominant peak corresponding to 816 Hz (16^{th} multiple of TPF) is the defect frequency. In cepstrum analysis, the defect frequency is called as defect quefrency of about 0.0012s (1/816Hz) which shows the variation in amplitude of acceleration for different conditions of the tool. Figure 5.10 (a) shows the cepstrum plot of vibration signal under healthy face milling tool condition, where the acceleration of dominant peak at quefrency (0.0012s) is about 0.015 m/s^2, which is considered as a reference for fault detection. With the faulty tool conditions such as flank wear, chipping and breakage, the magnitude of the acceleration signal is found to be increased at defect quefrency (0.0012s). In case of flank wear condition, 16^{th} multiple of tooth passing quefrency (0.0012s) has the acceleration of about 0.031 m/s^2, which implies the presence of faults in the milling tool. For breakage and chipping conditions, the acceleration value at quefrency 0.0012s is about 0.035 m/s^2 and 0.04 m/s^2 respectively, which signifies the increase in the level of faults during milling process.

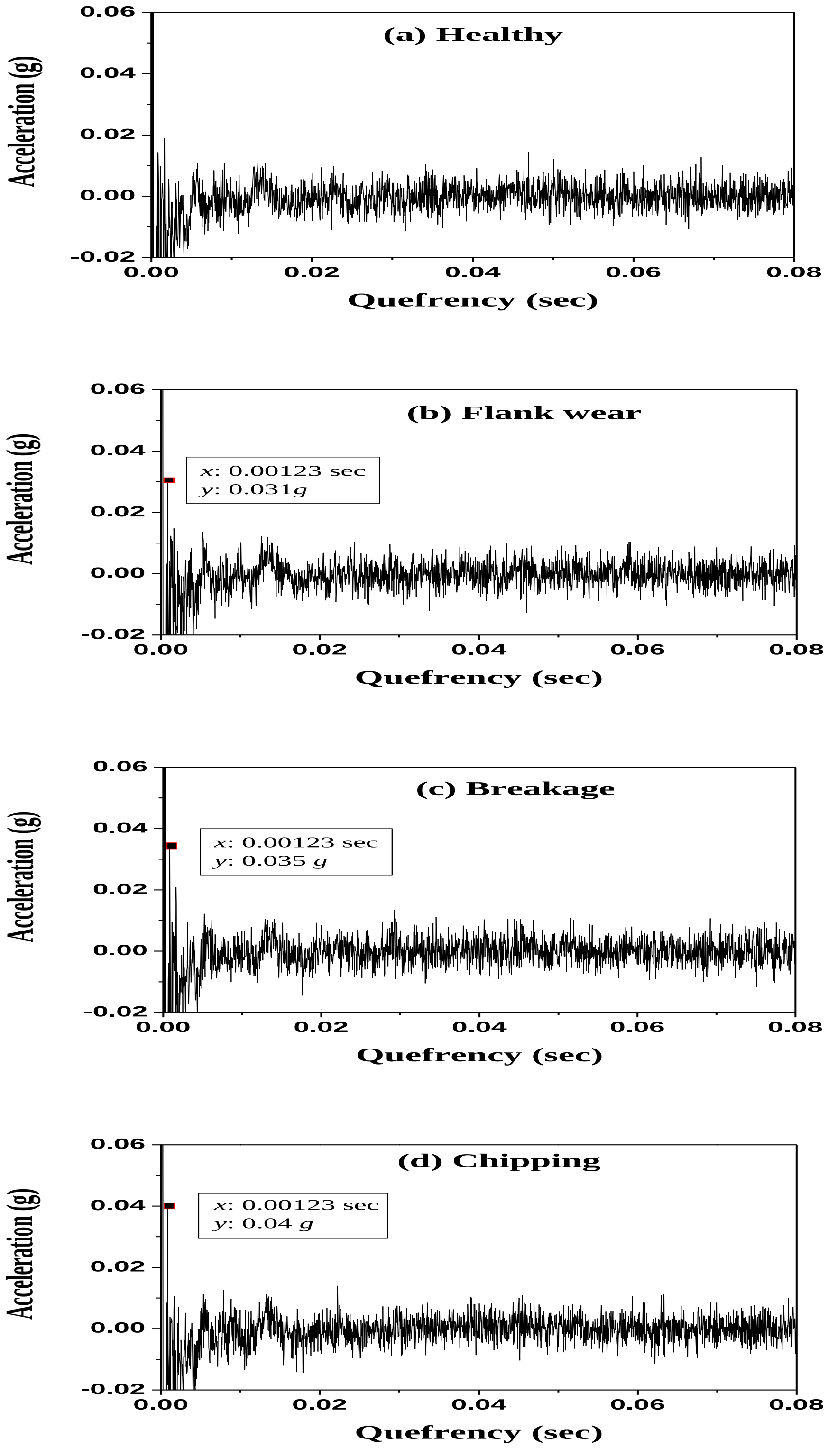


Figure 5.10 Cepstrum plots of vibration signals (a) healthy, (b) flank wear, (c) breakage and (d) chipping conditions

5.4.2 Sound signals

The cepstrum plots of the face milling tool under different conditions such as, healthy, flank wear, breakage and chipping conditions using sound signals are as shown in Figure 5.11.

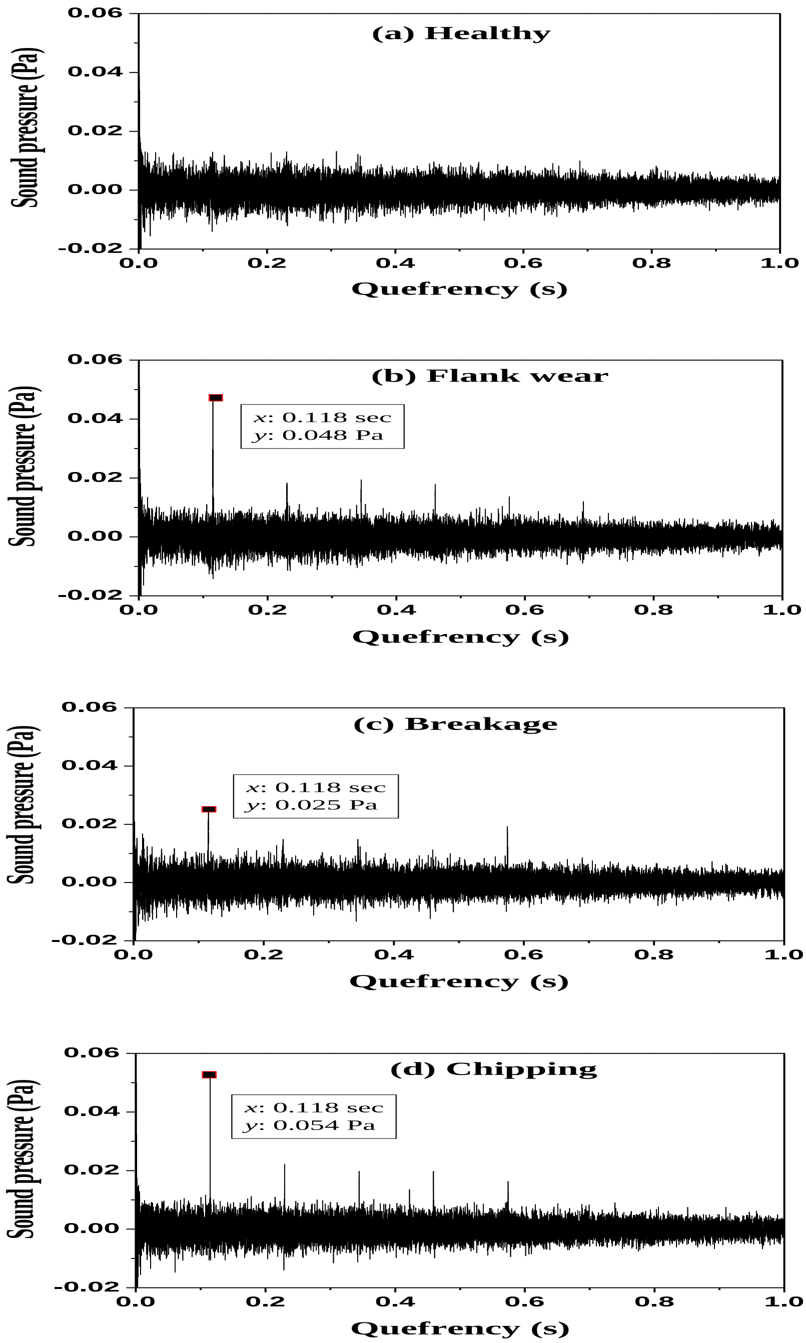


Figure 5.11 Cepstrum plots of sound signals (a) healthy, (b) flank wear, (c) breakage and (d) chipping

The fundamental spindle rotating frequency is about 8.5 Hz (510 rpm) and the corresponding quefrency is about 0.118 sec. In the present study, the fundamental rotational quefrency (0.118 sec) is the defect quefrency of the sound signal. Figure 5.11(a) shows the cepstrum plot of a healthy tool where there is no dominant peak at any quefrency of cepstrum plot. As the faults (flank wear, breakage and chipping) are introduced into the milling tool, the sound pressure at defect quefrency (0.118sec) is found to be increased. In cases of flank wear condition, breakage condition and chipping condition, the corresponding fundamental rotational quefrencies (0.118sec) of the milling tool have the sound pressure values of about 0.048 Pa, 0.025 Pa and 0.054Pa respectively, which implies the presence of faults in the milling tool.

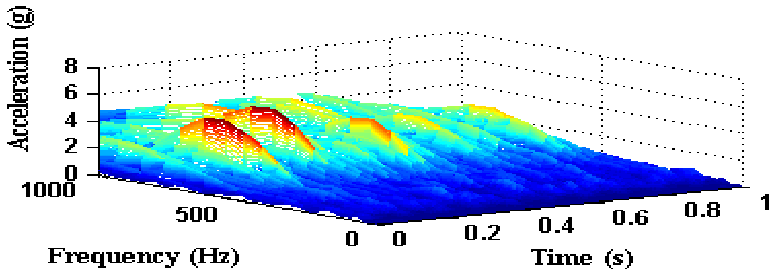
From the above discussion of spectrum and cepstrum analyses of the face milling tool using vibration and sound signals, it can be visualized that even with the presence of defect in the tool, it is quite difficult to identify the particular time at which the defect frequency/quefrency occurred. Wavelet analysis will provide both time and frequency information of a healthy and faulty conditions of the tool.

5.5 WAVELET ANALYSIS

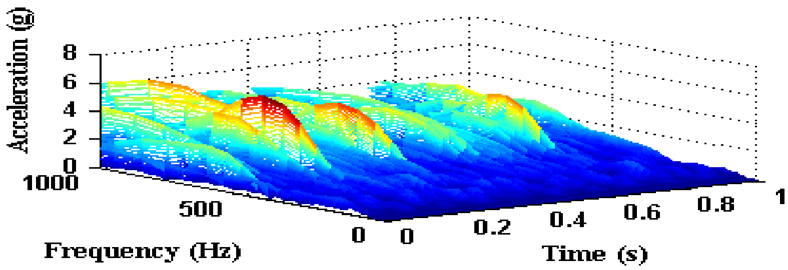
5.5.1 Vibration signals

The acquired vibration signals under different milling tool conditions are analysed using CWT technique. The CWT is one of the wavelet transform techniques which represents the given signal in time-frequency domain. Figure 5.12 illustrates the CWT plots of the milling machine spindle vibration with healthy and fault conditions of the face milling tool.

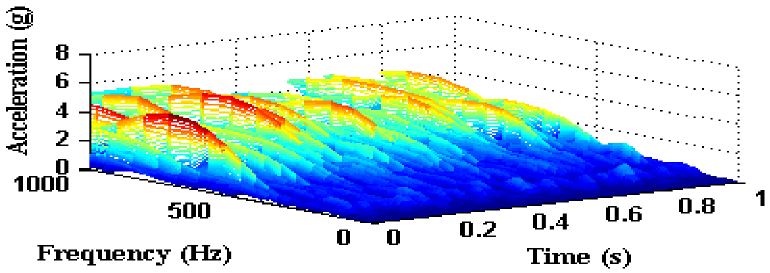
(a) Healthy



(b) Flank wear



(c) Breakage



(d) Chipping

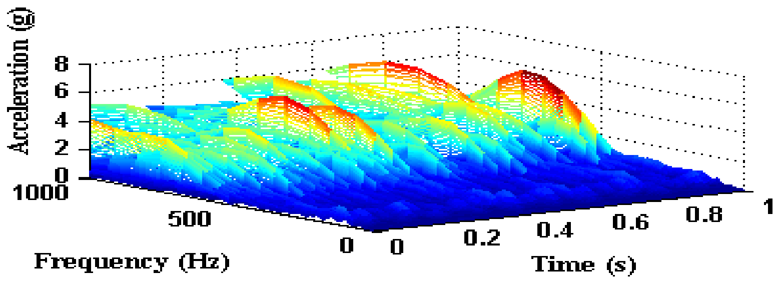


Figure 5.12 CWT plots of vibration signals (a) healthy, (b) flank wear, (c) breakage and (d) chipping

Figure 5.12 depicts variation in intensity of high frequency band at 816 Hz, as the faults occur in the milling tool. The presence of high-frequency component at 816 Hz (16^{th} multiple of TPF) which is one of the harmonics of TPF. Figure 5.12 (a) depicts the CWT plot of healthy tool condition. Occurrence of different faults such as flank wear, chipping and breakage in the milling tool increases the intensity of the high frequency (816 Hz) band as shown in Figure 5.12 (b), (c) and (d). This variations in intensity of high frequency band indicates the existence of fault in the milling tool.

5.5.2 Sound signals

The acquired sound signals from the set of experiments are analysed using CWT technique to identify the face milling tool condition. Figure 5.13 illustrates CWT plots of sound signals during face milling operation with healthy and fault conditions of the milling tool. Observation shows that there is some high intensity of frequency of 127Hz (15^{th} multiple of spindle rotation frequency) for all conditions of the face milling tool. Figure 5.13 (a) depicts the CWT plot of healthy face milling tool condition. Whereas, Figure 5.13 (d) illustrates the CWT plot of chipping tool condition, wherein the intensity of the high frequency (127 Hz) band has been increased, when it is compared with the CWT plot of healthy tool condition. Small variation in acceleration corresponding to frequency of 127 Hz has been observed due to the presence of faults such as flank wear and breakage (Figure 5.13 (b) and (c)). But it is very difficult to identify the exact time and frequency for each condition of milling tool. Hence CWT plots are very difficult to analyse the condition of tool using sound signals.

(a) Healthy

(b) Flank wear

(c) Breakage

(d) Chipping

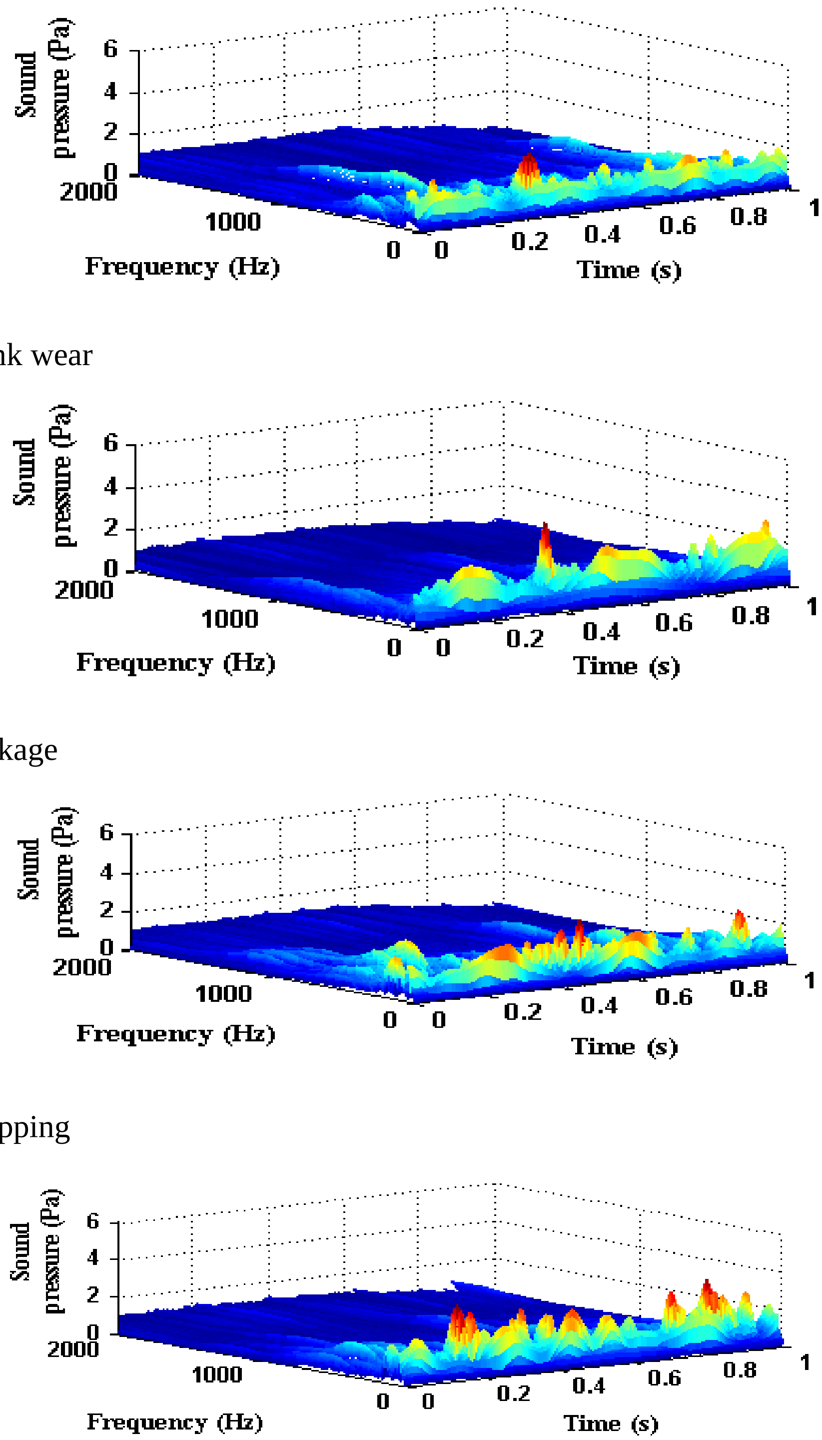


Figure 5.13 CWT plots of sound signals (a) healthy, (b) flank wear, (c) breakage and (d) chipping

Generally, conventional data processing is computed in time or frequency domain and is not suitable for analysing non-stationary signals. However, spectrum analysis has provided an information about the face milling tool condition in terms of TPF in case of vibration signals, and the harmonics of spindle rotation frequency in case of sound signals. Also cepstrum technique can be used as validation to spectrum analysis which provides the information about corresponding fault occurrences in terms of variation of defect quefrencies. Wavelet analysis is appropriate for characterizing machine vibration signatures with narrow band-width frequencies lasting for a short time period. Wavelets have limited bandwidth in the frequency domain and compact bandwidth in the time domain (Loutridis 2004; Bianchini et al. 2011). Though the advanced signal processing technique such as CWT has been used, it has not provided sufficient information about the milling tool conditions using both vibration and sound signals. The detection of fault using these techniques is difficult and it needs a highly skilled and experienced technician who has clear understanding of the techniques used and also thorough knowledge about the machine in which the fault is detected.

5.6 SUMMARY

This chapter has illustrated the analysis of vibration and sound signals acquired for healthy and different faulty face milling tool conditions using the time domain plots, modal analysis, frequency domain plots, cepstrum plots and wavelet transform plots for detecting the faults. It was found that the time domain signals analysis gives overall vibration level but do not provide any fault diagnostic information. Spectrum analysis is the most widely used signal processing technique, but sometimes quite difficult to identify the defect frequency and it requires domain knowledge. Cepstrum analysis is a suitable technique to identify and distinguish the fault quefrencies. Wavelet analysis is three dimensional representation of a signal which is inherently suited to indicate transient events in the signals. Since face milling process generates non-stationary signals and complex signals, fault diagnosis of cutting tool can be effectively monitored using advanced signal processing technique rather than traditional approaches. Machine learning approach is one of the promising tools which can be easily applied for fault diagnosis. Chapter 6 presents the techniques used for fault diagnosis of the face milling tool using machine learning approach for online tool condition monitoring.

CHAPTER-6

FAULT DIAGNOSIS USING MACHINE LEARNING TECHNIQUES BASED ON VIBRATION SIGNAL

6.1 INTRODUCTION

Machine learning is an area of artificial intelligence involving developing techniques to allow computers to learn. More specifically, machine learning is a method for creating computer programs by the analysis of data sets. Many of the machine learning methods is iterative in nature and they require high speed processors. The aforesaid developments accelerate the application of machine learning methods for solving problems in real time. Fault diagnosis is one of the application areas, where machine learning methods are widely used. This chapter describes the investigation of the vibration signals of the face milling tool based on machine learning methods used for fault diagnosis.

6.2 MACHINE LEARNING APPROACH

Machine learning technique has three phases, they are feature extraction, feature selection and feature classification. In feature extraction, statistical features, histogram features, discrete wavelet features and empirical mode decomposition features will be extracted from the collected sound and vibration signals. In the feature selection technique, a subset of the existing features is selected without any transformation. The decision tree algorithm is a feature selection technique in the present study. Machine learning process has two stages in the third phase. In the first stage, the classification algorithms are trained with the help of selected features from the training data of various fault signals. In the second stage, the trained algorithm is tested with the help of selected features from the test data. The classification phase identifies the faulty component. The support vector machine (SVM), artificial neural network (ANN), Naïve Bayes, decision tree and K-star algorithms are used as classifiers in the present research work.

The flow chart of machine learning system for fault diagnosis of the face milling tool is as shown in Figure 6.1.

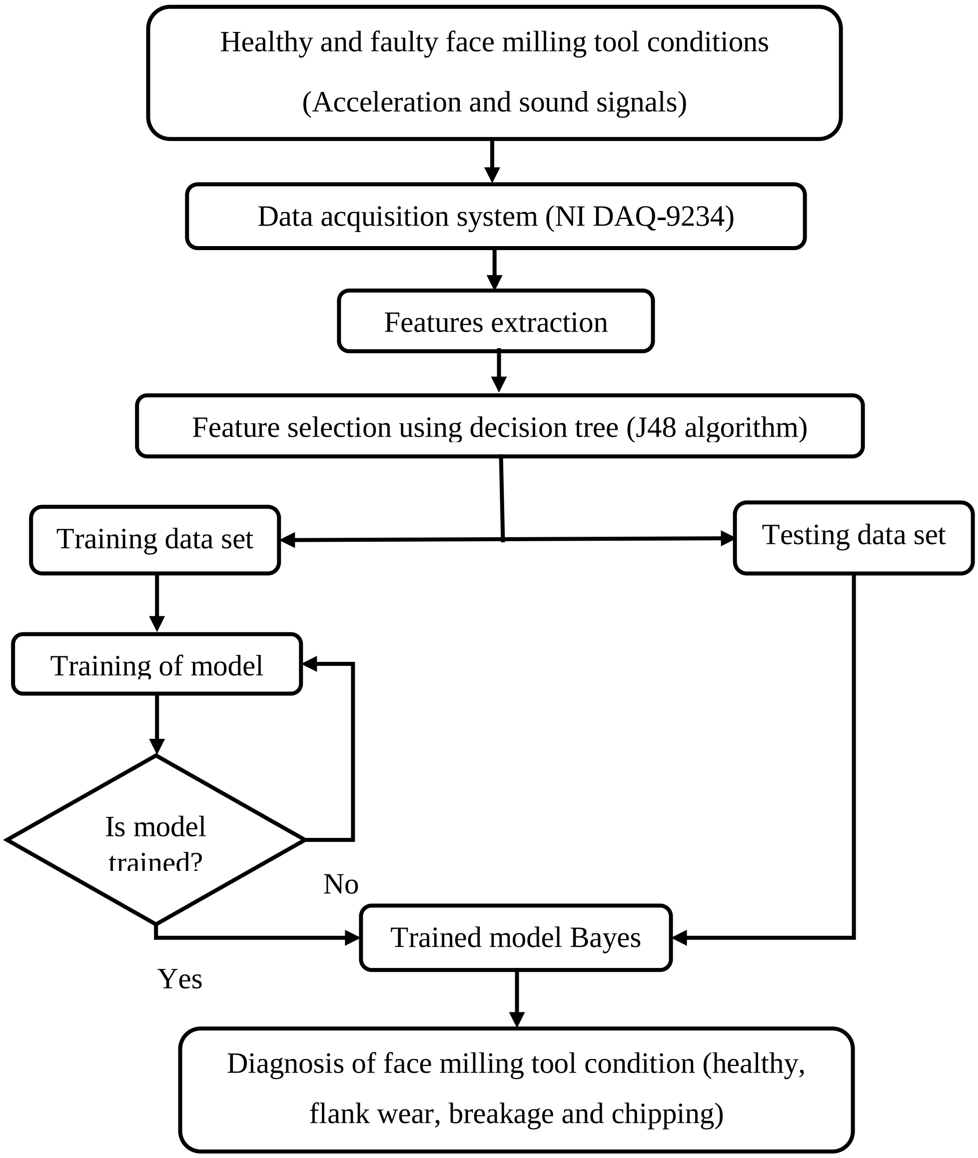


Figure 6.1 Flowchart of machine learning technique

A lot of research work has been carried out to identify the capability of machine learning methods to perform fault diagnosis. Most of the works considered one or two components with small number of fault classes. The number of fault classes depends on the number of components and its faults. It is essential to check the classification ability of machine learning methods for multi-tooth machining process such as face milling tool fault diagnosis. It is also important to find out the influence of a number of components or fault classes on the capability of machine learning methods in face milling for fault diagnosis. Because, the increase in number of fault classes increases the possibility of resemblance in signal pattern and it causes difficulty in classification process. Very few researchers have reported the sound and vibration signals analyses for fault diagnosis process using machine learning techniques. Hence, a detailed study is required in this field. Since sound signal based fault diagnosis can be a cost effective method, it will be very helpful for small and medium scale industries. The following section will provide the detailed analysis and discussion of fault diagnosis of the face milling tool based on machine learning technique using vibration signals.

6.3 FAULT DIAGNOSIS USING VIBRATION SIGNALS BASED ON MACHINE LEARNING APPROACH

The acquired acceleration signals are analysed and diagnosed the tool conditions through machine learning techniques. The present study deals with the feature extraction using statistical, histogram, EMD and DWT methods. Then feature selection using decision tree method and classification process using artificial intelligent techniques such as SVM, ANN, J48, Naïve Bayes and K-star models. Each step is explained with analysing the experimental results which can be referred in the forthcoming sections.

6.3.1 Fault diagnosis using statistical features

From the acceleration data, descriptive statistical features like skewness, mode, standard error, maximum, minimum, range, sum, mean, standard deviation, median, sample variance and kurtosis are assessed to serve as features. These parameters are called as statistical features. The computed statistical parameters (only two signals samples per each class) are tabulated in Table 6.1. These parameters will be treated as an input to the J48 algorithm for feature selection.

Table 6.1 Extracted statistical features from the vibration signals

Class	**Sample No.**	**Values**											
		Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum
Healthy	1	0.0243	0.0245	-0.0497	0.8807	3.9219	15.3818	0.6351	0.1250	41.4618	-23.1508	18.3110	622.2670
	2	0.0212	0.0245	-0.0570	0.8105	3.9116	15.3005	0.4934	0.1098	41.2557	-22.1705	19.0850	542.7800
Flank wear	1	0.0284	0.0224	-0.0177	-1.3340	3.5770	12.7952	0.4355	0.0444	32.3080	-17.6541	14.6540	726.3192
	2	0.0250	0.0220	-0.0022	-1.1067	3.5125	12.3374	0.3725	0.0581	30.7936	-16.0741	14.7196	640.4023
Breakage	1	0.0232	0.0175	0.0355	-1.0110	2.7991	7.8350	0.7033	-0.0176	29.6810	-15.8492	13.8318	594.2592
	2	0.0220	0.0175	0.0162	-0.1877	2.7974	7.8253	0.7437	-0.0195	25.3959	-13.2222	12.1737	563.8599
Chipping	1	0.0130	0.0176	0.0151	1.5416	2.8112	7.9028	0.4217	-0.0035	22.9801	-11.6243	11.3558	333.9146
	2	0.0156	0.0175	0.0322	0.7588	2.7993	7.8362	0.4478	-0.0119	25.7421	-13.4494	12.2927	400.2567

6.3.1.1 Feature selection using decision tree

The J48 algorithm used the data set for making the decision tree as a result of feature selection. The given data set of 200 samples fed to the algorithm and decision tree is illustrated in Figure 6.2. The rectangular blocks indicate classes (condition of the face milling tool). Within the parenthesis there are two numbers separated by a slash in rectangular blocks. The first number (in case of two numbers) or only the number represents the number of data points (samples) which helps in making the decision.

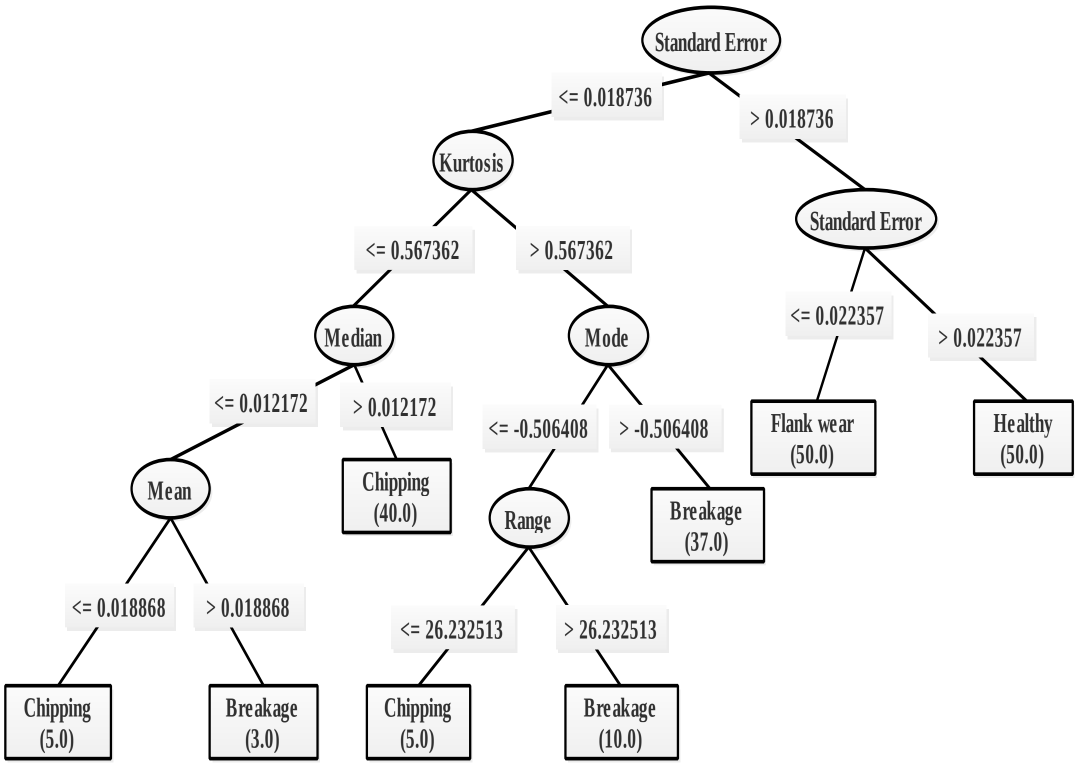


Figure 6.2 Decision tree of statistical features of vibration signal

All extracted descriptive statistical parameters were used as an input to the decision tree and significant features were selected out of the extracted features. As seen from Figure 6.2, the tree structure of different classes has been formed in such a way that when standard error is greater than 0.022357 value it is classified as healthy condition, whereas, when the standard error is greater than 0.018736 and less than/equal to 0.022357 value it is classified as flank wear condition and so on. The tool conditions (healthy, flank wear, breakage and chipping) are represented as leaves in the tree. Out of 12 features, six features are selected by decision tree such as mean, kurtosis, range, median, mode and standard error are the significant features. These selected features are treated as an input to the classifiers such as SVM, ANN, Naïve Bayes, decision tree and K-star models.

6.3.1.2 Classification

Obtained results from the classifiers are mapped based on 10-fold cross validation test mode. Cross validation is a resampling approach which enables to obtain a more honest error rate estimate of the results computed on the whole dataset. The standard way of predicting the error rate of a learning technique given a single, fixed sample of data is to use stratified 10 fold cross validation (Witten and Frank 2005). The output of the classifier is a confusion matrix. Table 6.2 shows the confusion matrix of the classifier and diagonal elements represent the correctly classified instances.

- ***Naïve Bayes algorithm***

Naive Bayes classifier makes use of condition probability for its classification. The six statistical features discussed earlier such as mean, kurtosis, range, median, mode and standard error which form the input to the classifier. The conditions of the face milling tool namely, healthy, flank wear, breakage and chipping are the possible outputs of the Naïve Bayes classifier. Table 6.2 shows the confusion matrix by the Naïve Bayes model.

Table 6.2 Naïve Bayes confusion matrix for statistical features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	46	4	**c-Breakage**
0	0	2	48	**d- Chipping**

From the confusion matrix, out of 200 instances only six instances were misclassified by a Naïve Bayes algorithm with the overall classification accuracy 97% for the given set of statistical features of the vibration signals.

- ***Decision tree algorithm***

Decision tree algorithm (J48 algorithm) performs both feature selection and classification simultaneously. Table 6.3 depicts the confusion matrix of decision tree for statistical features.

Table 6.3 Decision tree confusion matrix for statistical features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
1	49	0	0	**b-Flank wear**
0	1	46	3	**c-Breakage**
0	0	8	42	**d- Chipping**

From Table 6.3, thirteen out of two hundred instances were misclassified and the overall classification accuracy from the decision tree was about 93.5%, which is less than the classification accuracy of the Naïve Bayes model. Hence, J48 with statistical features for fault diagnosis of the face milling tool is not considered.

- ***Artificial neural network***

The classification accuracy of ANN with statistical features for milling tool fault diagnosis application is investigated. The ANN results are presented in Table 6.4.

Table 6.4 ANN confusion matrix for statistical features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	46	4	**c-Breakage**
0	0	5	45	**d- Chipping**

From the confusion matrix, one can notice that nine samples were misclassified. The overall classification accuracy is found to be 95.5% and the performance of the classifier can be accepted in the fault diagnosis area. However, the combination of ANN and statistical features for the fault diagnosis of the face milling tool is not preferable.

- ***Support vector machine***

The confusion matrix of the SVM model for statistical features of vibration signals are presented in Table 6.5.

Table 6.5 SVM confusion matrix for statistical features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	45	5	**c-Breakage**
0	0	5	45	**d- Chipping**

From the confusion matrix, out of 200 instances only 10 instances were misclassified with classification efficiency of 95%. As the classification efficiency is considerably less as compared to Naïve Bayes model's performance (96.5%), SVM with statistical features for fault diagnosis of cutting tool is not superior.

- ***K-star algorithm***

The six statistical features of vibration signals were given as an input to the K-star algorithm. The identified classification of the face milling tool conditions are presented in the Table 6.6.

Table 6.6 K-star algorithm confusion matrix for statistical features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	43	7	**c-Breakage**
0	0	2	48	**d- Chipping**

Table 6.6 illustrated the confusion matrix with K-star algorithm as the classifier. Here, only nine instances were misclassified and K-star algorithm provided the classification efficiency of about 95.5% for the given vibration signals.

- ***Summary***

The statistical features were extracted from the acquired vibration signals and feature selection was performed using decision tree (J48 algorithm) technique. The performances of the selected features set in fault classification was presented. The summary of classification efficiencies of different classifiers with statistical features is as shown in Table 6.7.

Table 6.7 Summary of classification efficiencies of different classifiers for statistical features of vibration signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	96.5	93.5	95.5	95	95.5

Table 6.7 depicted the Naive Bayes classifier has provided a highest classification efficiency of about 96.5% with statistical features as compared to the performances of other classifiers.

6.3.2 Fault diagnosis using histogram features

Observing the time domain plots pertaining to all classes of the milling tool, one can notice that the variation in acceleration amplitude from class to class. The histogram plot is a better graph to show the range of variation in the plots. These variations are analysed by using bins of the signal which can be used as set features. Figure 6.3 shows the histogram plots of the vibration signals of face milling tool under different conditions (healthy, flank wear, breakage and chipping).

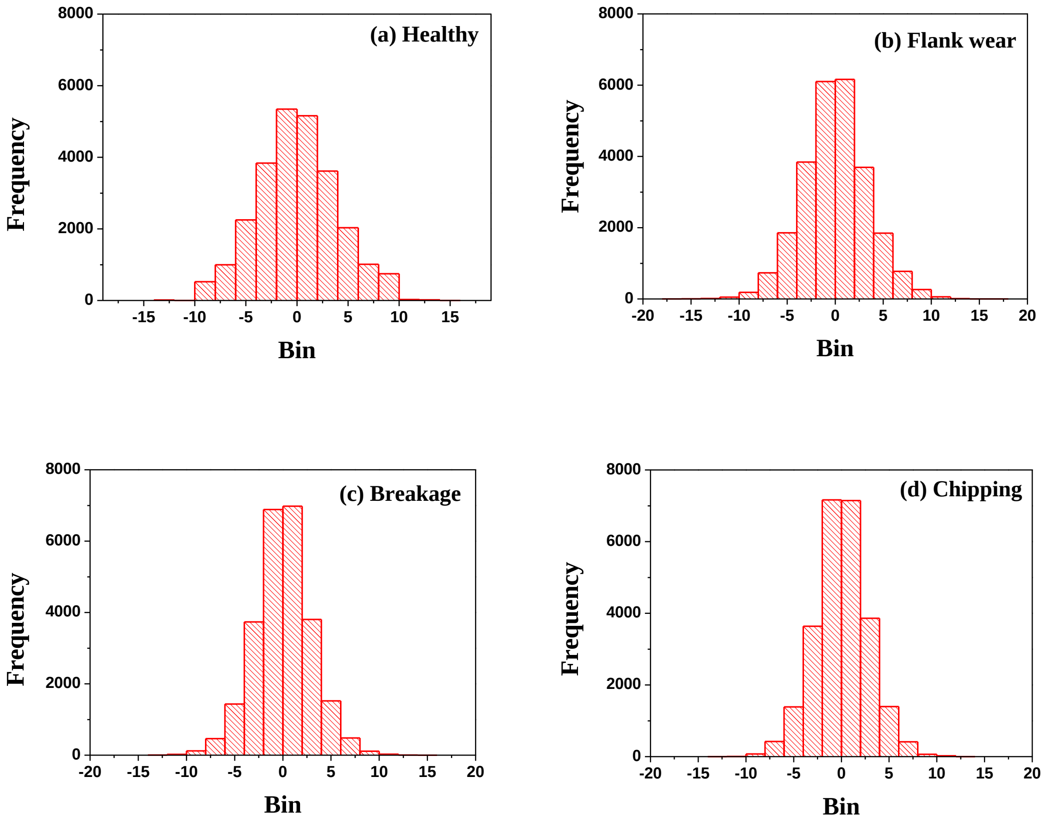


Figure 6.3 Histogram plots of vibration signals for different conditions of the face milling tool

Following the criteria for extracting the histogram features as mentioned in section 3.1.1.2, the bin width and bin range are selected based on the maximum and minimum values of the signals pertaining to all conditions and each bin was considered as a feature. Twenty different sets of histogram features were extracted from the vibration signals. Each set of features were treated as an input to the classifier and the results from the classifier were analysed. Twenty different sets of histogram features were analysed using different classifiers such as, SVM, ANN, Decision tree, K-star and Naïve Bayes models. Out of which, K-star model has given the better classification accuracy. Figure 6.4 shows the classification accuracies of K-star model for different sets of histogram features.

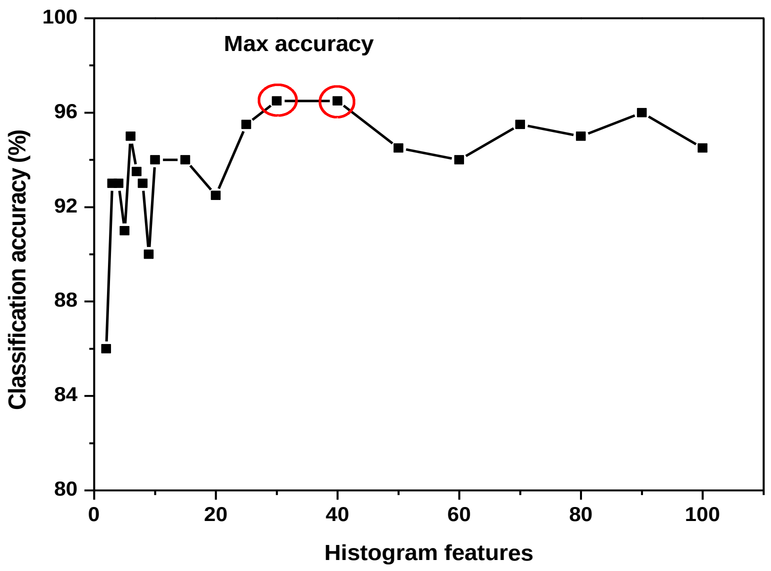


Figure 6.4 K-star classification accuracy for different sets of histogram features

From Figure 6.4, K-star model yielded a maximum classification accuracy of about 96.5% for both the thirty set and the forty set of histogram features. After this, the classification accuracy of the model attained was in the range between 94% and 96% for different sets of features (for 50, 60, …, 100 features). Table 6.8 depicts the set of thirty histogram features (f1 to f30) and out of 200 samples of vibration signals, only two samples pertaining to each condition of the milling tool are shown in the table. In this table, the features f1, f2, f3, f4, f27, f28, f29 and f30 are set to zero value for all conditions of the milling tool.

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Table 6.8 Thirty set of histogram features extracted from the vibration signals

Face milling tool condition	Sample No.	Histogram features																					
		f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}	f_{17}	f_{18}	f_{19}	f_{20}	f_{21}	f_{22}	f_{23}	f_{24}	f_{25}	f_{26}
Healthy	1	2	4	1	42	12	32	83	1734	2915	4126	4820	4159	2881	1775	99	49	23	92	25	14	4	0
	2	1	5	2	47	14	39	88	1593	2792	4081	4956	4174	2829	1731	97	50	26	12	42	16	7	3
Flank wear	1	2	2	1	33	78	23	69	1423	2863	4383	5146	4566	3047	1753	81	33	14	51	13	2	0	0
	2	0	1	8	22	67	24	62	1482	2780	4436	5215	4688	3009	1686	82	33	12	33	12	1	0	0
Breakage	1	0	0	1	10	37	11	35	1011	2414	4755	6727	5404	2842	1260	47	14	44	6	2	0	0	0
	2	0	1	4	10	32	14	39	988	2446	4898	6469	5379	2795	1259	53	17	55	15	1	0	0	0
Chipping	1	0	0	1	4	19	77	34	1047	2389	4849	6613	5422	2984	1236	44	13	18	7	1	0	0	0
	2	0	0	0	2	19	94	31	1032	2450	4856	6609	5416	2929	1260	47	12	19	4	0	0	0	0

Some of the extracted feature values are having significant differences for different conditions of the milling tool. Selecting those features is an important task for effective classification and doing it manually demands more expertise; however, the effectiveness of the features is not guaranteed. By using a suitable algorithm, the best features are selected and also can yield better classification accuracy. The decision tree technique is a popular method for feature selection in the area of fault diagnosis.

6.3.2.1 Feature selection using decision tree

All extracted features are treated as an input to the decision tree for selecting the best features which helps to improve the classification accuracy of the diagnostic tool. The output of the decision tree is formed as a tree like structure as shown in Figure 6.5.

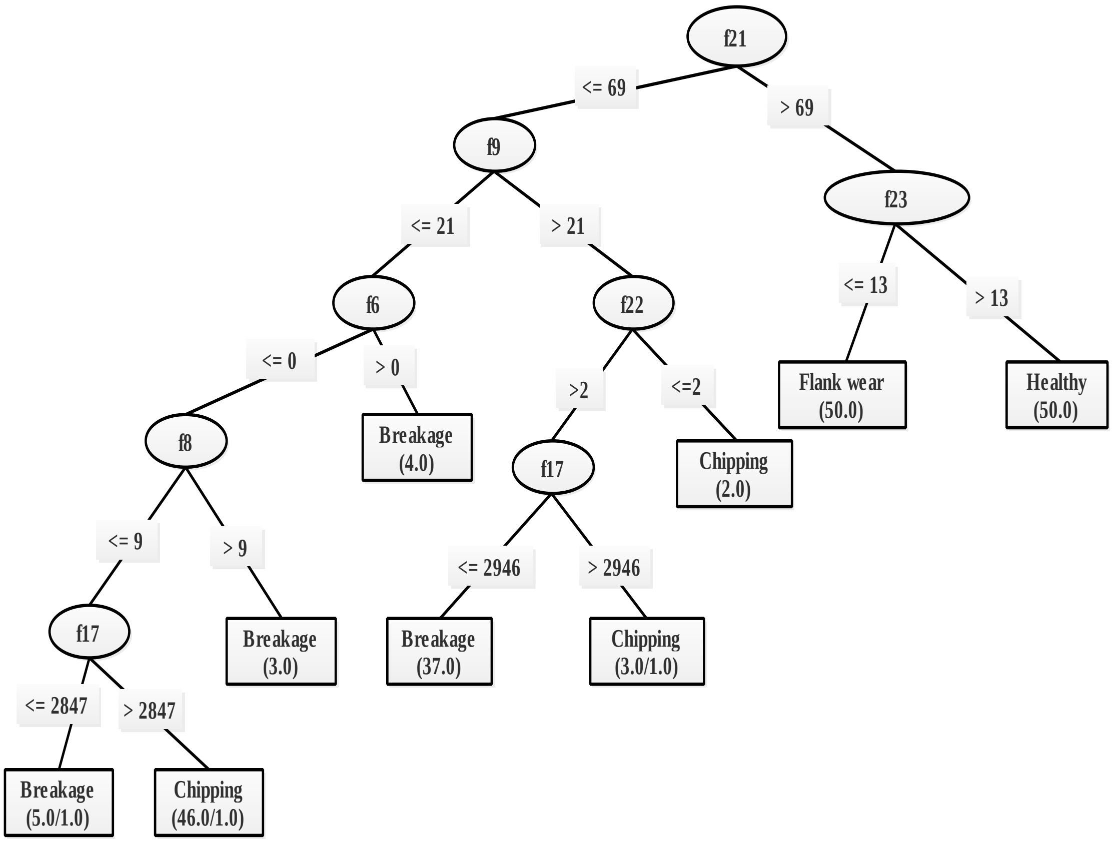

Figure 6.5 Decision tree for a set of thirty histogram features of vibration signal

The decision tree has been constructed for the set of thirty histogram features in such a way that when the feature f21 is greater than 69 and f23 is greater than 13, it is classified as 'healthy' face milling condition. When the feature f21 is greater than 69 and f23 is less than or equal to 13, then it is classified as 'flank wear' condition, and the remaining classes (breakage and chipping) have been organised in the tree when the feature f21 is attain less than or equal to 69. The features f6, f8, f9, f17, f21, f22 and f23 are selected as significant features from the tree and these features are used as an input to the classifier.

6.3.2.2 Classification

Classifications using histogram features with different classifiers were studied. The classifiers such as SVM, ANN, Naïve Bayes, decision tree and K-star models were used and their performances on histogram features are reported as follows.

- ***K-star algorithm***

In this study, K-star algorithm is used as a classifier to distinguish the face milling tool conditions. The selected features are fed to the model and the output of the classifier is the confusion matrix which illustrate the classification of different conditions of the face milling tool. The confusion matrix for the given set of histogram features (30 features) of vibration signals is as shown in Table 6.9.

Table 6.9 K-star confusion matrix for histogram features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	43	7	**c-Breakage**
0	0	0	50	**d- Chipping**

As seen from the confusion matrix, out of 200 instances, 7 instances were misclassified by a K-star algorithm with the overall classification accuracy 96.5% for the set of thirty histogram features. The classification efficiency of K-star model is considerably good and K-star with histogram features for fault diagnosis of the face milling tool is attractive.

- ***Naïve Bayes algorithm***

The confusion matrix of the Naïve Bayes model for the given set of histogram features (30 features) of vibration signals is as shown in Table 6.10. From the confusion matrix, 189 instances are correctly classified with classification efficiency of 94.5%. As the classification efficiency is considerably less as compared to the classification efficiency of the K-star model. The Naive Bayes algorithm with histogram features for fault diagnosis of the face milling tool is not very preferable.

Table 6.10 Naïve Bayes confusion matrix for histogram features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	1	41	8	**c-Breakage**
0	0	2	48	**d- Chipping**

- ***Artificial neural network***

The seven selected histogram features of vibration signals were set as an input to the ANN model. Table 6.11 depicts the confusion matrix of ANN.

Table 6.11 ANN confusion matrix for histogram features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	47	3	**c-Breakage**
0	0	6	44	**d- Chipping**

From the confusion matrix, it is observed that only nine instances were misclassified and the classification efficiency (about 95.5%) is considerably good, but still the accuracy of the classification by ANN is lesser than the K-star model (96.5%). Hence, the ANN classifier with histogram features for fault diagnosis of face milling tool is not considered.

- ***Support vector machine***

Table 6.12 depicts the confusion matrix of the SVM model with histogram features of 30 set. The confusion matrix which shows that the nine instances were misclassified. The classification efficiency of the SVM classifier is 95.5%, which indicates that the performance of the SVM classifier is lesser than the performance (96.5%) of the K-star classifier.

Table 6.12 SVM confusion matrix for histogram features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	44	6	**c-Breakage**
0	0	3	47	**d- Chipping**

- ***Decision tree algorithm***

J48 algorithm makes use of information gain and entropy for its classification. Its classification/confusion matrix is presented in Table 6.13.

Table 6.13 Decision tree confusion matrix for histogram features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
1	47	2	0	**b-Flank wear**
0	1	39	10	**c-Breakage**
0	0	4	46	**d- Chipping**

From the confusion matrix, one can observe that there are only eighteen misclassifications. The overall classification efficiency is found to be 91%. As the classification efficiency is considerably low when compared to K-star algorithm, decision tree technique (J48 algorithm) with histogram features for fault diagnosis of cutting tool is not preferable.

- ***Summary***

The histogram features were extracted from the acquired vibration signals and feature selection was performed using the decision tree (J48 algorithm) technique. The performances of the selected features set in fault classification has been presented. The summary of classification efficiencies of different classifiers with histogram features is as shown in Table 6.14. From the table, one can notice that the K-star model has performed well (96.5% classification efficiency) as compared to the performances of other classifiers mentioned in Table 6.14 in case of histogram features of vibration signals. Thus, K-star model with histogram feature extraction method can be preferred for fault diagnosis of the face milling tool.

Table 6.14 Summary of classification efficiencies of different classifiers for histogram features of vibration signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	94.5	91	95.5	95.5	**96.5**

6.3.3 Fault diagnosis using EMD features

Fifty samples of vibration signals pertaining to four different conditions of the face milling tool were acquired. These samples were analysed through the amplitude energy of IMFs using EMD technique. Sampling length of about 0.2 seconds were taken to plot IMFs. Figure 6.6 and Figure 6.7 illustrate the eight IMFs of different face milling tool conditions.

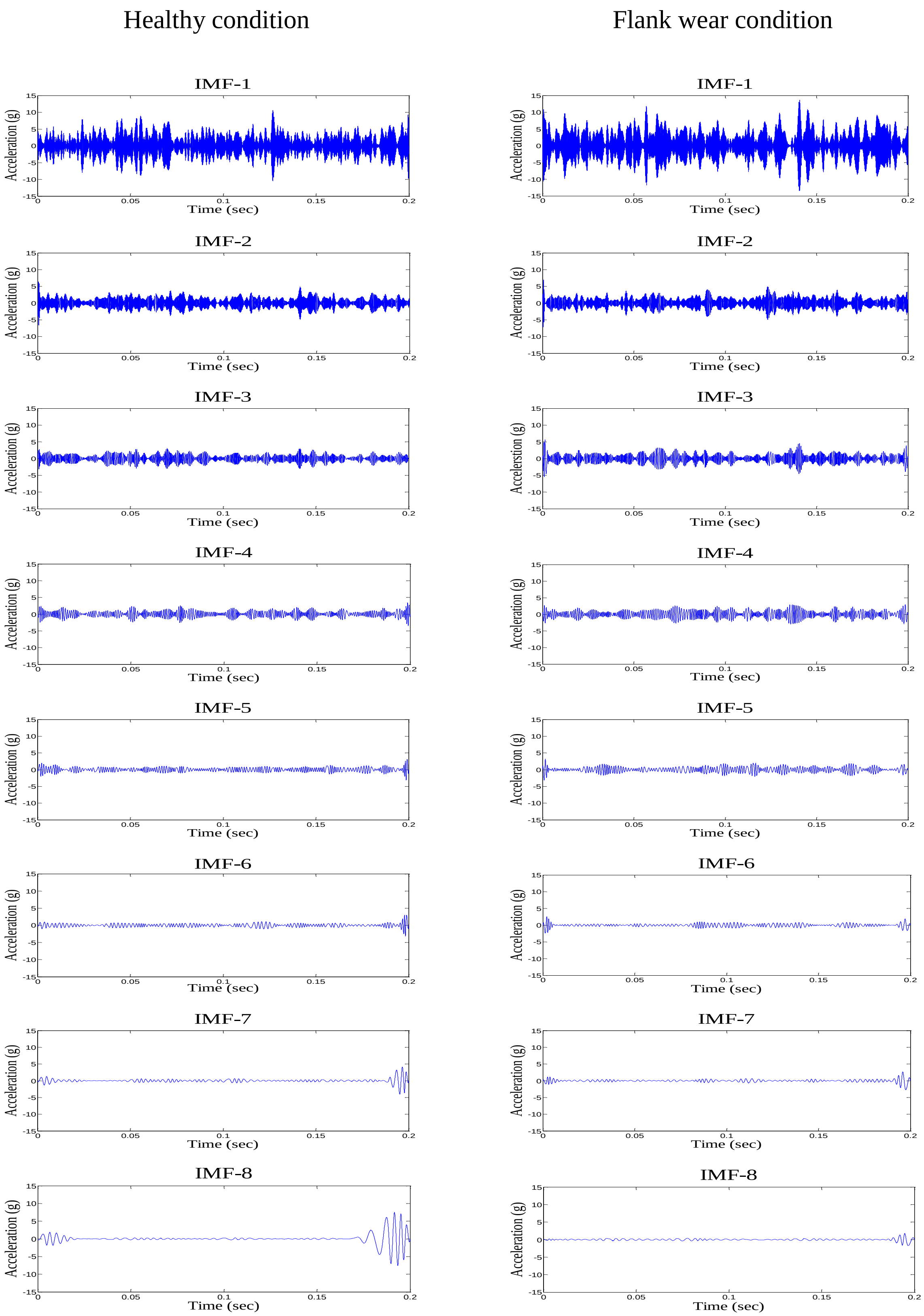

Figure 6.6 Eight IMFs of healthy and flank wear tool conditions

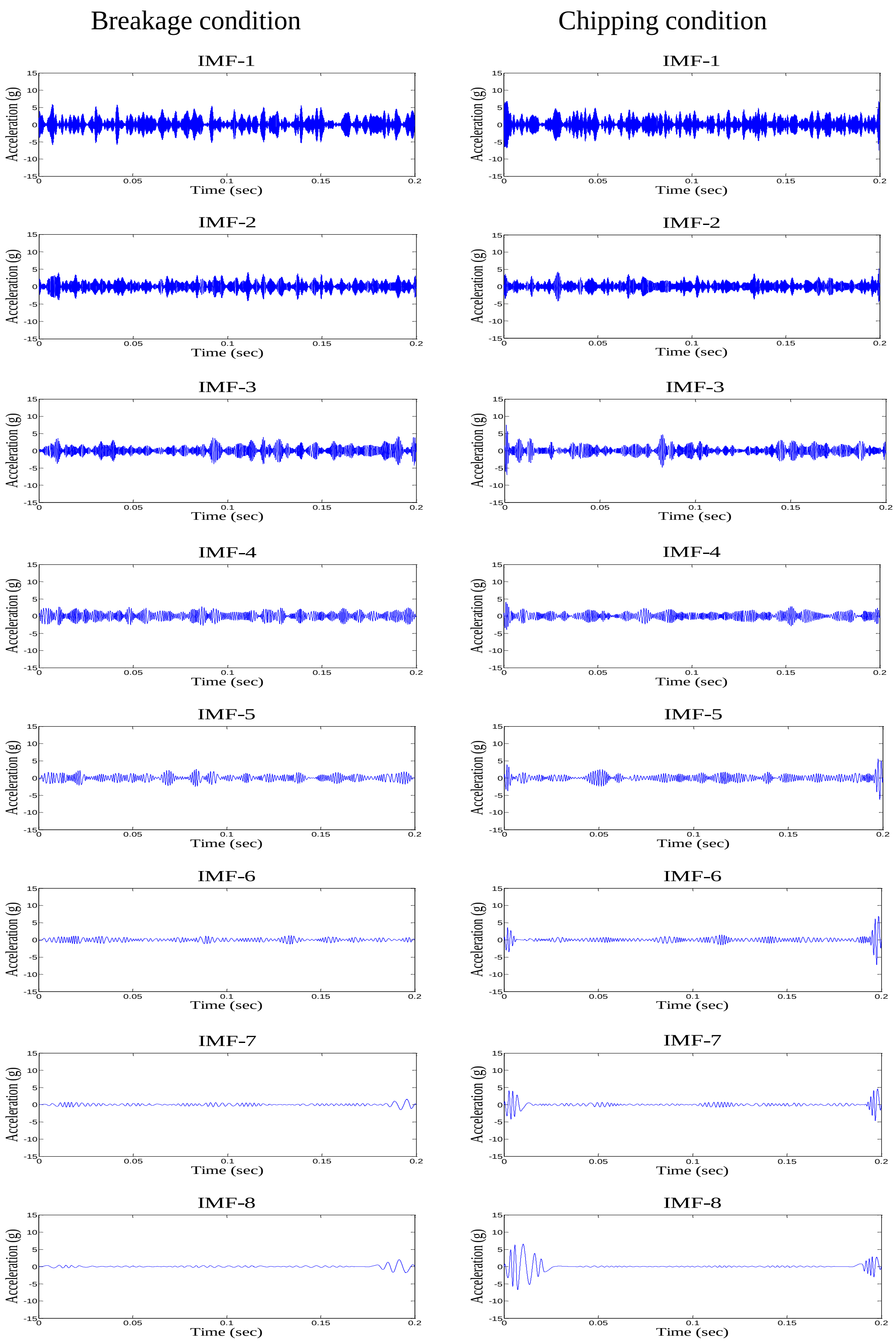

Figure 6.7 Eight IMFs of breakage and chipping tool conditions

In order to quantify these IMFs, amplitude energy is computed by using equation (3.10) and considered as an EMD feature. These EMD features of vibration signals pertaining to each class (two samples of each class) are tabulated in Table 6.15.

Table 6.15 EMD features of vibration signals

Face milling tool condition	Sample No.	EMD features							
		E1	E2	E3	E4	E5	E6	E7	E8
Healthy	1	0.9834	0.1409	0.0810	0.0611	0.0298	0.0183	0.0275	0.0275
	2	0.9733	0.1787	0.0983	0.0741	0.0437	0.0285	0.0382	0.0382
Flank wear	1	0.9365	0.2625	0.1847	0.1037	0.0711	0.0372	0.0373	0.0373
	2	0.9287	0.2852	0.1740	0.1258	0.0908	0.0353	0.0174	0.0174
Breakage	1	0.8457	0.3352	0.2909	0.2225	0.1673	0.0883	0.0359	0.0359
	2	0.7504	0.4302	0.3044	0.3024	0.2240	0.1011	0.0606	0.0606
Chipping	1	0.6980	0.3530	0.4284	0.2916	0.2629	0.1739	0.1004	0.1004
	2	0.7739	0.2920	0.4012	0.2378	0.1108	0.1129	0.1913	0.1913

6.3.3.1 Feature selection by decision tree

All EMD features represent the characteristics of a signal, out of which some features provide enough information than others. Hence, all EMD features are fed to the decision tree (J48 algorithm) for the selection of the best features. Figure 6.8 depicts the decision tree for EMD features of vibration signals. It has formed a tree like structure such that when E3 is less than or equal to 0.135002, then it classified as healthy condition. Also, if E3 lies in between 0.135002 and 0.221872, then it is classified as flank wear condition and so on. The decision tree for EMD features is as shown in Figure 6.8 and it provided E1, E3, E6 and E7 as salient features. The classification will be carried out using these selected features.

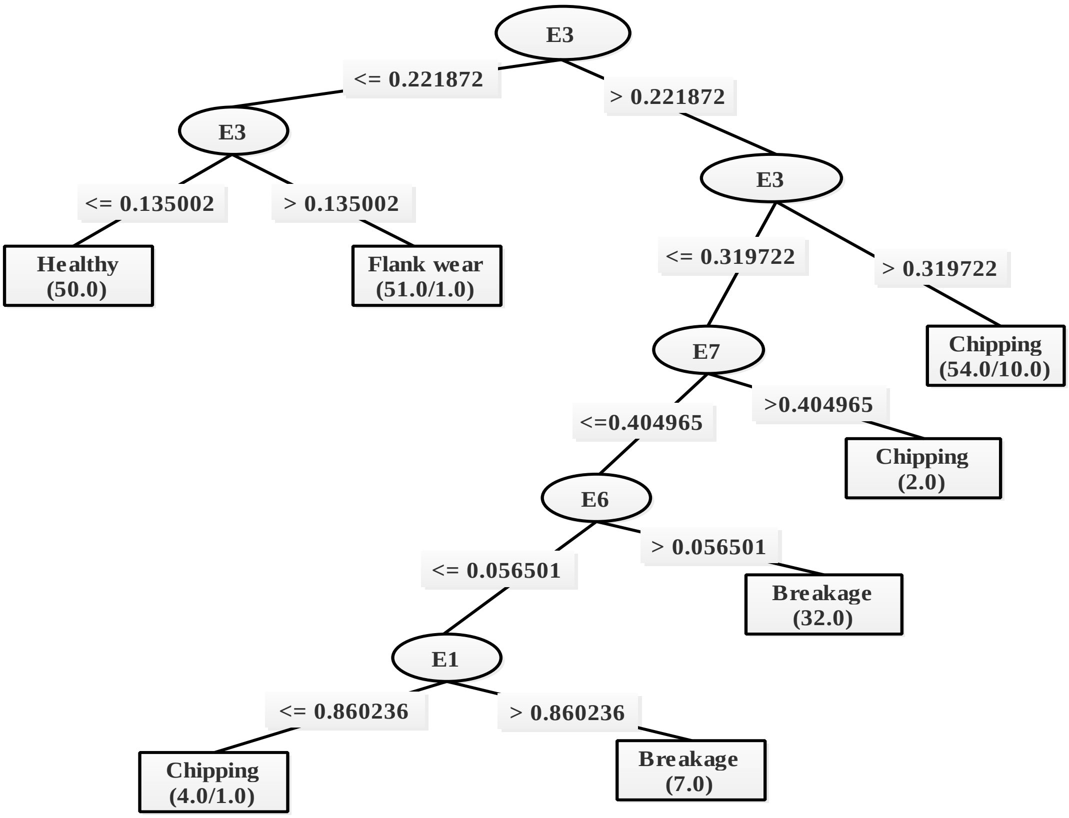

Figure 6.8 Decision tree for EMD features of vibration signal

5.3.3.2 Classification

The analysis of EMD features of vibration signals using classifiers such as SVM, ANN, Naïve Bayes, decision tree and K-star models has been carried out. The selected features such as E1, E3, E6 and E7 of all conditions of a face milling tool are the input to the classifiers. The test mode of the classifier is 10-fold cross validation, which has been considered for the analysis. The results in the form of confusion matrix from each classifiers are reported as follows.

- ***Artificial neural network***

The confusion matrix for vibration signals of the face milling tool is as shown in Table 6.16. A data set of 200 samples consists of 50 samples from each class. From Table 6.16, out of 200 instances, 23 instances were misclassified by ANN model with classification accuracy about 88.5% for the given vibration signals.

Table 6.16 ANN confusion matrix for EMD features of vibration signals

a	**b**	**c**	**d**	**Class**
48	1	0	1	**a-Healthy**
1	47	2	0	**b-Flank wear**
0	1	39	10	**c-Breakage**
0	0	7	43	**d- Chipping**

- ***Decision tree algorithm***

The decision tree (J48 algorithm) confusion matrix is as shown in Table 6.17. From the confusion matrix, 175 instances were correctly classified with classification efficiency of 87.5%. As the classification efficiency is considerably good, but it is lesser than the ANN model. Hence, the decision tree with EMD features for fault diagnosis of milling tool is not attractive.

Table 6.17 J48 confusion matrix for EMD features of vibration signals

a	**b**	**c**	**d**	**Class**
49	1	0	0	**a-Healthy**
0	49	1	0	**b-Flank wear**
0	0	40	10	**c-Breakage**
0	1	12	37	**d- Chipping**

- ***Naïve Bayes algorithm***

The selected four EMD features were the input to the Niave Bayes model. Table 6.18 depicts the Naïve Bayes classification.

Table 6.18 Naïve Bayes confusion matrix for EMD features of vibration signals

a	**b**	**c**	**d**	**Class**
48	1	0	1	**a-Healthy**
0	49	0	1	**b-Flank wear**
0	2	42	6	**c-Breakage**
0	1	14	35	**d- Chipping**

From the confusion matrix, 28 instances were misclassified out of 200 instances. The overall classification efficiency is found to be 87%. As the classification efficiency is considerably low as compared to ANN classifier, thus Naïve Bayes classifier with EMD features for fault diagnosis of milling tool is not preferable.

- ***K-star algorithm***

The K-star results are presented in the form of confusion matrix as shown in the Table 6.19.

Table 6.19 K-star confusion matrix for EMD features of vibration signals

a	**b**	**c**	**d**	**Class**
49	1	0	0	**a-Healthy**
0	49	1	0	**b-Flank wear**
0	0	38	12	**c-Breakage**
0	0	13	37	**d- Chipping**

From the confusion matrix, 27 instances were misclassified out of 200 instances. The overall classification efficiency is found to be 86.5%, which is lesser than all classifiers. Hence, the K-star model with EMD features for fault diagnosis of the face milling tool is not considered.

- ***Support vector machine***

The four selected EMD features of vibration signals are given as an input to the SVM model. The identified classification efficiency as confusion matrix is presented in Table6.20.

Table 6.20 SVM confusion matrix for EMD features of vibration signals

a	**b**	**c**	**d**	**Class**
49	1	0	0	**a-Healthy**
1	48	1	0	**b-Flank wear**
0	2	41	7	**c-Breakage**
0	0	12	38	**d- Chipping**

From the confusion matrix of SVM classifier with EMD features, it is found that only 24 instances were misclassified and the classification efficiency is about 88%. The classification efficiency of SVM is good for fault diagnosis, but lesser than ANN model. Thus SVM model with EMD features are not preferred.

- ***Summary***

The EMD features were extracted from the acquired vibration signals and feature selection was performed using decision tree (J48 algorithm) technique. The performances of the selected features set in fault classification was presented. The summary of classification efficiencies of different classifiers with EMD features is as shown in Table 6.21. From the table, one can notice that the ANN model has performed well (88.5% classification efficiency) as compared to the performances of other classifiers mentioned in Table 6.21 in case of EMD features of vibration signals.

Table 6.21 Summary of classification efficiencies of different classifiers for EMD features of vibration signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	87	87.5	**88.5**	88	86.5

6.3.4 Fault diagnosis using DWT features

Discrete wavelet transform method is used to analyse the vibration signals. It decomposes the given signal into two components; high frequency component and low frequency component. The low frequency component will be discretised further. The high frequency component at every step of discretisation is treated as a feature in DWT method. From the acquired vibration signals, eight discrete wavelet features (V1, V2… V8) were extracted for each class of the face milling tool. Table 6.22 shows the discrete wavelet features using the DWT, out of 50 samples only two samples relating to each condition of the tool are tabulated. These features were treated as an input to the decision tree for the selection of the salient features which provide best classification accuracy.

Table 6.22 Discrete wavelet features of vibration signals

Face milling tool condition	Sample No.	Wavelet coefficient							
		V1	V2	V3	V4	V5	V6	V7	V8
Healthy	1	6.12	27.8	30.3	17.1	13.7	5.52	2.14	1.24
	2	6.34	29.0	31.7	19.0	13.7	5.96	2.67	1.35
Flank wear	1	4.58	21.6	26.5	20.4	13.0	5.67	2.44	1.36
	2	4.47	20.8	25.1	20.2	12.7	6.03	1.81	1.36
Breakage	1	2.63	12.0	18.7	21.7	15.1	5.52	2.49	1.31
	2	2.67	12.4	19.7	22.4	13.2	5.67	2.80	1.46
Chipping	1	2.26	10.6	16.8	20.5	12.6	5.48	2.17	1.37
	2	2.20	10.2	17.0	19.4	11.9	5.37	2.71	1.27

6.3.4.1 Feature selection by decision tree

Decision tree technique (J48 algorithm) was used for feature selection, all extracted wavelet features pertaining to four classes were fed to the algorithm and formed decision tree as depicted in Figure 6.9. The rectangular blocks indicate classes (condition of the tool). With reference to Figure 6.9, V2 feature is a root node of the tree, based on this feature (V2) the tree structure was carried out. When V2 value is greater than 21.6, it is classified as a healthy condition, while the V2 value is greater than 12.7 and less than or equal to 21.6 it is classified as a flank wear and so on. The five features such as V1, V2, V3, V5 and V6 were selected out of eight wavelet features from the decision tree. The detailed accuracy classification is discussed in the following section.

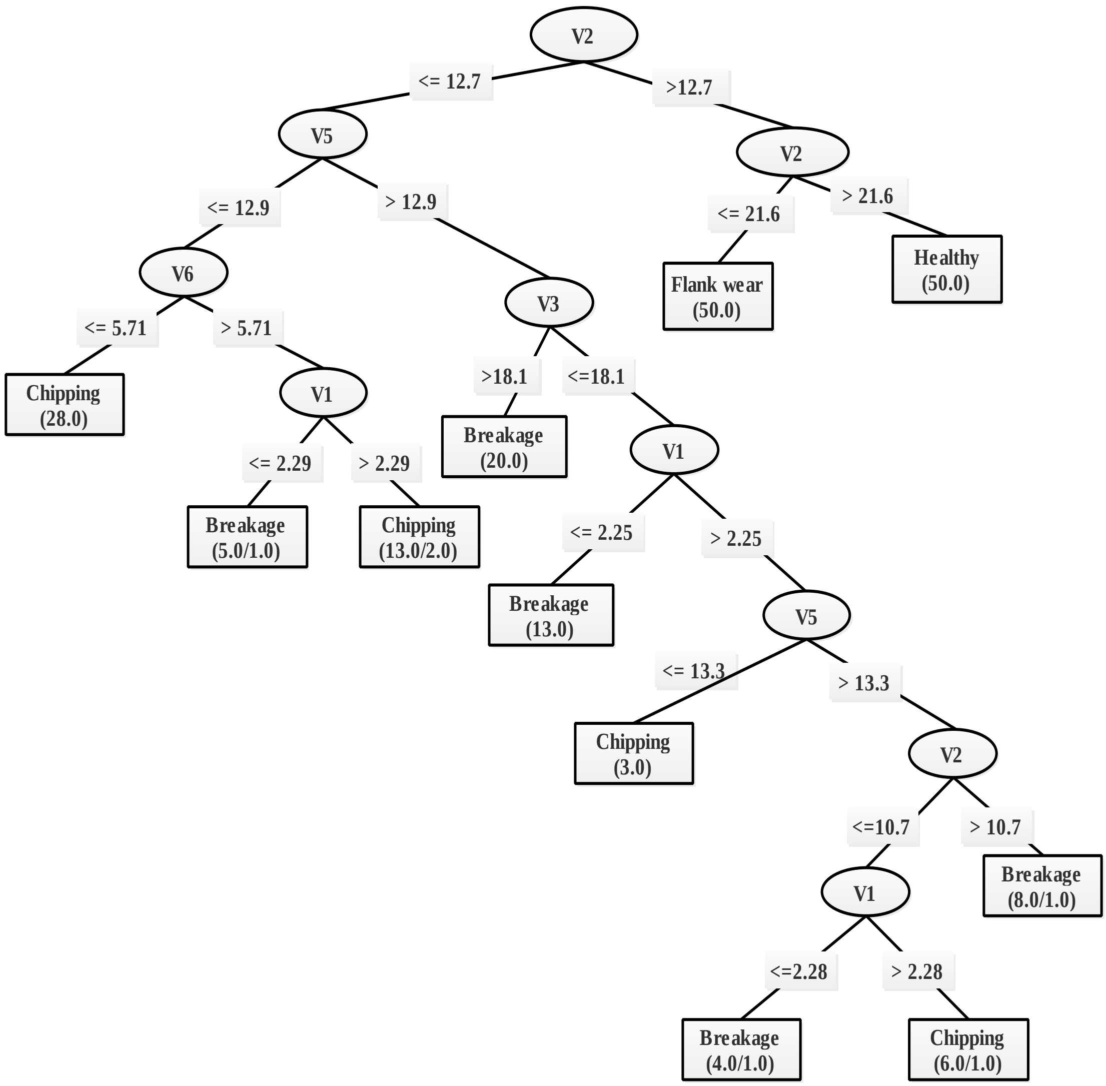

Figure 6.9 Decision tree of DWT features of vibration signal

6.3.4.2 Classification

The selected wavelet features were treated as an input and fed to the classifiers such as SVM, ANN, Naïve Bayes, Decision tree and K-star models. The results obtained from the models were analysed and discussed below.

- ***Support vector machine***

The selected wavelet features such as V1, V2, V3, V5 and V6 were treated as an input to the SVM models. The confusion matrix by the SVM model for DWT features of vibration signals is as shown in Table 6.23.

Table 6.23 SVM confusion matrix for DWT features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	42	8	**c-Breakage**
0	0	9	41	**d- Chipping**

Table 6.23 shows the classification of face milling tool conditions by the SVM classifier with 183 out of 200 instances were correctly classified and the classifier provided a classification accuracy of about 91.5 %. The classification accuracy obtained by the SVM model can be considered for fault diagnosis.

- ***Naïve Bayes algorithm***

The Naïve Bayes model is used to classify the different conditions of the milling tool using selected DWT features of vibration signals. The confusion matrix from the model represents the classification as shown in Table 6.24. From the confusion matrix, only 18 instances, out of 200 instances were misclassified and the classification efficiency is found to be 91%. Obtained classification efficiency can be accepted for fault diagnosis, but it is lesser than the classification efficiency (91.5%) of the SVM classifier. Thus, the combination of the Naïve Bayes model and DWT features for fault diagnosis of the face milling tool is not preferable.

Table 6.24 Naïve Bayes confusion matrix for DWT features of vibration signal

a	**b**	**c**	**d**	**Class**
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	40	10	**c-Breakage**
0	0	8	42	**d- Chipping**

- ***Decision tree algorithm***

Table 6.25 depicts the confusion matrix by the decision tree algorithm using selected DWT features of the vibration signals.

Table 6.25 Decision tree confusion matrix for DWT features of vibration signal

a	b	c	d	Class
50	0	0	0	**a-Healthy**
1	49	0	0	**b-Flank wear**
0	1	36	13	**c-Breakage**
0	0	11	39	**d- Chipping**

From the confusion matrix, one can observe that there are 174 out of 200 instances correctly classified. The overall classification efficiency is found to be 87%. As the classification efficiency is considerably low when compared to SVM and Naïve Bayes algorithms, decision tree technique (J48 algorithm) with DWT features for fault diagnosis of cutting tool is not preferable.

- ***Artificial neural network***

Table 6.26 illustrates confusion matrix of the ANN classifier. From the confusion matrix, 182 instances were correctly classified with classification efficiency of 91%. As the classification efficiency is considerably low when compared to SVM classifier, the ANN algorithm with DWT features for fault diagnosis of milling tool is not appropriate.

Table 6.26 ANN confusion matrix for DWT features of vibration signal

a	b	c	d	Class
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	43	7	**c-Breakage**
0	0	11	39	**d- Chipping**

- ***K-star algorithm***

The confusion matrix which represents the classification of the face milling tool conditions using DWT features is as shown in Table 6.27. From the confusion matrix, only twenty three instances were misclassified. As the classification efficiency is about

88.5% which is lesser than the classification efficiency (91.5%) of SVM model. Hence, the K-star with DWT features for fault diagnosis of milling tool is not preferable.

Table 6.27 K-star confusion matrix for DWT features of vibration signal

a	b	c	d	Class
50	0	0	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
0	0	35	15	**c-Breakage**
0	0	8	42	**d- Chipping**

- ***Summary***

The DWT features were extracted from the acquired vibration signals and feature selection was performed using decision tree (J48 algorithm) technique. The performances of the selected features set in fault classification was presented. The summary of classification efficiencies of different classifiers with DWT features is as shown in Table 6.28. From the table, one can notice that the SVM model has performed well with 91.5% classification efficiency when compared to the performances of other classifiers.

Table 6.28 Summary of classification efficiencies of different classifiers for DWT features of vibration signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	91	87	91	**91.5**	88.5

6.3.5 Overall conclusion from the vibration signal analysis based on machine learning approach

The comparison of performances of classifiers and different features extraction methods which are used in the study of fault diagnosis of the face milling tool using vibration signals is as shown in Table 6.29.

Table 6.29 Comparison of classification accuracies of the classifiers with different features

Feature	Feature selection	Classifier	Correctly classified instances	Incorrectly classified instances	Classification accuracy
Statistical	Decision tree	**Naïve Bayes**	**194**	**06**	**97.0%**
		SVM	190	11	95.0%
		ANN	191	09	95.5%
		K-star	191	12	95.5%
		J48	187	13	93.5%
Histogram		Naïve Bayes	189	11	94.5%
		SVM	191	09	95.5%
		ANN	191	09	95.5%
		K-star	193	07	96.5%
		J48	182	18	91.0%
Empirical mode decomposition		Naïve Bayes	174	26	87.0%
		SVM	176	24	88.0%
		ANN	177	23	88.5%
		K-star	173	27	86.5%
		J48	175	25	87.5%
Discrete wavelet transform		Naïve Bayes	182	18	91.0%
		SVM	183	11	91.5%
		ANN	182	18	91.0%
		K-star	177	23	88.5%
		J48	174	26	87.0%

From Table 6.29, one can say that the Naïve Bayes model has employed a maximum classification accuracy of about 97% with statistical features as compared to other classifiers with any features extraction techniques listed in the table. Also the combination of K-star model with histogram feature technique has provided a good classification accuracy of about 96.5%, which is nearer to the highest classification accuracy 97% (obtained by the Naïve Bayes model with the statistical features). However, the performance (96.5% classification accuracy) by the K-star model with histogram features can also be considered for fault diagnosis, but this combination takes more time to compute the histogram features when compared to the combination of the Naïve Bayes classifier and statistical features. Hence, the Naïve Bayes technique can be chosen as a best classifier with statistical features method and can be suggested for fault diagnosis of the face milling tool using vibration signals.

6.4 SUMMARY

This chapter has mainly presented the details of the machine learning techniques which are used in the present study. Feature extraction method such as statistical, histogram, DWT and EMD methods were elaborated, then followed by the explanation about features selection method such as decision tree technique. Further classifiers such as ANN, SVM, Naïve Bayes, decision tree and K-star models were used for classification. Also the analysis of vibration signals using machine learning techniques in fault diagnosis of the face milling tool was explained thoroughly with the usage of statistical, histogram, EMD and DWT features and concluded with best classifier-feature combination.

CHAPTER-7

FAULT DIAGNOSIS USING MACHINE LEARNING TECHNIQUES BASED ON SOUND SIGNAL

7.1 OVERVIEW

In this chapter, an investigation of sound signals of the face milling process in fault detection and classification of the face milling tool conditions has been carried out using machine learning technique. Obtained results from the experiments are analysed and discussed using different features and different artificial intelligence techniques. Each section will give the detailed description of the fault diagnosis of the face milling tool based on different features.

7.2 FAULT DIAGNOSIS USING SOUND SIGNALS BASED ON MACHINE LEARNING APPROACH

Fault diagnosis of the face milling tool using sound signal based on machine learning approach was carried out. The acquired sound signals under different face milling tool conditions were used to extract some features such as, statistical features, histogram features, EMD features and DWT features. Then feature selection was carried out using decision tree technique. Classification of the face milling tool was carried out based on selected features using classifiers such as Naïve Bayes, SVM, ANN, K-star and J48 (decision tree) algorithms.

7.2.1 Fault diagnosis using statistical features

A set of descriptive statistical features are extracted from the sound signals. Table 7.1 illustrates the statistical features of two signal samples per each condition of the face milling tool.

Table 7.1 Extracted statistical features from the sound signals

Class	Sample No.	Values											
		Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum
Healthy	1	0.0047	0.0021	-0.0008	-0.1173	0.3380	0.1142	0.2875	0.0509	3.1001	-1.3385	1.7617	119.8537
	2	0.0045	0.0021	0.0014	0.1332	0.3396	0.1153	0.1079	0.0848	2.9797	-1.4425	1.5372	115.9749
Flank wear	1	0.0031	0.0023	0.0044	0.4839	0.3695	0.1365	0.1911	0.0012	3.0104	-1.5726	1.4379	79.4889
	2	0.0030	0.0023	0.0048	0.0045	0.3726	0.1388	-0.0072	0.0144	2.7904	-1.4182	1.3722	77.5929
Breakage	1	0.0033	0.0022	0.0031	0.3900	0.3506	0.1229	0.2305	0.0064	3.3660	-1.8440	1.5220	85.4592
	2	0.0036	0.0021	0.0005	0.1677	0.3425	0.1173	0.1100	0.0426	2.9428	-1.3021	1.6407	92.2724
Chipping	1	0.0029	0.0025	0.0059	0.0532	0.3921	0.1538	0.1172	-0.0359	3.4112	-1.6874	1.7238	74.1537
	2	0.0024	0.0024	0.0015	0.0996	0.3867	0.1496	0.2311	0.0195	3.4268	-1.7139	1.7129	61.7769

7.2.1.1 Feature selection using decision tree

The given data set of 200 samples fed to the J48 algorithm (decision tree) and the output of the decision tree is a set of significant features as illustrated in Figure 7.1. Observation shows that out of 12 features, nine features are selected by J48 algorithm such as mean, kurtosis, median, mode, standard deviation, skewness, maximum, minimum and standard error which are the significant features. These selected features are treated as an input to the classifier. The detailed classification of the tool conditions using different classifiers is illustrated in the following section.

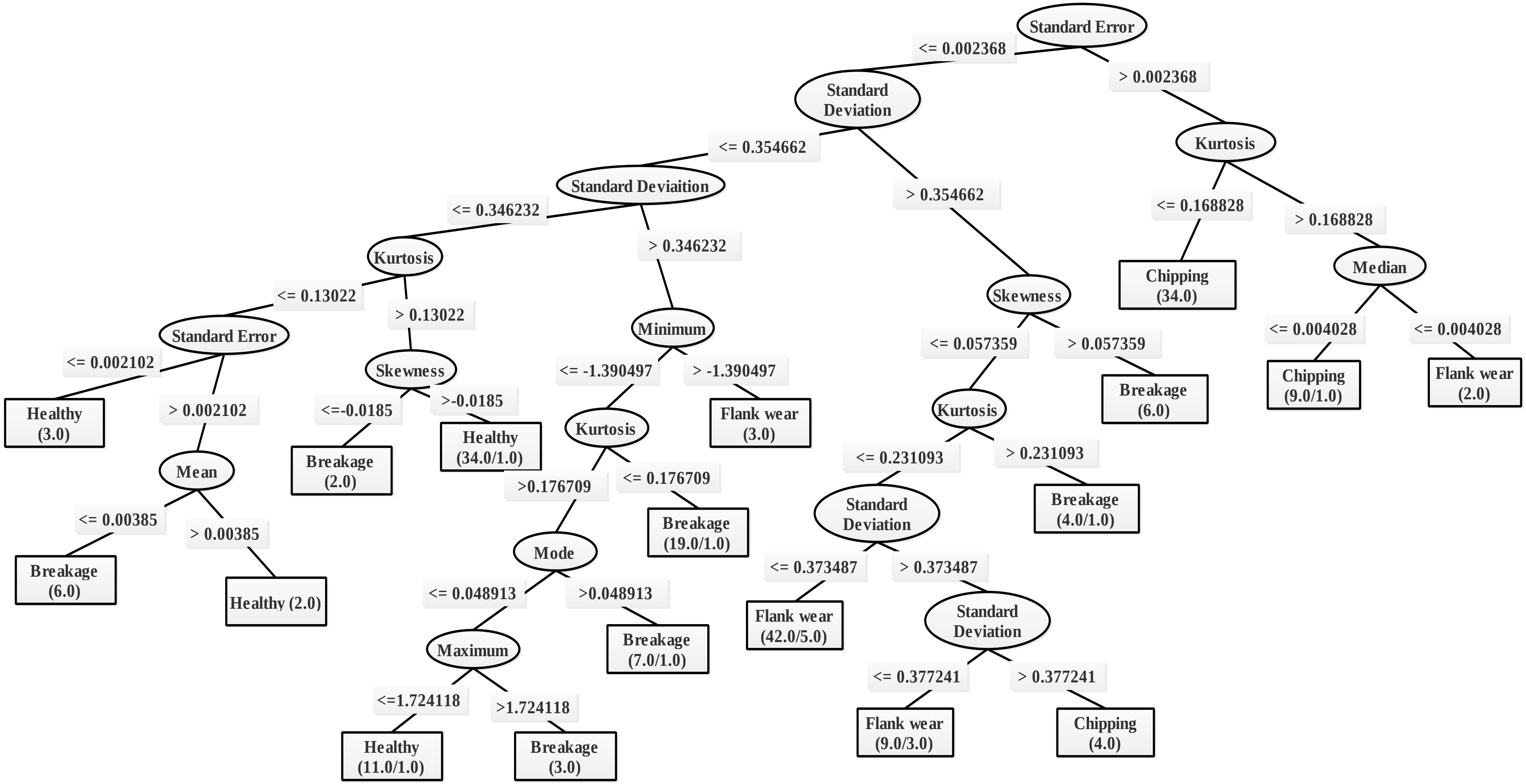

Figure 7.1 Decision tree for statistical features of sound signal

7.2.1.2 Classification

The classification of the face milling tool conditions have been carried out using selected features. The different classifiers such as ANN, SVM, Naïve Bayes, decision tree and K-star algorithms are used to distinguish the different milling tool conditions. The performance of each classifier are reported as follows.

- ***Support vector machine***

SVM is an emerging classifier in fault diagnosis. Table 7.2 shows the confusion matrix of the SVM classifier and the diagonal elements represent the correctly classified instances.

Table 7.2 SVM confusion matrix for statistical features of sound signals

a	**b**	**c**	**d**	
33	0	17	0	**a-Healthy**
0	42	6	2	**b-Flank wear**
15	10	25	0	**c-Breakage**
0	10	0	40	**d- Chipping**

From the confusion matrix, out of 200 instances, 60 instances were misclassified by a SVM algorithm with the overall classification accuracy of about 70% for the given sound signals. The classification accuracy is very low, thus the SVM classifier with statistical features is not preferred for fault diagnosis of the face milling tool.

- ***Artificial neural network***

ANN is one of the classifiers in the area of fault diagnosis/condition monitoring. The salient statistical features were fed to the ANN classifier and classification of the milling tool is represented as a confusion matrix as shown in Table 7.3. From the confusion matrix, out of 200 instances, 140 instances were correctly classified and the classification accuracy was found to be 70% which is quite low for fault diagnosis. Hence, the ANN with statistical features combination based on sound signals is not preferable for condition monitoring of the face milling tool.

Table 7.3 ANN confusion matrix for statistical features of sound signals

a	**b**	**c**	**d**	
37	0	13	0	**a-Healthy**
0	32	10	8	**b-Flank wear**
16	10	24	0	**c-Breakage**
0	3	0	47	**d- Chipping**

- ***Naïve Bayes algorithm***

The selected features of sound signals were used to classify the face milling tool conditions using the Naïve Bayes model. Table 7.4 depicts the confusion matrix by the model which illustrate the classification of the tool conditions.

Table 7.4 Naïve Bayes confusion matrix for statistical features of sound signals

a	**b**	**c**	**d**	
36	0	14	0	**a-Healthy**
0	37	7	6	**b-Flank wear**
17	10	23	0	**c-Breakage**
0	9	0	41	**d- Chipping**

From the confusion matrix, 63 out of 200 instances were misclassified by the classifier and the overall classification accuracy was about 68.5% which is very less for fault diagnosis. Thus, the combination of Naïve Bayes and statistical features of sound signal is not attractive in fault diagnosis of the face milling tool.

- ***Decision tree algorithm***

The decision tree (J48 algorithm) confusion matrix is as shown in Table 7.5. From the confusion matrix, 141 instances were correctly classified with classification efficiency of 70.5%. Since the classification efficiency is considerably low, the decision tree with statistical features is not considered for fault diagnosis of the face milling tool.

Table 7.5 J48 confusion matrix for statistical features of sound signal

a	b	c	d	Class
34	2	14	0	**a-Healthy**
0	36	9	5	**b-Flank wear**
16	9	25	0	**c-Breakage**
0	4	0	46	**d- Chipping**

- ***K-star algorithm***

K-star algorithm has performed the classification of the face milling tool conditions using selected statistical features of the sound signals. Table 7.6 illustrates the confusion matrix of the K-star model for statistical features.

Table 7.6 K-star confusion matrix for statistical features of sound signal

a	b	c	d	Class
28	3	19	0	**a-Healthy**
1	34	6	9	**b-Flank wear**
14	8	27	1	**c-Breakage**
0	13	1	36	**d- Chipping**

From Table 7.6, 125 out of 200 instances were correctly classified and the classification accuracy was found to be 62.5% which is very less for fault diagnosis. Hence, the K-star model with statistical features is not preferable for fault diagnosis.

- ***Summary***

The statistical features were extracted from the acquired sound signals and feature selection was performed using decision tree technique. The performances of the different classifiers were analysed using selected features and the summary of classification efficiencies of different classifiers is as shown in Table 7.7. From the table, one can notice that, all the classification accuracies are found to be low which cannot be acceptable for fault diagnosis. Hence, none of the classifiers with statistical feature of sound signals is preferred for fault diagnosis of the face milling tool.

Table 7.7 Summary of classification efficiencies of different classifiers for statistical features of sound signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	68.5	70.5	70	70	62.5

7.2.2 Fault diagnosis using histogram features

Histogram features are another set of time domain signal features and the extracted histogram features are used to diagnose the faults in machine tool/process. In the present study, the histogram features were extracted from the acquired sound signals and the analysis was carried out based on the machine learning approach. Figure 7.2 shows the histogram plots of the sound signals of face milling tool under different conditions (healthy, flank wear, breakage and chipping).

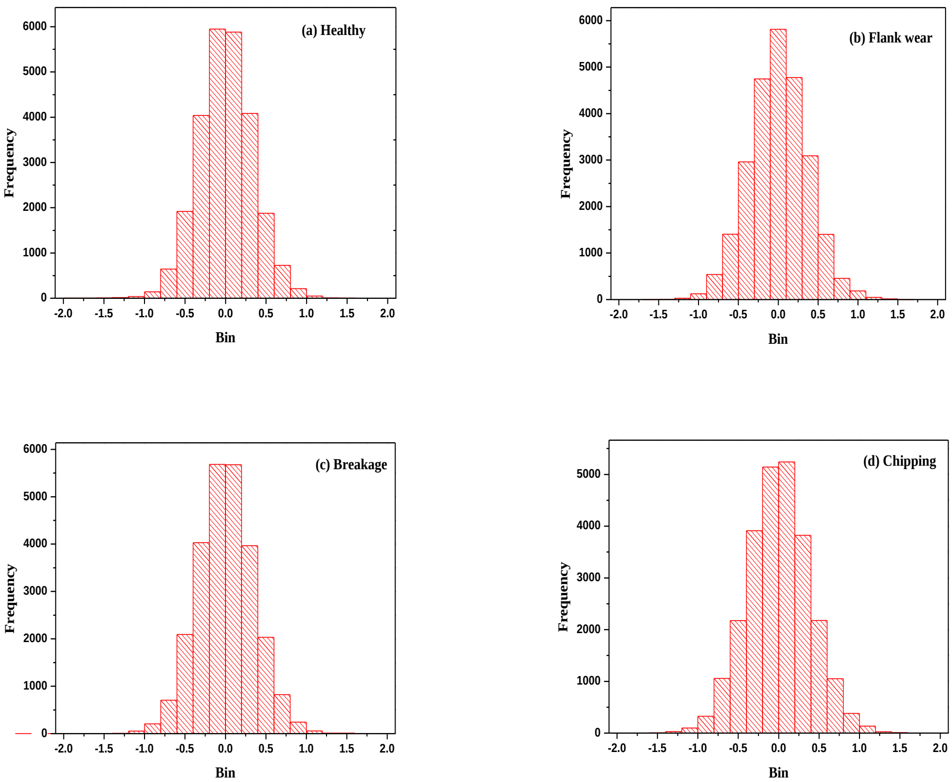

Figure 7.2 Histogram plots of sound signals for different conditions of the face milling tool

Twenty different sets (2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 25, 30, 40, 50, 60, 70, 80, 90 and 100) of histogram features were extracted from the sound signals. Each set of features were treated as an input to the classifier and the results from the classifier were analysed. The set of 50 features has provided better results for classifying the face milling tool when compared with other sets of histogram features. The performances of the classifiers for the 50 set of histogram features with decision tree as a feature selection method are explained in the following sections.

7.2.2.1 Feature selection using decision tree

The extracted fifty set of histogram features were used as input to the decision tree algorithm. The output from the algorithm is tree based structure as shown in Figure 7.3.

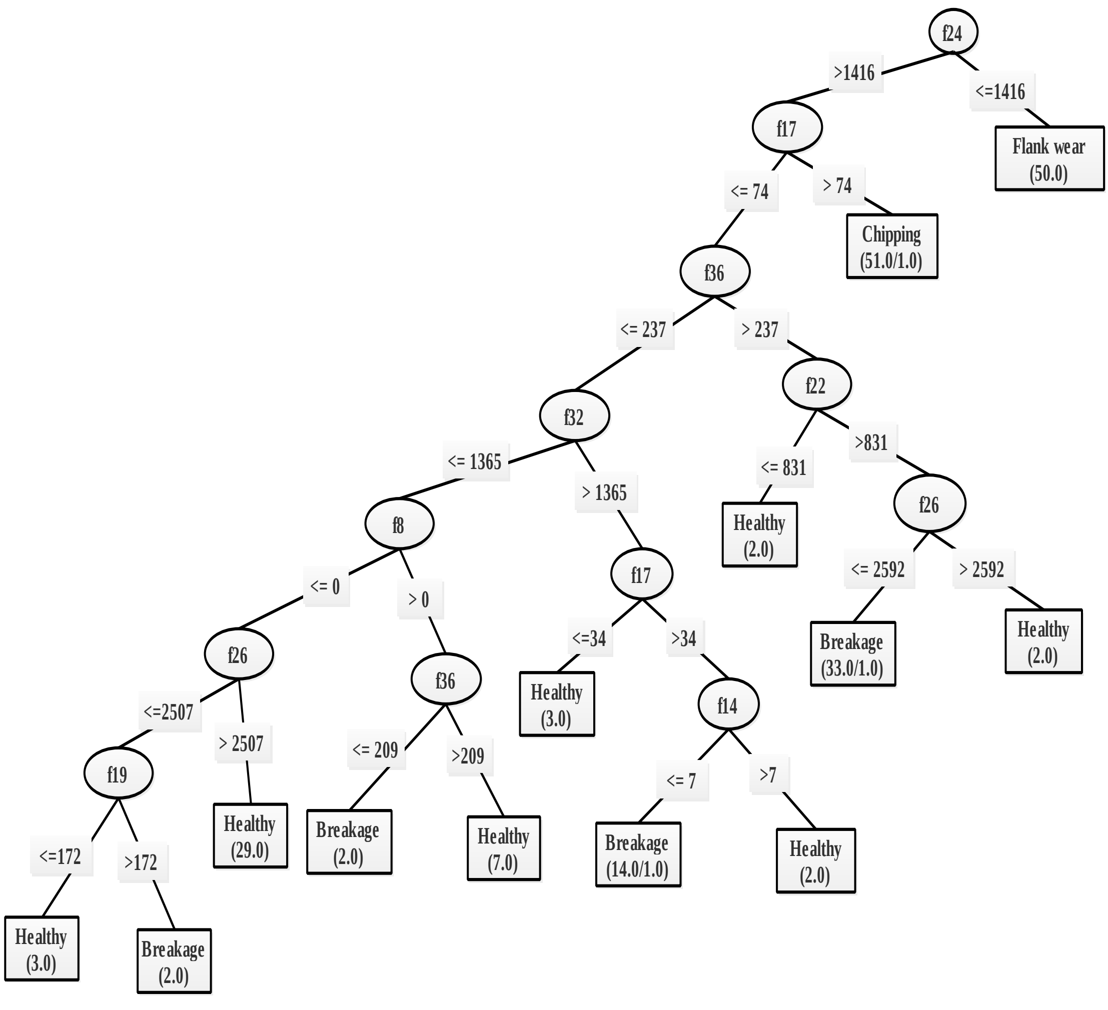

Figure 7.3 Decision tree for the 50 set of histogram features of sound signal

From Figure 7.3, f24 feature is the root node, based on the value of f24, the tree has been formed and the output from the tree are the salient features such as f8, f14, f17, f19, f22, f24, f26, f32 and f36. These selected features will be used as input to the classifiers.

7.2.2.2 Classification

Fault classification using histogram features of sound signals with different classifiers were studied. The performances of the classifiers such as Naïve Bayes, decision tree, SVM, ANN, and K-star models on histogram features in face milling tool condition monitoring are reported as follows.

- ***Decision tree algorithm***

The selected features were used as input to the J48 algorithm for fault classification of the face milling tool. The confusion matrix of the decision tree with histogram features is depicted in Table 7.8. From the confusion matrix, out of 200 instances, only 28 instances were misclassified and the classification efficiency was found to be 86%. The decision tree algorithm has provided a good classification efficiency which can be acceptable for fault diagnosis.

Table 7.8 Decision tree confusion matrix for histogram features of sound signal

a	**b**	**c**	**d**	**Class**
34	0	16	0	**a-Healthy**
0	49	1	0	**b-Flank wear**
7	0	40	3	**c-Breakage**
0	0	1	49	**d- Chipping**

- ***Naïve Bayes algorithm***

The confusion matrix with Naïve Bayes algorithm as classifier is given in Table 7.9. Observation shows that the Naïve Bayes algorithm has provided a misclassification of about 29 out of 200 instances and classification accuracy of about 85.5% for the given sound signals. The classification efficiency is less when compared with the decision tree technique, thus the Naïve Bayes algorithm with histogram features is not preferable for fault diagnosis of the face milling tool.

Table 7.9 Naïve Bayes confusion matrix for histogram features of sound signal

a	**b**	**c**	**d**	**Class**
38	0	12	0	**a-Healthy**
0	49	0	1	**b-Flank wear**
15	0	34	1	**c-Breakage**
0	0	0	50	**d- Chipping**

- ***Artificial neural network***

The nine selected histogram features of sound signals were used as input to the ANN algorithm. Table 7.10 illustrates the confusion matrix by ANN classifier with histogram features.

Table 7.10 ANN confusion matrix for histogram features of sound signal

a	**b**	**c**	**d**	**Class**
30	0	20	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
15	0	35	0	**c-Breakage**
0	0	0	50	**d- Chipping**

From the confusion matrix, it can be noticed that only 35 instances were misclassified and the classification efficiency of about 82.5% is considerably good, but still the accuracy of the classification by ANN is lesser than the K-star algorithm (86%). Hence, the ANN classifier with histogram features for fault diagnosis of face milling tool is not considered.

- ***Support vector machine***

Nine selected histogram features are used as input to the SVM classifier and the output of the classifier is the confusion matrix representing the classification of the face milling tool as shown in Table 7.11. The confusion matrix shows that the 28 instances were misclassified. The classification efficiency of the SVM classifier is 86%, which indicates that the SVM classifier has provided the same result as decision tree classifier, but more number of instances (16 instances) of breakage condition were misclassified as healthy condition when compared with the performance of decision tree classifier. Hence, the SVM model with histogram features is not preferred for fault diagnosis of the face milling tool.

Table 7.11 SVM confusion matrix for histogram features of sound signal

a	**b**	**c**	**d**	**Class**
39	0	11	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
16	0	33	1	**c-Breakage**
0	0	0	50	**d- Chipping**

- ***K-star algorithm***

The selected features are fed to the K-star algorithm. The confusion matrix obtained by the classifier for the given set of histogram features (50 features) of sound signals is as shown in Table 7.12.

Table 7.12 K-star confusion matrix for histogram features of sound signal

a	**b**	**c**	**d**	**Class**
36	0	14	0	**a-Healthy**
0	50	0	0	**b-Flank wear**
19	0	31	0	**c-Breakage**
0	0	1	49	**d- Chipping**

As seen from the confusion matrix, out of 200 instances, 34 instances were misclassified by a K-star algorithm with the overall classification accuracy of about 83%. The classification efficiency of K-star algorithm is considerably low as compared to the decision tree model. Thus, the K-star classifier with histogram features for fault diagnosis of the face milling tool is not preferable.

- ***Summary***

The sound signals were used by extracting the histogram features and feature selection was carried out using decision tree technique. The performances of the different classifiers with selected features were compared and presented. The summary of classification efficiencies of different classifiers with histogram features is as shown in Table 7.13.

Table 7.13 Summary of classification efficiencies of different classifiers for histogram features of sound signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	85.5	**86**	82.5	86	83

From Table 7.13, the decision tree classifier has performed well (86% classification efficiency) when compared to the performances of other classifiers in the case of histogram features of sound signals. Thus, the decision tree algorithm with histogram feature extraction method using sound signals can be preferred for fault diagnosis of the face milling tool.

7.2.3 Fault diagnosis using EMD features

EMD features of sound signals pertaining to four different conditions of the milling tool were extracted. First eight IMFs of sound signals for each condition of the face milling tool are plotted as shown in Figure 7.4 and Figure 7.5.

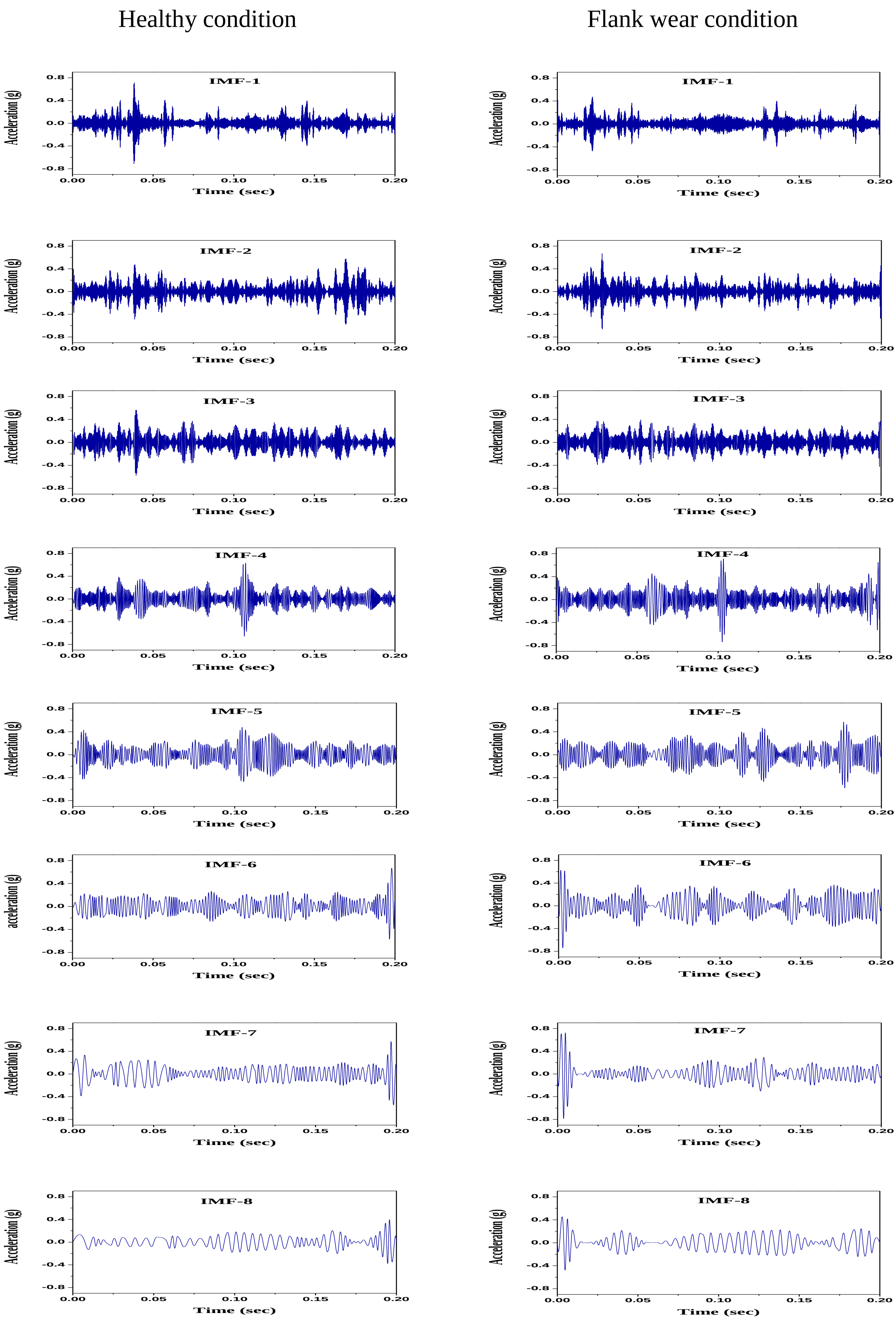

Figure 7.4 Eight IMFs of healthy and flank wear tool conditions of sound signal

Breakage condition　　　　Chipping condition

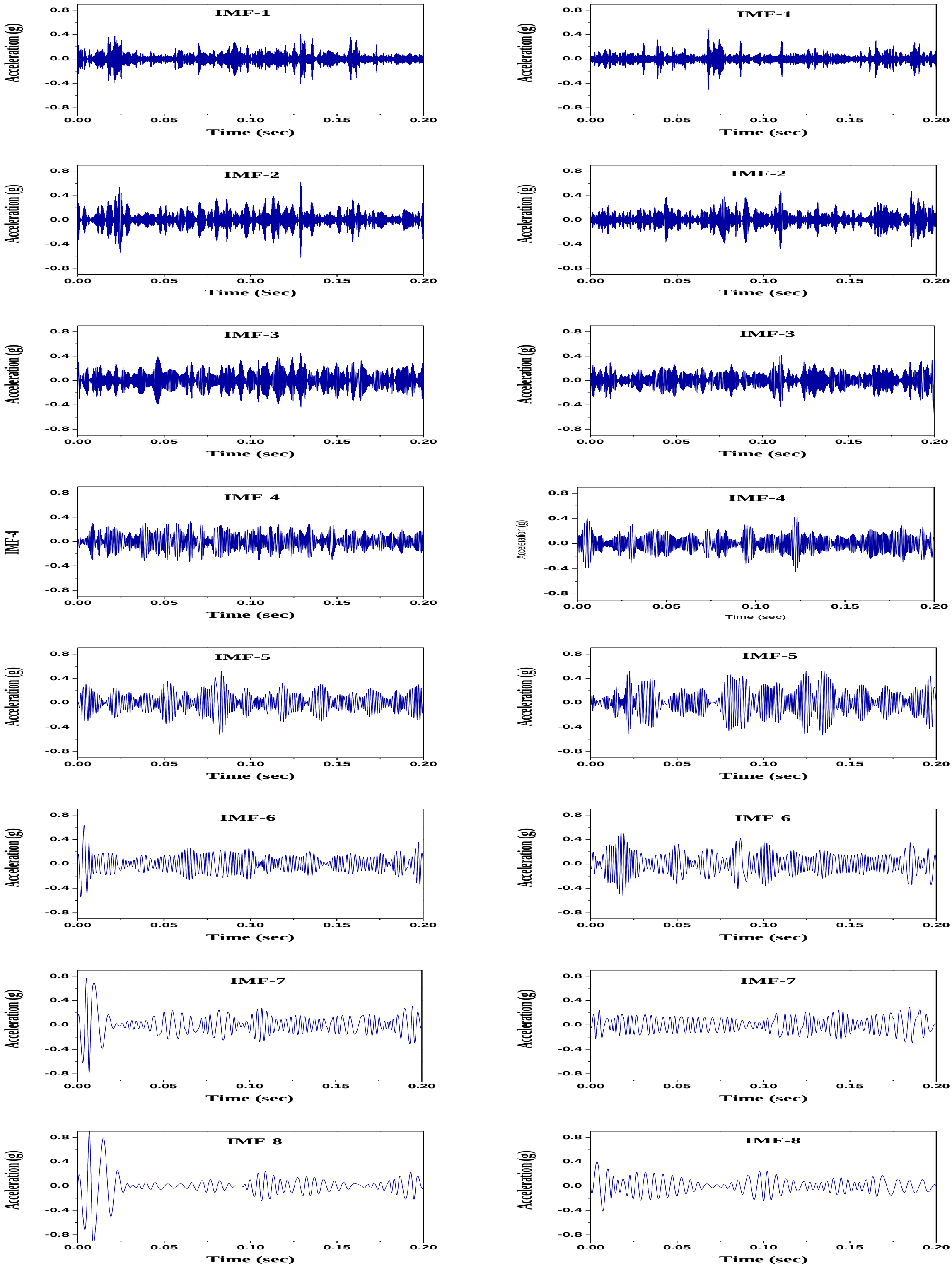

Figure 7.5 Eight IMFs of breakage and chipping tool conditions of sound signal

In order to quantify these IMFs, amplitude energy is computed by using equation 3.10 and considered as EMD features. These EMD features of sound signals pertaining to each class (two samples of each class) are presented in Table 7.14.

Table 7.14 EMD features of sound signals

Face milling tool condition	Sample No.	EMD features							
		E1	E2	E3	E4	E5	E6	E7	E8
Healthy	1	0.2192	0.2404	0.3689	0.3133	0.5901	0.4251	0.2559	0.2559
	2	0.1677	0.3284	0.4339	0.4582	0.5047	0.3261	0.2289	0.2289
Flank wear	1	0.1138	0.1958	0.2446	0.4217	0.6933	0.2880	0.2715	0.2715
	2	0.1134	0.1712	0.2819	0.2872	0.6322	0.3903	0.3492	0.3492
Breakage	1	0.1651	0.2343	0.3013	0.3631	0.4881	0.4769	0.3388	0.3388
	2	0.1514	0.2687	0.3573	0.4689	0.5827	0.4239	0.1378	0.1378
Chipping	1	0.1212	0.1841	0.2841	0.2955	0.6336	0.5225	0.2334	0.2334
	2	0.1206	0.1443	0.2043	0.3622	0.4971	0.5773	0.3250	0.3250

7.2.3.1 Feature selection by decision tree

All extracted EMD features are fed to the decision tree (J48 algorithm) for the selection of the best features. The decision tree provided the significant EMD features such as E1, E2, E3, E4, E5, E6 and E7. These selected features are used for classification of the face milling tool in the following section.

7.2.3.2 Classification

The selected features of all conditions of a face milling tool are used as input to the classifiers such as decision tree algorithm, K-star algorithm, ANN, SVM, and Naïve Bayes algorithm.

- ***Naïve Bayes algorithm***

The confusion matrix obtained by the Naïve Bayes classifier for sound signals of the face milling tool is as shown in Table 7.15.

Table 7.15 Naïve Bayes confusion matrix for EMD features of sound signal

a	b	c	d	
27	6	13	4	**a-Healthy**
1	24	6	19	**b-Flank wear**
17	6	22	5	**c-Breakage**
4	16	4	26	**d- Chipping**

Out of 200 instances, 101 instances were misclassified by Naïve Bayes with classification accuracy of about 49.5% for the given sound signals which cannot be accepted for condition monitoring.

- ***Decision tree algorithm***

The selected EMD features were used as input to the decision tree classifier and Table7.16 depicts the confusion matrix by decision tree which represents the classification of the face milling tool conditions.

Table 7.16 Decision tree confusion matrix for EMD features of sound signal

a	b	c	d	
23	9	16	2	**a-Healthy**
4	21	7	18	**b-Flank wear**
19	10	15	6	**c-Breakage**
7	18	3	22	**d- Chipping**

From the confusion matrix, out of 200 instances only 81 instances were correctly classified and the classification accuracy of the decision tree classifier was about 40.5%. Since the classification efficiency of the classifier is very less and it cannot be accepted for fault diagnosis.

- ***Artificial neural network***

The confusion matrix produced by the ANN classifier with EMD features of the sound signal is illustrated in Table 7.17. From the confusion matrix, only 94 instances out of 200 instances were correctly classified with the overall classification accuracy was about 47% for the given sound signals. The classification efficiency of ANN algorithm is quite low and cannot considered for fault diagnosis.

Table 7.17 ANN confusion matrix for EMD features of sound signal

a	**b**	**c**	**d**	
29	8	12	1	**a-Healthy**
6	24	5	15	**b-Flank wear**
23	8	18	1	**c-Breakage**
3	16	8	23	**d- Chipping**

- ***Support vector machine***

The selected features are fed to the SVM classifier. The confusion matrix represents the classification of the face milling tool conditions obtained by the SVM classifier with EMD features of sound signals is as shown in Table 7.18. Here, out of 200 instances, only 93 instances were correctly classified by SVM with classification accuracy of about 46.5% for the given sound signals. The results obtained from the classifier was found to be very less and not suitable for fault diagnosis.

Table 7.18 SVM confusion matrix for EMD features sound signal

a	**b**	**c**	**d**	
22	7	16	5	**a-Healthy**
1	20	5	24	**b-Flank wear**
16	2	26	6	**c-Breakage**
3	16	6	25	**d- Chipping**

- ***K-star algorithm***

The K-star algorithm is used as a classifier to distinguish the conditions of the face milling tool and Table 7.19 shows the confusion matrix with the K-star classifier. From the confusion matrix, only 83 out of 200 instances were correctly classified and the overall efficiency was found to be 41.5% which is very less and cannot be preferred for the classification/fault diagnosis.

Table 7.19 K-star confusion matrix for EMD features sound signal

a	**b**	**c**	**d**	
19	8	19	4	**a-Healthy**
8	20	5	17	**b-Flank wear**
13	7	24	6	**c-Breakage**
7	19	4	20	**d- Chipping**

- ***Summary***

The EMD features were extracted from the acquired sound signals and feature selection was performed using decision tree technique. The performances of the selected features set in fault classification was presented. The summary of classification efficiencies of different classifiers with EMD features of sound signals is as shown in Table 7.20.

Table 7.20 Summary of classification efficiencies of different classifiers for EMD features of sound signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	49.5	40.5	47	46.5	41.5

The observation shows that all the classifiers provided less classification accuracy which cannot be considered for fault diagnosis/condition monitoring using EMD features of sound signals. Thus, the EMD feature extraction method with any of the classifiers is not preferable for fault diagnosis of the face milling tool.

7.2.4 Fault diagnosis using DWT features

From sound signals, eight discrete wavelet features (V1, V2… V8) were extracted for each class of the face milling tool. Table 7.21 illustrates the discrete wavelet features, out of 50 samples only two samples pertaining to each condition of the tool are tabulated. These features were treated as input to the decision tree for the selection of the prominent features which helps in better classification.

Table 7.21 Discrete wavelet features of sound signals

Face milling tool condition	Sample No.	Wavelet coefficient							
		V1	V2	V3	V4	V5	V6	V7	V8
Healthy	1	0.01	0.06	0.19	0.42	0.87	0.86	1.00	0.17
	2	0.02	0.07	0.19	0.40	0.78	0.79	1.12	0.20
Flank wear	1	0.02	0.06	0.20	0.45	1.01	0.98	1.18	0.21
	2	0.02	0.06	0.18	0.48	1.06	1.01	1.19	0.19
Breakage	1	0.02	0.06	0.18	0.42	0.84	0.84	1.18	0.14
	2	0.02	0.07	0.19	0.35	0.69	0.70	0.62	0.09
Chipping	1	0.02	0.07	0.21	0.52	1.22	0.94	1.17	0.24
	2	0.02	0.07	0.21	0.51	1.22	1.10	1.22	0.24

7.2.4.1 Feature selection by decision tree

All extracted wavelet features pertaining to four classes were fed to the decision tree algorithm and the output of the model is tree like structure as shown in Figure 7.6. The observation shows that V5 is the root node which has provided maximum information about the face milling tool condition when compared with the other remaining features. Based on the feature V5, the decision tree was formed in such a way that when V5 and V4 are greater than 0.94 and 0.498 respectively and also V5 is greater than 1.1, it is classified as ‘chipping’ condition and so on. The observation also shows that all extracted DWT features (V1-V8) have given thorough information about the tool condition. All extracted DWT features are used as input to the classifier. The classification performances by the different classifiers are discussed in the following section.

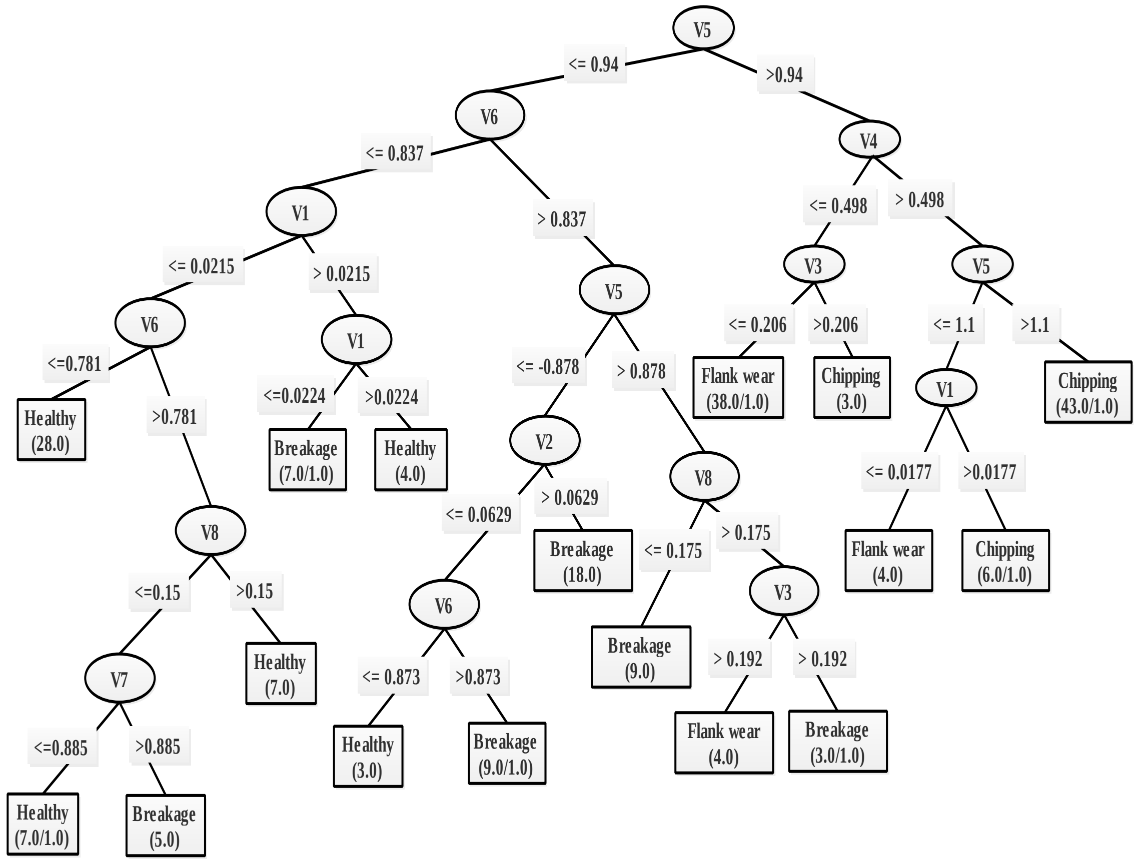

Figure 7.6 Decision tree of DWT features of sound signal

7.2.4.2 Classification

Classifications using DWT features of sound signals with different classifiers were studied. The classifiers such as, K-star, ANN, SVM, Naïve Bayes and decision tree algorithms were used and their performances on DWT features are reported.

- ***Support vector machine***

The extracted DWT features (V1 – V8) are used as input to the SVM classifier. The results obtained from the classifier is the confusion matrix as shown in Table 7.22. From the confusion matrix, 166 out of 200 samples were correctly classified and the overall classification efficiency of about 83% by the SVM classifier. This classifier can be considered for the study of fault diagnosis in the face milling process.

Table 7.22 SVM confusion matrix for DWT features of sound signal

a	b	c	d	Class
40	0	10	0	**a-Healthy**
0	42	5	3	**b-Flank wear**
8	4	38	0	**c-Breakage**
0	4	0	46	**d- Chipping**

- ***Decision tree algorithm***

The confusion matrix of the decision tree classifier represented as classification of the face milling tool conditions as shown in Table 7.23.

Table 7.23 Decision tree confusion matrix for DWT features of sound signal

a	b	c	d	Class
41	0	9	0	**a-Healthy**
0	42	3	5	**b-Flank wear**
12	5	32	1	**c-Breakage**
0	3	0	47	**d- Chipping**

Table 7.23 shows that only 38 out 200 instances were misclassified and the overall classification efficiency by the classifier was found to be 81% which can be considered for fault diagnosis, but the classification efficiency by the decision tree classifier is lesser than the SVM classifier. Thus the combination of the decision tree and DWT techniques is not preferred for the fault diagnosis of the face milling tool.

- ***Naïve Bayes algorithm***

The eight DWT features were used as input to the Niave Bayes algorithm. Table 7.24 depicts the confusion matrix obtained by the Naïve Bayes classifier. From the confusion matrix, 157 out of 200 instances were correctly classified. The overall classification efficiency is found to be 78.5%. As the classification efficiency of the Naïve Bayes classifier is considerably low when compared to the SVM classifier. Thus the Naïve Bayes classifier with DWT features for fault diagnosis of milling tool is not preferable.

Table 7.24 Naïve Bayes confusion matrix for DWT features of sound signal

a	b	c	d	Class
41	0	9	0	**a-Healthy**
0	42	4	4	**b-Flank wear**
13	7	30	0	**c-Breakage**
0	6	0	44	**d- Chipping**

- ***K-star algorithm***

The result obtained from the K-star model is presented in the form of confusion matrix as shown in Table 7.25. From the confusion matrix, 47 instances out of 200 instances were misclassified. The overall classification efficiency is found to be 76.5%, which is lesser than all classifiers. Hence, the K-star algorithm with DWT features is not considered for fault diagnosis of the face milling tool.

Table 7.25 K-star confusion matrix for DWT features of sound signal

a	b	c	d	Class
32	0	18	0	**a-Healthy**
0	43	6	1	**b-Flank wear**
13	4	33	0	**c-Breakage**
0	4	1	45	**d- Chipping**

- ***Artificial neural network***

The selected DWT features of sound signals are given as input to the ANN classifier. The identified classification efficiency in the form of confusion matrix is presented in Table 7.26.

Table 7.26 ANN **c**onfusion matrix for DWT features of sound signal

a	b	c	d	Class
39	0	11	0	**a-Healthy**
0	42	4	4	**b-Flank wear**
14	2	34	0	**c-Breakage**
0	5	0	45	**d- Chipping**

From the confusion matrix, it is noticed that only forty instances were misclassified and the classification efficiency is about 80%. The classification efficiency of ANN is good for fault diagnosis, but lesser than the SVM classifier. Thus the ANN algorithm with DWT features is not preferred for fault diagnosis of the face milling tool.

- ***Summary***

The DWT features of sound signals were used to diagnose the faults in the face milling tool and feature selection was performed using decision tree technique. The performance of the selected features set in fault classification was presented using different artificial intelligence techniques. The summary of classification efficiencies of different classifiers with DWT features is as shown in Table 7.27.

Table 7.27 Summary of classification efficiencies of different classifiers for DWT features of sound signals

Classification accuracy (%)	Naïve Bayes	J48	ANN	SVM	K-star
	78.5	81	80	**83**	76.5

From Table 7.27, the SVM classifier has performed well with 83% classification efficiency when compared with the performances of other classifiers using DWT features of sound signals. Hence, the combination of SVM classifier and DWT features of sound signal can be referred for fault diagnosis of the face milling tool.

7.2.5 Overall conclusion from the sound signal analysis based on machine learning approach

The comparison of performances of artificial intelligence techniques with different features extraction methods for fault diagnosis of the face milling tool is as shown in the Table 7.28.

Table 7.28 Comparison of classification accuracies of the classifiers with different features

Feature	**Feature selection**	**Classifier**	**Correctly classified instances**	**Incorrectly classified instances**	**Classification accuracy**
Statistical	Decision tree	Naïve Bayes	137	63	68.5%
		SVM	140	60	70.0%
		ANN	140	60	70.0%
		K-star	125	75	62.5%
		J48	141	59	70.5%
Histogram		Naïve Bayes	171	29	85.5%
		SVM	172	28	86.0%
		ANN	165	35	82.5%
		K-star	166	34	83.0%
		J48	**172**	**28**	**86.0%**
Empirical mode decomposition		Naïve Bayes	99	101	49.5%
		SVM	93	107	46.5%
		ANN	94	106	47.0%
		K-star	83	117	41.5%
		J48	81	119	40.5%
Discrete wavelet transform		Naïve Bayes	157	43	78.5%
		SVM	166	34	83.0%
		ANN	160	40	80.0%
		K-star	153	47	76.5%
		J48	162	38	81.0%

Table 7.28 shows the classification accuracies of different classifiers with different type of extracted features from the acquired sound signals. The observation shows that the

decision tree technique provided maximum classification accuracy of about 86% with histogram features when compared with any other combination of type of feature and type of classifier. Hence, the decision tree technique can be preferred as a best classifier when compared with any other techniques listed in Table 7.28 with histogram features extracted from the acquired sound signals.

7.3 SUMMARY

This chapter has revealed the results of investigations undertaken to find suitability of sound signals to detect and diagnose the face milling tool condition. Experimental tests were carried out while face milling of steel alloy 42CrMo4 using carbide inserts type face milling cutter for regular intervals of time with different tool conditions such as healthy, flank wear, chipping and breakage conditions. Sound signals were acquired, while machining under different tool conditions. Acquired signals were analysed using machine learning techniques. From the acquired signals, statistical features, histogram features, DWT features and EMD features were extracted. The J48 algorithm (decision tree) was used for important feature selection. ANN algorithm, J48 algorithm, Naïve Bayes algorithm, SVM algorithm and K-star algorithm was used to classify the different face milling tool conditions. Based on the results obtained, the proposed methodology with machine learning techniques can be suggested for developing an on-line TCM system for the face milling process.

CHAPTER-8

CONCLUSIONS

8.1 SUMMARY

Machining processes are among the most common industrial operations used in every day in industries. Therefore, process monitoring and fault diagnosis of machining operations are very important and useful to the industry. Although considerable research has been conducted in this field, there is still lack of monitoring algorithm which is reliable, robust, accurate, inexpensive, automatic, practical and independent from the operating conditions. This research has been planned to reach this goal and select the best diagnostic method by applying and combining conventional signal processing and artificial intelligence methods in the field of machining monitoring. Condition monitoring of the milling tool using vibration signal and sound signal is one of the cost effective methods when compared with other signals such as cutting force signal, AE signal, current signal, etc. The research work is concerned with fault the diagnosis of the face milling tool by analysing two different types of signals: sound and vibration signals and also with the aid of the new signal processing methods such as continuous wavelet transform and empirical mode decomposition techniques.

This thesis has provided an easy overview of different tasks involved in monitoring the condition of the face milling tool. The main tasks are state of the art and different types of signal processing. The second and important task was to collect the vibration and sound signals under different types of face milling tool conditions such as, healthy condition, flank wear condition, cutting tip breakage condition and chipping on rake face near cutting edge condition. The processing and analysis of acquired signals have two modules, they are (i) fault detection of the face milling tool based on signal processing techniques and (ii) fault diagnosis of the face milling tool based on machine learning techniques. In the first module, the acquired vibration and sound signals were analysed and identified the face milling tool conditions using signal processing techniques such as time-domain analysis, spectrum analysis, cepstrum analysis and continuous wavelet transform analysis. The next module was to classify the signals into different categories depending on their similar properties based on machine learning approach. It includes three steps: feature extraction, feature selection and classification. The information about the various faults of face milling tool was extracted as features from the signals. Statistical features, histogram features, EMD features and DWT features were extracted from vibration and sound signals. In the second phase of machine learning method, decision tree algorithm was used for selecting the prominent features from the extracted features. The feature classification algorithms were employed to identify the faults by classification of features. Five classifying algorithms such as ANN algorithm, SVM algorithm, Naïve Bayes algorithm, decision tree algorithm and K-star algorithm were trained and used for diagnosing the faults in the face milling tool. The performances of the classifiers were analysed and compared based on different features extracted from the vibration and sound signals to select the best feature-classifier combination in condition monitoring of the face milling tool.

8.2 KEY CONTRIBUTIONS

The main contributions of this study are as follows,

1. In this present work, attempt has been made to explore the new artificial intelligence technique such as K-star algorithm to classify the different face milling tool conditions.

2. Combination of vibration and sound signals in face milling tool monitoring using data mining approach through machine learning techniques has been studied and carried out comparative studies.

3. EMD and histogram features extraction methods are applied for both vibration and sound signals in TCM of face milling process.

8.3 CONCLUSIONS

In this study, signal processing techniques and machine learning technique were used to analyse the vibration and sound signals under healthy and fault conditions for diagnosing the faults in face milling tool. Based on the experimental results and discussions, the following conclusions are drawn.

- Time-series plots provide insufficient diagnostic information in both vibration and sound signals of different face milling tool conditions.

- Spectrum plots are used to detect faults in the milling tool. Though the information about faulty tool condition as a frequency component of the vibration and sound signals can be predicted, but they do not provide any time information about faults.

- In cepstrum plots, it is very useful to assess defect quefrency namely fundamental rotating quefrency of milling tool in both vibration and sound signals and observation shows that the amplitude of this quefrency varies with the increase in fault level.

- CWT plots of vibration and sound signals have provided insufficient information about conditions of the face milling tool in time-frequency domain.

- The Navie Bayes classifier has provided a better classification efficiency of about 97% and found to be effective, when compared to other classifiers in fault diagnosis of the face milling tool using vibration signals.

- The decision tree classifier has provided a better classification efficiency of about 86% and found to be effective in comparison with other types of classifiers in fault diagnosis of the face milling tool using sound signals.

- Current studies on fault diagnosis of the face milling tool reveals that, statistical features have provided better classification efficiency in comparison with all other feature types and Naïve Bayes classifier is the best among all other classifiers in combined analysis of vibration and sound signals during face milling for the given process condition and work material of steel alloy 42CrMo4 and this combination can be recommended for the applications of TCM of the face milling process.

8.4 FUTURE WORK

The following suggestions are recommended for improving the accuracy in existing methods for diagnosing the faults in milling tool during the process in future studies:

- Microcontroller based portable hardware kit can be fabricated with the suitable machine learning approach for the automated fault diagnosis.
- Unlike vibration and sound signals, some other signals such as, motor current signal, acoustic emission (AE) signal, etc. can be used to predict the tool condition.
- Cutting fluids and tribological studies can be carried out to explore the additional information for developing efficient tool condition monitoring systems.

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List of Publications based on PhD Research Work

Sl. No.	Title of the Paper	Authors (In the same order as in the paper, underline the Research Scholar's name)	Name of the Journal / Conference / Symposium, Vol., No., Pages	Month & Year of Publication	Category *
1	Fault diagnosis studies of face milling cutter using machine learning approach	Madhusudana, C. K., Budati, S., Gangadhar, N., Hemantha Kumar and Narendranath, S.	Journal of Low Frequency Noise, Vibration and Active Control, Vol. 35(2), 128-138. (Sage Publication)	May, 2016	1
2	Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal	Madhusudana, C. K., Hemantha Kumar and Narendranath, S.	Engineering Science and Technology, an International Journal Vol. 19(3), 1543–1551. (Elsevier Publication)	May, 2016	1
3	Face Milling Tool Condition Monitoring using Sound Signal	Madhusudana, C. K., Hemantha Kumar and Narendranath, S.	International Journal of System Assurance Engineering and Management, Vol. 8(2), 1643-1653 (Springer Publication)	March, 2017	1
4	Use of Discrete Wavelet Features and Support Vector Machine for Fault Diagnosis of Face Milling Tool	Madhusudana, C. K., Gangadhar, N., Hemantha Kumar and Narendranath, S.	Structural Durability and Health Monitoring, an International Journal (Accepted) (Tech Science Publication)	February, 2016	1
5	Fault Detection of Face Milling Cutter through Spectrum, Cepstrum and Wavelet Analysis	Madhusudana, C. K., Hemantha Kumar and Narendranath, S.	Journal of Vibration Analysis, Measurement and Control, Vol. 4(1), 10-28. (Columbia International Publication)	June, 2016	1

6	Effect of Cutting Speed and Feed Rate on Cutting Force, Temperature and Stress in Face Milling of Steel Alloy 42CrMo4 using Computational Approach	Madhusudana, C. K., Hemantha Kumar and Narendranath, S.	International Conference on All India Manufacturing Technology, Design and Research (AIMTDR-2016), COEP, Pune, India.	December, 2016	3
7	Fault Diagnosis of Face Milling Tool using Decision Tree and Sound Signal	Madhusudana, C. K., Hemantha Kumar and Narendranath, S.	The International Conference on Materials, Manufacturing and Modelling (ICMMM)-2017, VIT University, Vellore, India.	March, 2017	3

* Category: 1 : Journal paper, full paper reviewed 2 : Journal paper, Abstract reviewed
3 : Conference/Symposium paper, full paper reviewed 4 : Conference/Symposium paper, abstract reviewed
5 : others (including papers in Workshops, NITK Research Bulletins, Short notes etc.)
(If the paper has been accepted for publication but yet to be published, the supporting documents must be attached.)

Research Scholar
Madhusudana C. K

Research Guide
Dr. Hemantha Kumar

Research Guide
Prof. Narendranath S.

List of Communicated Papers

1. **Madhusudana C. K.,** Hemantha Kumar and Narendranath S., (2016). "Vibration based Fault Diagnosis of Face Milling Tool using Empirical Mode Decomposition Features and Artificial Neural Network", International Journal of Condition Monitoring. (Taylor and Francis Publication)

   Status: Under Review.

BIO-DATA

1. **Name** : Madhusudana C. K.
2. **Father's Name** : Kumaraswamy
3. **Date of Birth** : 12/12/1987
4. **Nationality** : Indian
5. **Marital Status** : Single
6. **Address** :

Permanent Address
S/o. Kumaraswamy
Chikkamandya,
Gopalpura Post,
Mandya Taluk and District,
Pin-571402, Karnataka, India

Work Place
Assistant Professor,
Department of Mechanical Engineering,
MVJ College of Engineering,
Near ITPB, Channasandra, Bengaluru,
Pin-560067, Karnataka, India.

7. **Mobile Number** : +91-7338513801
8. **E-mail id.** : madhu_mech7@yahoo.in
9. Educational Qualification :

Qualification	College/school	University/Board	Year of Passing	Performance
Ph.D. in Mechanical Engineering	National Institute of Technology Karnataka	National Institute of Technology Karnataka	2017	---------------
M.Tech in Machine Design	BMS College of Engineering, Bangalore, Karnataka.	Visvesvaraya Technological University, Belgaum, Karnataka.	2012	76.04%
B.E in Mechanical Engineering	PES College of Engineering, Mandya, Karnataka.	Visvesvaraya Technological University, Belgaum, Karnataka.	2009	68.03%

I declare that above information is true and correct to best of my knowledge and belief.

(Madhusudana C. K.)