

FAULT DIAGNOSIS OF ELECTRIC MOTORS USING VIBRATION SIGNAL ANALYSIS

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DECLARATION


I hereby certify that the work which is presented in dissertation entitled, "Fault Diagnosis of Electric Motors using Vibration Signal Analysis", in partial fulfillment of the requirements for the award of the degree of Master of Engineering in Electronic Instrumentation & Control, submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of Dr. M. D. Singh. It refers others researcher's work which is duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in the text and references.

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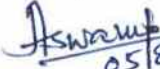
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NOMENCLATURE

FFT	:	Fast Fourier Transform
SVM	:	Support Vector Machine
ANN	:	Artificial Neural Network
KNN	:	K-nearest neighbour
IM	:	Induction Motor
DC	:	Direct Current
IC	:	Internal combustion
PSD	:	Power spectral density
EDM	:	Electro discharge machining
RMS	:	Root mean square
d	:	Bearing ball diameter
D_m	:	Pitch diameter
α	:	Contact angle of rolling element
Z	:	Number of rolling elements
f	:	Speed of rotation
PKI	:	Proportional K-interval

ABSTRACT

Electric motors find their application in almost every industry or plant. As the processes of various plants rely on these machines, presence of any fault in the motor is a matter of great concern and in such situations an efficient fault diagnosing technique must be developed to locate the fault and rectify it in least possible duration.

As motor bearing faults are the most abundant faults present in an electric motor, this research work presents fault diagnosis methods of these faults using vibration signal analysis. A public domain vibration database containing vibration signals acquired both for normal operation as well as motor's operation with inner and outer raceway, rolling element faults present was used for analysis. The presence of bearing faults in the motor was detected using time domain analysis of statistical features of vibration data. Further the fault location was fetched using cepstrum analysis of vibration signals. Then lastly, fault classification was performed using Support Vector Machine (SVM), Artificial Neural Network (ANN) and K-Nearest Neighbour (KNN) classifiers. Two different cases of faults were considered, first with faults of uniform dimensions and second with faults of varying dimensions introduced in the motor bearing components.

A hybrid model for bearing fault diagnosis and severity level classification has been proposed in this research work. The cepstrum analysis technique presented possesses the capability to locate any type of bearing fault present. The classifiers used have produced high accuracies for bearing fault classification and also detected the severity level of the fault present.

CHAPTER 1

INTRODUCTION

Electric motors are the backbone of various industrial processes and these machines are required to operate continuously during such processes, making proper functioning of these motors utmost important. As the occurrence of any fault can reduce the reliability of the equipment and also increase its operational and maintenance cost, there exists a growing need for developing efficient methods of fault detection as well as diagnosis.

Various types of faults associated with electric motors are bearing faults which include bearing failure or damage, irregularities in air gap which can be static or dynamic type, improper connections of stator winding, breakage of motor's rotor bars or cracks in end rings of rotor, bent motor shaft which may lead to rubbing between the rotor and stator which can further damage the stator's core and windings, rotor's mechanical unbalance etc. Amongst these faults, bearing related faults are most abundantly found in electric motors. Thus, detection and location of the faults becomes a major concern in order to reduce the downtime of a plant or industrial equipment.

1.1 Overview

Fault diagnosis is essential for the reliable operation of electric motors which find an extensive use in plants and industries. Various methods and approaches have been presented earlier to overcome this issue, some of them are- vibration analysis, noise analysis, stator current analysis, oil analysis etc. However, vibration proves to be the best parameter to detect various fault conditions such as misalignment, mechanical looseness, imbalance, bearing wear etc. Thus vibration signal analysis is an optimum for bearing fault detection and diagnosis.

1.2 Objective

Various methods have been proposed to detect the presence of any fault in an electric motor or to detect its abnormal behaviour. However, mere differentiation between faulty and healthy motor operation is not sufficient to prevent the breakdown of a motor but also fault diagnosis i.e. locating the fault is also necessary to reduce the downtime and maintenance

cost of a plant. The objective of this work is to detect and locate the fault present in an electric motor so that corrective measures can be adopted at their earliest thus, increasing the plant efficiency. This task is accomplished in this work using various signal processing and analysis techniques followed by fault classification to diagnose the fault present using different data classification algorithms. This research work is divided into following phases:

- 1) Acquiring vibration data from the motor under consideration.
- 2) Analysing the time domain data using various time domain statistical parameters in order to detect any fault present.
- 3) Analysing data using signal processing techniques like Fast Fourier Transform (FFT) and Cepstrum analysis used for fault detection and diagnosis respectively.
- 4) Further implementation of fault classification techniques which include classifiers- Support Vector Machine (SVM), Artificial Neural Networks (ANN) and K-Nearest Neighbor (KNN).

1.3 Thesis Organization

Chapter 1: This chapter provides an introduction to the research work carried out and also presents the objective of this research.

Chapter 2: This chapter presents an introduction to electric motors, various types of electric motors available, its components, common faults found in them and their causes. Various fault diagnosis methods of electric motors are also discussed. A literature review of related work is also covered in this chapter.

Chapter 3: This chapter addresses the challenges faced in the experimental setup done to acquire vibration data.

Chapter 4: This chapter presents the acquisition of vibration data used in this research and the experimental setup involved in it. It also includes the methodologies adopted in order to achieve the objective of the research. Techniques- time domain analysis using statistical features acquired from vibration data, cepstrum analysis and bearing fault classification using SVM, ANN and KNN classifiers have been presented in this chapter.

Chapter 5: This chapter presents the results obtained using the above mentioned techniques and is the portion of utmost importance amongst the entire research work.

Chapter 6: This chapter provides a conclusion of the research work presented and also the future scope of work in this research area is presented in this chapter.

CHAPTER 2

ELECTRIC MOTOR AND ITS FAULT DIAGNOSIS TECHNIQUES

2.1 Electric Motors and their types

Electric motors form an interface between electrical and mechanical system of any equipment as they are a means to convert electrical form of energy into mechanical one. Thus forming an integral part of the electrical system. An electric motor may be designed in numerous ways, which leads to formation of a variety of motors with each of them possessing different operating characteristics. These different characteristics then allow the type motor to be chosen based on the application for which its use is intended. Different types of motors available are:

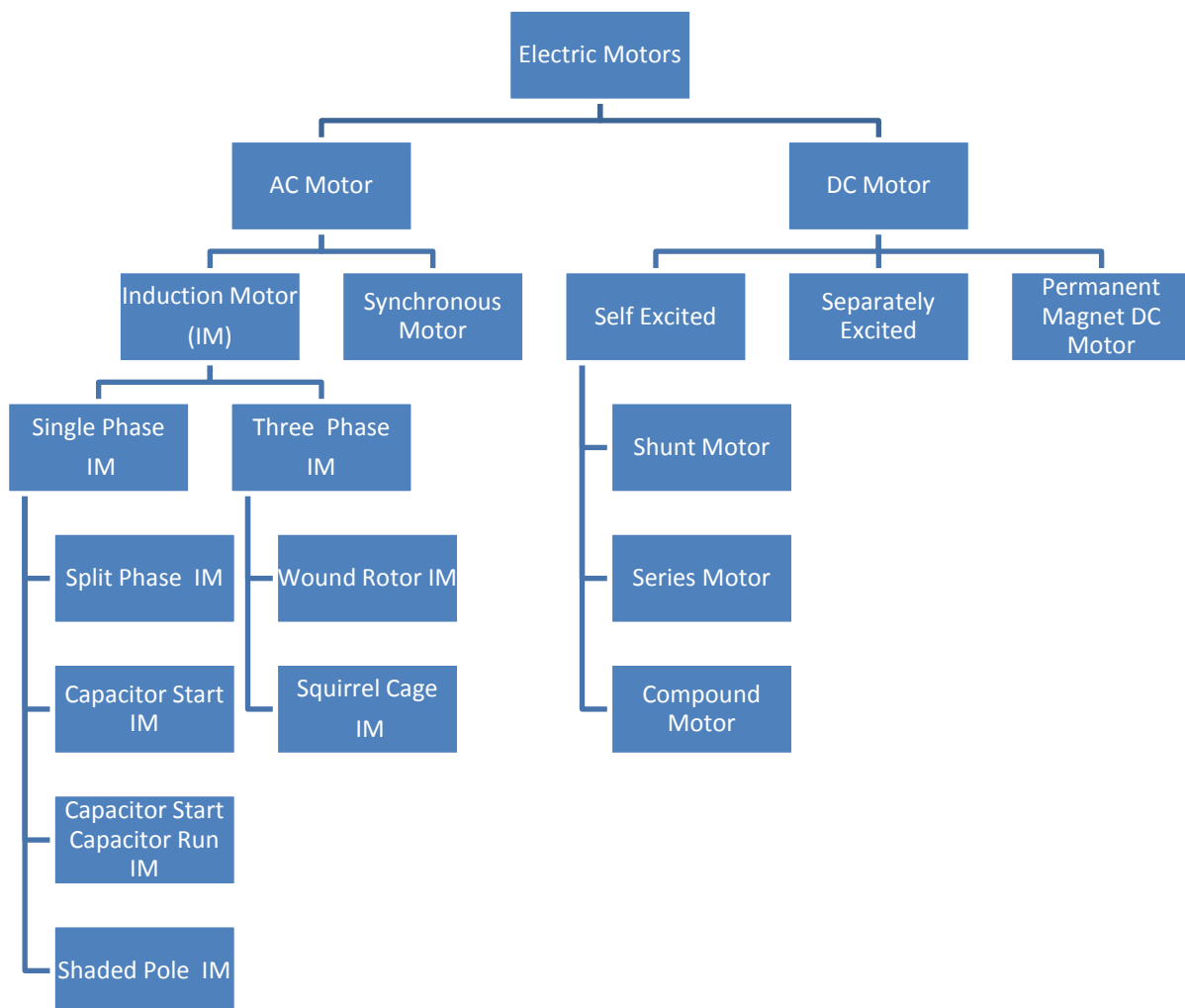


Figure 2.1- Classification of Electric Motors

2.2 Components of an AC motor

An AC motor is a type of electric motor which is driven by alternating current. The major components of AC electric motors include- rotor, stator, windings, air gap and bearings. The stator which is the stationary part of the motor contains the coils which are fed with ac supply in order to produce the rotating magnetic field in the motor. Inside it lays the rotor which also produces a rotating magnetic field and is connected to the rotating shaft of the motor to produce the output. The magnetic forces produced between the rotor and the stator poles result in average torque which in turn drives the motor load. Air gap refers to the distance that lies between the rotor and the stator. The air gap is intended to be kept minimum, an increase in the air gap has adverse effect on a motor's operation.

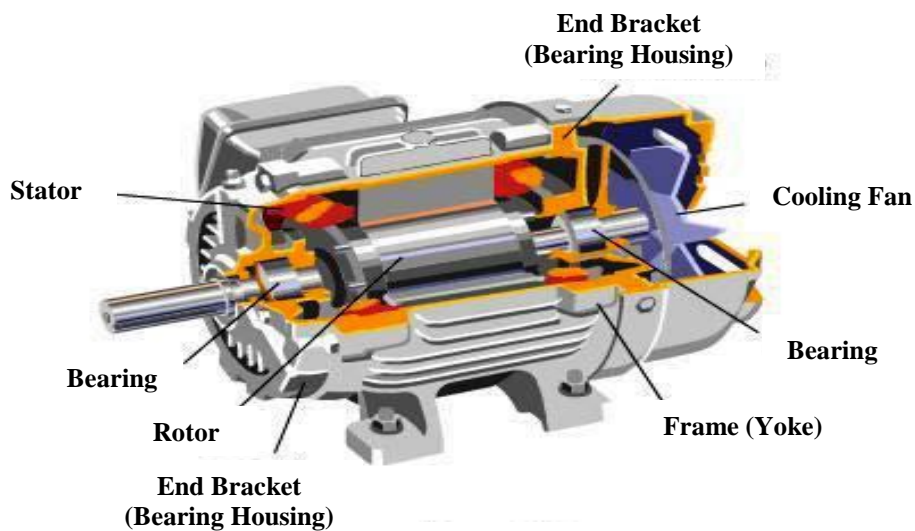


Figure 2.2- Components of a motor

Bearings are mounted on the shaft of the motor. They provide support to the rotor and allow the rotor to turn. The rolling element bearing comprises of inner and outer raceway, rolling elements and cage as depicted in Figure 2.3.

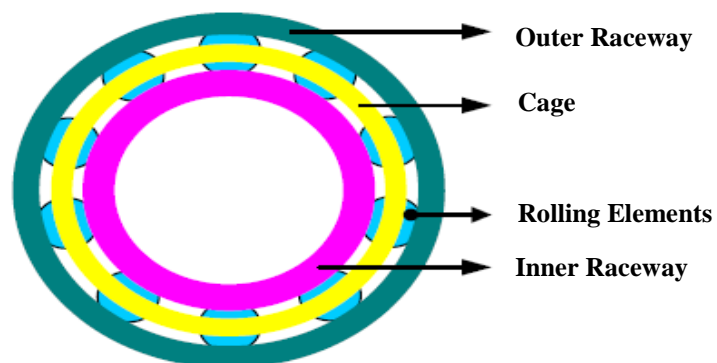


Figure 2.3- Rolling Element Bearing Components [1]

The rolling element bearings rotate in between the inner and outer raceway and minimize the friction for rotational motion. The cage of the bearings provides uniform spacing in order to guide for the rolling elements in the raceway during their movement.

2.3 Faults in induction motors

Faults which are found in electric motors can be broadly classified into two types-

- Electrical faults
- Mechanical faults

Factors which lead to these faults are shown in Figure 2.4.

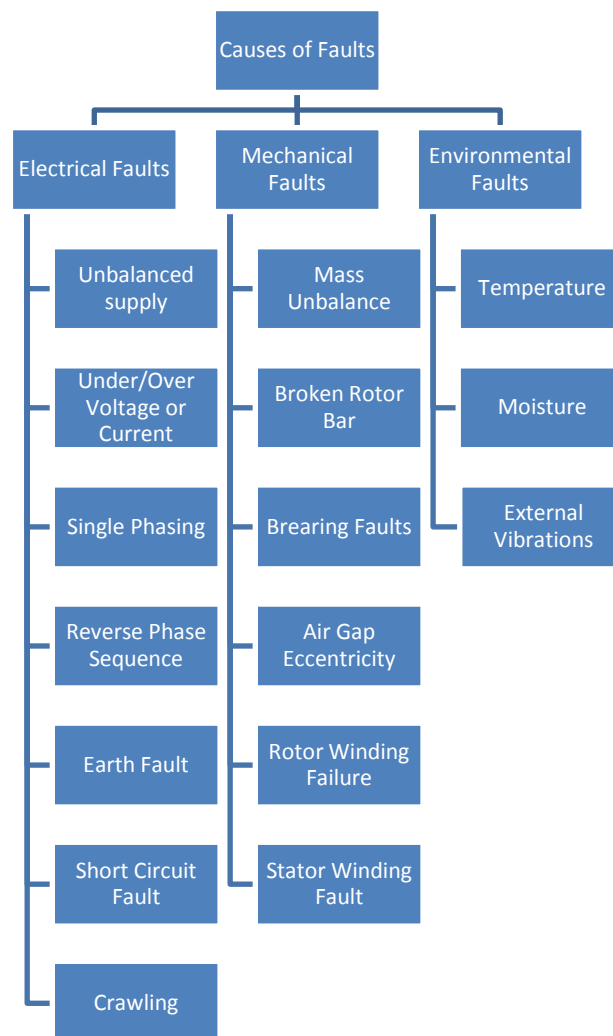


Figure 2.4- Causes of faults in electric motor

Major mechanical faults which occur in an electrical motor are discussed below:

- **Broken Rotor Bar Fault:** This type of fault is may occur due to manufacturing defect, or non uniform stress in the cage which further may cause failure of the motor during its rotation. If in case a crack appears in the rotor bar that location may get overheated leading to breakage of that rotor bar. Further due to this the neighboring bars may carry even more current than their normal capacity which may lead to an increase in the mechanical as well as thermal stresses causing it to crack. Starting and stopping the motor more frequently may also cause cracks to appear in the rotor bars. Occurrence of bearing faults may also increase the mechanical stress on the rotor bars causing it to break.



Figure 2.5- Broken rotor bar fault introduced in squirrel cage [2]

- **Mass Unbalance of Rotor:** This occurs mainly due to a manufacturing defect, asymmetrical addition or removal of mass around rotor's centre of rotation, bent in shaft or some internal misalignment. A severe case may also cause a portion of the rotor surface to wear out if the rotor and stator surfaces rub against each other due to unbalanced electromagnetic pulling of rotor.
- **Bearing Faults:** This includes any physical wear and tear of the inner race, outer race or the rolling element i.e. ball. Bearing proves to be the weakest component of a motor in terms motor failure. These are the largest cause of faults found in motors. They can result due to large temperature rise, excessive loads, long term operations may result in fracture or even removal of some material from the race or ball surface.

Misalignment in bearings may wear the ball and race surfaces resulting in temperature rise of the bearings. Corrosion may take place due to deterioration of lubricant or handling bearings carelessly at the time of installation. Temperature rise, contamination of lubricant and also a restricted flow of the lubricating material result in wear of the rolling elements and the races which further results in overheating effect. A very high bearing temperature causes the lubricant to melt and run out of the bearing. Basically bearing failures occur due to increase in friction between the bearing parts resulting in temperature rise and also increased vibrations of the motor. Thus monitoring the motor's vibration and temperature can prove to be helpful for monitoring bearing's condition. In order to acquire the vibration signal the accelerometer needs to be placed as close as possible to the bearings being analysed.

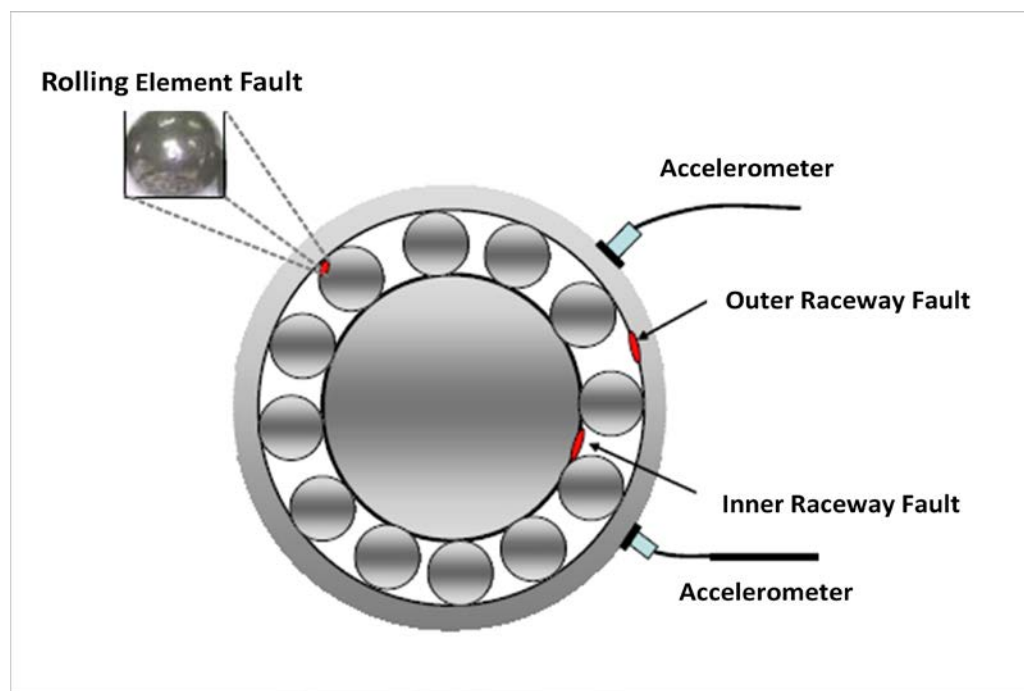


Figure 2.6- Bearing Fault's Location

- **Stator Fault:** These faults can be present either in stator laminations, stator frame or its windings. Various stresses such as electrical, thermal, mechanical and environmental stress may cause these faults. Stator winding faults (also known as inter turn short circuit faults) occur mainly due to failure of its insulation. Short circuit faults occur in the winding then the entire or a part of the winding gets shorted. The short circuit can occur between turns of a single winding, between coils of a single phase, between turns of two different phases, between turns of all phases, between the winding and the stator core and open circuit fault when there is a breakage in the winding. An open

circuit fault occurs when the entire or a part of the winding gets disconnected and there is no flow of current in that line or phase.



Figure 2.7- Damaged stator

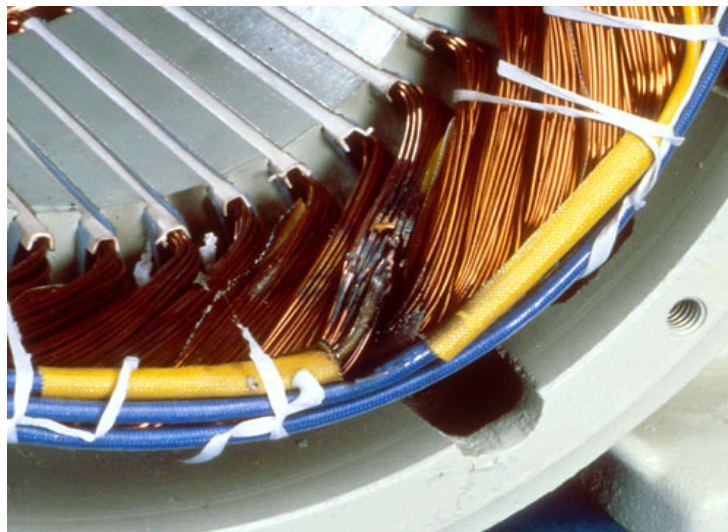


Figure 2.8- Insulation failure of motor's stator winding

2.4 Electric motor fault diagnosis methods

The presence of faults in an electric motor can be sensed by analysis of various operating parameters such as using the techniques of thermal monitoring which is accomplished by measuring the temperature of the motor. Thermal monitoring can be helpful in detecting some types of stator fault as well as bearing faults present in a motor. With the occurrence of a short circuit fault between two turns of the same stator winding the temperature rises but it might the temperature rise may be very slow to detect the presence of this fault until it approaches to a severe condition. Also in case of bearing faults the temperature of the bearing rises due to increased friction in between the bearing components thus making this

abnormal temperature an indication of faulty condition which can be detected using thermal monitoring of the motor. Noise monitoring is another technique that analyses the acoustic noise spectrum produced by the motor for detection of any fault present in it. However this technique is not quite efficient as the noise in the background may reduce the accuracy of the fault being detected. Current signature analysis technique is also used for diagnosing different faults present in a motor such as broken rotor bars, shorted stator winding turns and air gap eccentricity. When the vibrations of a motor increase the magnitude of corresponding harmonic components of stator current also increases. These components can then be detected in the stator current thus enabling the detection of faults. Vibration analysis is a widely used method for fault diagnosis of motors. Vibration analysis proves to be a mature and effective technique for diagnosing faults [3]. This technique is capable of diagnosing all types of motor faults[4][5]. Using the vibration signal of a motor various types of faults such as bearing faults, gear faults, air gap eccentricities and imbalance in rotor can be detected.

2.5 Literature Review

Iorgulescu M *et al.* [6] used analysis of vibration and current signals of an induction motor in order to detect bearing faults. Significant differences in vibration and current spectrum of healthy and faulty bearing motor was observed. The motor condition was evaluated using electric motor's vibration monitoring. Further diagnostic procedure of bearing faults used a neural network whose output represented three different operating conditions i.e. healthy bearing, damaged bearing and asymmetrical supply. However, this work failed to detect the location of bearing fault present.

Mahmmad AK *et al.* [7] used ANN model for fault diagnosis of bearings in an induction motor based Elman network. FFT analysis followed by envelope analysis was adopted. 16 time, frequency and both time and frequency domain features were extracted and then 9 selected using distance evaluation technique were further fed to the ANN network for fault diagnosis. Sensitivity analysis of induction motor bearings was also performed.

Korkua S *et al.* [8] presented study of rotor imbalance faults. The wireless health monitoring technique presented used ZigBee based wireless sensor network. The detection technique of rotor imbalance was verified at different levels of fault severity i.e. the rotor imbalance was introduced using different weights of 5, 10, 15 and 20 grams. The rotor imbalance indicator i.e. RMS value and crest factor of the acquired vibration signals using a tri-axial accelerometer was used to estimate the measure of fault severity.

Kankar PK *et al.* [9] achieved fault diagnosis of motor ball bearings using ANN and SVM technique. The defects considered in this work are inner raceway with rough surface, crack in outer raceway and corrosion pitting in the bearing balls. Statistical techniques were used to extract features in time domain. 73 instances were present in input data and 15 attributes were considered. Then ANN and SVM were used for classification after feature selection and the classification accuracies obtained were 71.2329% and 73.9726% respectively. It was observed that severe vibrations are produced with rough inner raceway and with corrosion pitting in the ball.

Iorgulescu M *et al.* [10] presented noise and vibration signal monitoring technique for detection and diagnosis of DC motor faults. FFT was applied to the noise signals acquired using microphones and vibration signals acquired using a piezoelectric accelerometer. This work showed that for correct diagnosis of faults vibrations corresponding to frequencies must be studied and also stated vibration signal study as a very efficient method for electric motor's fault diagnosis.

Ma J *et al.* [11] used wavelet packet-cepstrum technique for fault detection of rolling bearings. The vibration signal was first decomposed with the help of wavelet packet, then energy of the decomposed reconstruction signal was obtained and the band with concentrated fault energy was selected. Cepstrum of the reconstructed signal was obtained to detect the fault. It was observed that the accuracy improves by introduction of energy feature in the wavelet-packet cepstrum method. However, the fault analysis in this work was limited to outer raceway bearing fault only.

Moosavian A *et al.* [12] presents fault diagnosis scheme for main journal bearings of an internal combustion (IC) engine using Power spectral density (PSD), K-nearest neighbor (KNN) and ANN techniques. Operating conditions of the journal-bearings considered in this work are normal operation, condition of oil starvation and extreme wear defect. PSD was evaluated for the vibration signals obtained during these conditions, thirty frequency domain features were extracted from the PSD values obtained. These features were then fed to KNN and SVM classifiers and the values of K i.e. number of nearest neighbors for KNN and that of number of hidden neurons for ANN were varied from 1 to 20, with step size of 1 to achieve better results. The results show that the performance of ANN is better than KNN, with the best classification result of 90.5% obtained with ANN for 5 hidden neurons whereas that with KNN was 85.7%.

Rastegari A *et al.* [13] performed condition based maintenance in an industrial environment taking into consideration the organizational aspects and technical constituents. This case study was performed in a manufacturing site in Sweden. The data used for analysis was obtained during a pilot project undertaken to implement condition based maintenance at the site. To monitor bearing conditions two main condition monitoring techniques used were shock pulse method and vibration analysis. The former method analysed high frequency shock waves produced by the rotating bearings. It was concluded that frequency analysis can prove to be a strong base for the predictive maintenance of a plant.

Shrivastava A *et al.* [14] presented an approach of fault detection and diagnosis through analysis vibration signals obtained from an induction motor. The operating conditions considered in this work were healthy bearing, defective ball, defective outer race and defective inner race. Sixty datasets of vibration signals were obtained for each operating condition in sixty days and were analysed in time domain using certain characteristic features and statistical parameters. The analysis provided means of differentiating healthy bearing from the one with defect in different bearing locations.

Sharma A *et al.* [15] diagnosed severity of bearing faults using support vector machine (SVM) and artificial neural network (ANN) techniques. Statistical features and other parameters such as Shannon, log energy and sure entropies were extracted from vibration signals and their sensitivity towards faults of varying severity was analysed. The faults considered are of two different defect dimensions i.e. 0.1778mm and 0.5334mm. Maximum classification efficiency obtained in this work using SVM and ANN with cluster membership filter is 100%.

Palácios RHC *et al.* [16] presented various methods for identification of faults present in induction motors such as Naive Bayes, k-Nearest Neighbor, Artificial Neural Network (MLP), SVM (Sequential Minimal Optimization), C4.5 Decision tree and Repeated Incremental Pruning to Produce error Reduction. The current signal amplitudes were analysed in the time domain for normal condition, stator fault, bearing fault and rotor faults present in three phase induction motors. The input data set consisted of 30 values of per phase currents. For stator faults KNN and ANN methods depicted better results attaining 100% accuracy. For rotor faults the accuracy reached with these two methods was 99.7%. For bearing faults KNN method attained 99.9% accuracy. For all faults classification accuracy achieved with ANN and KNN methods exceeded 92.5%.

Table 2.1- Summary of previous work

Author	Fault location	Signals analysed	Defect type	No. of features	Methodology used	Fault Severity level	Outcomes/Accuracy
Iorgulescu M et al. (2008)	Motor bearings	Vibration and current signals	Damaged bearing, asymmetrical supply	-	Neural networks	Uniform	Fault detection
Mahmmad AK et al. (2008)	Motor bearings	Vibration signals	Bearing faults	16	ANN	Uniform	Bearing faults diagnosed
Korkua S et al. (2010)	Rotor	Vibration signals	Rotor imbalance	2	RMS value, crest factor analysis	Varied: 5,10,15 and 20g rotor imbalance	Rotor imbalance detected
Kankar PK et al. (2011)	Motor bearings	Vibration signals	Inner raceway fault with rough surface, crack in outer raceway and corrosion pitting in balls	15	ANN, SVM	Uniform	ANN 71.2329% SVM 73.9726%
Iorgulescu M et al. (2012)	DC motor faults	Vibration and noise signals	Displaced permanent magnet, short circuit to collector	-	FFT	Uniform	Motor's operating condition analysed
Ma J et al. (2013)	Motor bearings	Vibration signal	Outer raceway fault	-	Wavelet-packet cepstrum technique	Uniform	Outer raceway fault detected

Moosavian A <i>et al. (2013)</i>	Bearings of IC engine	Vibration signals	Oil starvation , extreme wear fault	30	PSD, ANN and KNN	Uniform	ANN 90.5% KNN 85.7%
Rastegari A <i>et al. (2014)</i>	Motor bearing	Vibration signals, shock pulses	-	-	Frequency analysis	Uniform	Predictive maintenance
Shrivastava A <i>et al. (2014)</i>	Motor bearings	Vibration signals	Defect in ball outer race and inner race	10	Time domain statistical parameters and characteristic features	Uniform	Differentiation between healthy and faulty condition.
Sharma A <i>et al. (2014)</i>	Motor bearings	Vibration signals	Ball defect, outer and inner race defect	7	SVM and ANN	Varied: 0.1778mm and 0.5334 mm	100%
Palácios RHC <i>et al. (2015)</i>	Stator, bearing and rotor	Current signals	Stator, bearing and rotor faults	30	SVM, KNN, ANN	Uniform	Stator and rotor faults: KNN 100% and ANN 99.7% accuracy. Bearing faults: KNN 99.9%. All faults ANN and KNN above 92.5%.

2.5.1 Summary

From the study of previous work, it is observed that vibration signal study being very efficient in electric motor's fault diagnosis [6, 10] has been widely used in this domain. Most of the previous work has been limited to monitoring the operation condition of the motor or limiting to detection of faulty motor operation [6, 10, 13, 14]. Where as mere detection of motor's faulty operating condition is not sufficient for ensuring its healthy operation, rather the fault type must also be identified.

A good volume of work has been presented which aims at identifying the type of fault present in a machine [7, 9, 11, 12, 15, 16]. Ma J *et al.* [11] has achieved good results for fault diagnosis using wavelet-packet cepstrum technique but has limited the study to only a single type of fault i.e. outer raceway bearing fault. Apart from bearing fault diagnosis another important aspect that must be studied is the identification of severity of fault that is present in a machine. Abbasion S *et al.* [17] presented multiple fault diagnosis of bearings using SVM classifiers and attained high fault detection accuracy but considered defects of uniform dimensions. Thus, the study of faults of varying severity levels has not been explored much. A few authors have considered faults of different severity levels, such as Korkua S *et al.* [8] presented rotor imbalance study while varying the amount of imbalance and Sharma A *et al.* [15] studied bearing faults of two different dimensions.

In this work both bearing fault diagnosis as well as bearing fault severity level detection has been presented. The bearing faults of three different defect sizes have been considered. The presence of fault has been detected using time domain analysis further fault diagnosis of uniform defect size achieved using cepstrum analysis. Finally, fault classification and detection of severity level is performed using SVM, ANN and KNN classifiers.

CHAPTER 3

CHALLENGES IN EXPERIMENTAL SETUP

A single phase induction motor of 1hp rating with 1440 RPM rated speed was used to acquire vibration signal under different operating condition. The vibration analyser used for the purpose of recording vibration data was CESVA SC310- Sound level meter and spectrum analyser. The vibration signals were sensed using a piezoelectric accelerometer.

3.1 Apparatus

3.1.1 Accelerometer

Accelerometers are devices used to measure acceleration. These are useful in measuring vibrations and also for orientation applications. Piezoelectric accelerometers use the piezoelectric properties of certain materials for measuring dynamic changes in parameters such as acceleration. A piezoelectric accelerometer contains a mass fixed to a piezoelectric crystal which is then mounted on accelerometer's case. When the accelerometer is exposed to vibrations due to its inertia the mass mounted on the piezoelectric crystal opposes any change in its position thus it exerts compressing and stretching forces on the crystal. Due to the piezoelectric properties of the crystal it produces a charge due to the force exerted on it. As force is directly proportional to acceleration (according to Newton's law) the charge output provides a measure of acceleration.

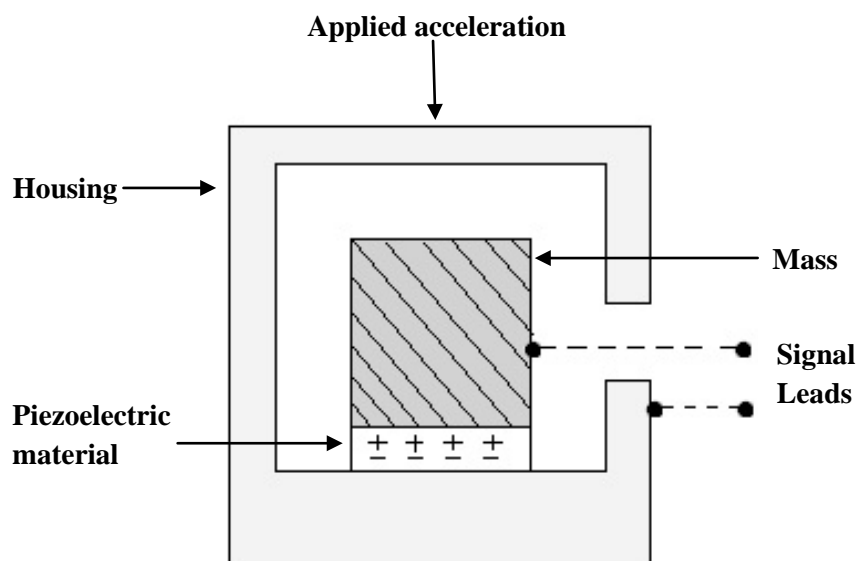


Figure 3.1- Components of a piezoelectric accelerometer

The accelerometer used was manufactured by IMI Sensors. The sensitivity of the accelerometer was 100mV/g and its frequency range was 0.33 to 10000 Hz. This industrial accelerometer contained a quartz sensing element which has an advantage over typical ceramic elements that it possesses superior thermal stability.

3.1.2 Spectrum Analyser

The module for vibration measurements of SC310 sound level meter is the perfect tool for a vibration measurement of machinery, vehicles etc. The FFT Frequency Analysis for Vibration mode of SC310 carries out a frequency analysis of acquired vibration data covering the frequency range of 0 Hz to 1 kHz in real time. Its computed frequency spectrum has 430 effective lines with a resolution of 2.5 Hz.

The accelerometer is mounted on the motor's surface using its magnetic base and connected on the other side to SC310 through a preamplifier PA001.

ACCELEROMETER MOUNTED ON MOTOR



PREAMPLIFIER



Figure 3.2- Vibration signal acquisition using CESVA SC310

3.1.3 Transferring Data to the PC Using CESVA Capture Studio

Capture Studio is a software application that allows display and retrieval of data from the SC310 instrument in real time. It provides a convenient and user friendly environment for obtaining, data acquired through the instrument in a digital format. It allows easy configuration of all the instrument parameters on a single screen, it allows downloading the

registers from the instrument memory to a PC and displays the data acquired both in graphical as well as numerical format.

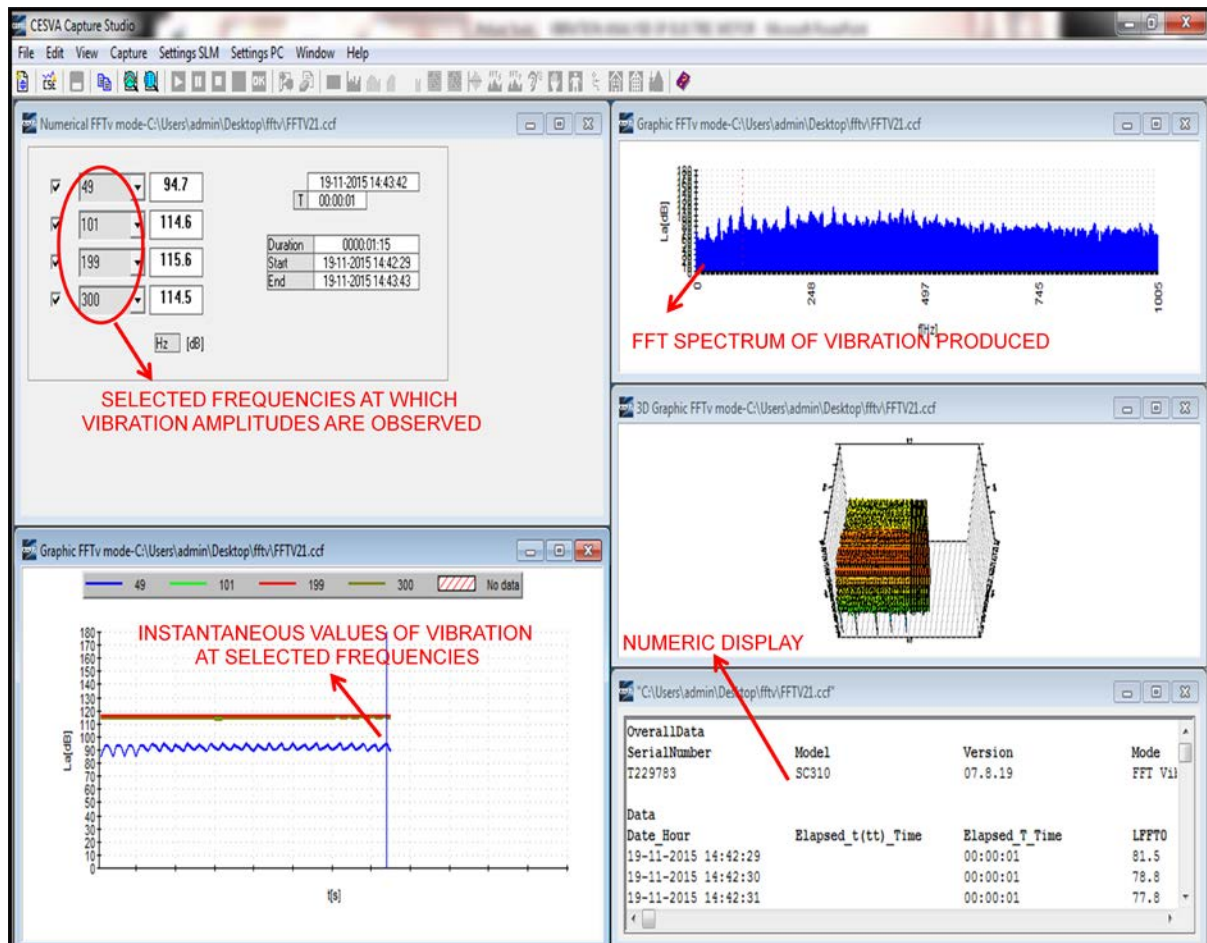


Figure 3.3- CESVA Capture Studio Features

3.2 Vibration Data Collected

The vibration signals produced by the motor were recorded under different operating conditions of the motor i.e. normal operation, motor tilted along its axis of rotation and motor tilted perpendicular to its axis of rotation as shown in the following figures.

It was observed that the vibration spectra comparison of the motor tilted along its axis and the one running under normal conditions showed that the vibration spectrum is almost similar in the two cases. Whereas, the vibration spectra comparison of the motor tilted perpendicular its axis and the one running under normal conditions, showed that the vibration amplitude generated by the motor when tilted perpendicular to its axis is greater than that when the motor is running under normal condition



(a)



(b)

Figure 3.4- (a) Motor running normally (b) Motor tilted along its axis



(a)



(b)

Figure 3.5- (a) Motor running normally (b) Motor tilted perpendicular its axis

3.3 Challenges

Following were the challenges faced while acquiring data:

- The vibration signal recorded using CESVA SC310 Spectrum analyser contained large amount of noise.

- The frequency range of the FFT mode inbuilt in the spectrum analyser was limited to 1005 Hz thus higher frequency values of vibration signal could not be analysed using this equipment.

3.4 Summary

Due to the above mentioned challenges faced in obtaining the vibration data online available data was used for research purpose.

CHAPTER 4

MATERIALS AND METHODOLOGIES

4.1 Data Collection

A public domain data provided by Case Western University, Bearing Data Centre has been used in this research work. Following is the detail of data acquisition as provided by the source:

The vibration data was acquired using an electric motor of 2hp rating. The test stand as depicted in figure 4.1 consists of the motor, torque transducer, dynamometer and control electronics. The motor shaft is supported by the test bearings. Faults were introduced in the motor bearing using EDM i.e. Electro Discharge Machining. Faults of varying diameters (ranging from 0.007 to 0.04 inches) were introduced in the inner raceway, outer raceway and rolling element. These bearings were then reinstalled into the motor and vibration signals were recorded for varying loads ranging from 0 to 3hp i.e. motor speed varying from 1797 to 1720 RPM. Faults with diameters 0.007 inches, 0.014 inches and 0.021 inches introduced in SKF bearings are considered in this work.

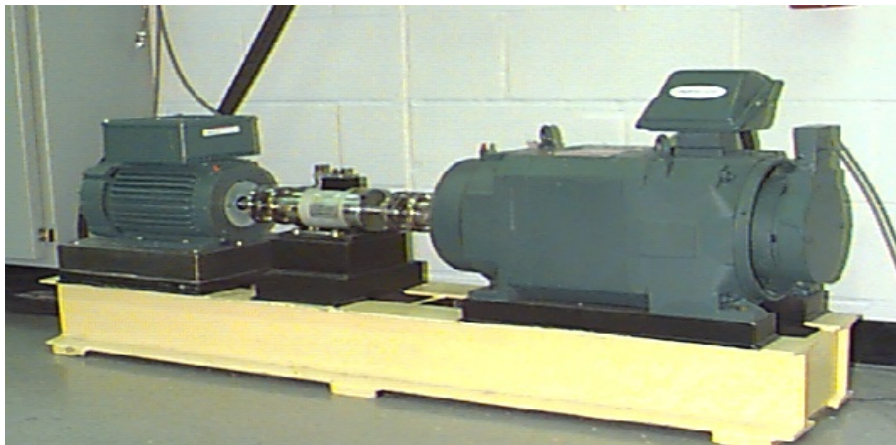


Figure 4.1- Experimental Setup [18]

Vibration signals were acquired using accelerometers mounted on the housing using magnetic bases. Signals were obtained by placing the accelerometer at 12 o'clock position for recording data at fan and drive end of the motor and also at the supporting base plate. Outer raceway faults are stationary in nature, therefore relative positioning of the load zone of bearing and the fault affects the vibrations produced by the motor. Thus, to avoid this test was

conducted for outer raceway faults introduced at 3 o'clock, 6 o'clock and 12 o'clock position. The data was recorded for normal bearings, single point fan and drive end faults introduced in the bearings. Vibration data was recorded using a 16 channel DAT recorder and the sampling rate of the digital data recorded was 12,000 samples per second for the accelerometer placed at the drive end and fan end of the motor [18]. This database is widely used for study of bearing related faults [19-28].

4.2 Methodologies

The first step towards fault diagnosis is detection of fault i.e. to observe any deviation from the normal behaviour of motor operation. This can be achieved using various signal processing techniques. The ones used in this work are:

- Time domain analysis of vibration signal using statistical feature analysis.
- Frequency domain analysis using Fast Fourier Transform (FFT)

After the faulty behaviour of the motor is detected fault present must be located i.e. fault needs to be diagnosed. This is achieved using following methods:

- Cepstrum Analysis
- Fault classification using Support Vector Machine (SVM), Artificial Neural Networks (ANN) and K-Nearest Neighbor (KNN).
- The classification is done using the time domain statistical parameters.

4.2.1 Time Domain Analysis

Time domain vibration signals were analysed using the following statistical features [29][7]:

Peak Value: Peak of the time signal is given by-

$$\max(X_i) \quad (4.1)$$

Variations in the peak value of the signal indicate change in signal on occurrence of impacts. Thus peak value can be used to identify occurrences of such impacts.

Mean (X_m): Mean value of data is given by-

$$\frac{1}{N} \sum_{i=1}^N X_i \quad (4.2)$$

Standard Deviation: Standard deviation of a signal is given by-

$$\sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - X_m)^2} \quad (4.3)$$

It depicts the deviation of a data value from the average or mean value. Low value of standard deviation depicts that a particular data value lies near to the mean value whereas a high value depicts that data value has a large variation from the mean value.

Root Mean Square (RMS): RMS value of a signal can be calculated as-

$$\sqrt{\frac{1}{N} \sum_{i=1}^N (X_i)^2} \quad (4.4)$$

RMS value helps to track the overall noise of a signal.

Crest Factor: Crest Factor of a signal can be calculated as-

$$\frac{\text{Peak Value}}{\text{RMS Value}} \quad (4.5)$$

The crest factor of a signal indicates the spikiness nature of a signal. It depicts how extreme the peaks of a signal are.

Skewness: Skewness of a signal can be calculated as-

$$\frac{\frac{1}{N} \sum_{i=1}^N (X_i - X_m)^3}{(\text{Standard Deviation})^3} \quad (4.6)$$

Skewness of a signal depicts the extent of asymmetry in a signal.

Clearance Factor: Clearance factor can be calculated as-

$$\frac{\text{Peak Value}}{\left(\frac{1}{N} \sum_{i=1}^N \sqrt{|X_i|}\right)^2} \quad (4.7)$$

It is defined as the ratio of peak value and the square of mean of square root signal's absolute value.

Kurtosis: Kurtosis can be calculated as follows-

$$\frac{\frac{1}{N} \sum_{i=1}^N (X_i - X_m)^4}{(\text{Standard Deviation})^4} \quad (4.8)$$

The kurtosis value of a signal depicts whether the signal is flat or peaked in nature.

Impulse Factor: Impulse factor of a signal can be calculated as-

$$\frac{\text{Peak Value}}{\frac{1}{N} \sum_{i=1}^N |X_i|} \quad (4.9)$$

It is defined as the ratio of the peak value of a signal to the mean of the absolute value of the signal.

Shape Factor: Shape factor of a signal can be calculated as-

$$\frac{\text{RMS Value}}{\frac{1}{N} \sum_{i=1}^N |X_i|} \quad (4.10)$$

It is defined as the ratio of the RMS value of a signal to the mean of the absolute value of the signal.

These calculated time domain statistical were then analysed to observe the presence of any fault or to sense any abnormal behaviour of the motor.

4.2.2 Cepstrum Analysis

Cepstrum analysis is a signal processing technique used in various applications such as speech analysis, gearbox analysis etc. to detect periodicity in a frequency spectrum. A cepstrum can be defined as the inverse fourier transform of the log magnitude of signal's fourier transform. Where a signal's fourier transform can be described as a technique used for extraction of a frequency domain signal from an input time domain signal.

Cepstrum of a time domain signal can be computed as:

$$\mathcal{F}^{-1}\{\log\{\mathcal{F}[f(t)]\}\} \quad (4.11)$$

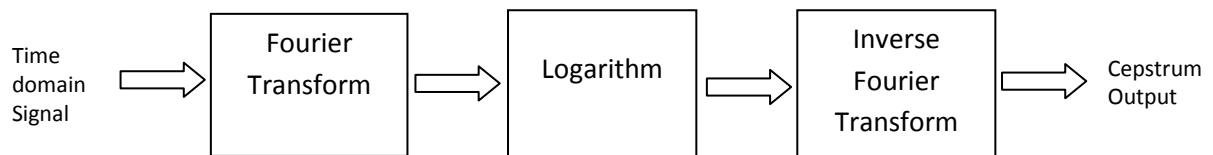


Figure 4.2- Flowchart for Cepstrum Computation

Cepstrum analysis helps in detection of repeated patterns of a spectrum, which makes it useful for differentiation of multiple faults which cannot be achieved using other primary spectra such as FFT, envelope spectra etc.

Quefrequency (measured in seconds) is the independent variable used in cepstrum analysis and it depicts the reciprocal of frequency spacing in the original spectrum.

4.2.2.1 Applications of Cepstrum Analysis

Cepstrum analysis technique finds its use in the following areas:

- Monitoring bearing and gearbox vibrations i.e. Machine Diagnostics
- Detection of bearing related faults
- Detection of gear faults
- Detection and removal of echo
- Speech signal analysis

4.2.2.2 Significant features

Following are the features of cepstrum analysis which make it useful in various fields:

- Detects repeated patterns in any spectra
- Detects the periodicities and frequency spacing
- Separates harmonic families

4.2.2.3 Cepstrum analysis for bearing fault diagnosis

The cepstrum plot peaks can be used to identify bearing fault frequencies which further indicate the presence of specific bearing faults. The bearing fault frequencies are given by the following expressions [30]:

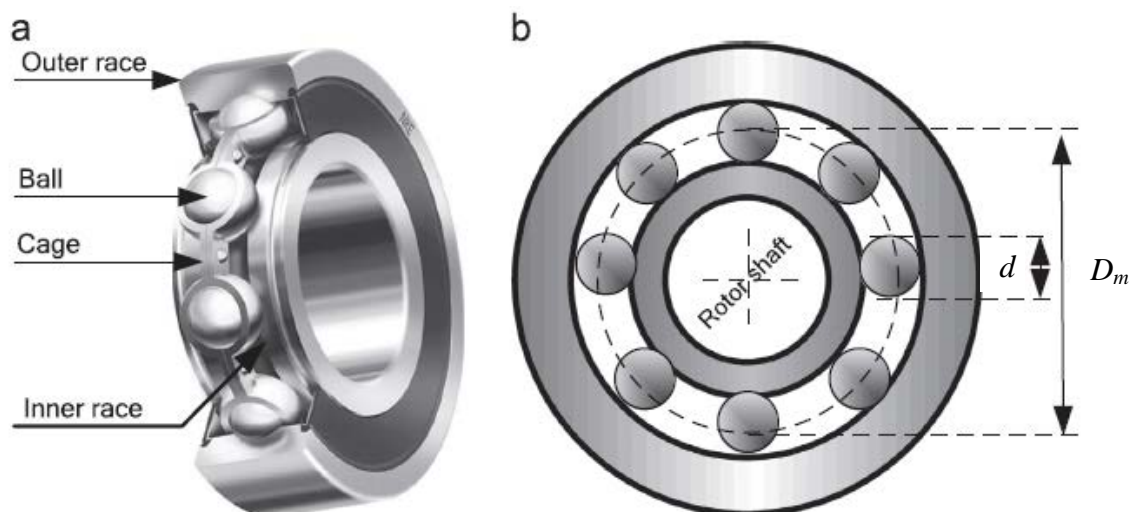


Figure 4.3- Geometry of rolling element bearing[19]

- Inner raceway fault, f_{ir} (Hz) :

$$\frac{Z}{2} \frac{f}{60} \left[1 + \left(\frac{d}{D_m} \right) \cos \alpha \right] \quad (4.12)$$

- Outer raceway fault, f_{or} (Hz):

$$\frac{Z}{2} \frac{f}{60} \left[1 - \left(\frac{d}{D_m} \right) \cos \alpha \right] \quad (4.13)$$

- Rolling element fault, f_{re} (Hz):

$$\frac{D_m}{d} \frac{f}{60} \left\{ 1 - \left[\left(\frac{d}{D_m} \right) \cos \alpha \right]^2 \right\} \quad (4.14)$$

Where,

d : symbolises ball diameter

D_m : symbolises pitch diameter

α : symbolises the contact angle of rolling element

Z : symbolises the number of rolling elements

f : symbolises the speed of rotation.

4.3 Fault Classification

4.3.1 Preprocessing of vibration data

The vibration data is first preprocessed using the following attribute filters:

- **Cluster Membership-** This filter uses density based clustering to obtain the cluster membership values. The filtered instances comprise of these cluster membership values added with the class attribute.
- **Proportional K-Interval (PKI) Discretize-** This filter discretizes the numeric attributes using equal frequency binning. This technique adjusts the number and also the size of the discretized intervals proportional to the no. of training instances. Thus, providing an appropriate tradeoff between intervals' granularity and the expected accuracy of the probability's estimation. A numeric attribute 'A' is considered to have no. of known instance values 'N' the proportionality coefficient used is $(N)^{1/2}$.

Therefore 'A' is discretized into $(N)^{1/2}$ intervals and each interval having $(N)^{1/2}$ instances in it. With an increase in the value of 'N' both the size and number of discretized intervals also increases.[31]

- **Normalize-** This filter normalizes all the numeric values in a data set. Thus the input data is adjusted to bring the resultant filtered data to a common scale.
- **Random Projection-** This filter reduces the data's dimensionality by taking its projection on a lower dimension sub-space with the help of a random matrix having unit length columns. This decreases the number of attributes present in the data yet preserves much of its variation at a low computational cost. Random projection filters are most suitable for use with Nearest Neighbor classifiers and also provide good results with Support vector machines. [32]

4.3.2 Classifiers used

Following classifiers are used for classification of bearing faults:

- Support Vector Machine (SVM)
- Artificial Neural Network (ANN)
- K-Nearest Neighbor (KNN)

4.3.2.1 Support Vector Machine (SVM)

The SVM finds its application in the field of classification and regression. It was introduced by Corinna Cortes and Vladimir Vapnik in the year 1995[33]. SVM works on the principle of mapping the data non-linearly to a high dimensional feature space for finding an optimal hyper-plane which has the ability to separate the classes present in input data by maximizing the margin in between the closest points of the classes as shown in following figure. The hyper plane separates objects belonging to different classes. For example in following Figure 4.4 the separating plane defines a boundary which has objects belonging to two separate classes on its either side.

There exist many planes which can separate data but the goal of SVM is to find the optimum one i.e. there is a single hyper plane which maximizes the margin (i.e. the minimum distance between the separating hyperplane and the closest input data point) and that hyper plane needs to be detected for optimum classification of data.

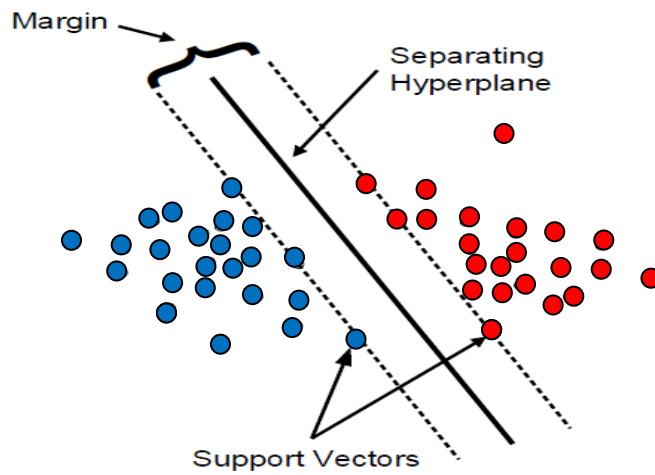


Figure 4.4- Data Classification Using SVM [34]

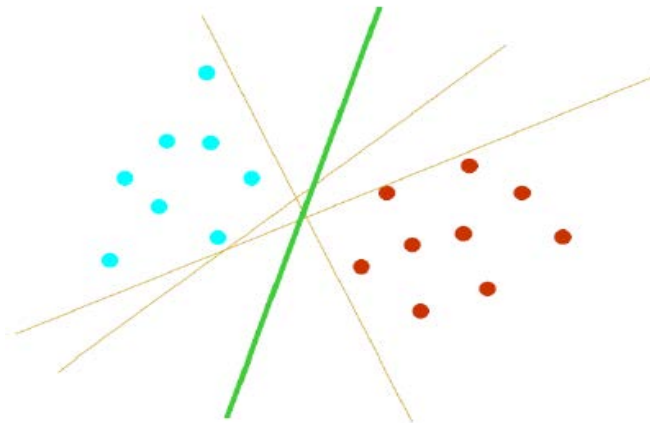


Figure 4.5- Finding the optimal hyper plane for data separation [35]

Since some data sets are not linearly separable thus data needs to be mapped to a higher dimensional space using a SVM kernel function.

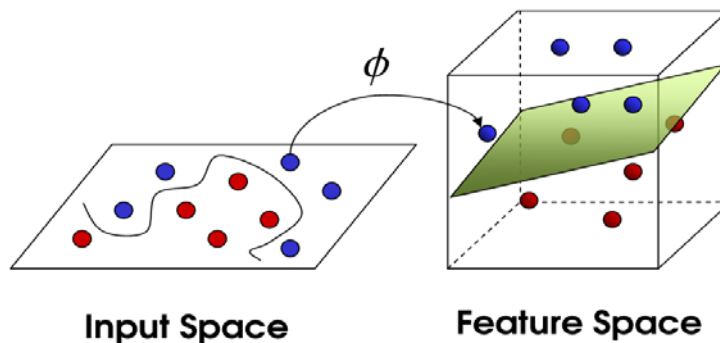


Figure 4.6- Mapping Non-linearly separable input data from input space to feature space

Kernel function is similarity function used for identification of unlabelled input data. The kernel can be linear, polynomial, gaussian RBF or sigmoid. Where the kernel function $K(X_a, X_b)$ can be computed as [36]:

- Linear : $(X_a \cdot X_b)$ (4.15)

- Polynomial : $(\gamma X_a \cdot X_b + C)^d$ (4.16)

- Gaussian RBF: $\exp(-\gamma |X_a - X_b|^2)$ (4.17)

- Sigmoid : $\tanh(\gamma X_a \cdot X_b + C)$ (4.18)

Where,

- γ is an adjustable parameter
- $K(X_a, X_b) = \phi(X_a) \cdot \phi(X_b)$ i.e. the dot product of input points mapped into a high dimensional feature space with the help of transformation function ϕ .

The above mentioned cases depict a two-class i.e. binary problem. In order to perform classification in a multiple class problem one method is to adopt multi-output SVM technique. This technique uses a single SVM classifier but the classifying function and calculation is very complex, the training and recognition consumes more time and also the classifying error increases with increase in the number of samples. The second method is to combine binary SVM classifiers to obtain multiple class SVM output. This is done using two algorithms i.e. using ‘one to one’ or ‘one to rest’ algorithm.

This work uses Polykernel or the polynomial kernel as the kernel function of SVM classifier and the value of penalty parameter (C) is optimized to attain maximum classification accuracy.

4.3.2.2 Artificial Neural Networks (ANN)

ANN can be referred to as an information processing tool which is inspired by the information processing mechanism of human brain. ANN constitutes large no. of interconnected neurons which work in unison towards solving a specific problem. ANN has several applications such as classification of data, pattern recognition etc. which are achieved through an ANN’s learning process.

Human brain is made up of a massive network of neurons. Every single neuron consists of a cell body called soma, dendrites which act as input channels and the axon which terminates at

the synapses. A neuron receives all its inputs through the dendrites, sums these received inputs and if the sum exceeds a certain threshold value an output is produced. This output might then be received by another neuron and might activate it.

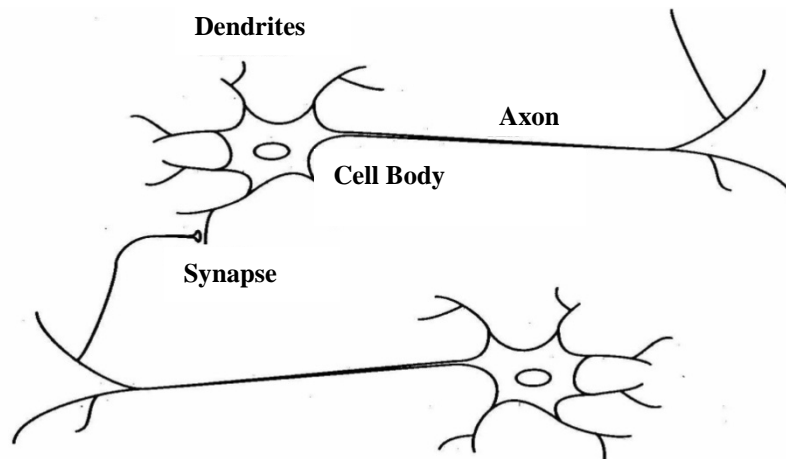


Figure 4.7- Biological neurons

As ANN are an imitation of human body's central nervous system, like in case of biological system learning involves the adjustments of synaptic connections between neurons learning in ANN works on similar principle. For an artificial neuron with 'n' inputs i.e. x_1, \dots, x_n having weights w_1, \dots, w_n , $\sum w_i \cdot x_i$ denotes the weighted sum of inputs which is passed further to ϕ i.e. the activation function which further produces an output signal. The multiplication of weights and inputs denotes the strength of synapse. A synapse having a larger value of weight is capable to transmit a stronger signal whereas the one with a smaller value of weight depicts weak synapse.

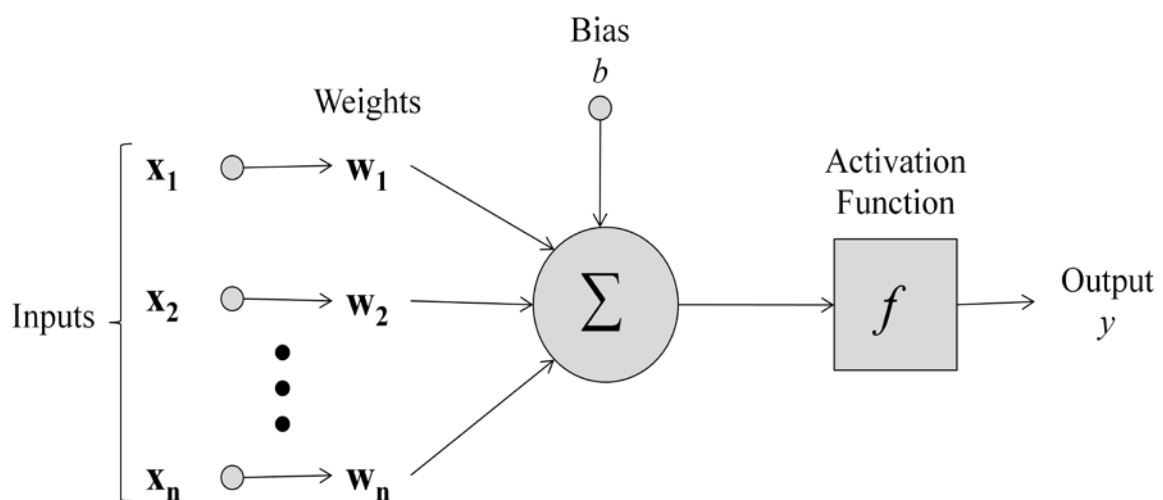


Figure 4.8- Artificial Neural Network

In order to process non-linearly separable data a single layer neural network is not sufficient thus for this purpose Multilayer Perceptrons (MLP) are used. A MLP is a feedforward ANN consisting of multiple layers with each layer connected to its next layer. The non-linearly separable input data is first projected into a space where it is changed into linearly separable data using a non-linear transformation. This intermediate layer is called the hidden layer. One or more hidden layers are then followed by an output layer.

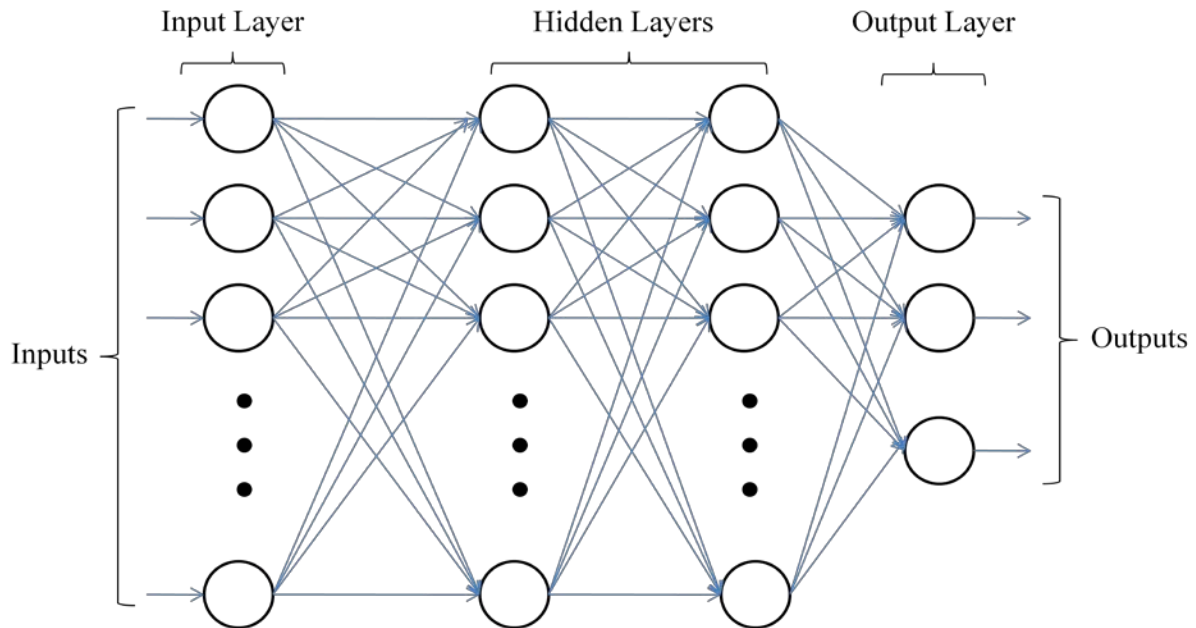


Figure 4.9- Multilayer Perceptron Model

MLP networks find their use in supervised learning problems which can be solved using Back-propagation Algorithm. It consists of two parts-

- Forward propagation in which predicted outputs are computed corresponding to the inputs.
- Backward propagation involves propagating the partial derivatives of cost function with respect to various parameters backwards through the network.
- The weights are then updated using an optimization technique such as gradient descent.
- These iterations are performed until the weights obtained converge.

The size of hidden layer used in this research work is 7 and 4 neurons are present in the output layer when uniform defect is introduced in the bearing components. In case of varied fault severity levels the size of hidden layer is 10 and the number of neurons in output layer

are also 10. The value of momentum is kept fixed at 0.2 and the learning rate value is varied between 0 and 1 and an optimum value is selected which provides maximum fault classification accuracy.

4.3.2.3 K-Nearest Neighbor (KNN)

KNN is an instance based learning technique. It is considered the simplest of all machine learning algorithms yet is very versatile and has been applied in various fields. The output of a KNN classification is a class membership. The object is assigned a class which is most common amongst its 'k' number of nearest neighbors (where k has a positive integer value). KNN predicts the outcome class on the basis of its 'k' nearest neighbors lying closest to the data point to be classified. Thus there must be a defined metric to calculate the distance between the point to be classified and other points neighboring it. The most commonly used distance computation technique is the calculation of Euclidean distance between the points. Euclidean distance is measured using the following formula:

$$D(x, y) = \sqrt{(x - y)^2} \quad (4.19)$$

Where x is the point to be assigned a class membership and y is an existing point belonging to a particular class.

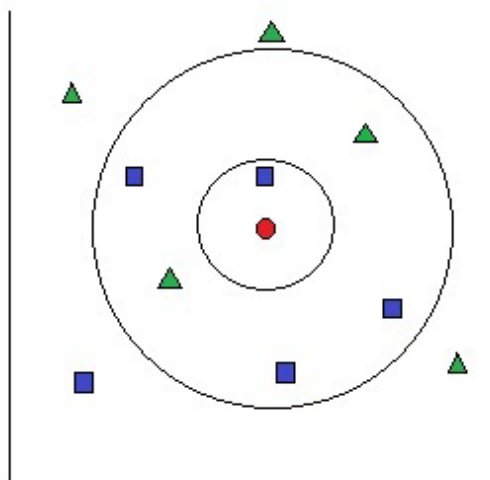


Figure 4.10- KNN classification example

For instance in the figure 4.10, the red point needs to be assigned a class i.e. either blue or green. For value of $k=1$, the nearest neighbor to the point is class blue thus it is assigned to that class. Now, for $k=5$ no. of out of the five nearest neighbors of the red point number of points belonging to class blue are more than those belonging to class green. Therefore, for $k=5$ the red point is assigned the blue class. Thus any new data point can be assigned a class

membership by adopting similar classification algorithm. This simple yet efficient technique involved in classification using KNN makes it a versatile algorithm.

In this work, four values of 'k' have been explored i.e. k=1, 3, 5 and 7. An optimum value of 'k' which corresponds to maximum fault classification accuracy is then selected.

CHAPTER 5

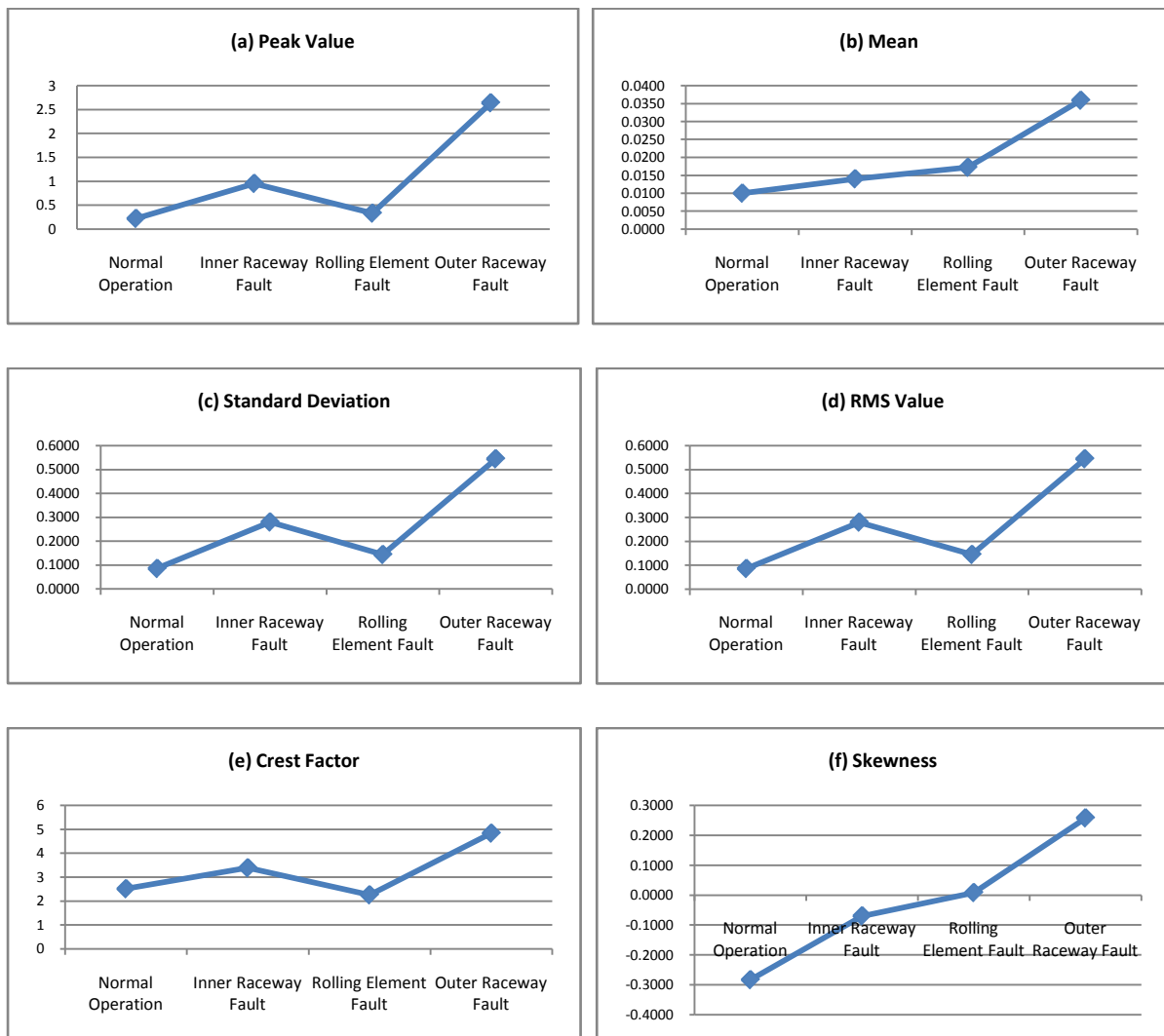
RESULTS & DISCUSSION

5.1 Time Domain Analysis

The time domain statistical parameters- peak value, mean, standard deviation, RMS value, crest factor, skewness, clearance factor, impulse factor and shape factor were extracted for normal operation as well as faulty i.e. inner, outer raceway and rolling element faults introduced in motor bearings.

5.1.1 Statistical Parameters

The variation of these parameters with the occurrence of faults at various bearing components having uniform defect dimension i.e. 0.007 inches is depicted by the following Figures 5.1 (a-j).



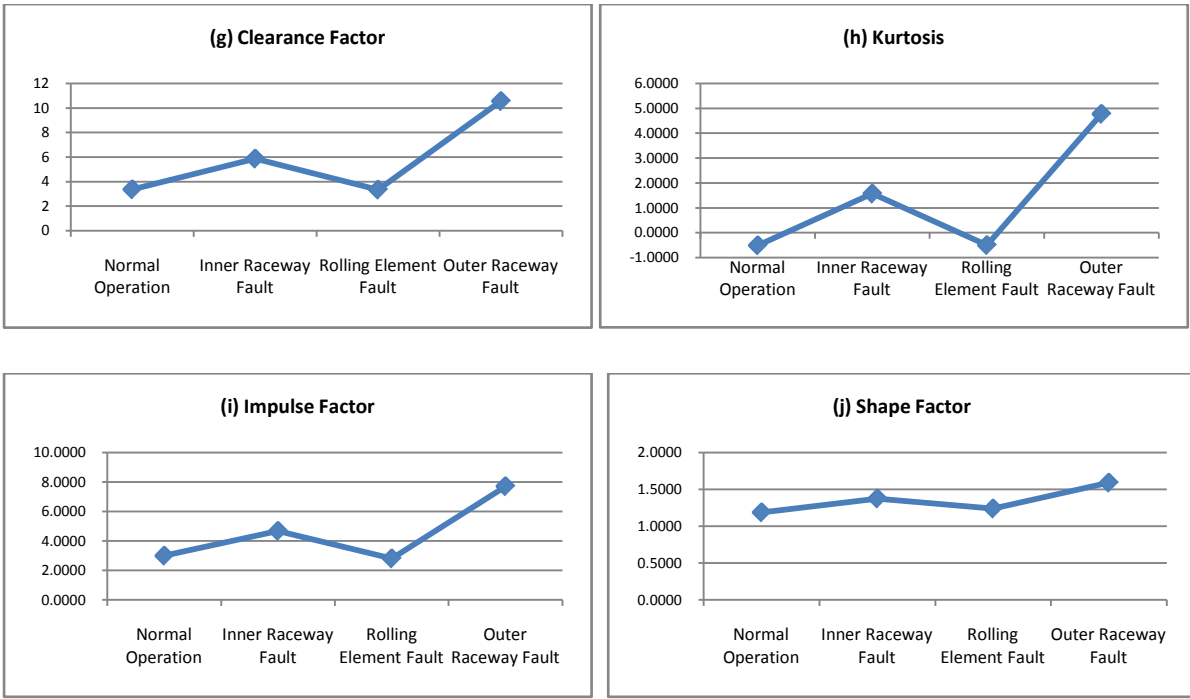


Figure 5.1- Variation of time domain statistical parameters with operating condition

A comparison of the extracted time domain statistical parameters is presented in Figure 5.2. The figure depicts time domain parameter values corresponding to the four motor operating conditions analysed in this work i.e. motor's normal operation and motor's faulty operation with the presence of inner raceway, rolling element and outer raceway faults.

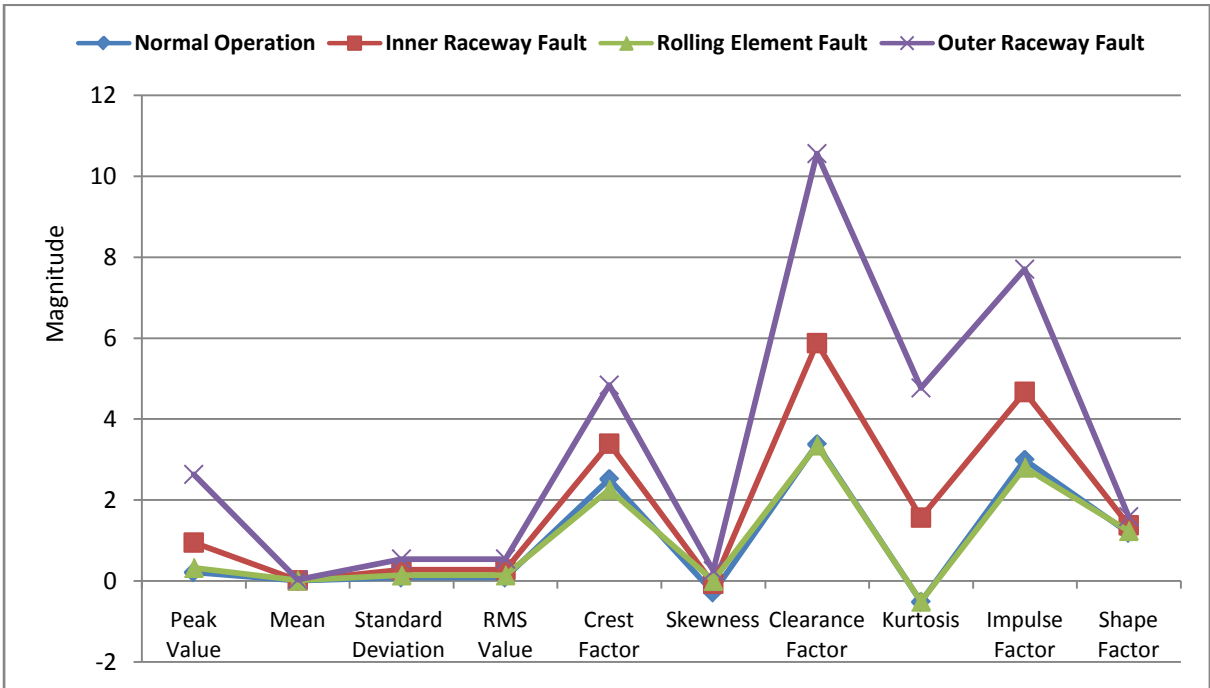


Figure 5.2- Variation of time domain statistical parameters with operating condition

5.1.2 Observations

It was observed from the graphical representation of parameters in Figures 5.1 and 5.2 that variations in parameter values between normal and faulty operation is significant. All extracted parameters- peak value, mean, RMS value, standard deviation, crest factor, skewness, kurtosis, clearance, impulse and shape factor have maximum value for fault in the outer raceway of the bearing next followed by the fault in inner raceway of the bearing. It can thus be deduced that parameter values increase with the occurrence of outer raceway and inner raceway faults in the motor. However, the parameter values for rolling element fault and motor's normal operation do not have significant difference. Thus presence of abnormal motor condition can be detected using this analysis but the identification of individual faults is still not feasible using this information.

5.2 Cepstrum Analysis

Cepstrum Analysis was performed on vibration data obtained at 1797 RPM i.e. under no load condition of motor operation. The motor tested to obtain the vibration database used a deep groove ball bearing, 6205-2RS JEM SKF. The dimensions of which are as follows:

Table 5.1- Bearing Dimensions

Ball Diameter	Inside Diameter	Outside Diameter	Thickness	Pitch Diameter
0.3126	0.9843	2.0472	0.5906	1.537

Using these bearing dimensions bearing fault frequencies calculated are as follows:

Table 5.2- Bearing Fault frequencies (multiples of the motor's running speed in Hz)

Inner Raceway Fault	Rolling Element Fault	Outer Raceway Fault
5.4152	4.7135	3.5848

The theoretically calculated bearing fault frequencies using bearing dimensions are:

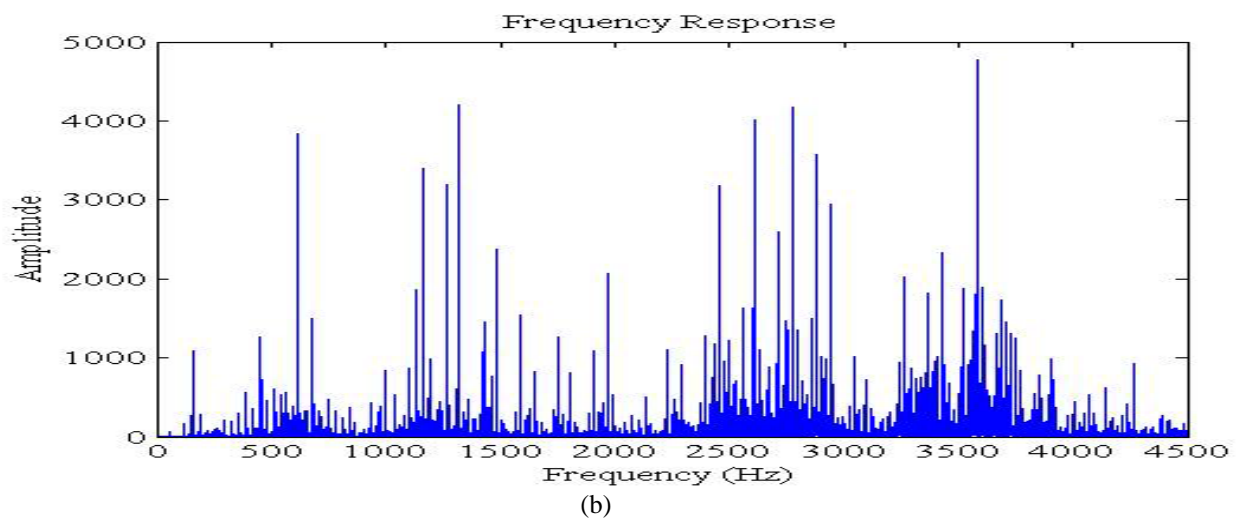
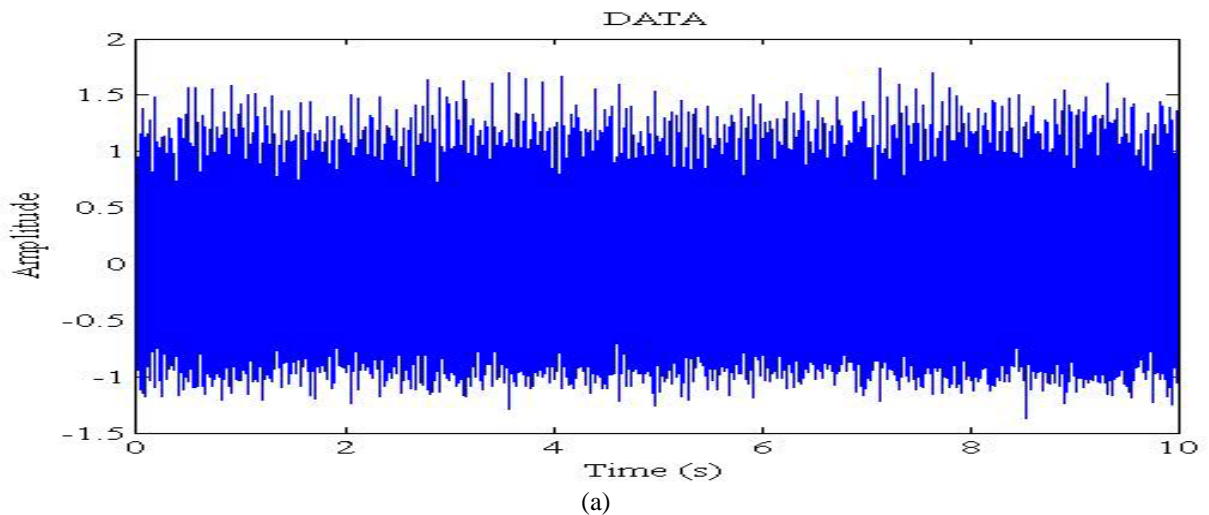
- Inner raceway fault frequency= $5.4152 \times \text{Running Speed in Hz} = 162.185\text{Hz}$
- Rolling element fault frequency= $4.7135 \times \text{Running Speed in Hz} = 141.169\text{ Hz}$
- Outer raceway fault frequency= $3.5848 \times \text{Running Speed in Hz} = 107.365\text{ Hz}$

Table 5.3- Theoretically obtained bearing fault frequencies and their corresponding quefrequency values

Operating Condition	Inner Raceway Fault	Rolling Element Fault	Outer Raceway Fault
Fault Frequency (Hz)	162.185	141.169	107.365
Corresponding Quefrequency (sec)	0.0062	0.0071	0.0093

5.2.1 Cepstrum Plots

Cepstrum plots were obtained by processing data in MATLAB. The cepstrum analysis of vibration data was performed for inner raceway, outer raceway and rolling element faults. Following are the time domain, FFT and Cepstrum plots obtained for the above mentioned operating conditions of motor bearings.



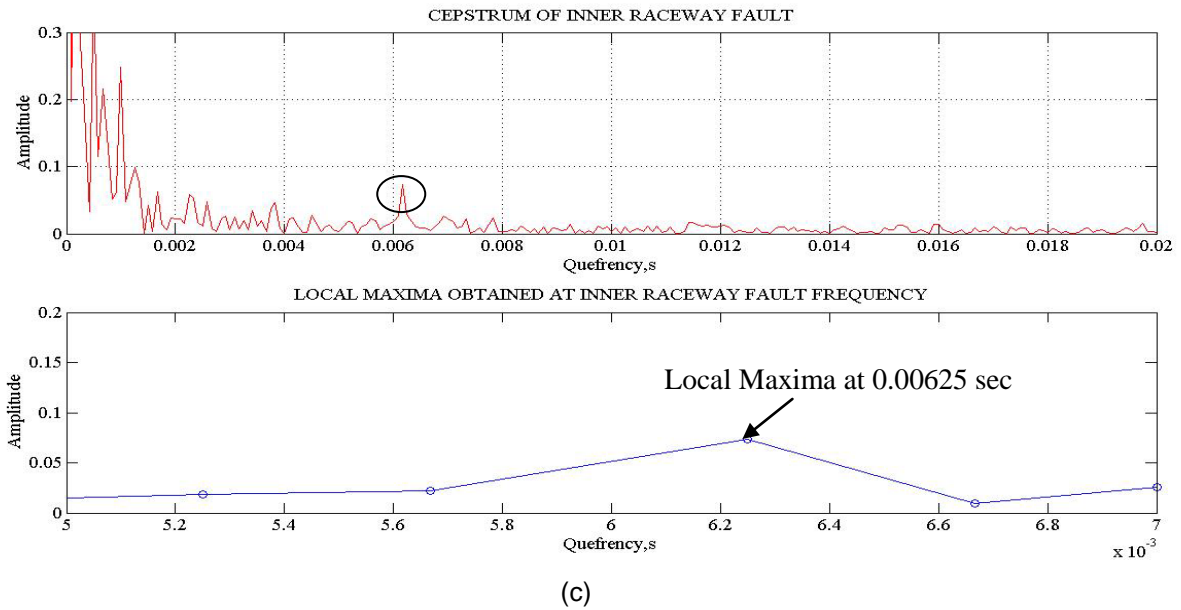
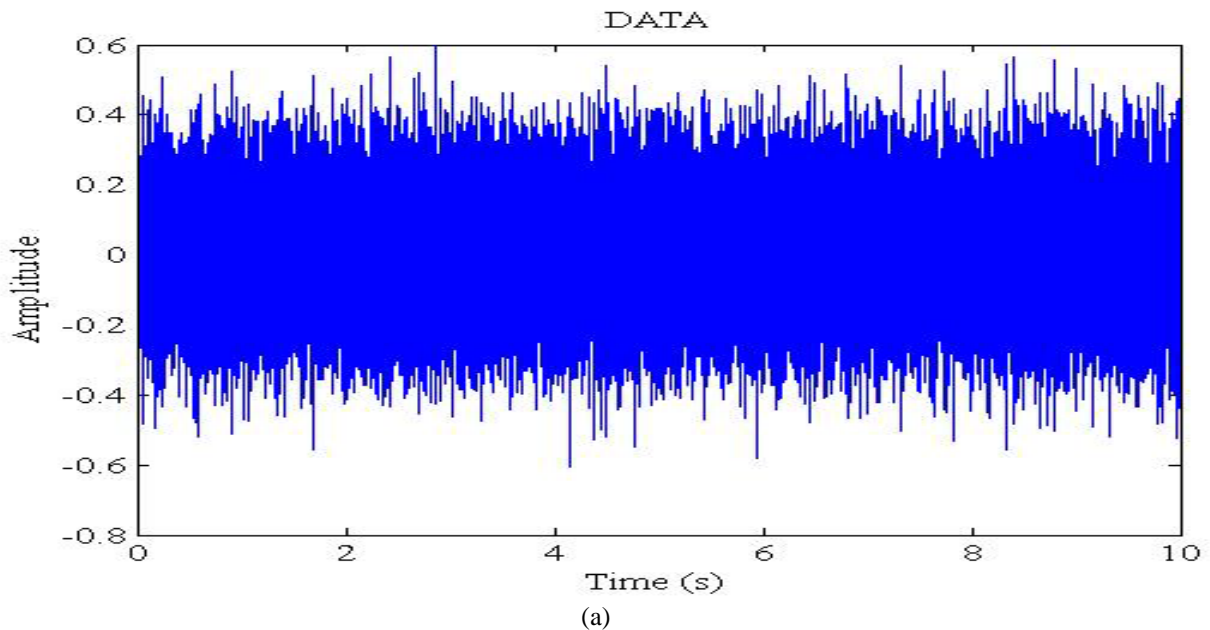


Figure 5.3- (a) Time domain Data (Inner Raceway Fault) (b) FFT of Inner Raceway Fault Signal
(c) Cepstrum Plot for Inner Raceway Fault

Figure 5.3 (a) depicts the time domain vibration data acquired after introduction of inner raceway fault of 0.007 inches in the motor bearing followed by figure 5.3 (b) which shows the Fast Fourier Transform (FFT) i.e. the frequency domain spectrum corresponding to the time domain vibration signal. The cepstrum plot obtained for inner raceway fault is shown in figure 5.3 (c), a peak is observed at quefrequency value 0.00625 sec which is also obtained as a local maxima by considering the quefrequency range from 5sec to 7sec.



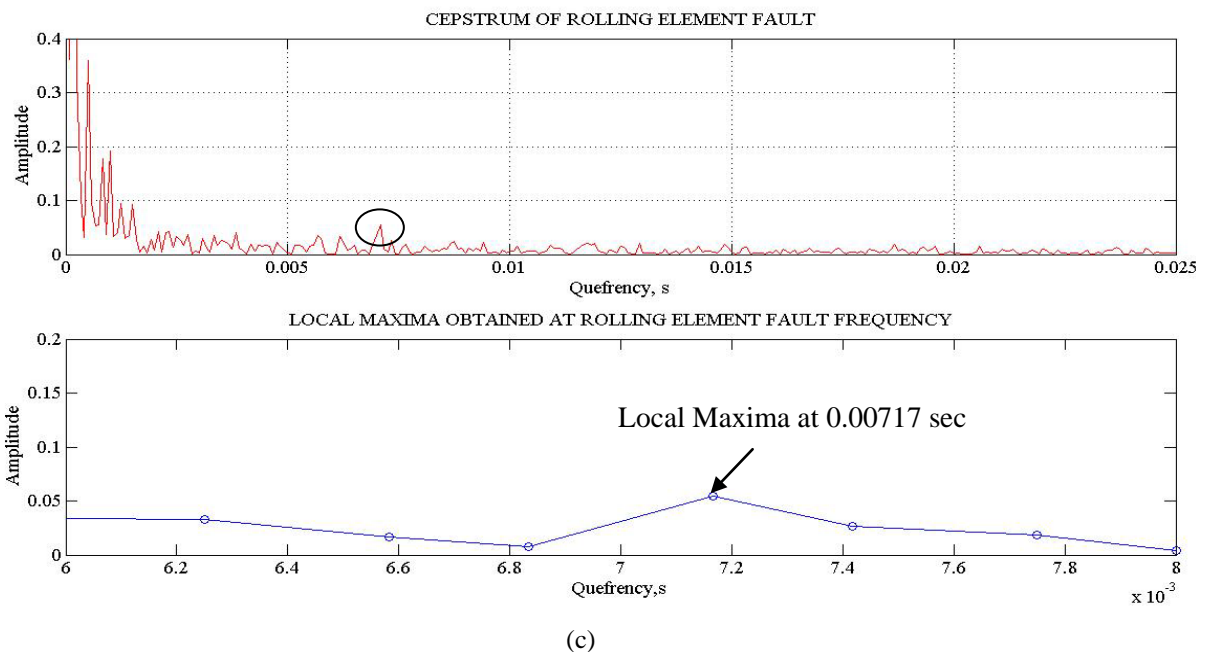
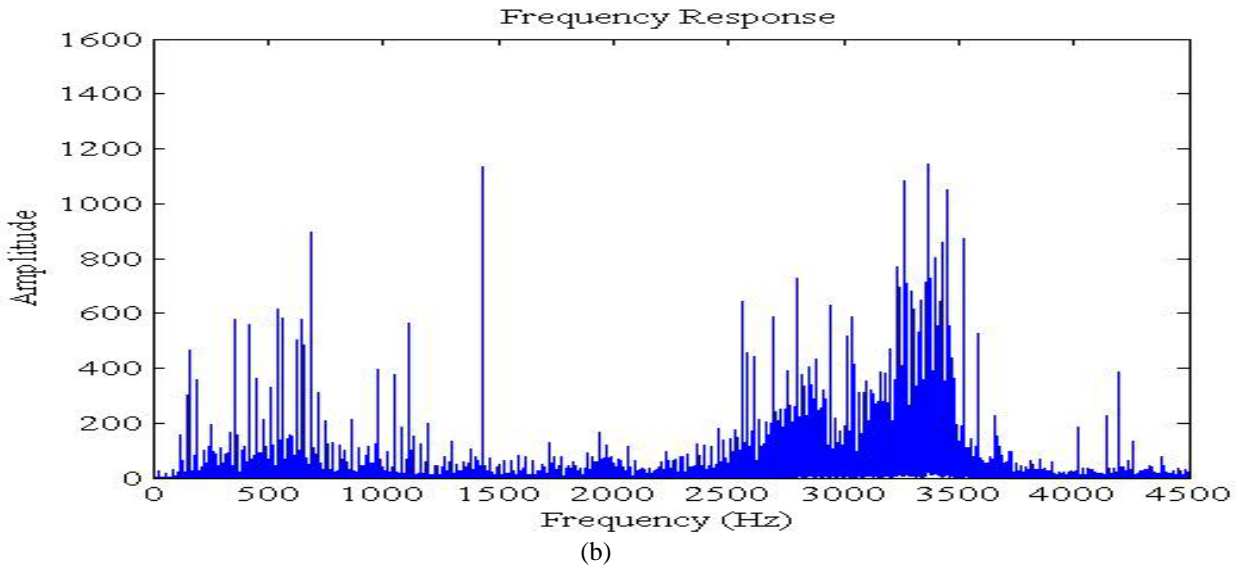


Figure 5.4- (a) Time domain Data (Rolling Element Fault) (b) FFT of Rolling Element Fault Signal (c) Cepstrum Plot for Rolling Element Fault

Figure 5.4 (a) depicts the time domain vibration data acquired after introduction of rolling element fault of 0.007 inches in the motor bearing. It can be observed from this figure that the amplitude of vibrations is lower as compared to those in case of inner raceway fault depicted in figure 5.3 (a). Similarly the amplitude of the FFT spectrum shown in figure 5.4 (b) for rolling element fault is much lower than that of inner raceway fault shown in figure 5.3 (b). The cepstrum plot obtained for rolling element fault is shown in figure 5.4 (c), a peak is observed at quefrency value 0.00717 sec which can also be observed as a local maxima by considering the quefrency range from 6sec to 8sec.

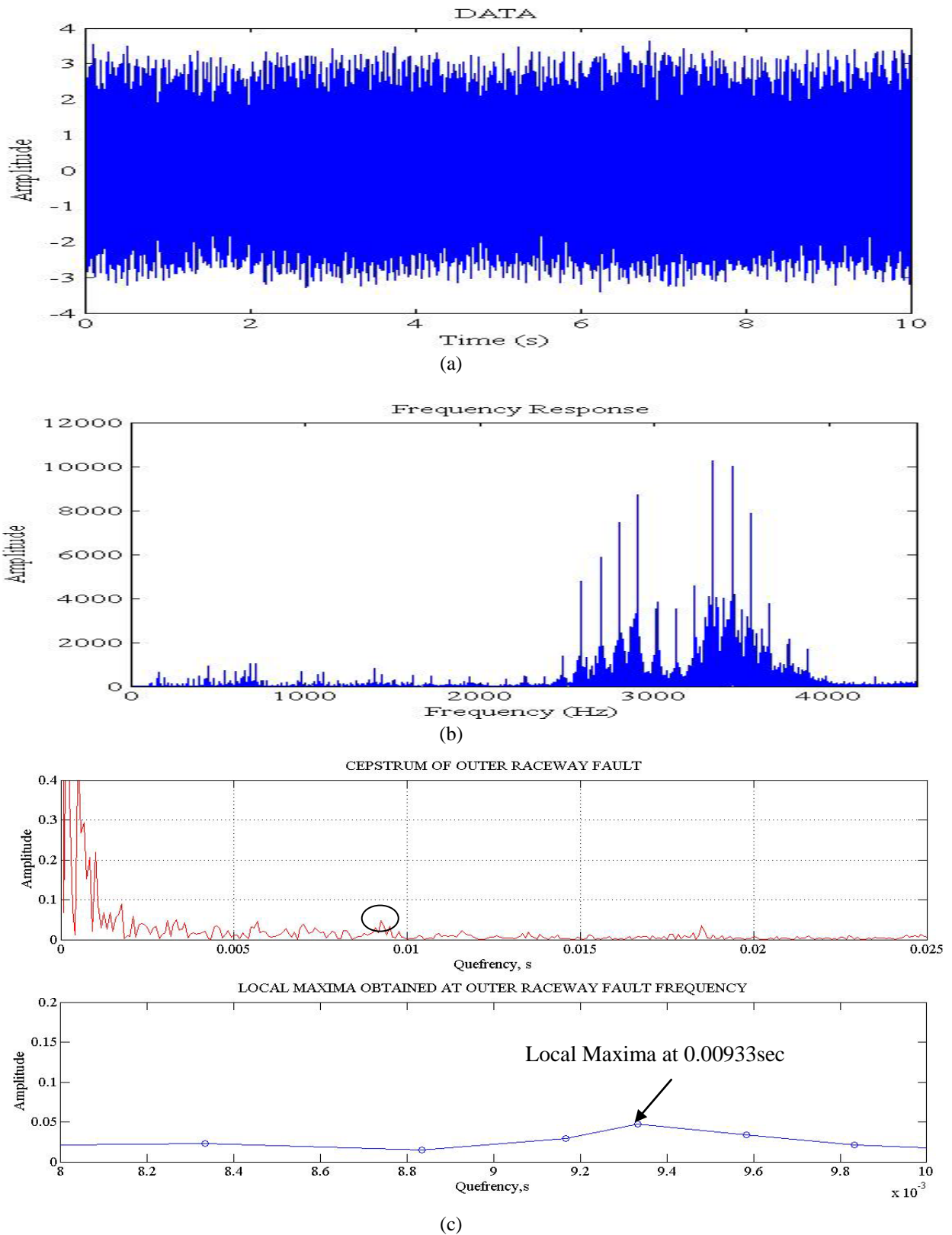


Figure 5.5- (a) Time domain Data (Outer Raceway Fault) (b) FFT of Outer Raceway Fault Signal (c) Cepstrum Plot of Outer Raceway Fault

Figure 5.5 (a) depicts the time domain vibration data acquired for outer raceway fault of 0.007 inches introduced in the motor bearing. This figure depicts that the vibrations are most

severe in this case as compared to those in case inner raceway and rolling element faults shown in figure 5.3 (a) and figure 5.4 (b). The FFT spectrum of outer raceway fault is shown in figure 5.5 (b), it can be observed that in this case the frequency components of large values are present between frequency range 2500Hz to 4000Hz. The cepstrum plot obtained for outer raceway fault is shown in figure 5.5 (c), a peak is observed at quefrequency value 0.00933 sec which can also be observed as a local maxima by considering the quefrequency range from 8sec to 10sec.

5.2.2 Observation

The peaks obtained in the cepstrum plots for different fault conditions correspond to quefrequency values theoretically calculated using bearing dimensions as depicted in following table 5.4.

Table 5.4- Bearing Fault Quefrequency values

Operating Condition	Calculated Quefrequency Value (s)	Quefrequency Value Corresponding To Cepstrum Plot Peaks (s)
Inner Raceway Fault	0.0062	0.00625
Rolling Element Fault	0.0071	0.00717
Outer Raceway Fault	0.0093	0.00933

Thus obtaining a peak in the cepstrum plot corresponding to a theoretically calculated fault frequency confirms the presence of a particular fault in the system. This achieves the objective of identification of type and also locating the fault present in the system.

5.3 Fault Classification

Motor bearing fault's classification was achieved using Support Vector Machine (SVM), Artificial Neural Networks (ANN) and K-Nearest Neighbor (KNN) classifiers. Following are the two cases considered:

- Uniform defect of 0.007 inches introduced in inner and outer raceway and the rolling element of the bearing individually.

- Defects of varying severity levels i.e. 0.007, 0.014 and 0.021 inches introduced in inner and outer raceway and the rolling element of the bearing one by one.

5.3.1 Fault Classification Accuracies Using Various Classifiers

Bearing fault classification is done using SVM, KNN and ANN classifiers. The time domain statistical parameters extracted from vibration fault data for uniform fault severity level and with varied fault severity level are first pre-processed using various attribute filters then fed to these classifiers. The fault classification is achieved using 10-fold cross validation technique and the classifiers parameters are optimized to attain best classification accuracy.

5.3.1.1 Support Vector Machine (SVM)

The statistical parameters extracted from vibration data obtained for normal operation and defects measuring 0.007 inches introduced in motor bearings were pre-processed using attribute filters- Cluster membership, Random projection, PKI Discretize and Normalize. The fault classification was then performed using SVM. Table 5.5 shows classification accuracies obtained using SVM classifier which employed 10-fold cross validation technique and used Polykernel with value of C=1. The maximum accuracy of 100% was obtained for cluster membership and PKI discretize attribute filters. Followed by random projection and normalize attribute filters providing 93.75% and 81.25% accuracies respectively with value of C=1.

Table 5.5- Fault Classification Using SVM (For Uniform Defect)

ATTRIBUTE FILTER	TIME TAKEN (s)	PENALTY PARAMETER (C)	CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	ERROR (%)	ACCURACY (%)
Cluster Membership	0.04	1	16	0	0	100
Random Projection	0.02	1	15	1	6.25	93.75
PKI Discretize	0.07	1	16	0	0	100
Normalize	0.02	1	13	3	18.75	81.25

Table 5.6- Fault Classification Using SVM (With Variation In Fault Severity Level)

ATTRIBUTE FILTER	TIME TAKEN (s)	PENALTY PARAMETER (C)	CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	ERROR (%)	ACCURACY (%)
Cluster	0.19	1	40	0	0	100
Membership						
PKI	0.26	1	35	5	12.5	87.5
Discretize						
Normalize	0.1	80	30	10	25	75

Table 5.6 shows classification results for time domain statistical parameters obtained from vibration data for faults of different severity levels introduced in the bearings. The data is first pre-processed using cluster membership, PKI discretize and normalize attribute filters and then fault classification is performed using SVM with 10-fold cross validation technique with Polykernel used as the kernel function. As shown in table 5.6 maximum fault classification accuracy of 100% is achieved using cluster membership attribute filter with the value penalty parameter C=1. Whereas, the classification accuracies obtained using PKI Discretize and normalize filter were 87.5% for C=1 and 75% for C=80 respectively which are much lower as compared to the accuracy obtained using cluster membership filter.

5.3.1.2 Artificial Neural Network (ANN)

ANN classifier used Back Propagation as the training algorithm for classification of vibration data. Sigmoid activation function was used. In case of uniform defects the size of hidden layer is 7 and that in case of variation in fault severity level the hidden layer size is 10.

Table 5.7- Fault Classification Using ANN (For Uniform Defect)

ATTRIBUTE FILTER	TIME TAKEN (s)	LEARNING RATE	CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	ERROR (%)	ACCURACY (%)
Cluster	0.19	0.3	16	0	0	100
Membership						
Random	0.04	0.3	14	2	12.5	87.5
Projection						
PKI	0.36	0.3	16	0	0	100
Discretize						
Normalize	0.04	0.3	14	2	12.5	87.5

As shown in table 5.7 the maximum fault classification accuracy of 100% was obtained for uniform severity level bearing faults using cluster membership and PKI discretize attribute filter and the value of learning rate set at 0.3. Whereas, random projection and normalize attribute filters yielded lower fault classification accuracies of 87.5% at learning rate=0.3.

Table 5.8- Fault Classification Using ANN (With Variation In Fault Severity Level)

ATTRIBUTE FILTER	TIME TAKEN (s)	LEARNING RATE	CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	ERROR (%)	ACCURACY (%)
Cluster Membership	0.31	0.3	40	0	0	100
PKI Discretize	1.19	0.3	32	8	20	80
Normalize	0.14	0.4	31	9	22.5	77.5

For classification of bearing faults of varied severity levels as shown in table 5.8 ANN classifier provided 100% classification accuracy using cluster membership filter with learning rate value set at 0.3. Next followed by 80% fault classification accuracy obtained using PKI discretize filter for 0.3 learning rate value. Lowest fault classification accuracy of 77.5% was obtained using normalize filter with learning rate set at 0.4.

5.3.1.3 K- Nearest Neighbor (KNN)

KNN classifier used for bearing fault classification used Euclidean distance as the distance function for nearest neighbor search. The value of ‘k’ i.e. no. of nearest neighbors in KNN classifier was optimized to achieve maximum classification accuracy possible.

Table 5.9- Fault Classification Using KNN (For Uniform Defect)

ATTRIBUTE FILTER	TIME TAKEN (s)	K	CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	ERROR (%)	ACCURACY (%)
Cluster Membership	0	1	16	0	0	100
Random Projection	0	3	16	0	0	100
PKI Discretize	0	1	15	1	6.25	93.75
Normalize	0	1	14	2	12.5	87.5

In case of bearing faults with uniform severity level fault classification accuracies obtained are using KNN depicted in table 5.9. Maximum fault classification with 100% accuracy was obtained using cluster membership filter with k=1 and also with random projection filter for k=3. Fault classification accuracy of 93.75% was achieved using PKI discretize filter and 87.5% with normalize filter for value of k=1.

Table 5.10- Fault Classification Using KNN (With Variation In Fault Severity Level)

ATTRIBUTE FILTER	TIME TAKEN(s)	K	CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	ERROR (%)	ACCURACY (%)
Cluster Membership	0	1	40	0	0	100
PKI Discretize	0	1	32	8	20	80
Normalize	0	1	32	8	20	80

Bearing faults of different severity levels when classified using KNN classifier yielded classification accuracies depicted in table 5.10. Maximum fault classification accuracy of 100% was obtained using cluster membership attribute filter with k=1, followed by 80% accuracy obtained using both normalize and PKI discretize filter with k=1.

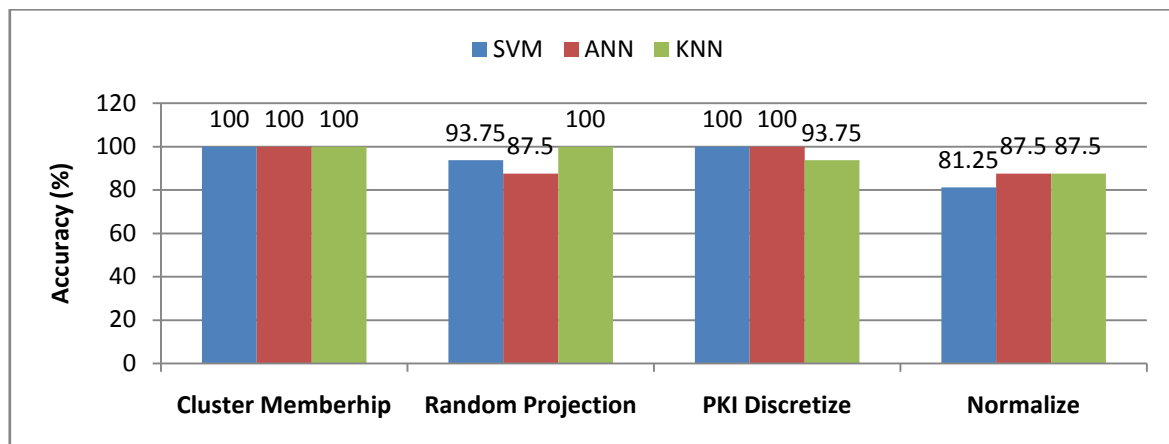


Figure 5.6- Comparison of uniform severity level bearing fault classification accuracies obtained using different attribute filters for SVM, ANN and KNN classifiers.

As shown in figure 5.6 SVM and ANN classifiers yield 100% fault classification accuracy in case of uniform defect size introduced in bearing components when used with cluster membership and PKI discretize attribute filters. KNN classifier achieved 100% fault

classification accuracy when applied with cluster membership and random projection attribute filter.

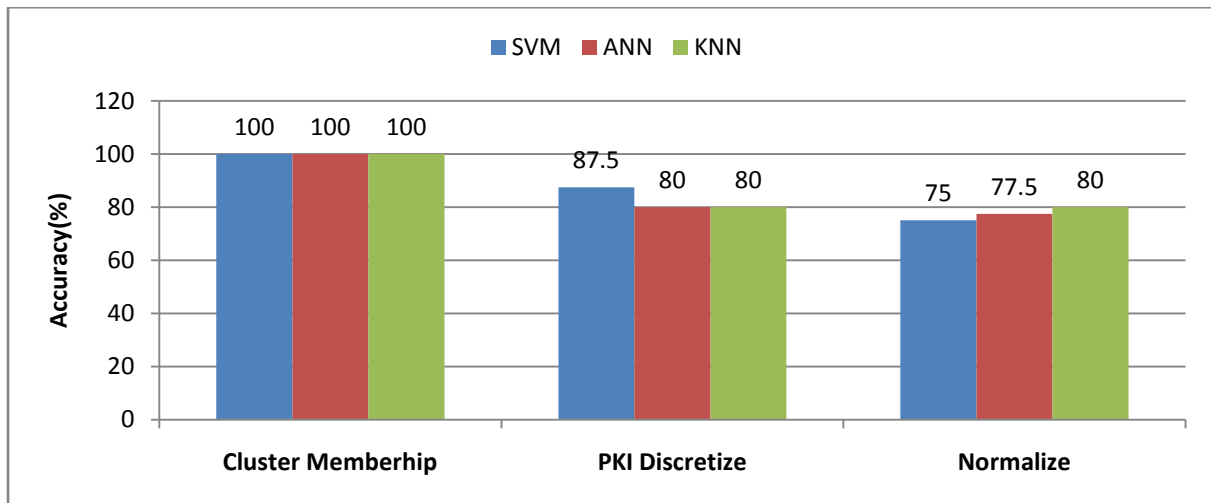


Figure 5.7- Comparison of varied severity level bearing fault classification accuracies obtained using different attribute filters for SVM, ANN and KNN classifiers.

As shown in figure 5.7 SVM, ANN and KNN provide 100% accuracy in classification of bearing faults with different defect dimensions when used with cluster membership attribute filter. PKI discretize and normalize attribute filters provide comparatively low fault classification accuracies.

5.4 Discussion

In this work various methodologies were adopted to achieve the objective of fault detection and diagnosis in induction machines. First one was time domain analysis of acquired vibration data which was useful for detection of an abnormal behaviour in motor operation as the vibration amplitudes became severe and also the parameter values showed an increase with the introduction of faults in the motor. However, this method failed to locate the fault present in the system. Then cepstrum analysis of data was performed and the results showed that peaks of the cepstrum plots were present at different fault frequencies respectively. This method thus proved to be useful in both fault detection as well as providing fault location. In the end fault classification was performed using classifiers- SVM, ANN and KNN for two cases, first with bearing faults of uniform dimensions and second with bearing faults of varying dimensions or severity levels were introduced. 100% classification accuracies were obtained in classification of uniform severity level faults with SVM and ANN classifiers using cluster membership and PKI discretize attribute filters and KNN classifier using cluster

membership and random projection attribute filters. When bearing faults of varying severity levels were considered 100% classification accuracy was obtained with all three classifiers used along with cluster membership attribute filter. The results signify that these classification algorithms can efficiently distinguish various bearing faults, thus providing a means to identify the type and severity level of fault prevailing in the motor bearings.

CHAPTER 6

CONCLUSION

Various types of faults may occur in an electric motor and can affect its performance, but a major type of fault that exists in electric motors is a bearing related fault. Ensuring a motor's optimum performance is the need of the hour. In order to achieve this objective, this research work presents various techniques for bearing fault diagnosis of electric motors.

This research uses a public domain database to study faults located at various components of the bearings. This database includes vibration data acquired at varying dimensions of faults introduced in the motor bearings which allows the bearing faults to be analysed at increasing fault severity levels. Different methodologies adopted in this work include time domain analysis for fault detection followed by cepstrum analysis technique which identifies the type of fault present. This forms a hybrid model of fault diagnosis. Further classification of uniform and varying severity level faults was performed using SVM, ANN and KNN employed along with various attribute filters, which yielded a maximum classification accuracy of 100% for all the three classifiers.

The techniques presented in this work not only detect the abnormal behaviour of motor bearings (i.e. the presence of some bearing fault in the motor) but also are capable to identify the type of fault thus fulfilling the objective of fault diagnosis. Apart from fault detection and fault location, another aspect covered is detecting the extent of 'fault severity'. Novelty of this work is that, it provides a complete solution to motor bearing related faults i.e. the proposed methodology is capable of bearing fault detection, finding its location and identifying the extent of its severity level.

The methodologies adopted in this research work have yielded high accuracies in fault diagnosis and classification- cepstrum analysis technique adopted is capable to locate any type of bearing fault present in the motor by identifying peaks in cepstrum plots corresponding to theoretically obtained bearing fault frequencies using bearing dimensions. Also the fault classification achieved using SVM, ANN and KNN classifiers has yielded 100% accuracy i.e. when these classifiers were applied to the pre-processed or filtered vibration data they were able to classifying different types and severity levels of bearing

faults correctly and accurately. Therefore the methodologies adopted in this research work are efficient and reliable in an electric motor's bearing fault diagnosis and can be used in any industrial environment to regulate the proper functioning of an electric motor.

6.1 Future Scope

Although the techniques adopted in this research work have been proved efficient in bearing fault diagnosis and indicating the fault's severity level but, this work concentrates on bearing faults introduced in bearing components individually i.e. one at a time. However, in practice faults may be present in various motor components simultaneously. Thus, in future a combination of various faults i.e. faults introduced at multiple motor components simultaneously may be studied to develop a more robust and diversified motor fault diagnosis model.

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