# MULTI SENSOR DATA FUSION BASED CONDITION MONITORING OF INDUCTION MOTOR

*A Thesis submitted in partial fulfilment of the requirements for the award of degree of*

**Master of Engineering**
**in**
**Electronics Instrumentation and Control**

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July 2012

# DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "**Multi Sensor Data Fusion Based Condition Monitoring of Induction Motor** " in partial fulfilment of the award of degree of **Master of Engineering** in **Electronics Instrumentation and Control** Submitted in the Electrical and Instrumentation Engineering Department, Thapar University , Patiala is an authentic record of my own work carried under the supervision of Ms. Ruchika Lamba , Lecturer, Department of Electrical and Instrumentation Engineering , Thapar University , Patiala, Punjab and Mr. Moon Inder Singh Assistant Professor Department of Electrical and Instrumentation Engineering, Thapar University , Patiala, Punjab.

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# ABSTRACT

With the increasing demand of technology in each and every phase of life, it should be such that the maximum people can avail it. With the advent of technology in the different areas such as defence, manufacturing process, oil refineries and power plants, the common necessity among all is the use of machinery for a long time with higher accuracy and greater sensitivity, so that maximum production can be obtained. In order to run the machinery for a long course of time and to make sure that the greater accuracy is achieved, it should be continuously monitored through some effective and reliable system. The maintenance of this machinery accounts for a large proportion of plant operating costs. Compared with the conventional scheduled maintenance strategy which is to stop the machine at pre-determined intervals, modern condition-based maintenance strategy stops the machine only before there is evidence of impending failure. With the development of cheaper sensors, it is now possible to use multi-modal sensor input to monitor machine condition in a collaborative and distributed manner.

The main objective of this thesis is to focus on the development of an intelligent multi-sensored engine with the condition monitoring tools. Significant efforts aim to develop a robust methodology for sensing and analysis under harsh environments, stressing its application to the fields of monitoring, fault diagnostics analysis and robotic industrial applications. The proposed process model will be used to facilitate the implementation of a common strategy to tackle the problem associated with the condition monitoring of the Induction motor using multi sensor data fusion technology.

This thesis looks in to different techniques of fault detection in induction motor and intelligent techniques to be implemented with a clear objective to diagnose the fault and its accuracy. The proposed method in this work allows continuous tracking of various types of fault in induction motor based on the offline/online data. These methods recognize the fault and diagnose them as well. In the first phase various faults are studied under different sections. After this, a suitable algorithm on WT is developed in MATLAB environment and applied on signal to detect the bearing fault. In the next phase the stator current condition is analysed for fault related to a stator current using the FIS Strategy. Finally, a hybrid fusion algorithm based on FIS is implemented for the detection of overall status of motor using the two known parameter i.e. (bearing fault & stator current).

# ACKNOWLEDGEMENT

During my M.E study at Thapar University, Patiala, Punjab, I have been fortunate to receive the valuable suggestions, guidance and support from my mentors, colleagues, family and friends.

First of all, I would like to express my most sincere gratitude to my supervisor **Ms. Ruchika Lamba**. She has been a wise and trusted guide throughout the entire process. Her guidance helped me to solve engineering problems and improve my communication skills. I am thankful to her that she has full confidence in my ability; much of this work would have not been completed without her vision and encouragement.

I also would like to thanks my Co-supervisor **Mr. Moon Inder Singh**, Assistant Professor Electrical and Instrumentation Engineering Department, Thapar University for his time to time guidance during my thesis work.

I am thankful to **Dr Smarajit Ghosh**, Head of Department, Electrical and Instrumentation Engineering Department, Thapar University, Patiala for his encouragement and support. I am thankful to all the faculty members and staff members of department of Electrical and Instrumentation Engineering, Thapar University for their support during my academic years.

We express our deep sense of gratitude to **Mr. Subhransu Padhee** for their valuable and encouraging guidance, which they played a major role in the formation of this project work.

This section will look incomplete if I fail to thank almighty God and all my near and dear friends and my family members who stood beside me, understood my academic goals and helped me to achieve it. Last but not least by any means, my heartiest thanks to all the persons, who made me what I am today; word fails to express my feelings for them.

**Tarun Naruka**

# CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# Chapter I
# Introduction

Induction motor plays a very crucial role in the industrial processes because of its higher reliability and its frequent integration in the commercially available instruments and many applications. Under normal conditions, its operation is safe and reliable but under abnormal conditions its operation may lead to faults which can lead to excessive downtimes and generate large undesirable economic losses. The AC induction motor is well suited to applications requiring constant speed operation. In general, the induction motor is cheaper and easier to maintain compared to DC motors and their other counterparts. They run at essentially from zero to full load, so these motors are frequently used in the industries [1.1, 1.2].

Traditionally maintenance procedures in industry follow two approaches as follow: First one is preventive maintenance and second one is breakdown maintenance. Nowadays there is a new maintenance procedure called predictive maintenance. An efficient condition-monitoring scheme is one that provides warning and predicts the faults at early stages. Monitoring system obtains information about the machine in the form of primary data and through the use of modern signal processing techniques; it is possible to give vital diagnostic information to equipment operator before it catastrophically fails [1.3, 1.4]. The problem with this approach is that the results require constant human interpretation. To automate the diagnostic process, recently a number of soft computing techniques have been proposed [1.5, 1.6, 1.7, 1.8]. The use of soft computing techniques increases the precision and accuracy of the monitoring systems [1.9].

## 1.1 Overview

The condition monitoring is essential for the effective and reliable operation of the induction motor which is extensively used in the many industries, process plants. The studies of the induction motor behaviour during the abnormal condition due to presence of unexpected faults and the possibility to diagnose these abnormal condition have been a challenging task for the electrical machine researchers .There are many condition monitoring methods which include chemical monitoring, acoustic monitoring, thermal monitoring etc but all these condition monitoring methods require expensive sensors and some specialized tools. In condition monitoring, the online/offline data is processed in real time for any unexpected error .The condition monitoring system does not fully rely on the past feedbacks of the machine, but online condition monitoring uses real time measurements while a machine is in running condition. Online/Offline condition monitoring of an electrical machine has become an area of an increasing interest and importance to electrical utilities and process industry. Owing to its effectiveness in preventing catastrophic failure of machine and reducing maintenance cost, condition monitoring has proved as a viable means to improve system reliability and to reduce the overall cost, especially where large machines are employed.

## 1.2 Objective

A single sensor is used to detect a single fault of induction machine, but it fails miserably to detect multiple faults. To detect multiple faults, multiple sensors are required. This work proposes a multi sensor fusion based approach of condition monitoring of the machine. The main aim of the work is to diagnose the common electrical and mechanical faults by using signal processing techniques.

The objective of the work is briefly addressed into the four phases:

(1) To acquire the multiple measurement data from online/offline (offline mode is used in our case) sources.

(2) The second phase investigates the bearing (vibration) related problem of induction motor and their effects. Based on these investigations, the different signal processing techniques like FFT, PSD, and DWT has been proposed and discussed to detect the fault.

(3) The third phase includes the diagnosis of electrical fault (stator current fault) by making the FIS (fuzzy inference system).

(4) The fourth phase involves the development of hybrid fusion algorithm for the two parameters i.e. bearing fault and stator current.

## 1.3 Outline of the Thesis

**Chapter 1** This chapter describes the introduction part of the work (condition monitoring), with the highlighted view on objective of the work which is to be carried out in the thesis.

**Chapter 2** It describes the concept of the multisensor data fusion and its need in the condition monitoring perspective with the light on some topics regarding types of fusion, their application in the military and non military domain.

**Chapter 3** It describes the overall structural view of the Induction motor with their types, major faults occurring in motor, different losses. It also highlights the domain of condition monitoring, need of condition monitoring and the application of condition monitoring in industries and their relevant merits and demerits.

**Chapter 4** This chapter describes the analysis of machine vibration (one of parameter of bearing fault) which is related to the mechanical domain.

**Chapter 5** This is the backbone of thesis and most of the work is carried out in MATLAB environment. It presents the most of the results of detection of the bearing fault by analysis of the vibration signal through some suitable signal processing techniques, as well as the detection of the stator current related problems by using the fuzzy inference system.

**Chapter 6** This chapter describes the fusion terminology from the practical point of view and a special hybrid fusion algorithm is a unique feature of this section.

**Chapter 7** This section deals with analysis of all the conclusions and discussions which has been done in the presented work so far with a brief overview on the future possibility of the remaining work in the same domain.

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# Chapter – II
# Multi Sensor Data Fusion

In recent years, there have been a growing interest in the use of multiple sources of information or data to increase the capabilities of intelligent machines and systems. Data fusion is a process of combining data from different information sources in order to make a better judgment. It plays an important role in many application domains. No single source of information can provide the absolute solution. Rapid evolution of microprocessors, advanced sensors, and new techniques has led to new capabilities to combine data from multiple sensors for improved inferences. Multisensor data fusion has received significant attention for both military and non military applications [2.1]. Data fusion techniques combine data from multiple sensors, and related information from associated databases, to achieve improved accuracies and more specific inferences than could be achieved by the use of a single sensor alone.

## 2.1 Data Fusion

In the engineering terminology, the term data fusion refers to the acquisition, processing and synergistic combination of information provided by various sources of data. `

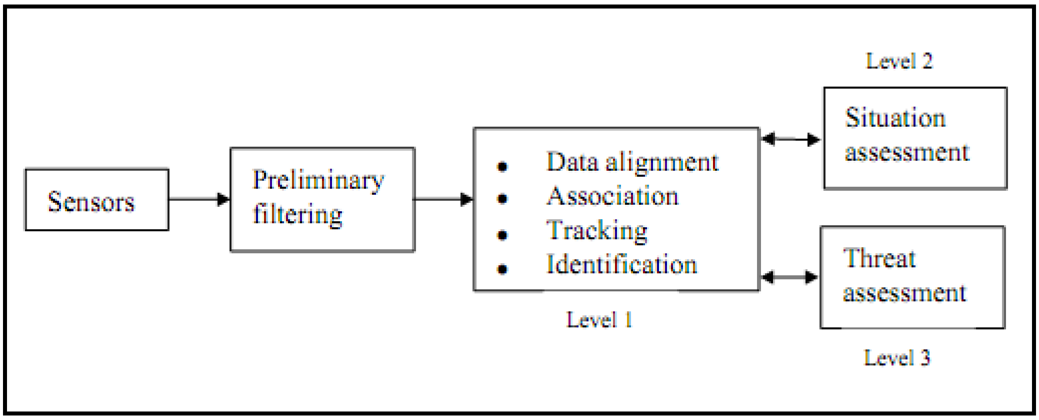

Figure 2.1 Basic Architecture of data fusion

The fundamental integration of data recorded from a multiple sensor system to obtain a more precise perception of the physical phenomena under analysis is known as data fusion. Here Figure 2.1 shows the architecture developed by JDL [2.2, 2.3].

- Level 1, object refinement, attempts to locate and identify objects. For this purpose, a global picture of the situation is reported by fusing the attributes of an object from multiple sources. The steps included at this stage are: Data alignment, prediction of entity's attributes (i.e. position, speed, type of damage, alert status, etc.), association of data to entities, and refinement of entity's identity.

- Level 2, situation assessment, attempts to construct a picture from incomplete information provided by level 1. That is, relate the reconstructed entity with an observed event (e.g. aircraft flying over hostile territory or a pipe liking). Level 2 processing develops a description of current relationships among objects and events in the context of their environment. Distributions of individual objects (defined by Level 1 processing) are examined to aggregate them into operationally meaningful combat unit sand weapon systems. In addition, situation refinement focuses on relational information (i.e., physical proximity, communications, causal, temporal, and other relations) to determine the meaning of a collection of entities [2.4, 2.5, 2.6]. This analysis is performed in the context of environmental information about terrain, surrounding media, hydrology, weather, and other factors. Situation refinement addresses the interpretation of data, analogous to how a human might interpret the meaning of sensor data. Both formal and heuristic techniques are used to examine, in a conditional sense, the meaning of Level 1 processing results.
- Level 3, threat assessment, interprets the results from level 2 in terms of the possible opportunities for operation. It analyses the advantages and disadvantages of taking one course of action over the other. Level 3 Processing (Threat Refinement) projects the current situation into the future to draw inferences about enemy threats, friendly and enemy vulnerabilities, and opportunities for operations. Threat assessment is especially difficult because it deals not only with computing possible engagement outcomes, but also assessing an enemy's intent based on knowledge about enemy doctrine, level of training, political environment, and the current situation. The overall focus is on intent, lethality, and opportunity. Level 3 processing develops alternate hypotheses about an enemy's strategies and the effect of uncertain knowledge about enemy units, tactics, and the environment. Game theoretic techniques are applicable for Level 3 processing.
- Level 4: A Process Refinement runs along these three levels to monitor performance, and to optimise allocation of sensors. Level 4 Processing (also

known as Process Refinement) may be considered meta-process, i.e., a process concerned about other processes. Level 4 processing performs four key functions[2.6]:

1. Monitors the data fusion process performance to provide information about real-time control and long-term performance,
2. Identifies what information is needed to improve the multilevel fusion product (inferences, positions, identities, etc.),
3. Determines the source specific requirements to collect relevant information (i.e., which sensor type, which specific sensor, which database), and
4. Allocates and directs the sources to achieve mission goals. This latter function may be outside the domain of specific data fusion functions.

Hence, Level 4 processing is shown as partially inside and partially outside the data fusion process

The hierarchical distribution of the JDL [2.3] model allows for the different levels to be broken down into sub- levels.

In this manner, level 1 could be further divided into four processes:

- Data alignment: At the data alignment stage, the data is processed to attain a common spatial and time frame.
- Data association: The data association could be further divided as association performed among data units of the same variable and between data units of different variables.
- Object estimation: Object estimation, on the other hand, could be sub-divided in terms of the processing approach taken (sequential or batch), parameter identification and estimate equations available, best-fit function criteria, and the optimisation of best-fit function approach sought.
- Object identity: The object identity stage could be subdivided into Feature extraction, identity declaration, and combination of identity declarations. At each of these lowest sub-levels, the mapping of different types of techniques could be easily allocated, and selected according to the case at hand. Level 2 Processing (Situation Refinement).

The strategy to implement data fusion varies from one application to the next, but three stages can commonly be identified. Depending on the problem, it is not always necessary to apply all the stages [2.7, 2.8]. The different stages which are to be implemented during data fusion are shown in figure 2.2.

| Pre Processing | Data Alignment | Post Processing |
|---|---|---|
| Image Processing | Correlation metrices | Classical Interference, Maximum aposteriori, Neyman Pearson |
| Wavelet | Figure of merit | Generalized Evidence, Damper Shafer |
| FFT, Cepstrum,Thresholding | Kalman Filtering | Voting, Consensus, Scoring |
| Linear and Non linear PCA | Clustering, Neural Network, Parametric templates, Voting, Entropy | Fuzzy Logic, Logical templates, Expert System |
|  | Least Square, Mean Square Error, Maximum likelihood |  |

Figure 2.2 A Method Map in Data Fusion

The different stages which are to be implemented are as follows.

- **Pre-processing**: Pre-processing includes reduction of the quantity of data whilst retaining useful information and improving its quality, with minimal loss of detail. The pre-processing may include feature extraction and sensor validation. Some of the techniques used include dimension reduction, gating for association thresholding, fourier transform, averaging, and image processing.

- **Data alignment**: where the techniques must fuse the results of multiple independent sensors, or possibly features already extracted in pre-processing. These include association metrics, batch and sequential estimation processes, grouping techniques, and model-based methods.
- **Post-processing**: combining the mathematical data with knowledge, and decision making. Techniques could be classified as knowledge-based, cognitive-based, heuristic, and statistical.

## 2.2 Classification of Data Fusion

The Figure 2.3 shows the classification of data fusion that can be broadly placed under two categories.

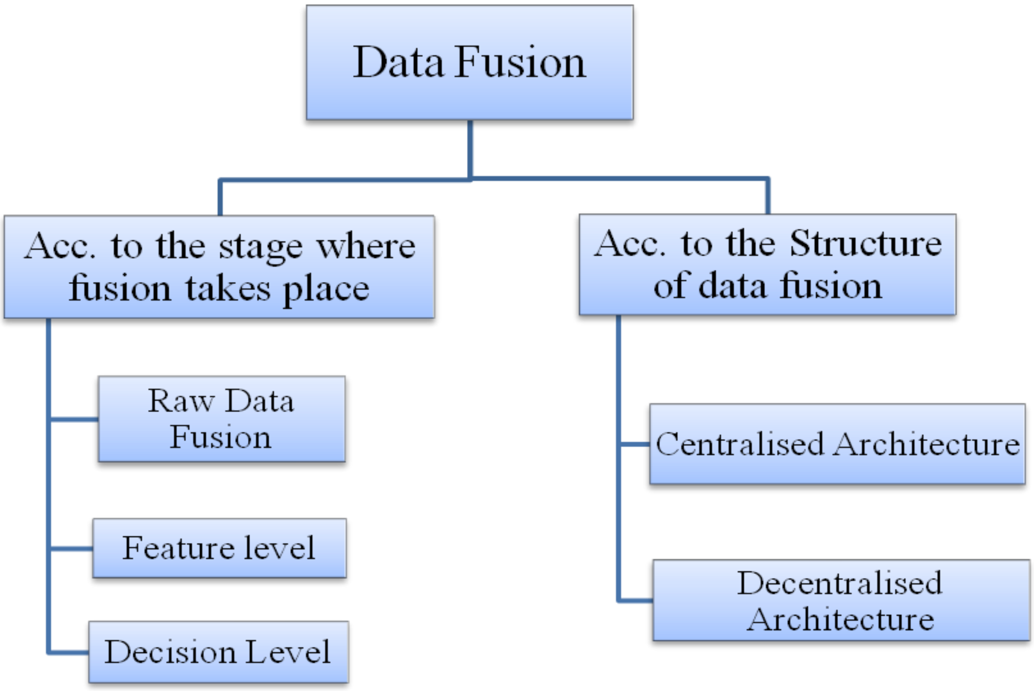

Figure 2.3 Classification of Data Fusion

The fusion of data takes place at different level of representation namely [2.9]

**2.2.1** **<u>Raw data fusion</u>:** fusion at the signal level/initial level of the sensor. In the raw data fusion methodology, the individual sensor generates the input which is send directly to the fusion centre where the raw data is robustly and redundantly merged or sensors are validated.

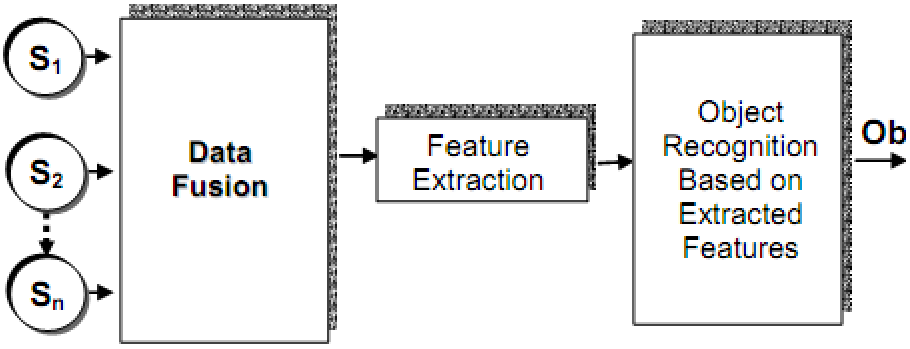

Figure 2.4 Raw Data Fusion

The different inputs from different sources to be fused can come from different sensors of the same basic type or they may come from different types of sensors. The sensors used for raw data fusion need to be accurately co-aligned so that their inputs will be in spatial registration.

### 2.2.2 <u>Feature level fusion</u>:

In the feature level fusion methodology, the specific features are extracted from the different sensors and after extracting the desired features the available features are sent to fusion centre where the features are fused accordingly [2.10, 2.11].In figure 2.5 the sensors $S_1, S_2 .........S_n$ can be of the same basic type or may belong to different categories .In the feature extraction unit, each sensor's individual characteristic feature is extracted before fusion occurs.

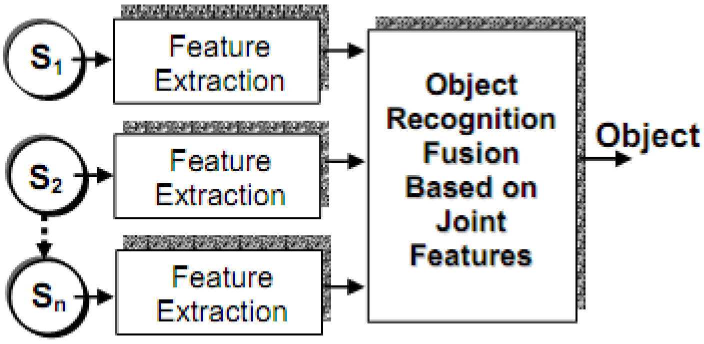

Figure 2.5 Feature level Fusion

**2.2.3 <u>Decision/object level fusion</u>**: This stage consists of fusion at the symbol level, where data with or without pre-processing measured is combined with processed data or a priori knowledge. This is one of the complex type of fusion level methodology, since the fusion takes place in the final stage after the data is fully processed at the initial stages [2.12, 2.13, 2.14, 2.15]. Figure 2.6 shows the steps involved in decision level fusion.

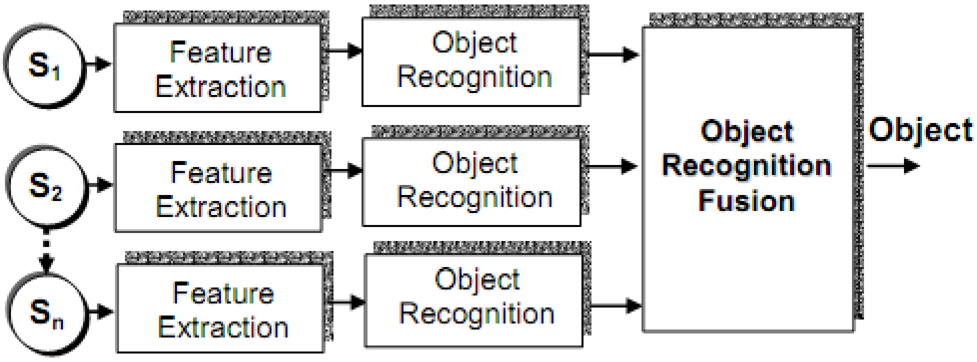

Figure 2.6 Decision/Object level Fusion

## 2.3 Types of Data Fusion

There are different types of fusion namely

- Central Fusion
- Distributed Fusion

**2.3.1 Central fusion -** The fusion of data could be done on raw data (centralised process) or on pre-processed locally fused data (decentralised process) [2.16]. In central fusion structure, all the information from the original sensors will be sent to the same fusion centre to generate larger observing space. The centralised architecture is computationally very intensive, but it possesses the advantage of developing a global view of the object from the original data, since all the information will be processed at the fusion centre, there is a large amount of data transmission in this structure, thus requires high processing speed.

**2.3.2 Decentralized fusion -** The decentralised architecture is less demanding on computational capabilities at the cost of adding complexity to the data fusion process, since each sensor has a processing unit. This feature is important to condition monitoring system. In distributed fusion structure, each sensor gives its own decision and the fusion is based on decisions rather than raw information, so data transmission load is greatly reduced. Sensors in the distributed fusion structure are independent of each other and need not be of the same type, so, even if some of the sensors fail, the system can still use the rest sensors to detect vehicle condition. Figure 2.7 & 2.8 shows the structure of centralized and decentralized fusion.

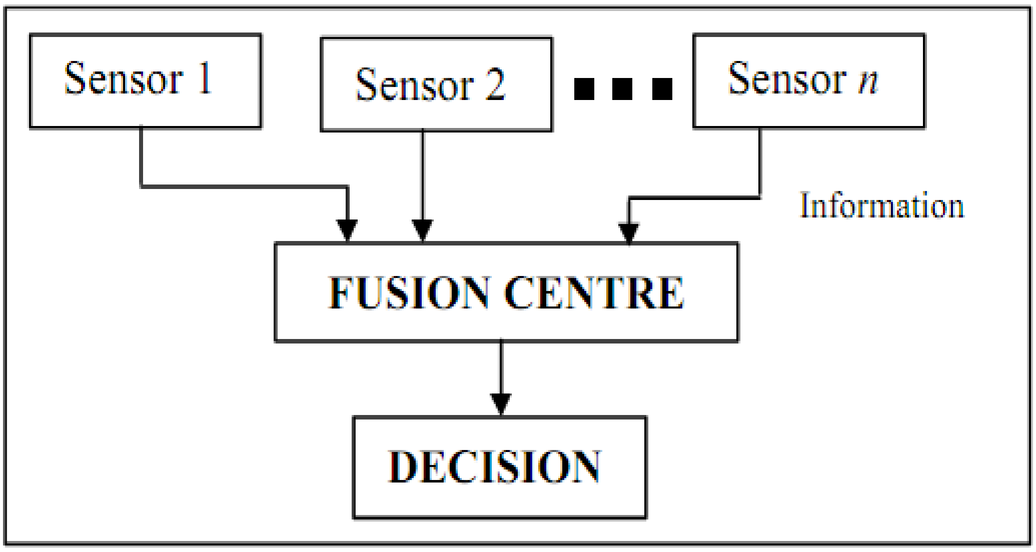

Figure 2.7 An Architecture of Centralized fusion

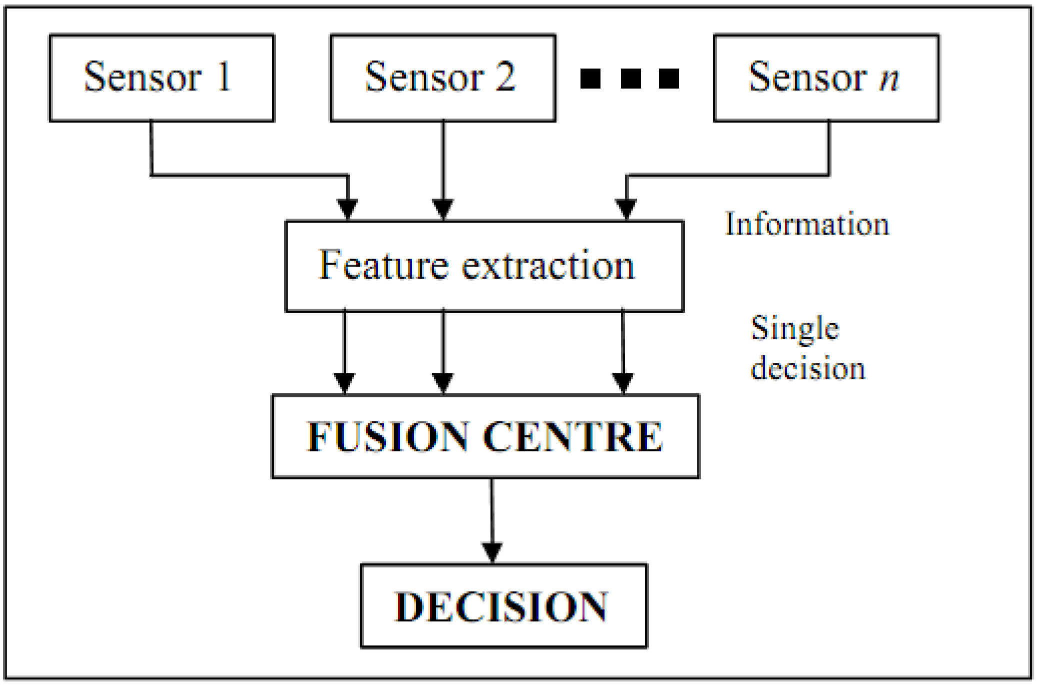

Figure 2.8 Decentralized fusion Architecture

The distributed fusion shown in Figure 2.9 is special case of fusion type where the sensors and their preprocesssing circuits are allocated in same unit, after having passed from the preprocessing and filtering stages, each sensor takes its own decision regarding fusion.

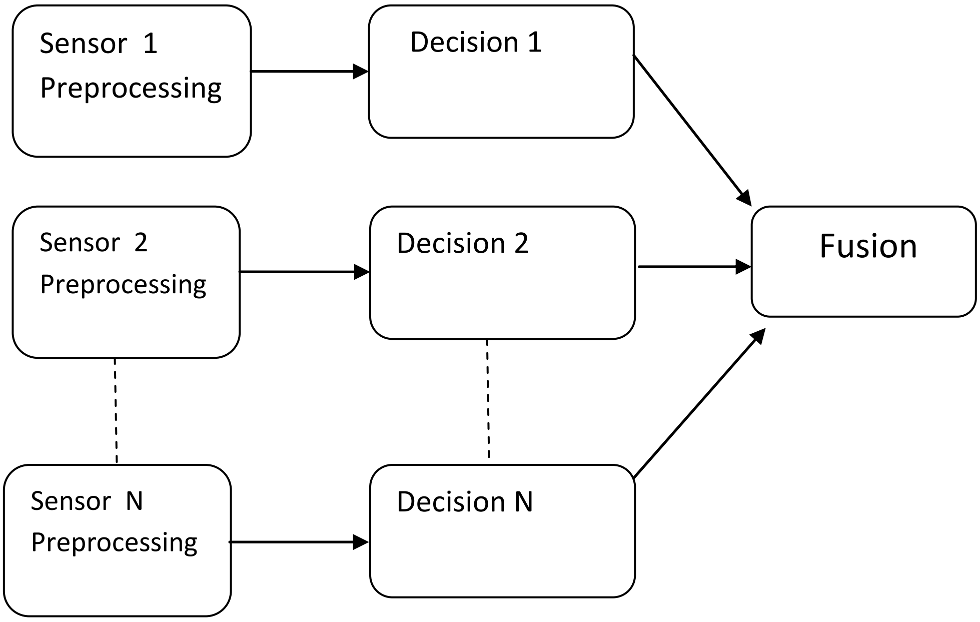

Figure 2.9 Distributed Fusion Structure

## 2.4 Advantages of Multi Sensor Data Fusion

i. Increased confidence: more than one sensor can confirm the same target.
ii. Reduced ambiguity: joint information from multiple sensors reduces the set of hypotheses about the target.
iii. Improved detection: integration of multiple measurements of the same target improves signal-to-noise ratio, which increases the assurance of detection.
iv. Increased robustness: one sensor can contribute information where others are unavailable, inoperative, or ineffective.
v. Enhanced spatial and temporal coverage: one sensor can work when or where another sensor cannot.
vi. Decreased costs: a suite of “average” sensors can achieve the same level of performance as a single, highly-reliable sensor and at a significantly lower cost.

## 2.5 Applications of Multi Sensor Data Fusion

The application of data fusion technology is basically in military and non-military government projects [2.17].

### 2.5.1 Military applications

1. Automated target recognition (e.g., for smart weapons)
2. Guidance for autonomous vehicles

3. Remote sensing
4. Battle-field surveillance
5. Automated threat recognition systems, such as identification-friend-foe-neutral (IFFN) systems

The military related application of multi sensor data fusion focuses on problems involving the location, characterization, and identification of dynamic entities such as emitters, platforms, weapons, and military units [2.18].

### 2.5.2 Non military applications

1. Monitoring of manufacturing processes
2. Condition-based maintenance of complex machinery
3. Robotics
4. Medical applications

## 2.6 Data Fusion: Condition monitoring perspective

Multi sensor data fusion approach (Figure 2.10) has rooted applications in the field of condition monitoring due to the fact that large amount of data should be processed if proper assessment of the machine's health is to be ensured [2.19]. The inspection of the machine could be performed on-line, in a continuous fashion, or off-line, on a scheduled basis. The data would then be processed in a sequential or in a batch manner, respectively. The data arriving to the fusion centre contain vibration, temperature, pressure, oil analysis, and other measurements that encapsulate the parametric properties of the system and can aid in its condition assessment. An important aspect of condition monitoring is the fidelity of information received by the sensor units. The data acquired must be consistent and noise-free. These aspects should be considered at the source level to alleviate the pre-processing of the information. On the other hand, the sample cycle should be small enough to be contained within the time over which faults in the machine develop, and input frequencies should be carefully selected to achieve the desired monitoring capabilities. After the data has been acquired at the source level, it passes through to the pre-processing unit for digital conversion and proper manipulation. At this stage, spectral analysis, correlation, time averaging, thresholding, and dimension reduction techniques are implemented based on the data at hand. The processed data is then pushed through to the fusion centre and routed according to the level of fusion sought i.e. raw data, feature, or decision level fusion [2.20].

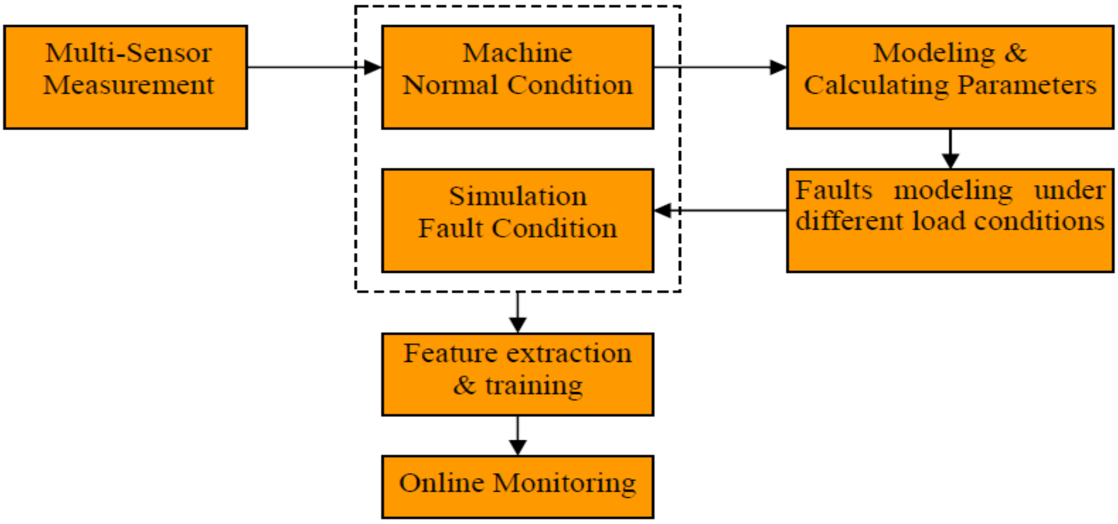

Figure 2.10 Multi sensor measurement techniques for condition monitoring of induction machine

## 2.7 Difficulties in Multi Sensor Data Fusion

Before a robust data fusion strategy can be logically submitted, there is a need to underline some of the difficulties arising with the application of data fusion, as well as other features that could be incorporated into the proposed model process. Some of the difficulties arising in multi-sensor data fusion can be summarised as follows [2.17].

- Diversity of sensors used: Nature, synchronisation, location, sensor outputs.
- Diversity of data representation: Imagery, spatial, statistical, and textual.
- Registration: The information sensored refers to the same entity. There is a need to check the consistency of the sensor measurements. This can be improved by objectively eliminating fallacious data sets.
- Calibration of the sensors when errors in the system operation occur.
- Limitations in the operability of the sensors.
- Deficiencies in the statistical models of the sensors and limitations in the algorithm development.

## 2.8 Literature review

**Lane M D Owsley et.al (1997)** uses SOFM to extract feature from vibration signal of induction motor and uses HMM to classify different fault data [2.21]. **Sinan Altug et.al (1999)** uses the neural network architecture for the detection of motor fault and its diagnosis[2.22]. **Zhongming et al (2001)** used WPD to detect both air gap eccentricity and broken rotor bar after giving a brief detail about the wavelet and feature extraction [2.23]. **G K Singh (2002)** reviewed the research aspect of multi phase induction machine drives. Multi phase induction machine is a potential alternative of the conventional 3 phase induction machine. This paper reviews the current development and issues and future challenges to design a multi phase induction machine drive [2.24]**. S.V. Wong et.al (2002)** studied the theory of optimization for detecting the faults in the motor rotor bearing using genetic algorithm [2.25]. **G K Singh et.al (2003)** studied the use of signal processing techniques to extract valuable information about machine health condition. The author studied about online and offline condition monitoring techniques [2.26]. **G K Singh et.al (2003)** carried out a survey of different techniques used in induction motor condition monitoring and fault diagnosis [2.27]. **B Samanata et.al (2003)** compared the working of ANN and SVM for fault detection and condition monitoring of induction motor. In case of SVM, features are optimized with the help of GA [2.28]. **Romero-Troncoso Rene de Jesus et.al (2004)** had a study about FPGA based online tool breakage detection system for CNC milling machine. It used DWT and autocorrelation algorithm to detect tool breakage [2.29]. **Hamidi et.al (2004)** presented the detection of mixed eccentricity fault using WPD, which was done by a modified winding function [2.30]. **Antonino et al (2005)** presented the detection and diagnosis of mixed eccentricities and rotor asymmetries with different sizes and conditions as well as effective oscillations due to the load torque or voltage that was studied individually [2.31]. **Antonino et al (2006)** presented many cases for fault diagnosis (mixed eccentricity, broken rotor, inter-turn and inter-coil stator short-circuits) using DWT at start up current of induction machines according to the stator parallel branches [2.32]. **Fulufhelo V Nelwamondo et.al (2006)** has reviewed feature extraction techniques to extract both linear and non linear features from vibration signal of a rotating machine. Features are extracted by MFD while considering two parameters like MFCC and Krutosis and bearing fault is classified using GMM and HMM. The result indicates that though computationally expensive HMM is a better classifier than GMM, while classifying bearing faults from time domain vibration signal [2.33]. **Tian Han et.al (2006)** has used wavelet transform, ANN and GA to predict the faults in induction machine. These techniques were implemented in stator current and the fault of induction machine is predicted. In pre processing of stator current signal, wavelet transform is used. GA is used to select the most significant feature vector, while ANN is used to predict the fault. The combination of all these techniques improves the diagnosis accuracy [2.34]. **Abhinav Saxena and Ashraf Saad (2007)** uses GA to select smaller subset of features that together form a genetically fit family for successful fault identification and classification task [2.35]. **Jafar and Javad (2007)** used Meyer wavelet in the WP structure to detect the bearing defect using SCA with energy comparison as the fault index [2.36]. **Bo Suk Yang et.al (2007)** surveys the use of support vector machine (SVM) for machine condition monitoring and fault detection. SVM produces higher accuracy in classification tasks for machine condition monitoring and fault diagnosis [2.37]. **Bin and Paghda (2008)** used the wavelet to detect the broken rotor bar, eccentricity and bearing due to current, voltage and instantaneous power, while the signals to noise ratio of the spectral components were examined under varying load condition of the single phase in the active cycle [2.38]. **C. Rodriguez-Donate et.al (2008)** implemented an embedded system with FPGA and SOC (System on Chip) for online monitoring of induction motor failures by measuring the vibration transient signals at the start-up with discrete wavelet transform. [2.39]**Jawad and Mansour (2009)** presented a review for most important indexes in the different types of eccentricities faults in the induction motors as well as the consequences and effects [2.40]. **Franco-Gasca et.al (2009)** presents a hardware signal processing unit implemented in a single field-programmable gate array (FPGA) for acquisition, conditioning, and basic signal monitoring in several machining processes. This model is reconfigurable and scalable so that it may be adapted to diverse conditions as an economical standalone unit since it does not require either computers or microprocessors [2.41]. **Luis Miguel Contreras-Medina et.al (2010)** developed a low-cost FPGA based on a multichannel vibration analyzer; this is capable of providing an automatic diagnosis of the motor state carrying out online continuous monitoring [2.42]. **Yixiang et al (2010)** used the lean model to assess the machine performance via DWT for the vibration and bearing induction motor faults [2.43]. **Luis Alfonso Rene J. Romero-Troncoso et.al (2011)** presents a novel methodology that is suitable for hardware implementation, which merges information entropy analysis with fuzzy logic inference to identify faults like bearing defects, unbalance, broken rotor bars, and combinations of faults by analyzing one phase of the induction motor steady-state current signal[2.44].

## 2.9 Chapter summary

This chapter presented a review of existing multi sensor technology along with the data fusion concept. This literature review covered a variety of topics like types of data fusion, their application and data fusion from condition monitoring perspective, along with the difficulties highlighted while using multi sensor. Hence, this chapter gives an overall idea about what the data fusion concept is all about and how it can be useful in the condition monitoring domain. In addition to data fusion the literature review has been revived regarding post work is also presented in this section.

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# Chapter - III

# Induction Motor & Its Condition Monitoring

## 3.1 Introduction

With adaption of AC system for distribution of electrical energy, AC motors are manufactured and are widely used in industrial applications. Figure 3.1 shows the classification of different AC motors are classified according to different point of view.

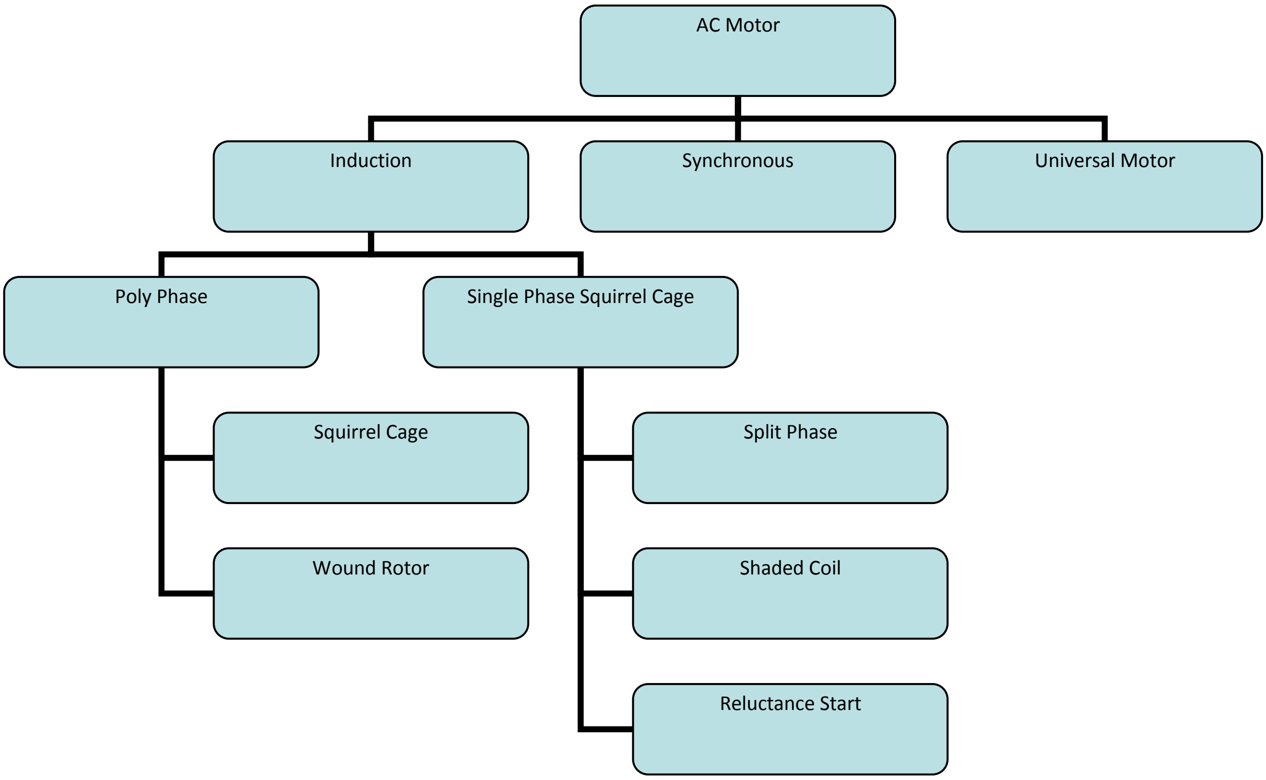


Figure 3.1 Classification tree of AC Machines

The induction motor is well suited to applications requiring constant speed operation. In general, the induction motor is cheaper and easier to maintain compared to DC motors and their other counterparts .They run at essentially from zero to full load, that’s why these motors are frequently used in the industries.

## 3.2 Construction of Induction Motor

An induction motor consists of a stator and a rotor. Figure 3.2 shows the construction of induction motor. The stator consists of a series of wire windings of very low resistance permanently attached to the motor frame. The internal construction of stator is shown in Figure 3.3(a). The rotor’s comprised of a number of thin bars, usually aluminium, mounted in a laminated cylinder. The bars are arranged horizontally and almost parallel to the rotor shaft. At the ends of the rotor, the bars are connected together with a “shorting ring.” The schematic view of rotor is shown in Figure 3.3(b). The rotor and stator are separated by an air gap which allows free rotation of the rotor. In the construction of rotor there are two types of windings namely [3.1, 3.2].

I. Squirrel-cage windings

II. Conventional 3-phase winding

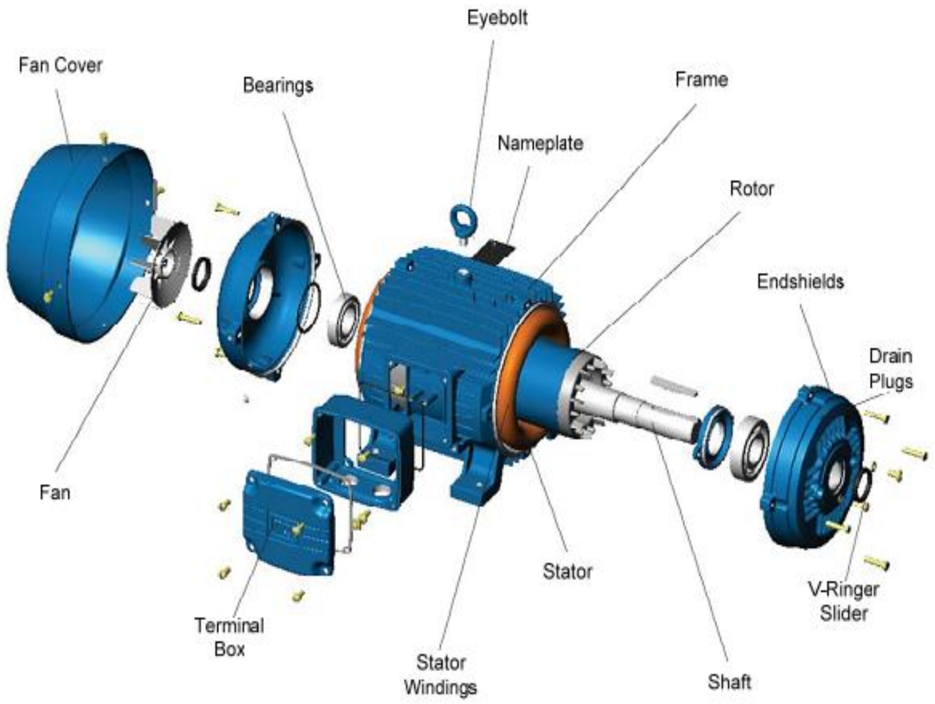


Figure 3.2 A typical view of 3 phase Induction Motor **(Courtesy of Electromotor WEGA, SA Brazil)**

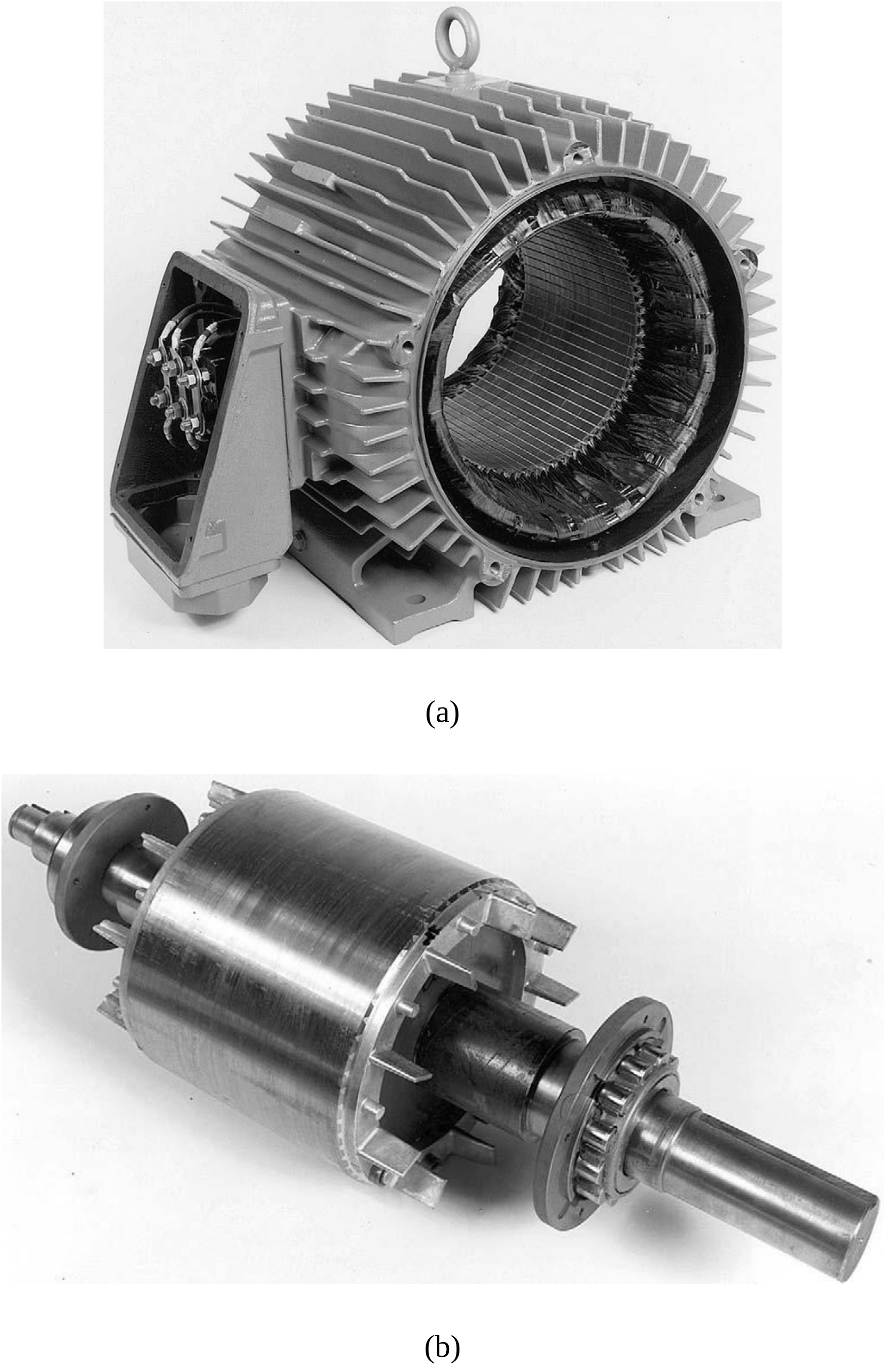


Figure 3.3 (a) Stator of 3 phase induction motor

(b) Rotor of 3 phase induction motor

### 3.2.1 Specifications of 3 phase Induction Motor

1. Power: 0.5 HP
2. Frequency: 50 Hz
3. Number of Phases: 3
4. Speed: 1500 RPM

5. Voltage 415 V
6. Current: 1.5 amp

### 3.2.2 Speed Torque Curve

Let us assume that the rotor is turning at the steady speed of n r/min in the same direction as the rotating stator field. Let the synchronous speed of the stator field be $n_s$ r/min. This difference between synchronous speed and the rotor speed is commonly referred to as the slip of the rotor; in this case the rotor slip is $n_s$- n, as measured in r/min. Slip is more usually expressed as a fraction of synchronous speed. The fractional slip S is given by Eq 3.1. The speed torque curve is explained in the Figure 3.4

$$s = \frac{n_s - n}{n_s} \tag{3.1}$$

$$\omega_m = (1 - s)\,\omega_s \tag{3.2}$$

$\omega_m$ is mechanical angular velocity and $\omega_s$ is synchronous angular velocity.

$$f_r = s f_e \tag{3.3}$$

The Figure 3.4 shows the relation between the torque and slip, it shows at low slip the torque is high for high rotor resistance while for the low rotor resistance initially the torque is low but as soon as speed increases the torque also increases up to certain level then after that torque decreases.

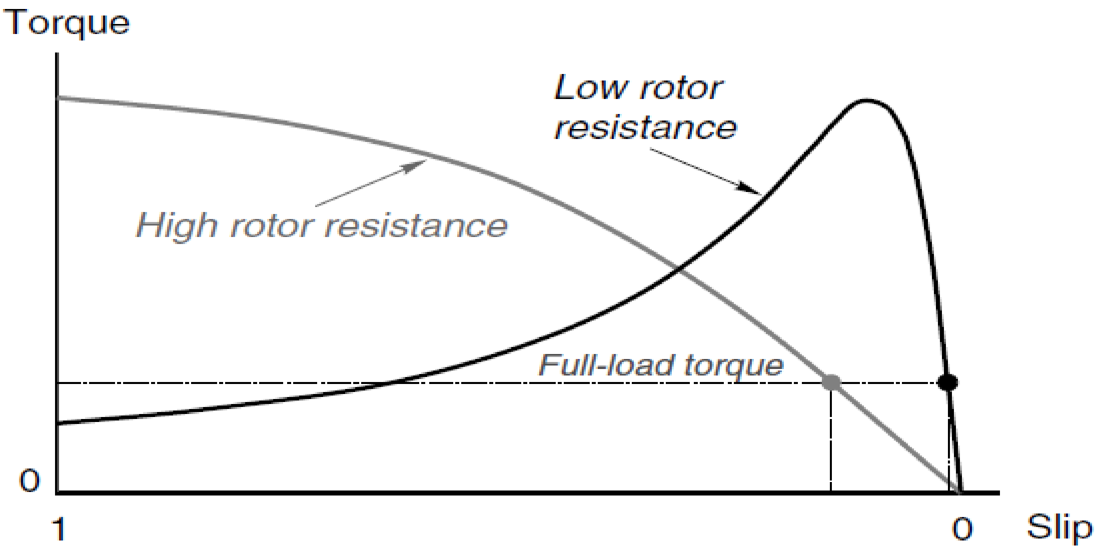


Figure 3.4 Characteristics curve between Torque and Speed

## 3.3 Equivalent Circuit of per Phase Induction Motor

An induction motor is essentially a transformer. In the transformer the load on the secondary is electrical where as in case of induction motor the load is mechanical which can be replaced by an equivalent electrical load of load resistance $R_L$ given by $\frac{R'_{2(1-s)}}{s}$ where $R'_2 = \frac{R_2}{K}$ is the rotor phase resistance and K is the turn-ratio of rotor to stator. The simplified equivalent circuit of an induction motor is shown in Figure 3.5.

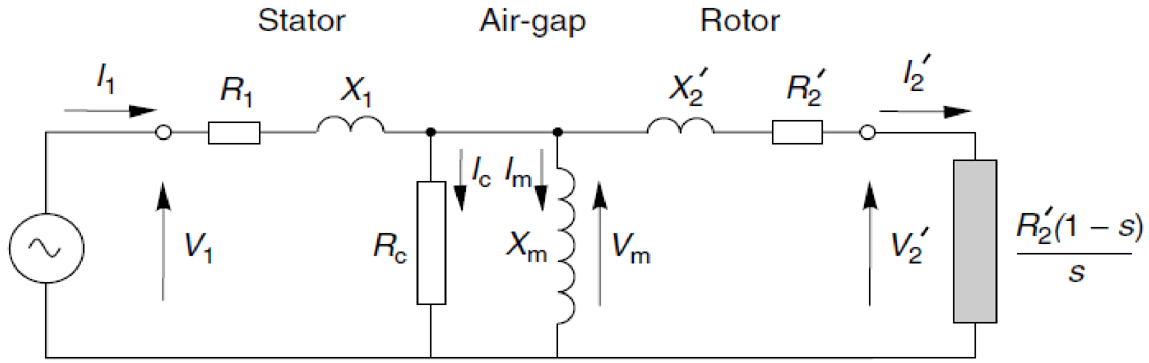


Figure 3.5 Equivalent Circuit of Induction motor

## 3.4 Losses in Induction Motor

Table 3.1 shows the percentage of various losses contributed in an Induction Motor

- Fixed Losses
- Variable Losses

### 3.4.1 Fixed losses

These losses are composed of mainly the following losses which occur in the stationary parts of the motor [3.3].

#### 3.4.1.1 Core loss

Core Loss is a Waste of Energy and Destroyer of Motors. All power applied to an electric motor is not converted to work. Principal sources of energy waste include winding loss ($I^2R$), windage, friction, stray load loss and loss in stator, rotor and armature cores. Studies have shown that depending on load, core loss is the first or second leading cause of energy waste in rewound motors, and can account for 25% or more of motor inefficiency [3.4].They vary with the core material and the geometry and with the input voltage.

### 3.4.1.2 Bearing friction and windage loss

Friction and windage loss are caused by friction in the bearings of the motor and aerodynamic losses associated with the ventilation fan and other rotating parts. Friction and windage losses results from bearing friction, windage and circulating air through the motor and account for 8 – 12 % of total losses [3.4]. These losses are independent of load. The reduction in heat generated by stator and rotor losses permits the use of smaller fan. The windage losses also reduce with the diameter of fan leading to reduction in windage losses.

### 3.4.1.3 Brush friction loss in WRIM

Brush losses model the losses caused by the voltage drop across brushes, as needed for Wound rotor induction machine (WRIM).

### 3.4.2 Variable Loss

### 3.4.2.1 Stator and Rotor Ohmic loss

Both these losses are accounted as the variable losses in the Induction motor. These losses are dependent on the load applied to the machine. Both varies as the square function of load (current).

### 3.4.2.2 Stray load loss

Stray load loss occurs in iron as well as in conductors. Their measurements are very complex. These losses vary according to square of the load current and are caused by leakage flux induced by load currents in the laminations and account for 4 to 5 % of total losses. These losses are reduced by careful selection of slot numbers, tooth/slot geometry and air gap.

Table 3.1: Total Losses in IM [3.5]

| S.No | Types of losses in IM | % total loss (Acc. To BEE) |
|---|---|---|
| 1. | Fixed loss/ Core loss | 25 |
| 2. | Variable loss: Stator $I^2R$ loss | 34 |
| 3. | Rotor $I^2R$ loss | 21 |
| 4. | Friction and bearing loss | 15 |
| 5. | Stray Load loss | 05 |

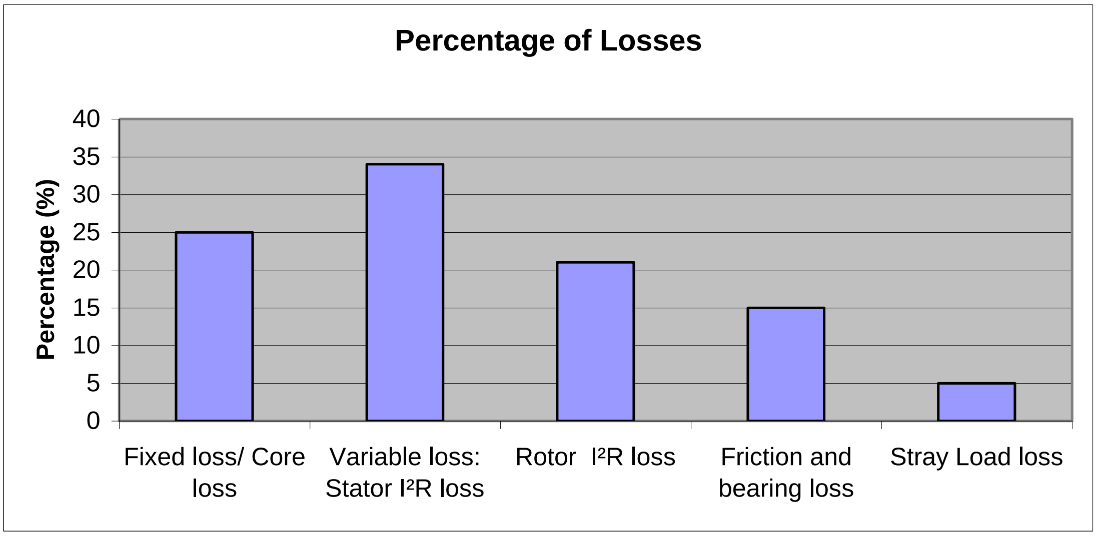


Figure 3.6 A graph showing the losses in the induction motor [3.5]

## 3.5 Types of faults in Induction Motor

There are various faults in induction motors. This section describes different faults. The different faults are classified in Figure 3.7 giving the classification based on the internal and external type of major faults occurring in the machine. The internal faults are placed under mechanical fault and electrical fault categories. While the external fault placed under electrical, mechanical and environmental fault. Similarly Figure 3.8 shows the common machine faults related to stator and rotor.

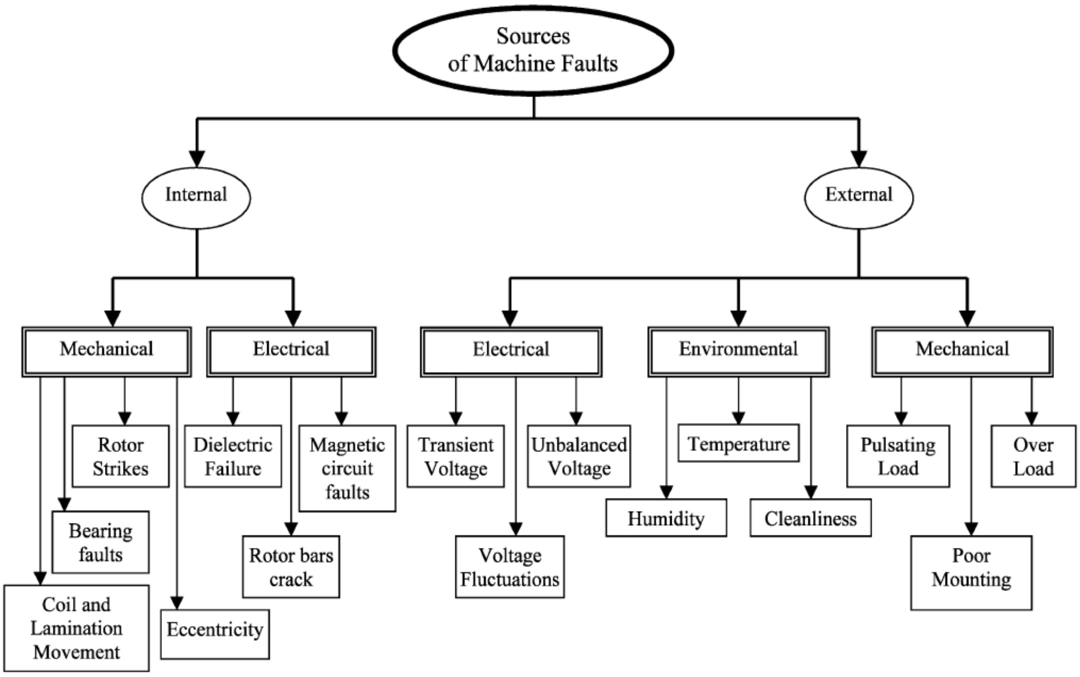


Figure 3.7 Classification for different faults in Induction motor [3.6]

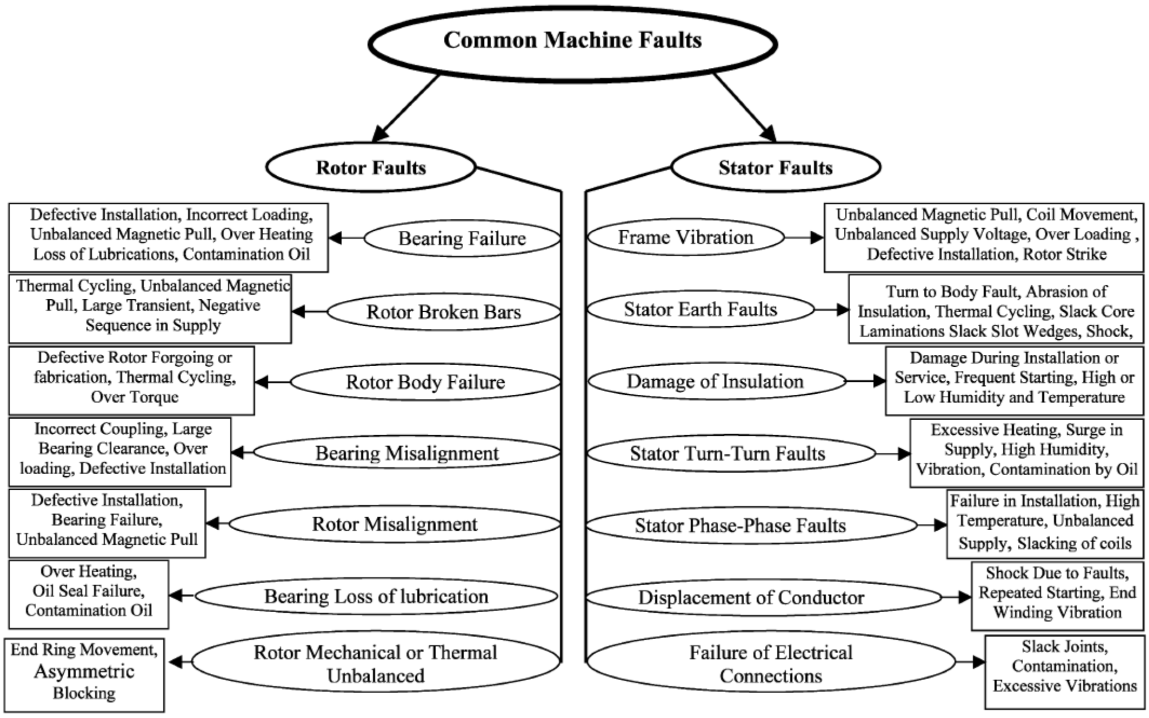


Figure 3.8 A Schematic view of common faults related to rotor and stator [3.7, 3.8]

### 3.5.1 Stator Faults

a. Stator faults resulting in the opening, shorting and grounding of one or more stator phase winding.

b. Rotor faults caused by the broken rotor bar or cracked rotor end rings.

c. Mechanical failure due to bearing failure and air gap eccentricities.

d. External faults due to incorrect connection of stator and utility supply.

These faults produce mechanical vibration, unbalanced air gap voltages and line current, increased torque pulsation, decreased average torque, increased losses, reduction in efficiency and cause excessive heating.

Deterioration of winding insulation can lead to inter turn with very large circular currents; if left undetected, phase phase or phase ground fault can occur leading to a catastrophic failure. Ground current flow leads to irreversible damage to the core due to excessive heating. Almost 25%-30% of all reported induction motor failure fall under this category. The asymmetry arising from turn faults in winding results in a negative and zero sequence (ground) components in the line current. However negative sequence current also caused by voltage unbalance, machine saturation etc.

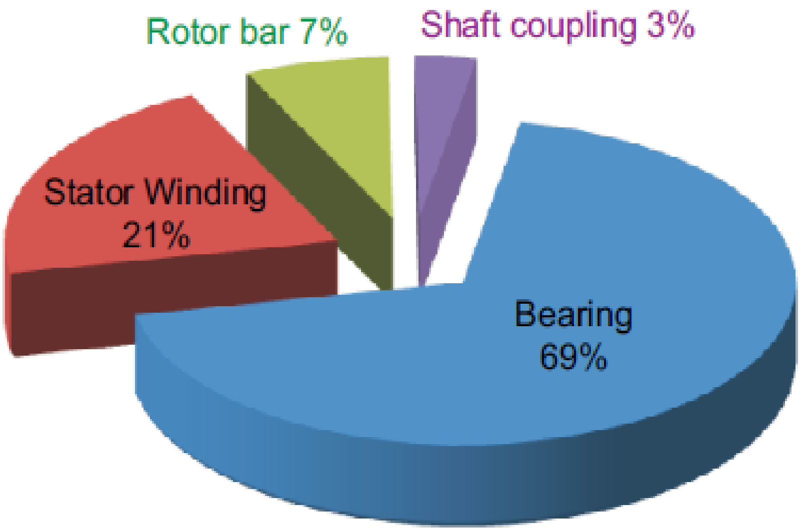


Fig 3.9: Chart showing the % of component failure [3.9]

### 3.5.2 Rotor faults

Rotor faults account for about 10% of total induction machine failures. The normal failure mechanism is a breakage or cracking of the rotor bars where they join the end-rings which can be due to thermal or mechanical cycling of the rotor during operation [3.9]. This type of fault creates the well-known twice slip frequency sidebands in the current spectrum around the supply frequency signal. The Main causes of the rotor faults are discussed below.

- Thermal stresses due to thermal overloaded and unbalance, hot spot or excessive losses rotor sparking (mainly fabricated rotor).
- Magnetic stresses caused by electromagnetic field, unbalance magnetic pull, electromagnetic noise and vibration.
- Residual stresses due to manufacturing problems.
- Dynamic stresses arise from shaft torque, centrifugal forces and cyclic stresses.
- Environmental stresses caused by contamination and abrasion.
- Mechanical stresses due to loose lamination, fatigued parts, bearing failure etc.

### 3.5.3 Bearing faults

The majority of electrical machines use ball or rolling element bearings and these are one of the most common causes of failure. These bearings consist of an inner and outer ring with a set of balls or rolling elements placed in raceways rotating inside these rings. Faults in the inner raceway, outer raceway or rolling elements produce unique frequency components in the measured machine vibration and other sensor signals. These bearing fault frequencies are function of the bearing geometry and the running speed. Bearing faults can also cause rotor eccentricity. A common cause for rolling element bearing failure is flaking, which occurs due to localised fatigue and results in the contamination of the lubricant oil with metal fragments. Other internal causes for bearing faults are vibration, inherent eccentricity and bearing current due to solid state drives. External causes are contamination and corrosion, improper lubricant and improper installation. About 40% of faults are bearing related [3.10].

### 3.5.4 Others

Eccentricity occurs when the rotor is not centred within the stator, producing a non-uniform air gap between them. This can be caused by defective bearings or manufacturing faults [3.11]. The variation in air gap disturbs the magnetic field distribution within the motor which produces a net magnetic force on the rotor in the direction of the smallest air gap. This so called “unbalanced magnetic pull” can cause mechanical vibration.

(Electric power research institute) EPRI conducted a survey in 1985 which consists of 5000 motors. 97% of the motors were squirrel cage induction motor. The Table 3.2 shows the comparison of the study done by the IEEE-IAS and EPRI regarding the different components failure. From the survey we can conclude that 40% of the failure in machine is due to bearing related.

Table 3.2 Percentage of failure by component [3.12]

| Failed Components | Percentage of Failure%(Approx) | |
|---|---|---|
| | IEEE-IAS | EPRI |
| Bearing related | 44 | 41 |
| Winding related | 26 | 36 |
| Rotor related | 08 | 09 |
| Others | 22 | 13 |

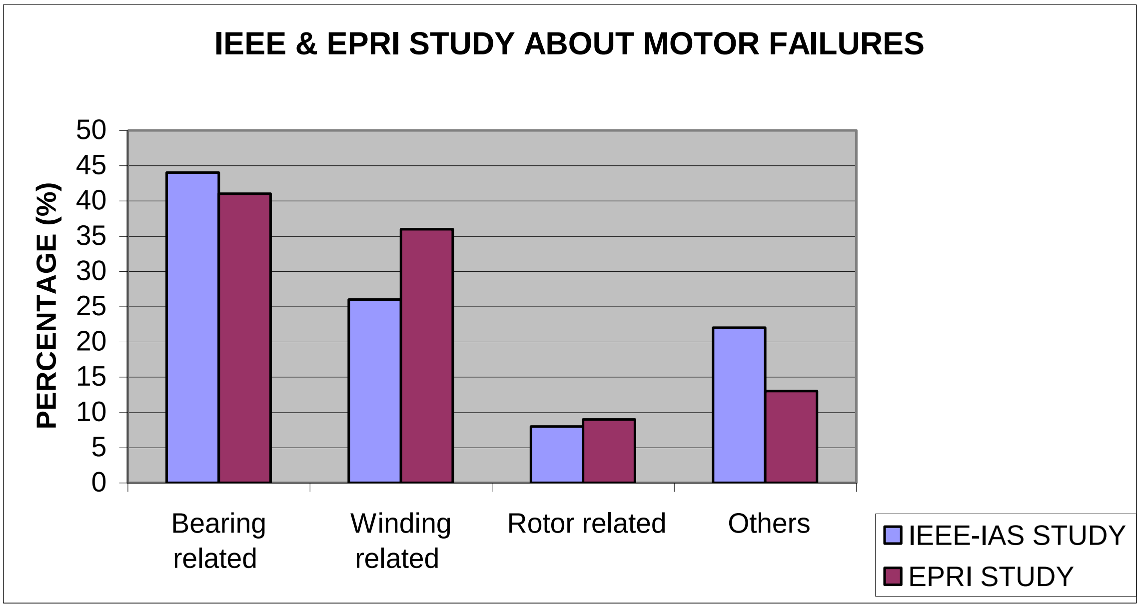


Figure 3.10 Graph showing comparison between faults for different standards

## 3.6 Condition Monitoring

Condition monitoring of Induction motor is the continuous assessment of performance and health of the machine throughout its useful operating life and diagnosing fault at their very inception. By condition monitoring, we simply mean that monitoring the overall parameters of the induction motor when it is running on its full load capacity through the effective measurement techniques so that the motor's life and its efficiency increases. In condition monitoring there are two major components one is the detection of fault through some effective and comprehensive techniques and the second one is the steps to reduce that effect which is lowering the efficiency of the induction motor, since we can't eliminate the existing error to the 100% extent [3.13, 3.14].

### 3.6.1 Need of Condition Monitoring

The maintenance of electric machines is essential for their efficient and safe operation in any industry. The lack of an effectively designed and implemented maintenance policy will result in increased downtime, increased capital losses from catastrophic failures and decreased personnel safety, so to overcome all these demerits condition monitoring is employed in the industry for safe and reliable operation of induction motor. From the economic point of view, all stated happenings in motor will lead to a decrease in the overall efficiency of the motor which is unacceptable in the industries since it may be lead to a temporary shutdown in the industry which is an economic furious condition. In general, electric motors are inherently reliable and require very little attention except at infrequent intervals when the plant is shutdown for inspection. Nevertheless like any mechanical system, electric motor do deteriorate and fail, unless they are being monitored effectively their anticipated failure can cause significant problems. In the electricity supply industry and petrochemical industry, such losses can be financially enormous. Condition monitoring of induction motor is therefore needed for the continuous assessment of the performance and health of the induction motor throughout its useful operating life [3.15, 3.16].

### 3.6.2 Advantages of Condition Monitoring

- Increased machine availability and reliability
- Improved operating efficiency
- Improved risk management (less downtime)
- Reduced maintenance costs (better planning)
- Reduced spare parts inventories
- Improved safety
- Improved knowledge of the machine condition (safe short-term overloading of machine possible
- Extended operational life of the machine
- Improved customer relations (less planned/unplanned downtime)
- Elimination of chronic failures (root cause analysis and redesign)
- Reduction of post overhaul failures due to improperly performed maintenance or reassembly.
- It provides an efficient way to diagnose the faults occurring in the induction motor.
- It uses certain signal processing techniques to detect the faults related to different parameters which provides us a detail analysis of problem.
- The CM is a non invasive technique of measurement, i.e. the measurement is made outside the induction motor (the internal body measurement is not required).

- The Condition Monitoring (CM) is useful for the areas such as offshore oil industry, petrochemical industry, gas terminal and oil refineries where the induction motor is frequently installed in large no.

### 3.6.3 Disadvantages of Condition Monitoring

There are, of course, some disadvantages also that must be weighed in the decision to use machine condition monitoring and fault diagnostics. These disadvantages are listed below.

- Monitoring equipment costs (usually significant).
- Operational costs (running the program).
- Skilled personnel needed.
- Strong management commitment needed.
- A significant run-in time to collect machine histories and trends is usually needed.
- Reduced costs are usually harder to sell to management as benefits when compared with increased profits.
- The sensors employed to take the measurement are quite costly. For e.g. the sensors used in the rotor diagnosis are vibration pickups, accelerometers, piezoelectric transducer which are very costlier as compared to other transducers.
- The set up required to diagnose the fault is very much complex.

## 3.7 Condition Monitoring of Induction Motor

With the rapid increase in production capabilities of modern manufacturing systems, plants are expected to run continuously for very long hours. By running for a long period, different kinds of faults can be encountered in machine which can severely affect the production process. Therefore, condition monitoring is gaining importance in industry. It can increase machine availability and continuous monitoring of machine health, warn of impending failure and to shut down a machine in order to prevent further damage.

It is required to detect, identify and then classify different kinds of failure modes that can occur within a machine system. Often several different kinds of sensors are employed at different positions to acquire vital signals from machine. These signals are analyzed and features are extracted in order to gain information of different faults of the machine and ultimately the health of the machine [3.12, 3.15].

## 3.8 Fault Diagnosis Techniques

In order to detect the fault of the Induction motor, some different techniques are used from time to time for fault diagnosis and its condition monitoring. As the technology is more advancing towards its peak, some necessary amendments are provided for the same to overcome the shortcomings in the past technology. For example, in the early 90's period model based diagnosis was very popular since on the basis of small models they analyzed the parameters of motor and then eradicate that error in the real system. There are some inherent disadvantages in the model approach, hence some other approaches are used for the fault diagnosis. Here a brief overview of the all the techniques is discussed which shows how the different techniques are used for fault diagnosis in the domain of Induction motor' condition monitoring [3.17, 3.18]. In Figure 3.11 different fault diagnosis techniques are briefly analyzed.

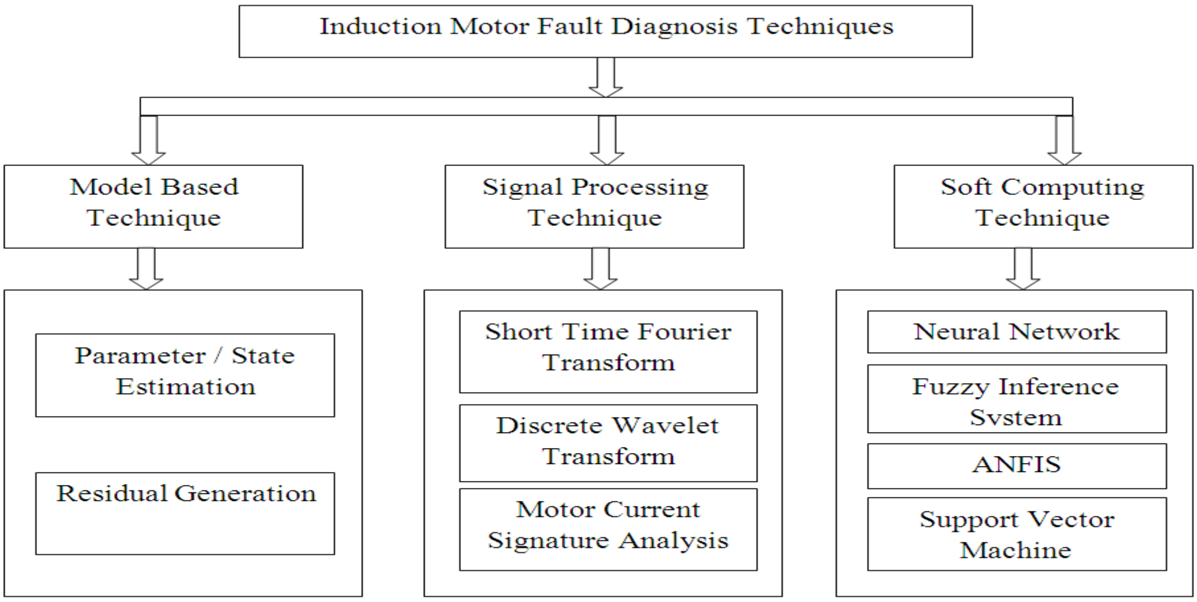


Figure 3.11 Different fault diagnosis techniques

### 3.8.1 FFT (Fast Fourier Transform):

Although the Discrete Fourier Transform (DFT) is the most straight mathematical procedure for determining frequency content of a time domain sequence, but it is terribly inefficient. As the number of points in the DFT increases to hundreds or thousands the amount of necessary number crunching becomes excessive. Since most bearing vibrations are periodical movements, it is easy to extract vibration features from the frequency domain using the powerful and popular FFT technique [3.19, 3.20]. A common use of Fourier transforms is to find the frequency components of a signal buried in a noisy time domain signal.

FFT is simply a computationally efficient way to calculate the DFT. By making the use of periodicities in the sines that are multiplied to do the transforms, the FFT greatly reduce the amount of calculation required. Functionally, the FFT decomposes the set of data to be transformed into a series of smaller data sets to be transformed. Then it decomposes those smaller sets into even smaller sets. At each stage of processing, the results of previous stage are combined in a special way. Finally it calculates the DFT of each small data set.FFT algorithm is used to detect the various motor related faults.

The Fast Fourier Transform (FFT) is an algorithm that efficiently computes the Discrete Fourier transform (DFT). The DFT of a sequence {x(n)} of length x is given by a complex valued sequence {X(k)} given by Eq 3.1

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j\frac{2\pi nk}{N}} \quad , \quad 0 \le k \le N-1. \qquad (3.1)$$

Let $W_N$ be the complex valued phase factor, which is an $N^{th}$ root of unity expressed by

$$w_N = e^{\frac{-j2\pi}{N}} \qquad (3.2)$$

Hence X(k) becomes

$$X(k) = \sum_{n=0}^{N-1} x(n) W_n^{nk} \quad , \quad 0 \le k \le N-1 \qquad (3.3)$$

Similarly Inverse is given by

$$X(n) = \frac{1}{N} \sum_{k=0}^{N-1} x(k) W_n^{-nk} \quad , 0 \le n \le N-1 \qquad (3.4)$$

### 3.8.2 Power Spectral Density

In statistical signal processing and physics, the spectral density, power spectral density (PSD) or energy spectral density (ESD), is a positive real function of a frequency variable associated with a stationary stochastic process, or a deterministic function of time, which has dimensions of power per Hz, or energy per Hz. It is often called simply the *spectrum* of the signal. Intuitively, the spectral density captures the frequency content of a stochastic process and helps in identifying periodicities. In physics, the signal is usually a wave, such as an electromagnetic wave random vibration or an acoustic wave. The spectral density of the wave, when multiplied by an appropriate factor, will give the power carried by the wave per unit frequency, known as the Power Spectral Density (PSD) of the signal.

The power spectral density function is nothing but it is the autocorrelation with the signal itself [3.21]. The power spectrum is computed from the basic FFT function. The power spectrum shows the power as the mean squared amplitude at each frequency line. Here the power density spectrum of the healthy and faulty signals are found with their imaginary and real parts respectively

### 3.8.3 Wavelet Transform

For many years, FFT has been used for signal processing of the stator current, as it is suitable for the study of a wide range of signals. Nevertheless, it only allows the extraction of the frequency content of a signal, eliminating the information concerning time-localization of the frequency components. STFT is better in this aspect, but implies some constraints regarding the selection of the optimum window size for data analysis. To overcome the previous shortcomings, the wavelet theory was introduced as a tool for analysing signals with frequency spectrum varying in time. It allows a time-localization of the frequency components occurring within the signal, being able to extract their time evolution [3.22]. This property makes possible the detection of characteristic patterns within the evolution of those components, which can be related to the occurrence of certain phenomena.

#### 3.8.3.1 Introduction

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes.

Wavelets are functions that can be used to decompose signal, similar to how to use complex sinusoids in the Fourier Transform to decompose signals. The wavelet transform computes the inner products of the analyzed signal and family of wavelets. In contrast with sinusoids, wavelets are localized in both the time and frequency domains, so wavelet signal processing is suitable for those signals whose spectral content changes over time. The adaptive time frequency resolution of wavelet signal processing enables us to perform the multi resolution analysis. The properties of wavelet and the flexibility to select wavelet make wavelet signal processing a beneficial tool for the feature extraction applications.

Just as the Fourier transform decomposes a signal into a family of complex sinusoids, the Wavelet transform decomposes the signal into a family of wavelets. Unlike sinusoids, which are symmetric, smooth and regular, wavelets can be symmetric and asymmetric, sharp or smooth, regular or irregular. The family of wavelets contains the dilated and translated version of a prototype function. Traditionally, the prototype function is called a mother wavelet. The scale and shift of wavelet determines how the mother wavelet dilates and translates along the time and space axis. For different types of signals, different types of wavelet can be selected that best matches the features of the signal. Therefore, reliable results can be generated through wavelet signal processing.

Fourier analysis techniques provide significant information on frequency components of signals under study, but offer no information regarding where a particular frequency was located in the time axis. In contrast, wavelet transforms offers time-frequency information of signals under study, thereby making wavelet transform methods more comprehensive than Fourier transforms in signal analysis.[3.23] Generally the fault information is a weak and short time duration signal. The Fourier transform, which identifies the frequency characteristics signal from the whole time domain signal, cannot describe the frequency content of a piecewise non-linear signal. The wavelet transform, by position movement on the time axis and the window scale change for the wavelet base $\psi$, has the capability to identify sudden or singular signals. Because the wavelet transform can extract all information in the fault signal obtained in the time-frequency domain, it provides a more sensitive means to diagnose faults than does the Fourier transform.

In Wavelet Signal Processing, Wavelet coefficients, at a first level of decomposition, are obtained from a signal under analysis by applying a mother wavelet. The process can be repeated if the mother wavelet is scaled and translated. The mother wavelet function (denoted by $\psi(t)$) and its scaling function (given as $\phi(t)$) describe a family of functions which are required to satisfy a number of criteria [3.24, 3.25]. It must have a zero mean denoted as in (Eq.3.5) i.e. average value of zero

$$\int_{-\infty}^{\infty} \psi(t)\,dt = 0 \tag{3.5}$$

In addition $\psi(t)$ must have a square norm of one as denoted in (Eq.3.6).

$$\int_{-\infty}^{\infty} \left|\psi(t)\right|^{2} dt = 0 \tag{3.6}$$

These requirements are ensured by having a mother wavelet that is absolutely and square integrable. The mother wavelet forms a family of wavelets when the function is scaled and translated in the time domain. When a mother wavelet is translated by a factor of a and scaled by a factor of b, it can be expressed in a generic form as follows

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{3.7}$$

The use of these wavelet functions provides a robust method of analyzing non-stationary signals to provide both frequency and time information. In practice, wavelet coefficients are obtained by a filter bank approach, with a low-pass filter and its complementary high-pass filter. The use of wavelets for induction machine fault detection is documented in various journals. They have been shown to yield satisfactory results for detecting electrical and mechanical faults [3.26].

**Choice of Wavelet Base**: For the wavelet transform, as opposed to for the Fourier transform, the choice of the wavelet base is flexible and may differ for different applications. It is possible that different results will appear when the same signal is analysed using different wavelet bases. Sometimes an unsuitable choice of the wavelet base will lead to no solution for the targeted problem. Therefore, it is difficult to select the wavelet base for different applications of the wavelet transform. At present, this choice mainly depends on experience.

## 3.8.3.2 Wavelet Transform Analysis

### 3.8.3.2 (i) Continuous Wavelet Transforms

Like the Fourier transform, the *continuous wavelet transform* (CWT) uses inner products to measure the similarity between a signal and an analyzing function. In the Fourier transform, the analyzing functions are complex exponentials, $e^{j\omega t}$. The resulting transform is a function of a single variable, ω.

In the CWT, the analyzing function is a wavelet, ψ. The CWT compares the signal to shifted and compressed or stretched versions of a wavelet. Stretching or compressing a function is collectively referred to as *dilation* or *scaling* and corresponds to the physical notion of *scale*. By comparing the signal to the wavelet at various scales and positions, a function of two variables is obtained. The two-dimensional representation of a one-dimensional signal is redundant. If the wavelet is complex-valued, the CWT is a complex-valued function of scale and position. If the signal is real-valued, the CWT is a real-valued function of scale and position. For a scale parameter, a>0, and position, *b*, the CWT is

$$C\left(a.b; f\left(t\right), \psi\left(t\right)\right) = \int_{-\infty}^{\infty} f\left(t\right) \frac{1}{\sqrt{a}} \psi^{*} \frac{t-b}{a} dt \tag{3.8}$$

Where * denotes the complex conjugate. Not only do the values of scale and position affect the CWT coefficients, the choice of wavelet also affects the values of the coefficients.

**Scale and Frequency**

Like the concept of frequency, *scale* is another useful property of signals and images. The scale factor is a inherently positive quantity, a>0. For sinusoids, the effect of the scale factor is very easy to see.

The scale factor ‘a’ is related (inversely) to the radian frequency ω. This general inverse relationship between scale and frequency holds for signals in general. Not only is a time-scale representation a different way to view data, it is a very natural way to view data derived from a great number of natural phenomena. The scale factor works exactly the same with wavelets. The smaller the scale factor, the more “compressed” the wavelet.

There is clearly a relationship between scale and frequency. The more stretched the wavelet, the longer the portion of the signal with which it is being compared, and therefore the coarser the signal features measured by the wavelet coefficients.

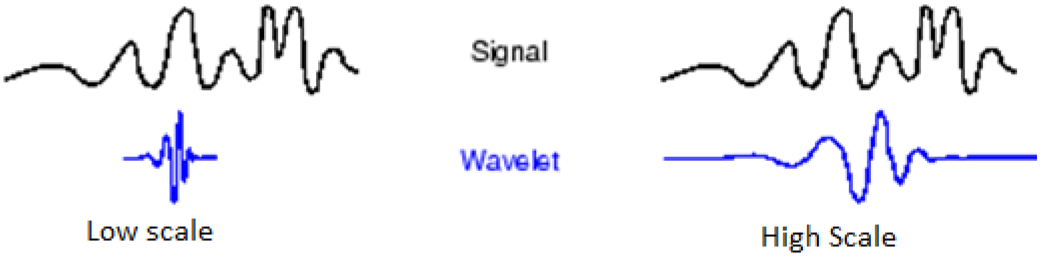


Figure 3.12 Scale variation in WT

To summarize, the general correspondence between scale and frequency is:

- Low scale $a$ ⇒ Compressed wavelet ⇒ Rapidly changing details ⇒ High frequency ω.
- High scale $a$ ⇒ Stretched wavelet ⇒ Slowly changing, coarse features ⇒ Low frequency ω.

### 3.8.3.2 (ii) Discrete Wavelet Transforms

In the discrete domain, the scale and shift parameters are discretized as $a = a_0^m$ and $b = nb_0$, and the analyzing wavelets are also discretized as follows:

$$\psi_{m,n}(t) = a_0^{\frac{-m}{2}} \psi\left(\frac{t-nb_0}{a_0^m}\right) \qquad (3.9)$$

where m and n are integer values. The discrete wavelet transform and its inverse transforms are defined in the Eq 3.10 and 3.11.

$$S_{m,n} = \int_{-\infty}^{+\infty} \psi'_{m,n}(t)s(t)dt \qquad (3.10)$$

$$\mathrm{s}(t) = k_\psi \sum_m \sum_n S_{m,n}\psi_{m,n}(t) \qquad (3.11)$$

Where $k_\psi$ is a constant value for normalization.

The function $\psi_{m,n}(t)$ provides sampling points on the scale-time plane: linear sampling points on the time (b-axis) direction but logarithmic in the scale (a-axis) direction.

The most common situation is that $a_0$ is chosen as:

$$a_0 = 2^{\frac{1}{v}} \qquad (3.12)$$

Where v is an integer value, and that v piece of $\psi_{m,n}(t)$ are processed as one group.

It turns out, rather remarkably, that if we choose scales and positions based on powers of two — so-called *dyadic* scales and positions — then analysis will be much more efficient and just as accurate. We obtain such an analysis from the *Discrete Wavelet Transform* (DWT).An efficient way to implement this scheme using filters was developed in 1988 by Mallat.

### 3.8.3.3 Multi-resolution Approach

Discrete Wavelet analysis is computed using the concept of filter banks. Filters of different cut-off frequencies analyse the signal at different scales. Resolution is changed by the filtering; the scale is changed by upsampling and downsampling. If a signal is put through two filters:

1. A high-pass filter, high frequency information is kept, low frequency information is lost.
2. A low pass filter, low frequency information is kept, high frequency information is lost.

Then the signal is effectively decomposed into two parts, a detailed part (high frequency), and an approximation part (low frequency). The subsignal produced from the low filter will have a highest frequency equal to half that of the original. According to Nyquist sampling theorem, the change in frequency range means that only half of the original samples need to be kept in order to perfectly reconstruct the signal. More specifically this means that up-sampling can be used to remove every second sample. The scale has now been doubled. The resolution has also been changed; the filtering made the frequency resolution better, but reduced the time resolution [3.24, 3.25]. The approximation sub-signal can then be put through a filter bank, and this is repeated until the required level of decomposition has been reached.

### 3.8.3.4 One-Stage Filtering: Approximations and Details:

In wavelet analysis, we often speak of *approximations* and *details*. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. The filtering process, at its most basic level, looks like as shown in Figure 3.13.

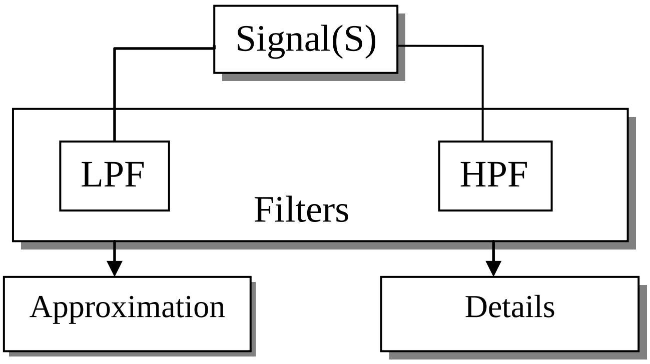


Figure 3.13 One stage filtering

The original signal, S, passes through two complementary filters and emerges as two signals. Suppose, for instance, that the original signal S consists of 1000 samples of data. Then the resulting signals will each have 1000 samples, for a total of 2000. These signals A and D are interesting, but we get 2000 values instead of the 1000 we had. There exists a more subtle way to perform the decomposition using wavelets, by keeping only one point out of two in each of the two 2000-length samples to get the complete information. This is the notion of *down sampling*. We produce two sequences called cA and cD. The process on the right, which includes down sampling, produces DWT coefficients.

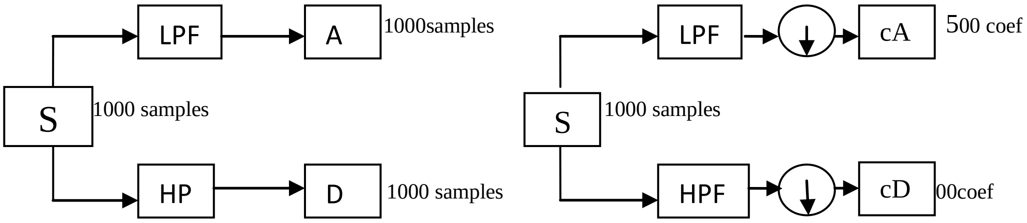


Figure 3.14 Generation of coefficients

### 3.8.3.5 Multiple-Level Decomposition

The decomposition process can be iterated, successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree [3.25].

The approximation obtained after first level of approximation is passed again into the decomposition high and low pass filters and the approximations and details are obtained again for the next level. This is done recessively for the level up to which decomposition is to be obtained. A schematic view of how the multi level decomposition takes place is shown in Figure 3.15

### 3.8.3.6 Number of Levels

Since the analysis process is iterative, in theory it can be continued indefinitely. In reality, the decomposition can proceed only until the individual details consist of a single sample or pixel. In practice, we’ll select a suitable number of levels based on the nature of the signal, or on a suitable criterion such *as entropy*

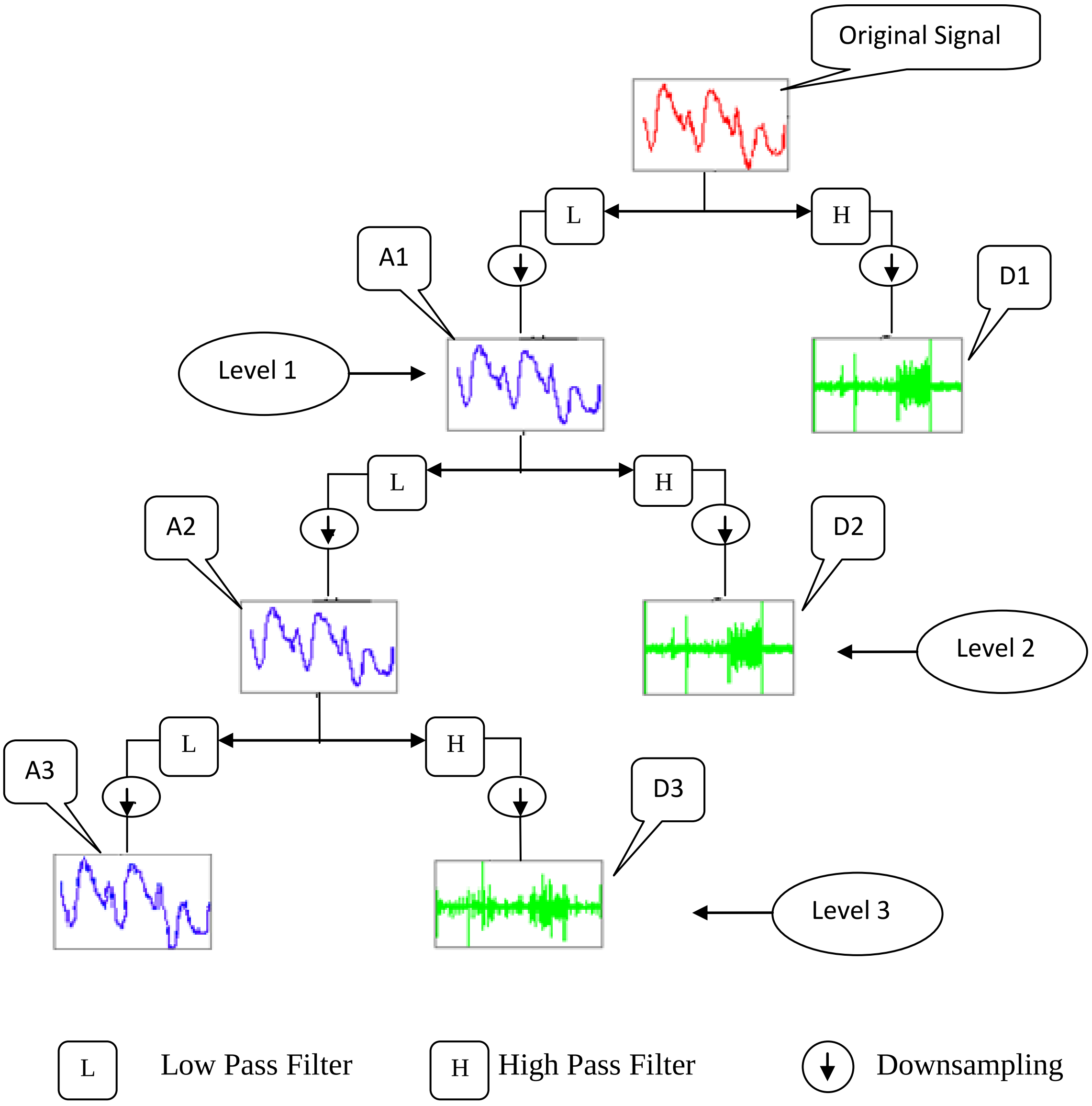


Figure 3.15 Multi level Decomposition

### 3.8.3.7 Wavelet Reconstruction

The discrete wavelet transform can be used to analyze, or decompose, signals and images. This process is called decomposition or analysis. The other half of the story is how those components can be assembled back into the original signal without loss of information. This process is called reconstruction, or synthesis as shown in the Figure 3.16. The mathematical manipulation that effects synthesis is called the inverse discrete wavelet transforms (IDWT).

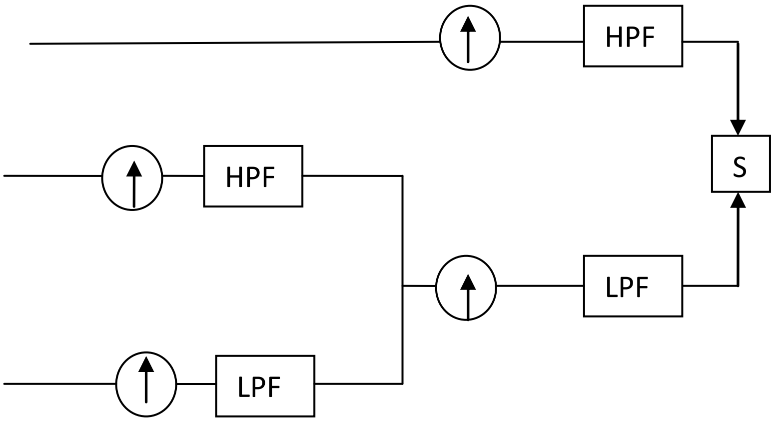
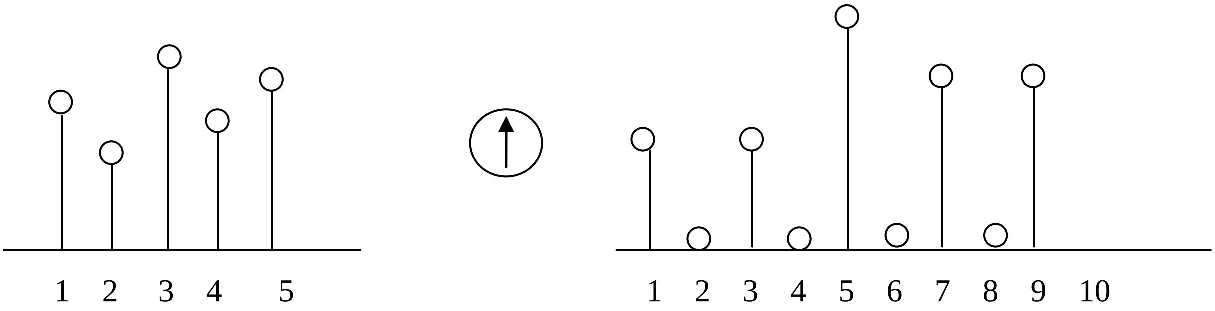


Figure 3.16 Wavelet reconstruction

Where wavelet analysis involves filtering and downsampling, the wavelet reconstruction process consists of upsampling and filtering. Upsampling is the process of lengthening a signal component by inserting zeros between samples. The upsamling notion is shown in Figure 3.17.



Signal component

Unsampled signal component

Figure 3.17 Components after upsampling

### 3.8.3.8 Reconstruction Filters

The choice of filter is crucial in achieving perfect reconstruction of the original signal. The downsampling of the signal components performed during the decomposition phase introduces a distortion called aliasing. It turns out that by carefully choosing filters for the decomposition and reconstruction phases that are closely related (but not identical), we can “cancel out” the effects of aliasing [3.22].The low and high-pass decomposition filters (L and H), together with their associated reconstruction filters (L' and H'), form a system of what is called quadrature mirror filters (Figure 3.18)

In fact, the choice of filters not only determines whether perfect reconstruction is possible, it also determines the shape of the wavelet we use to perform the analysis. To construct a wavelet of some practical utility, you seldom start by drawing a waveform. Instead, it usually makes more sense to design the appropriate quadrature mirror filters, and then use them to create the waveform.

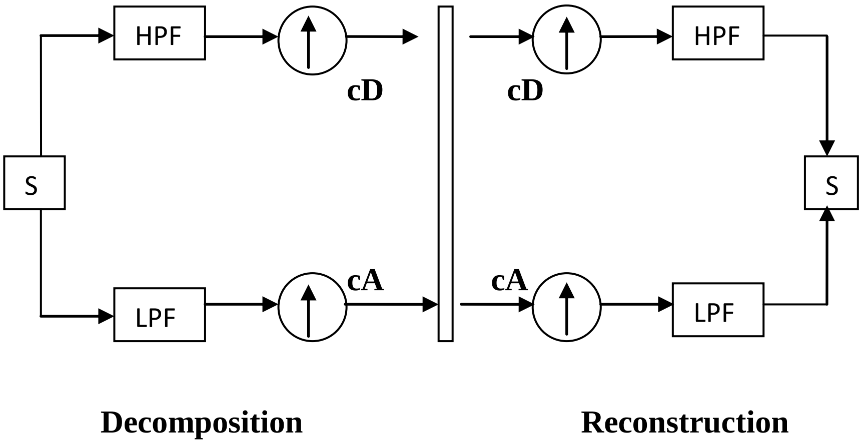


Figure 3.18 Decomposition and Reconstruction of the signal

### 3.8.3.9 Reconstructing Approximations and Details

It is possible to reconstruct original signal from the coefficients of the approximations and details which is shown in the Figure 3.19

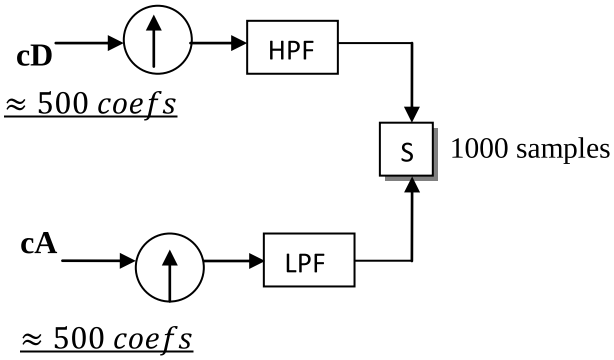


Figure 3.19 Reconstruction of Signals by coefficients

It is also possible to reconstruct the approximations and details themselves from their coefficient vectors (Figure 3.20). As an example, let’s consider how we would reconstruct the first-level approximation A1 from the coefficient vector cA1. We pass the coefficient vector cA1 through the same process we used to reconstruct the original signal. However, instead of combining it with the level-one detail cD1, we feed in a vector of zeros in place of the detail coefficients vector: The process yields a reconstructed approximation A1, which has the same length as the original signal S and which is a real approximation of it. Similarly, we can reconstruct the first-level detail D1, using the analogous process.

The reconstructed details and approximations are true constituents of the original signal. In fact, we find when we combine them that

$$A1 + D1 = S \tag{3.13}$$

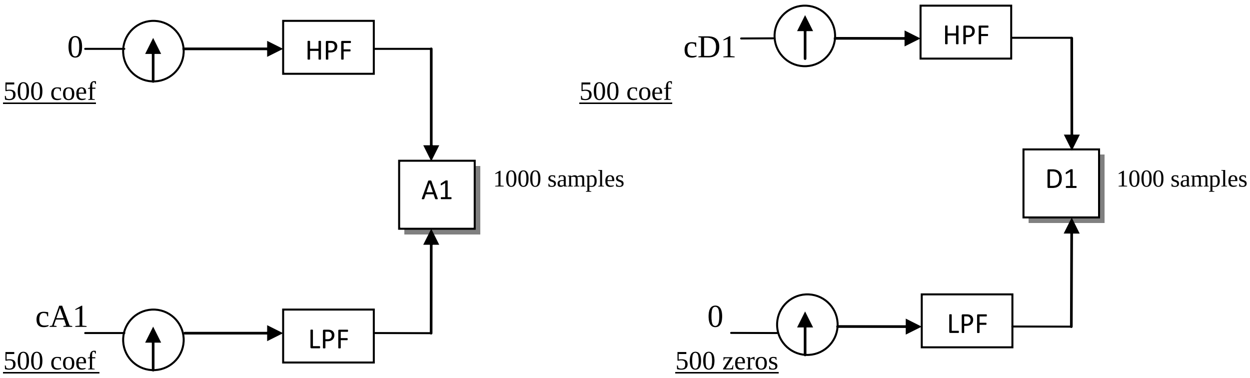


Figure 3.20 Reconstructing the Approximations & Details with the zero padding

Note that the coefficient vectors cA1 and cD1 because they were produced by downsampling and are only half the length of the original signal, so they cannot directly be combined to reproduce the signal. It is necessary to reconstruct the approximations and details before combining them.

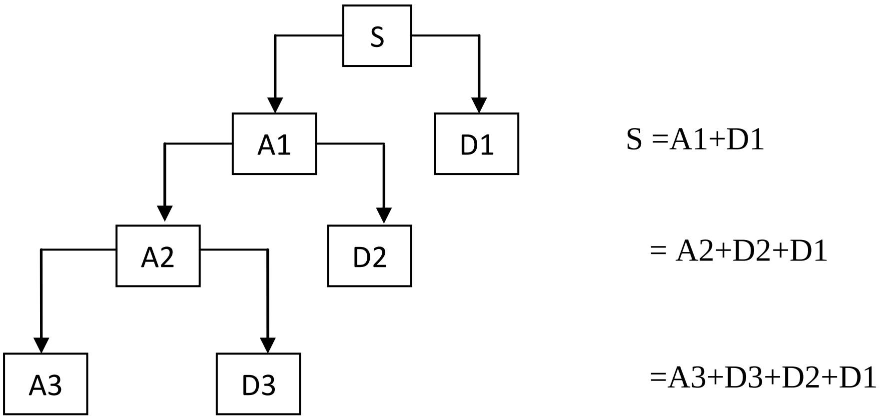


Figure 3.21 Multi level Analysis

### 3.8.4 Wavelet Families:

Several families of wavelet that have proven to be special are discussed here. These are the prototype wavelet used for different functions related to the wavelet analysing. Some of the basic wavelets are presented as follows.

### 3.8.4.1 Haar

Any discussion of wavelets begins with Haar wavelet, the first and simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies db1.

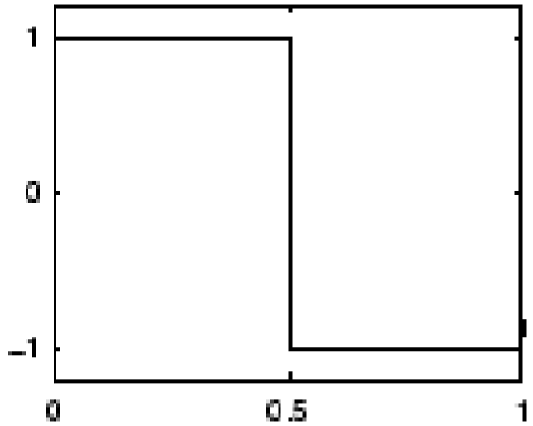
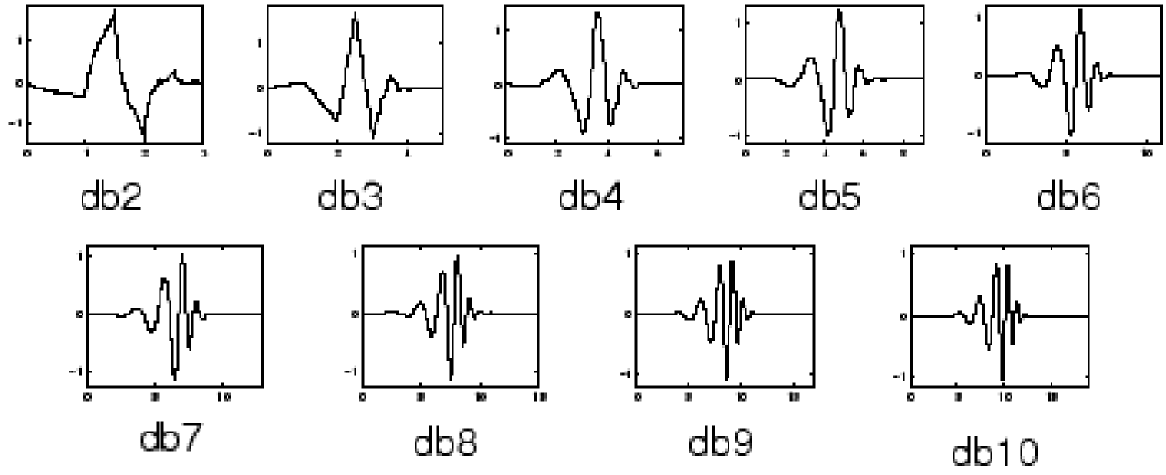


Figure 3.22 Wavelet function psi of Haar wavelet

### 3.8.4.2 Daubechies

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets thus making discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written as dbN, where N is the order, should be a +ve integer and db the "surname" of the wavelet.

Here is the wavelet functions psi of the next nine members of the family:


db2 db3 db4 db5 db6

db7 db8 db9 db10

Figure 3.23 Wavelet function psi of dbN wavelet

## 3.9 Chapter Summary

This chapter presented a view regarding the details of induction motor, construction, its losses; different faults are widely covered under the different sections. This chapter also presented a review of condition monitoring details which are discussed under the different headings like need of condition monitoring, application and their relative merits and demerits. In addition, the different techniques of fault detection of condition monitoring is also discussed by giving due credit to the advanced signal processing techniques like FFT, DWT.

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# Chapter IV
# Machine Vibration and Its Analysis

## 4.1 Importance of the Study of Vibration

Most human activities involve vibration in one form or other. In recent times, many investigations have been motivated by the engineering applications of vibrations, such as the design of machines, foundations, structures, engines , turbines and control systems.

Most prime movers have vibrational problems due to the inherent unbalance in the engines. The unbalance may be due to faulty design or poor performance. Imbalance in diesel engines, for example can cause ground waves sufficiently powerful to create a nuisance. In turbines, vibration cause spectacular mechanical failures. In all these situations, the structure or machine component subjected to vibration can fail because of material fatigue resulting from the cyclic variation of the induced stress [4.1]. Furthermore, the vibration cause more rapid wear of machine parts such as bearings and gears and also create excessive noise. In machines, vibration causes fasteners such as nuts to become loose. In many engineering systems, a human being acts as an integral part of the system. The transmission of vibration to human beings results in discomfort and loss of efficiency. vibration of instruments panels can cause their malfunction or difficulty in reading the meters. Thus one of the important purposes of vibration study is to resolve vibration through proper design of machines and their mountings [4.1].

## 4.2 Vibration and its classification

Any motion that repeats itself after an interval of time is called Vibration or oscillation. The swinging of a pendulum and the motion of a plucked string are typical examples of vibration. The theory of vibration deals with the study of oscillatory motions of bodies and the forces associated with them.

Vibration can be classified in several ways. Some of the important classifications are as follows:

### 4.2.1 Free and Forced Vibration

**Free Vibration**: If a system, after initial disturbances, is left to vibrate on its own, the ensuing vibration is known as free vibration. No external force acts on the system. The oscillation of a simple pendulum is an example of free vibration.

**Forced Vibration**: If a system is subjected to an external force (often, a repeating type of force), the resulting vibration is known as forced vibration. The oscillation that arises in machine such as diesel engine is an example of forced vibration.

If the frequency of the external forces coincides with one of the natural frequencies of the system, a condition known as resonance occurs, and the system undergoes dangerously large oscillations.

### 4.2.2 Undamped and Damped Vibration

If no energy is lost or dissipated in friction or other resistances during oscillation, the vibration is known as undamped vibration. If any energy is lost or dissipated in friction or other resistances during oscillations, the vibration is known as damped vibration. In many physical systems, the amount of damping is so small that it can be disregarded for most engineering purposes.

### 4.2.3 Linear and Nonlinear Vibration

If all the basic components of a vibratory system the spring, the mass, and the damper behave linearly, the resulting vibration is known as linear vibration. If the vibration is linear, the principle of superposition holds good, and the mathematical techniques of analysis are well developed .On the other hand, if any of the basic components behave nonlinearly the vibration is called nonlinear vibration. For non linear vibration, the superposition principle is not valid, and the techniques of analysis are less well known. Since all vibratory systems tend to behave nonlinearly with the increasing amplitude of oscillation, a knowledge of nonlinear vibration is desirable in dealing with practical vibratory systems.

### 4.2.4 Deterministic and Random Vibration

If the value or magnitude of the excitation (force or motion) acting on a vibratory system is known at any given time, the excitation is called deterministic. The resulting vibration is called as deterministic vibration. In some cases, the excitation is nondeterministic or random; the value of the excitation at a given time cannot be predicted. Examples of random excitation are wind velocity, road roughness, and ground motion during earthquakes. If the excitation is random, the resulting vibration is called random vibration. In case of random vibration, the vibratory response of the system is also random; it can be described only in terms of statistical quantities.

## 4.3 Bearing in Machine

Motor systems are very important in modern society. They convert almost 60% of the electricity produced throughout the world into other forms of energy to provide power to other equipment. In the performance of all motor systems, bearings play an important role. Many problems arising in motor operations are linked to bearing faults. Thus fault diagnosis or condition monitoring of a motor system is inseparably related to the diagnosis of the bearing assembly. Due to the close relationship between motor system development and bearing assembly performance, it is difficult to imagine the progress of modern rotating machinery without consideration of the wide application of bearings. In addition, the faults arising in motors are often linked with bearing faults around (40%) [4.2]**,** Moreover, according to an IEEE motor reliability study[4.3], bearing faults have been shown to be the most frequent faults in induction machines (41%) followed by stator (37%) and rotor faults (10%). In many instances, the accuracy of the instruments and devices used to monitor and control the motor system is highly dependent on the dynamic performance of bearings.

Bearing vibration can generate noise and degrade the quality of a product line which is driven by a motor system. Heavy bearing vibration can even cause the entire motor system to function incorrectly, resulting in downtime for the system and economic loss to the customer [4.4]. Proper monitoring of bearing vibration levels in a motor system is highly cost effective in minimizing maintenance downtime—both by providing advance warning and lead time to prepare appropriate corrective actions, and by ensuring that the system does not deteriorate to a condition where emergency action is required. Thus, it is important to include bearing vibration diagnosis into the scheme of motor system fault diagnosis. The main aim of this thesis work is the early detection of bearing vibration faults in electrical induction machines using signal processing tools.

## 4.4 Bearing fault

The fault is assumed to be modelled as a small hole created from a missing piece of material on the corresponding element. Bearing defects may be categorized as “distributed” or “local”. Distributed defects include surface roughness, waviness, and misaligned races and off size rolling elements. Localized defects include cracks, pits and spall on the rolling surfaces. The dominant mode of failure in rolling element bearings is spalling or flaking of the races or the rolling elements. Localized defects generate a series of impact vibrations every time a running rolles passes over the surface of a defect whose amplitude and period are calculated by position of defect, speed and bearing dimension. Therefore, vibration analysis is a conventional method for bearing fault detection.

Local or wear defects cause periodic impulses in the vibration signals. Amplitude and period of these impulses are determined by shaft rotational speed, fault location and bearing dimensions.

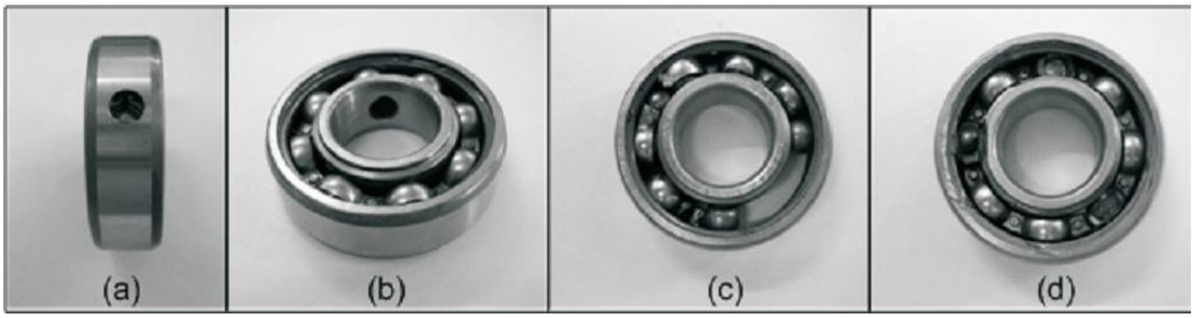

Figure 4.1: Four defective bearings showing (a) outer race defect, (b) inner race defect, (c) cage defect, (d) ball defect

## 4.5 Types of bearing faults

Bearing faults can be classified according to the location of faults. The different faults occurring in a rolling element bearing [4.5] can be classified according to the damaged element are as follows.

- Inner raceway
- Outer raceway
- Ball defect
- Cage defect

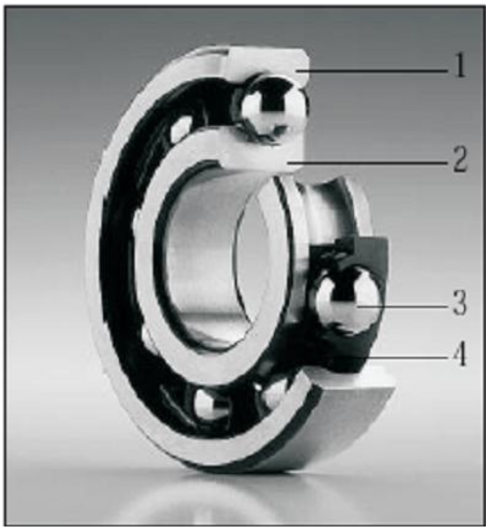

Figure 4.2: Parts of a deep groove ball bearing showing

1: Outer race, 2: inner race, 3: ball, 4: cage.

Figure 4.3: Crank in the outer race

Figure 4.4: hole in the Outer race

Figure 4.5: Deformation of the protective shield

Figure 4.6: Corrosion

Bearing fault can be detected by detecting the increased vibration in high frequency spectra (2 – 60 Hz).

When a ball is defective or when it rolls over a defective raceway, it produces an impact against the raceway which generates a detectable vibration. These vibrations occur at predictable frequencies depending on which surface of the bearing contains the fault, on the geometrical dimensions of the bearing and on the rotational speed of the rotor $f_r$. Therefore, there is one predictable characteristic fault frequency $f_v$ in the vibration spectrum for each of the four main parts of a given bearing, running at a certain rotor speed

Hence, a characteristic frequency $f_c$ can be associated with the each type of bearing fault. This frequency corresponds to the periodicity of the occurrence of the abnormal physical phenomenon related to the existence of the fault. Basically there are five basic motions that are used to describe the dynamics of bearing elements, with each movement having a corresponding frequency [4.6, 4.7, 4.8]. The characteristics frequency associated with the each bearing fault are as follows.

**4.5.1 Shaft Rotational Frequency($f_s$)**: As bearings are often used to form a bearing–rotor system, the speed of the rotor (or shaft) is very important to the movements of bearings. All other frequencies are a function of this frequency.

**4.5.2 Fundamental Cage Frequency**: It is related to the motion of the cage. It can be derived from the linear velocity of point on the cage $v_c$, which is the mean of the linear velocity of inner raceway $v_i$ and outer raceway $v_0$ i.e. $v_c = \frac{v_0 + v_i}{2}$ when $v_c$ is divided by radius of cage i.e. $r_c = \frac{D_c}{2}$ we get the fundamental cage frequency $f_c$. Fundamental cage frequency is given by

$$f_c = \frac{f_s}{2}\left(1 - \frac{d}{D}\cos\alpha\right) \tag{4.1}$$

**4.5.3 Ball defect /ball rotational frequency**: It is the rate of rotation of a ball about its own axis in a bearing. Therefore it can be calculated from either the ball pass inner raceway $f_{BPI}$ and the ball pass out raceway frequency $f_{BPO}$, both will give the same results. The ball rotational frequency is two times the ball spin frequency and can be calculated as

$$f_B = \frac{D}{d} f_s \left(1 - \frac{d^2}{D^2}\cos^2\alpha\right) \tag{4.2}$$

**4.5.4 Inner race defect or Ball pass Inner raceway frequency**: It indicates the rate at which the ball passes a point on the track of the inner raceway. The value of the $f_{BPI}$ is equal to the No. of bearing ball n multiplied by the difference between shaft rotational frequency $f_s$ and fundamental cage frequency $f_c$.

$$f_{BPI} = n\left(f_s - f_c\right) = \frac{nf_s}{2}\left(1 - \frac{d}{D}\cos\alpha\right) \tag{4.3}$$

**4.5.5 Outer race defect or Ball pass outer raceway frequency**: Similarly to the ball pass inner raceway frequency $f_{BPI}$ , the $f_{BPO}$ , is defined as the rate at which the ball pass a point on the track of the outer raceway, value of $f_{BPO}$ is the function of the No of bearing balls n and the difference between the outer raceway frequency $f_0$ and the fundamental cage frequency $f_c$.

$$f_{BPO} = n\left(f_c - f_0\right) \tag{4.4}$$

$$f_{BPO} = nf_c = \frac{nf_s}{2d}\left(1 - \frac{d}{D}\cos\alpha\right) \tag{4.5}$$

In Eq.(4.1) to (4.5) $f_s$ is the shaft rotation frequency , n is the number of rollers, d is the roller to the diameter , D is the pitch diameter of the bearing , and $\alpha$ is contact angle.

These five frequencies are denoted as the shaft rotational frequency ($f_s$), the fundamental cage frequency ($f_c$), the ball pass inner raceway frequency ($f_{BPI}$ ), the ball pass outer raceway frequency ($f_{BPO}$), and the ball rotational frequency ($f_b$). These frequencies are illustrated in Figure 4.7.

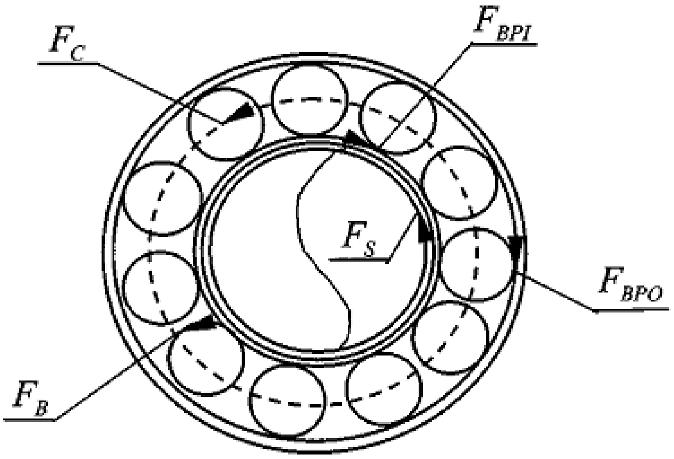

Figure 4.7 Basic Frequencies in the Bearing

Frequency-domain studies show that, when defects exist in a bearing, the defects will generate some of the above frequencies in the vibration signals. Many publications have discussed the use of these five frequencies to identify defects in a bearing assembly [4.9, 4.10, 4.11]. For defects on the raceway of a rolling bearing, each time a roller hits the defective raceway, the corresponding ball pass inner raceway frequency ($f_{BPI}$) or ball pass outer raceway frequency($f_{BPO}$) will be excited. If the defective area is large, harmonics of ($f_{BPI}$) or ($f_{BPO}$), will also be present as an indication of the severity of the defects [4.9,4.10,4.11].For defects existing on a bearing roller, usually, two times the ball rotational frequency $2f_B$ will be generated. This is because the roller hits both the inner and outer raceways each time it spins on its own axis. In most cases, this frequency will be modulated with other existing frequencies, such as ($f_{BPI}$) and ($f_{BPO}$) resulting in a more complicated spectrum. Occasionally, if the defective area on the roller is very large, the system natural frequency will also be excited and modulated with two times the ball rotational frequency.

## 4.6 Factors for vibration analysis

**4.6.1 Root Mean Square (RMS)** value of the vibration acceleration can be used for primary health investigation of the machine. It is defined as

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \mu\right)^2} \tag{4.6}$$

Here N is the number of samples. Xi is amplitude of individual samples, $\mu$ is the mean value of the sample.

**4.6.2 Crest Factor** [4.12] is the ratio of peak value with the RMS value. Crest Factor of radial vibration signal is used to indicate rolling bearing faults.

**4.6.3 Skewness** [4.12] is the measure of symmetry. or more precisely, the lack of symmetry about its mean. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point of Gaussian distribution.

$$c(skewness) = \frac{\frac{1}{N}\sum\left(x_i - \mu\right)^3}{\sigma^3} \tag{4.7}$$

Here N is the number of samples. Xi is amplitude of individual samples, $\mu$ is the mean value of the sample, $\sigma$ is variance.

**4.6.4 Kurtosis** is a measure of whether the data are peaked or flat relative to a normal distribution [4.13]. A uniform distribution would be the extreme case. High kurtosis indicates a "peaked" distribution and low kurtosis indicates a "flat" distribution near the mean value

$$k(kurtosis) = \frac{\frac{1}{N}\sum\left(x_i - \mu\right)^4}{\sigma^4} \tag{4.8}$$

Here N is the number of samples. Xi is amplitude of individual samples, $\mu$ is the mean value of the sample, $\sigma$ is variance.

## 4.7 Chapter Summary

The most prevalent faults in the bearing of induction motor are described in details in this chapter. The overview of different types of vibration is presented since vibration is one of the parameter that is associated with the bearing fault. This chapter contains all the details associated with the bearing faults and the characteristic frequency associated with each bearing fault. In addition to above all some vibration factor analysis parameters are also discussed.

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# Chapter V

# Detection of Bearing Faults and Stator Current Fault

## 5.1 Introduction

This part of work is focussed on the detection of the bearing fault for vibration signal analysis and also for the detection of the faults related to stator current for the overall analysis of the induction motor condition assessment. Bearing plays a important part in the reliability and performance of all machine systems. The results of many study shows that bearing problems accounts for over 40% of the machine failure. In the ongoing chapter, the analysis has been done to find the application of advanced signal processing techniques for detection of bearing faults. In any electromechanical system, the bearing fault is critical for functioning of machinery, so they form the major topic of discussion in this chapter. Broadly, this section contains two part (i)Bearing fault detection using signal processing techniques, (ii) detection of stator current fault. The data for all the processing related to vibration is collected from source [5.1].

## 5.2 Bearing Fault detection using Signal processing techniques

The first step for condition monitoring and fault detection is to develop an analysis technique that can be used to diagnose the observed signal to get useful information. There are several useful signal processing techniques which are very useful for fault diagnosis purpose these are classified below.

### 5.2.1 Detection of bearing fault using Fast Fourier Transform(FFT)

In order to diagnose the bearing faults of induction motor located in the vibration signal of the motor, the FFT is carried out using the MATLAB programming, which significantly distinguished between the healthy and faulty vibration signal. In FFT all the localized faults are appeared in the particular frequency band in which they lie. Since, for each bearing fault, there is an associated frequency that can be identified in the spectrum. The faults are detected by comparing the amplitude of specific frequencies of healthy and faulty samples.

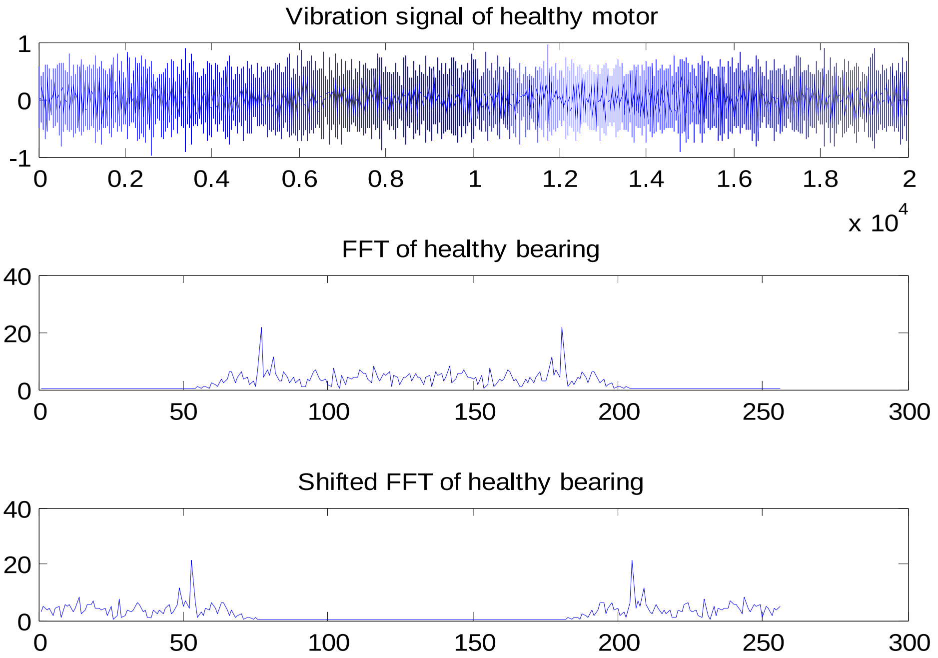

Figure 5.1 FFT spectra of healthy bearing

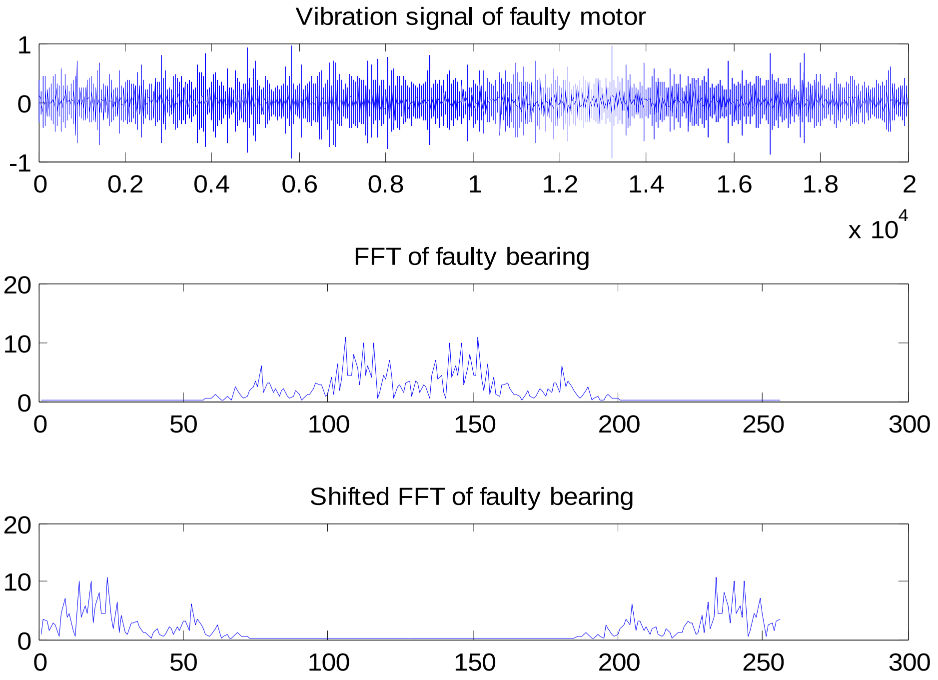

Figure 5.2 FFT spectra of faulty bearing

### 5.2.2 Results and Discussion

In the spectrum shown in the Figure 5.1 and Figure 5.2, which is of healthy and faulty bearing containing vibration signals, the two figures clearly showing the remarkable difference, since in the case of healthy signal the spectrum is smooth, spread over the whole area while in the case of faulty signal the fault is concentrated around the 100Hz-150Hz., which indicates localized faults in the faulty sample.

### 5.2.3 Detection of bearing fault using Power spectral density (PSD)

The power Spectral density (PSD) of any signal shows that how much energy the signal contains in itself. The PSD is nothing but the autocorrelation of the signal with itself. It is the similarity between observations as a function of the time separation between them. It is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal which has been buried under noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. In order to detect the fault the PSD of the healthy and faulty signal has been taken using the MATLAB programming. The PSD spectrum density has been splitted into the imaginary and real parts so that the clear picture regarding existence of fault has been obtained.

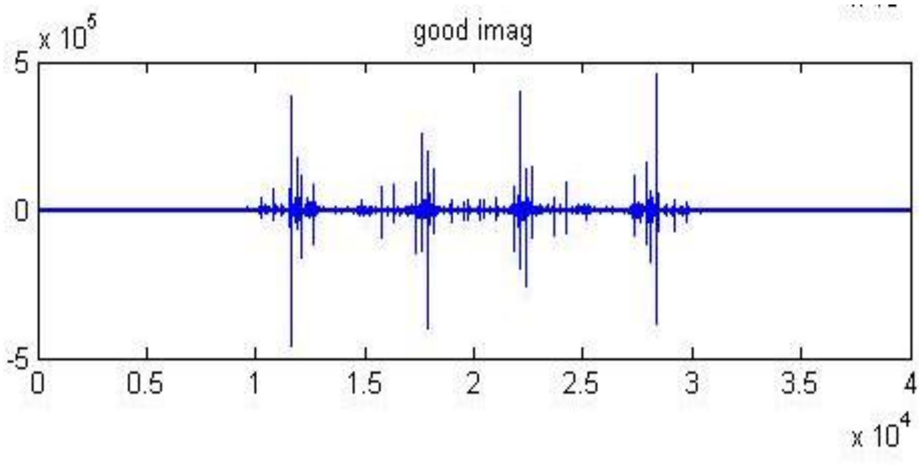

Figure 5.3 Power Spectral density spectrum of healthy bearing (imaginary part)

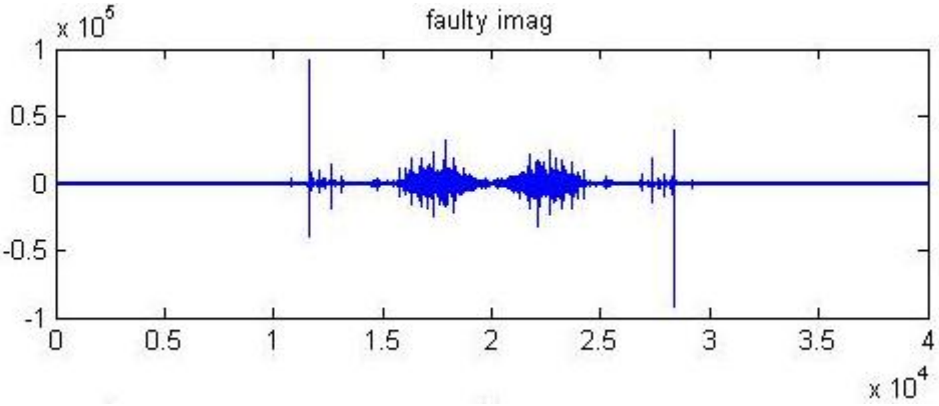

Figure 5.4 Power spectral density spectrum of faulty bearing (imaginary part)

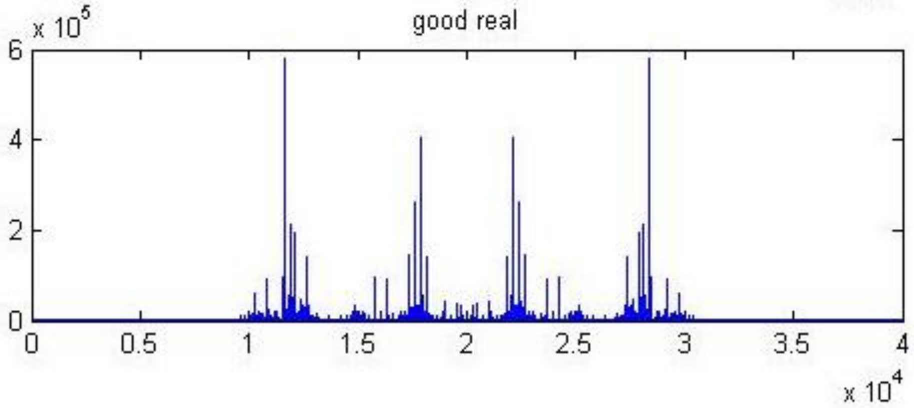

Figure 5.5 Power Spectral density spectrum of healthy bearing (real part)

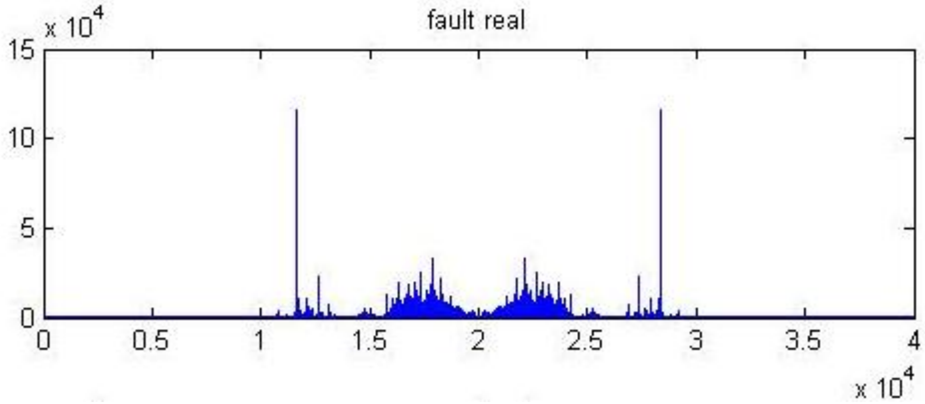

Figure 5.6 Power Spectral density spectrum of faulty bearing (real part)

### 5.2.4 Results and Discussion

The PSD is obtained for the two data sets i.e. one with the good bearing and the second one with the faulty bearing. In the good bearing (Figure 5.3 & 5.5) significant repeated patterns are observed in the form of spikes which indicates the good condition of induction motor since, there is no observance of the repeated patterns in the faulty bearing

(Figure 5.4 & 5.6) hence we can conclude from the PSD that some fault exists in the second data set, but we don't know the particular frequency at which the fault occurs. So we opt for another processing technique to find the fault at some particular frequency level.

### 5.2.3 Detection of bearing fault using Wavelet Transform

The FFT and PSD analysis only reveals the information regarding the fault that whether the fault is existed in the signal or not, the two signal processing techniques can't give the information regarding fault that which type of specific fault the signal contains in itself. One of the serious drawback of the FFT is that it is not suitable for analysing the transient signals because the time information is lost in the transformation. This problem may be overcome by using the Wavelet Transform. The wavelet analysis is useful regarding that it will give the full details of the frequency components in which the respective fault lies.

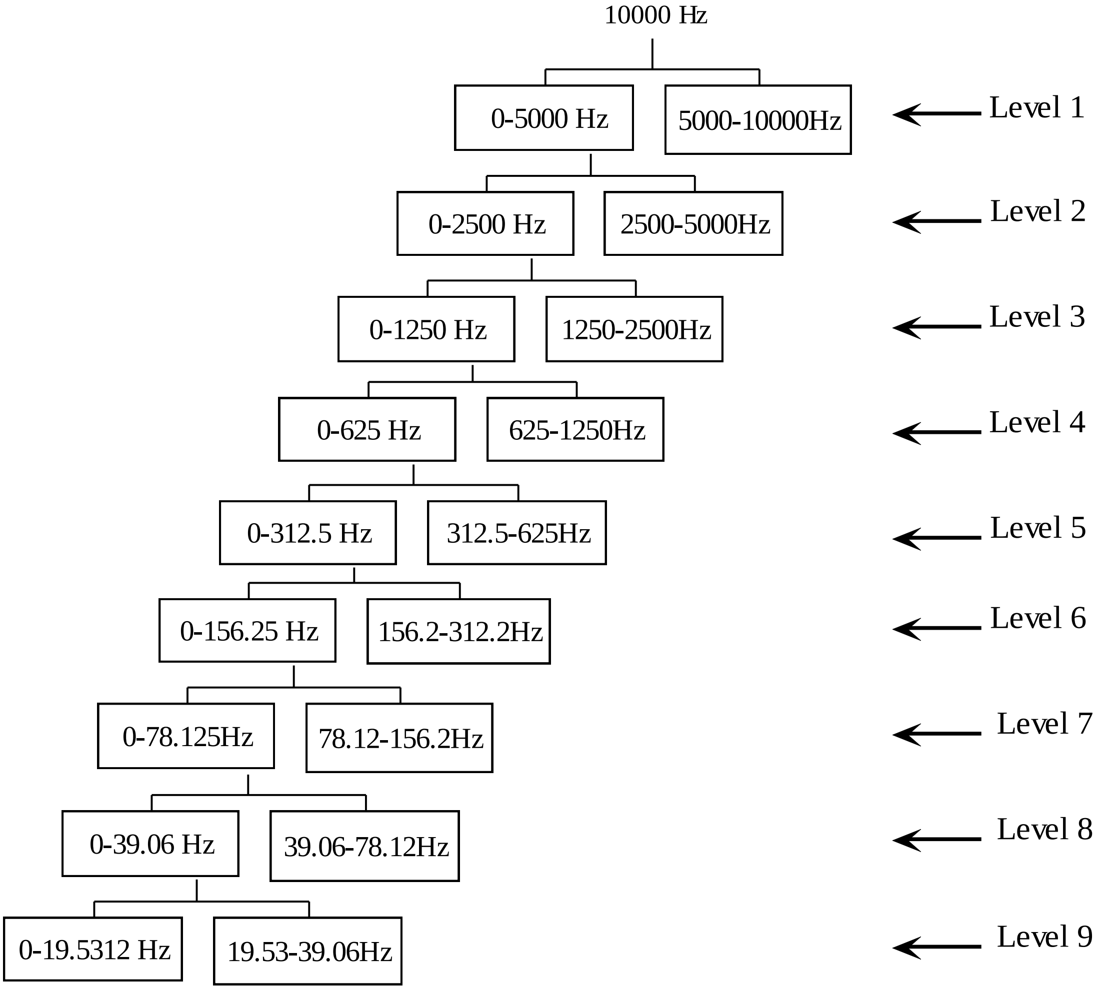

Figure 5.7 Decomposition at Different Levels (Samples = 10000 Hz )

In the presented work here the signal is undergone through Wavelet analysis, in which the signals are decomposed into the subsequent levels till the significant results are obtained. In figure 5.7 the decomposition of signals at different levels are highlighted. At each level there are two parts Approximation and details, the detail part is kept as it is while the approximate part is once again decomposed (in figure 5.7 the decomposition is achieved up to the $9^{th}$ level) into further stages. The different frequency band details which are obtained by the decomposition of signal at subsequent levels are highlighted in Table 5.1. The flow graph for the analysis of good and faulty signals are highlighted in the figure 5.8

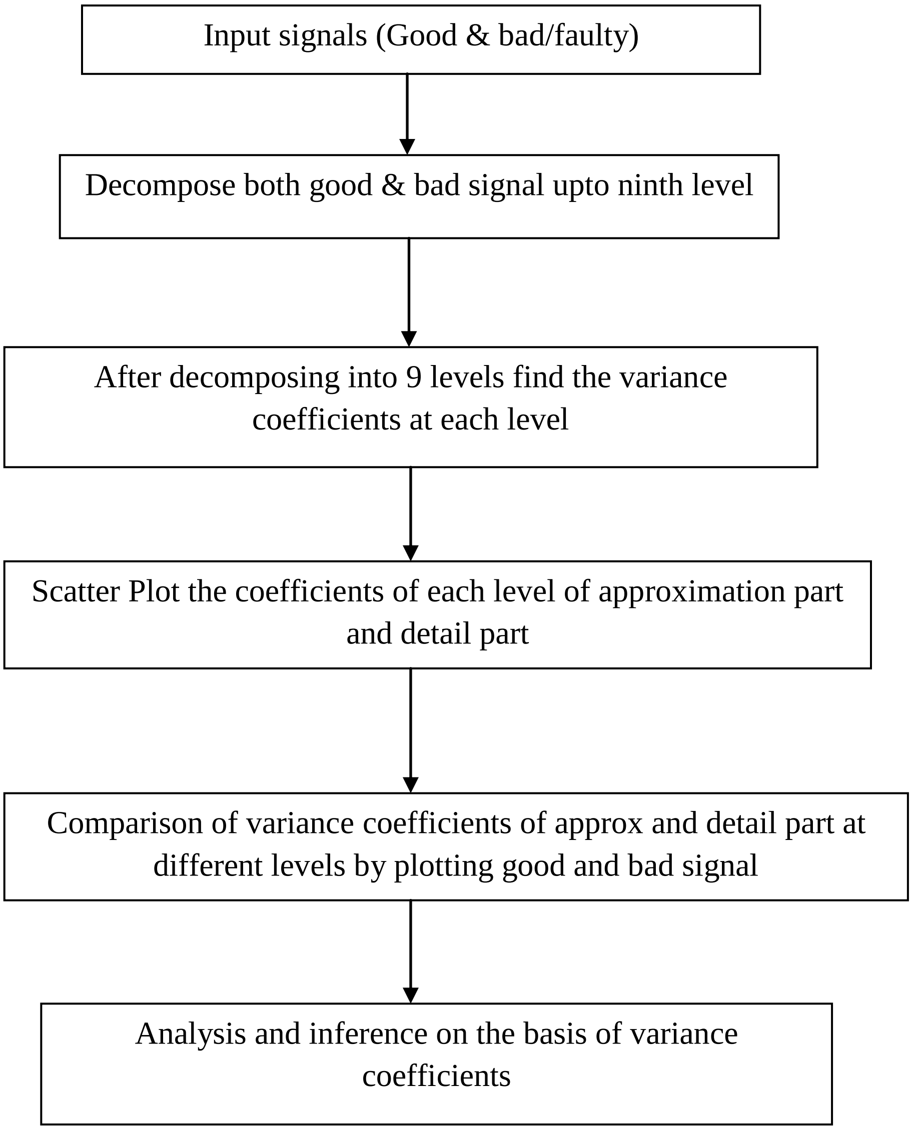

Figure 5.8 Flow graph for analysis of good and faulty signal

Table 5.1 Decomposition details at different levels

| Sr. No. | Decomposition Details | Frequency Bands (Hz) |
|---|---|---|
| 1. | Detail at level 1 | 5000-10000 Hz |
| 2. | Detail at level 2 | 2500-5000 Hz |
| 3. | Detail at level 3 | 1250-2500 Hz |
| 4. | Detail at level 4 | 625-1250 Hz |
| 5. | Detail at level 5 | 312.25-625 Hz |
| 6. | Detail at level 6 | 156.25-312.25 Hz |
| 7. | Detail at level 7 | 78.125-156.25 Hz |
| 8. | Detail at level 8 | 39.0625-78.125 Hz |
| 9. | Detail at level 9 | 19.5312-39.0625 Hz |

### 5.2.4 Results and Conclusions

The wavelet transform results at different level (9 levels) have been shown in the Figure 5.8 to 5.17. Although there is no significant changes has been observed in the first six levels because it contains the higher frequency components , so possibility of existing a fault is diminishes but as soon as we observe the next three levels i.e. $7^{th}$ ,$8^{th}$, $9^{th}$ level there is a remarkable difference between the data sets of the healthy and faulty bearing. From the Figure 5.14, 5.15, 5.16 it has been clearly indicating that there exists a fault at the low frequency components which supports our results and observations which we had taken during the literature review. Further, the frequency at which particular bearing fault occur is also observed from the $7^{th}$ ,$8^{th}$, $9^{th}$ level which confirms our prediction about the particular fault in the particular frequency band. These specific bearing faults are tabulated in the Table 5.2 with their corresponding frequency components.

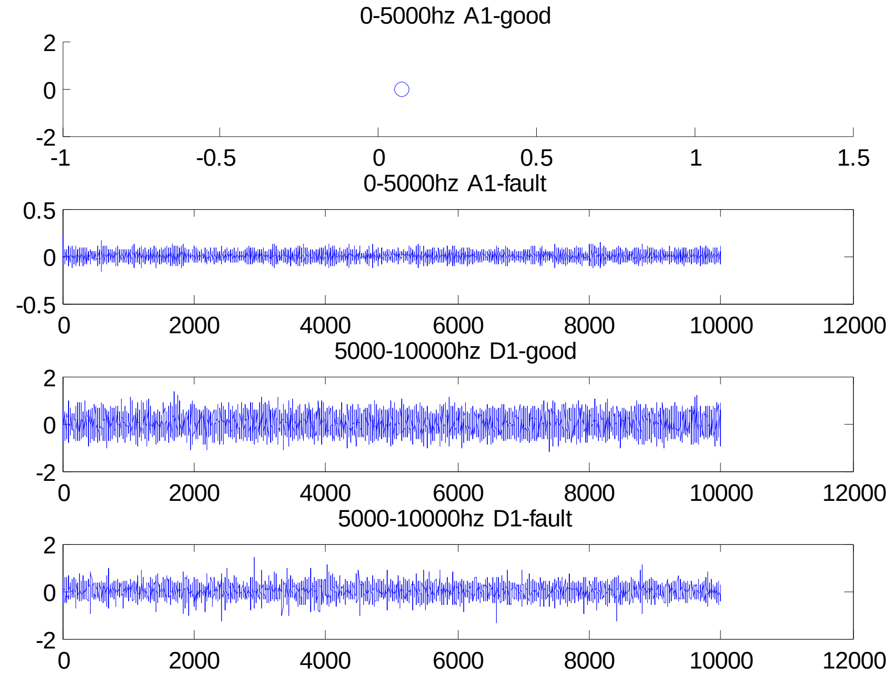

Figure 5.9 Signal Decomposition at $1^{st}$ level

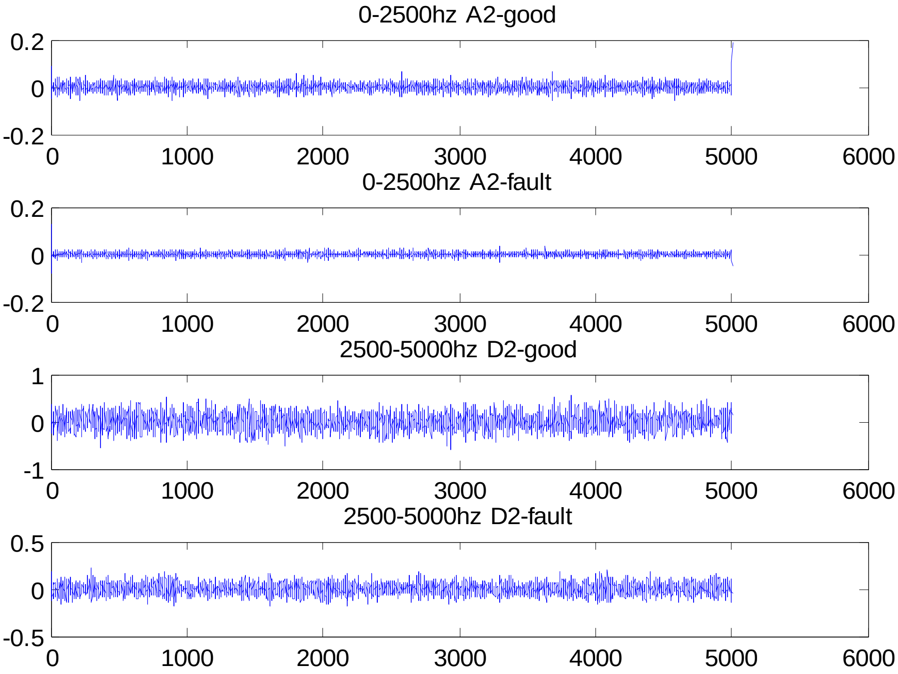

Figure 5.10 Signal Decomposition at $2^{nd}$ level

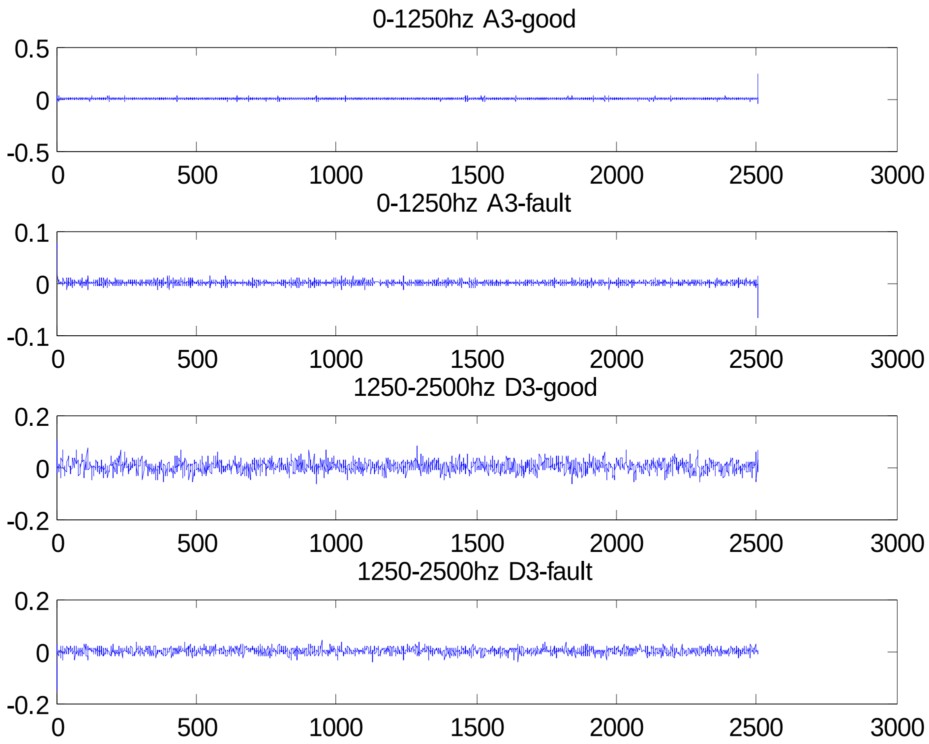

Figure 5.11 Signal Decomposition at $3^{rd}$ level

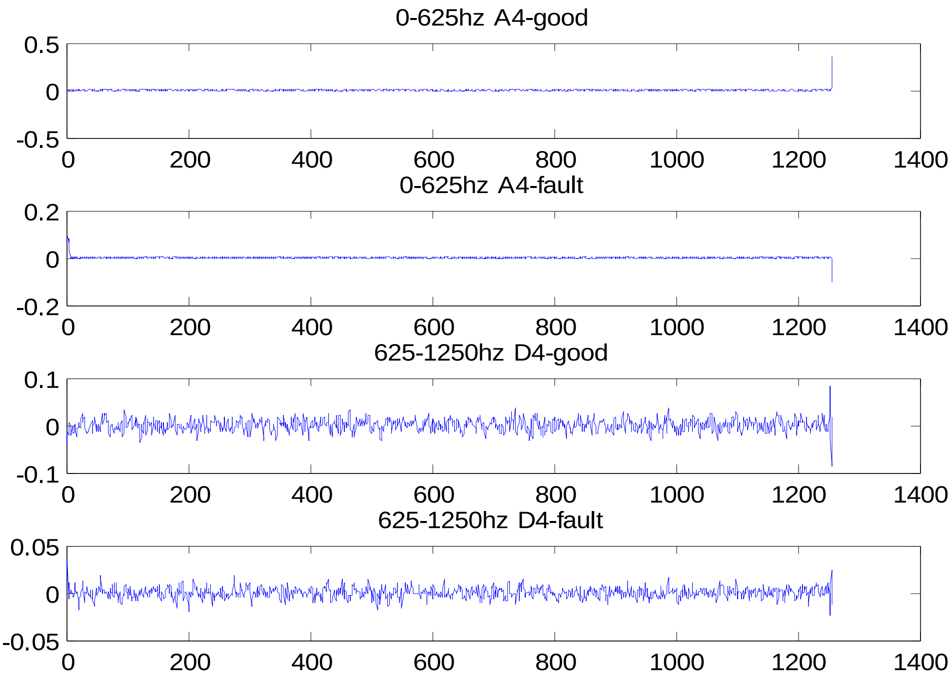

Figure 5.12 Signal Decomposition at $4^{th}$ level

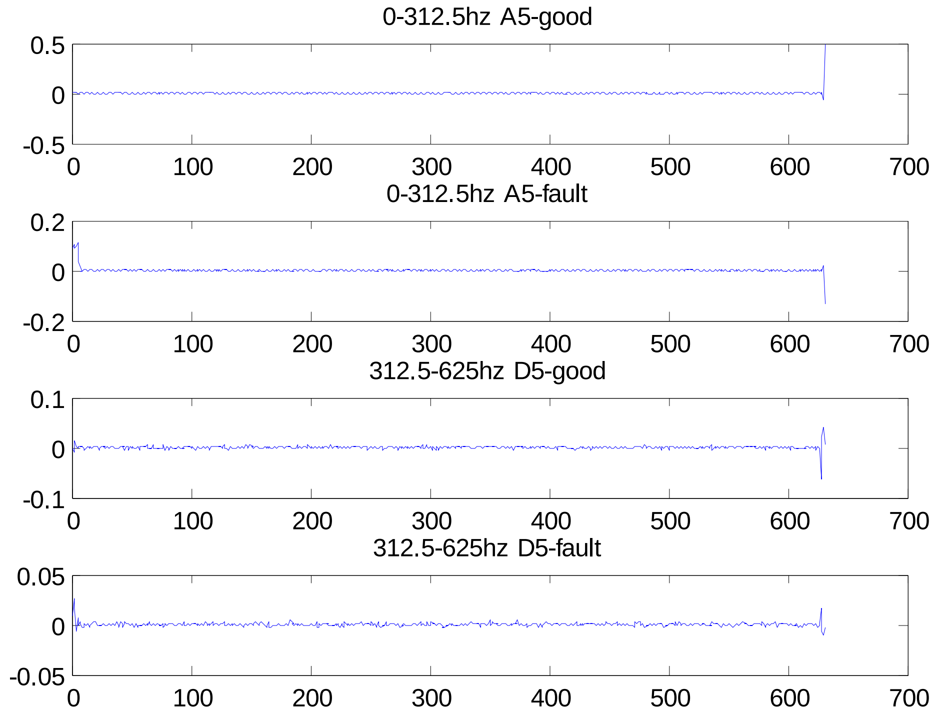

Figure 5.13 Signal Decomposition at $5^{th}$ level

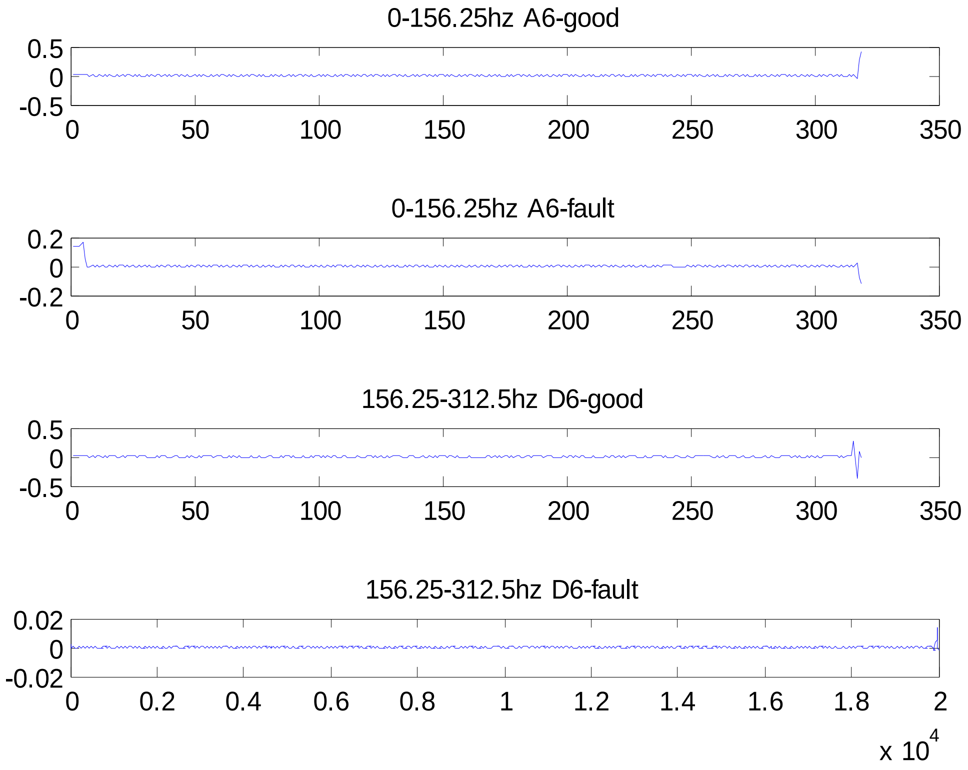

Figure 5.14 Signal Decomposition at $6^{th}$ level

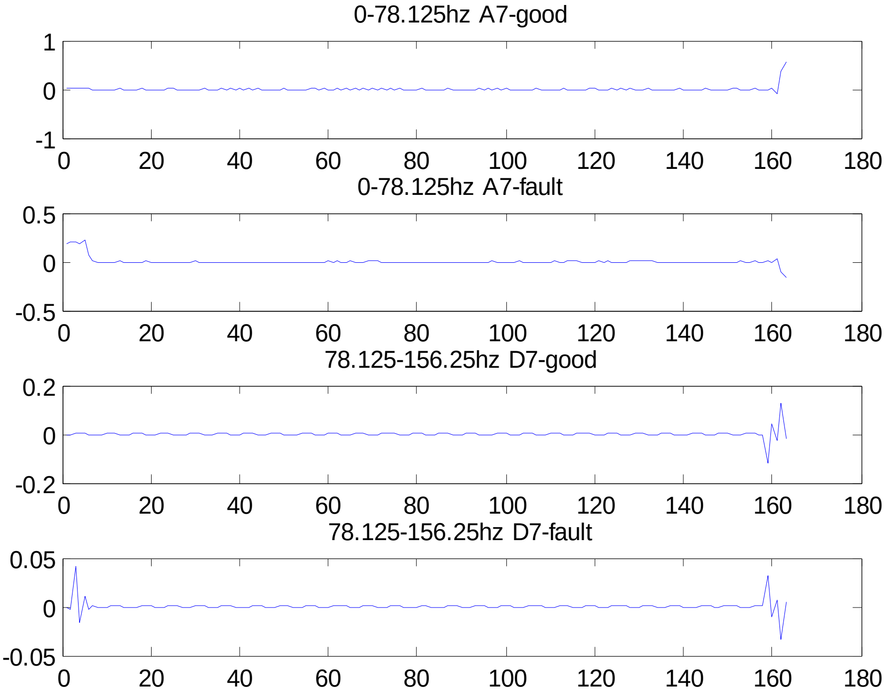

Figure 5.15 Signal Decomposition at $7^{th}$ level

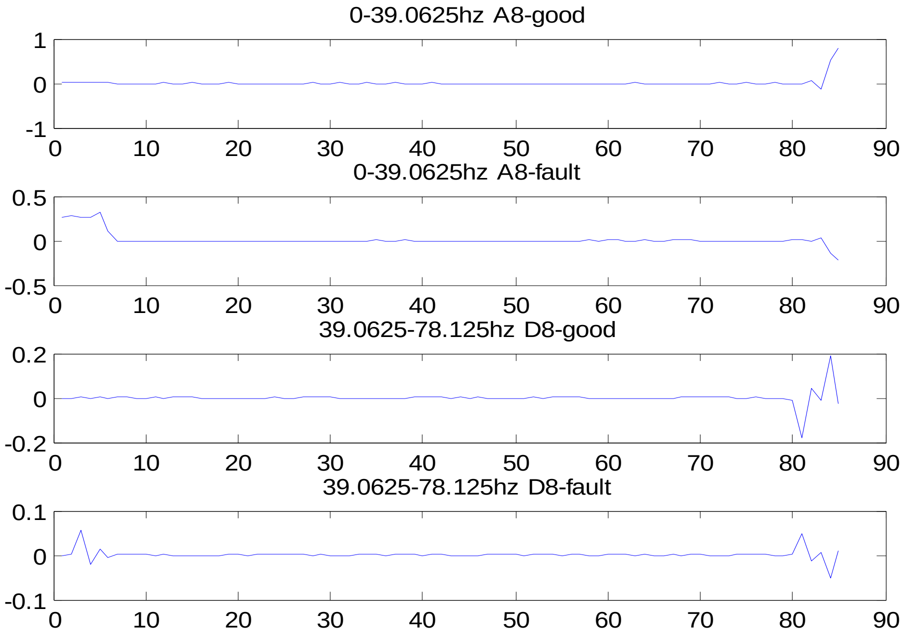

Figure 5.16 Signal Decomposition at $8^{th}$ level

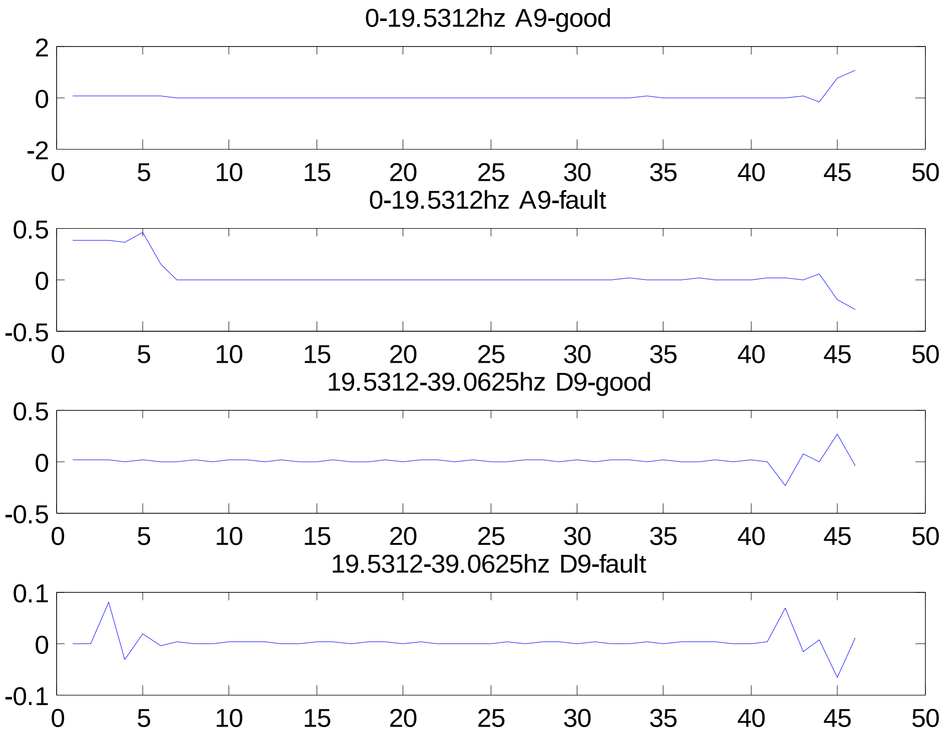

Figure 5.17 Signal Decomposition at $9^{th}$ level

Table 5.2 Types of Bearing faults & frequency band

| S. No | Type of Bearing fault | Frequency band (Hz) |
|---|---|---|
| 1 | Ball pass Inner raceway frequency/Inner raceway defect | Around 150 Hz |
| 2 | Ball pass Outer raceway frequency/Outer raceway defect | 60-80 Hz |
| 3 | Ball defect frequency | Below 60 Hz |

Further , to confirm the authencity of result that whether they are correct or not, we took the coefficients of approximation part and details part at each level(Figure 5.17 to 5.25) and calculated the variance at each level of approximation and details part(tabulated in Table 5.3) and plotted the graph between the approximation coefficients of healthy and faulty data (shown in figure 5.26) and similarly also a graph has been plotted between the details coefficients at each level for healthy and faulty data (shown in figure 5.27) .

Note → Blue colour = good bearing Red = faulty bearing

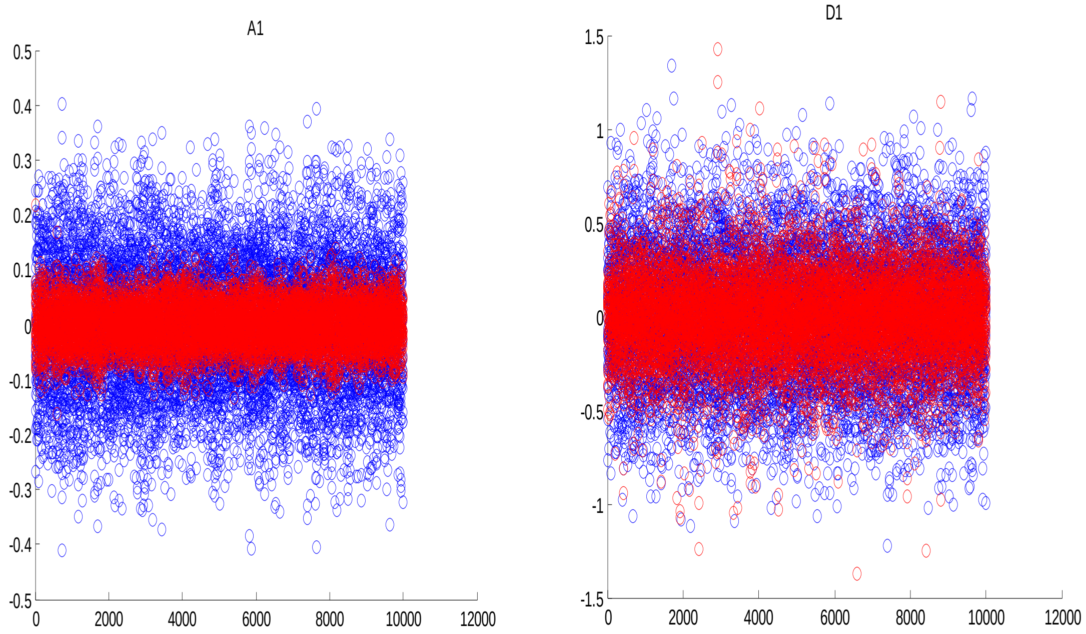

Figure 5.18 Plot of Coefficients at $1^{st}$ level i.e A1, D1

In Figure 5.18 comparison of variance of coefficients at First level are plotted for good and faulty(bad) signals. In the approximation the bad signal are restricted around centre(-0.1 to 0.1) , the good signals are ranging around -0.3 to 0.3. While in the detail part some bad signals are scattered while the good signals lying in -1 to 1.

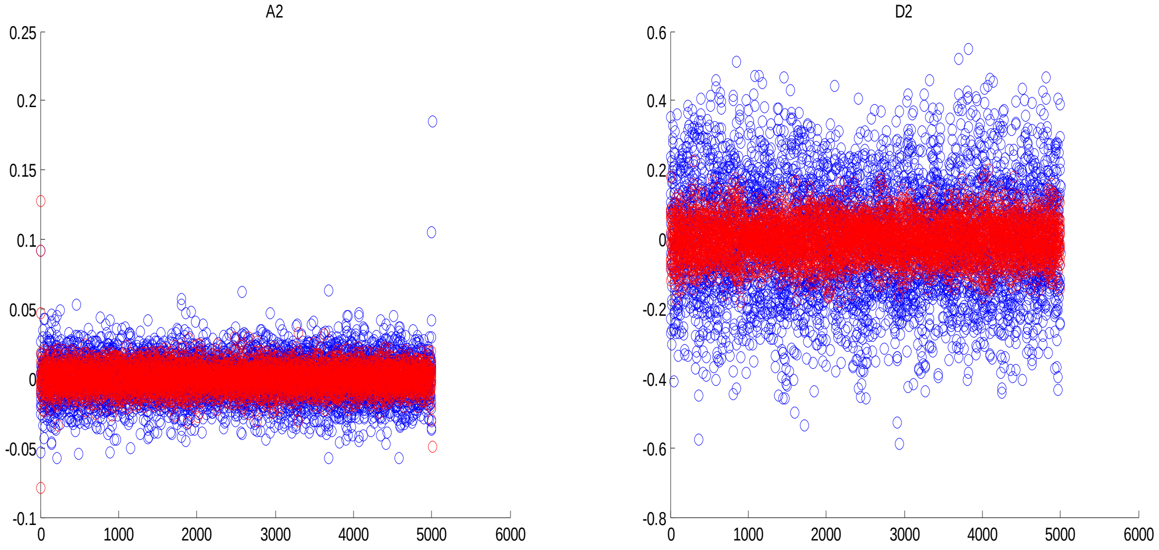

Figure 5.19 Plot of Coefficients at $2^{nd}$ level i.e. A2, D2

In Figure 5.19 comparison of variance of coefficients at Second level are plotted for good and faulty(bad) signals. In the approximation the bad signals are around -0.025 to 0.025 and good signals are scattered in the vicinity -0.05 to 0.05.While in the detail band the bad signal are lying in the region -0.1 to 0.1 and good signals are around -0.4 to 0.4.

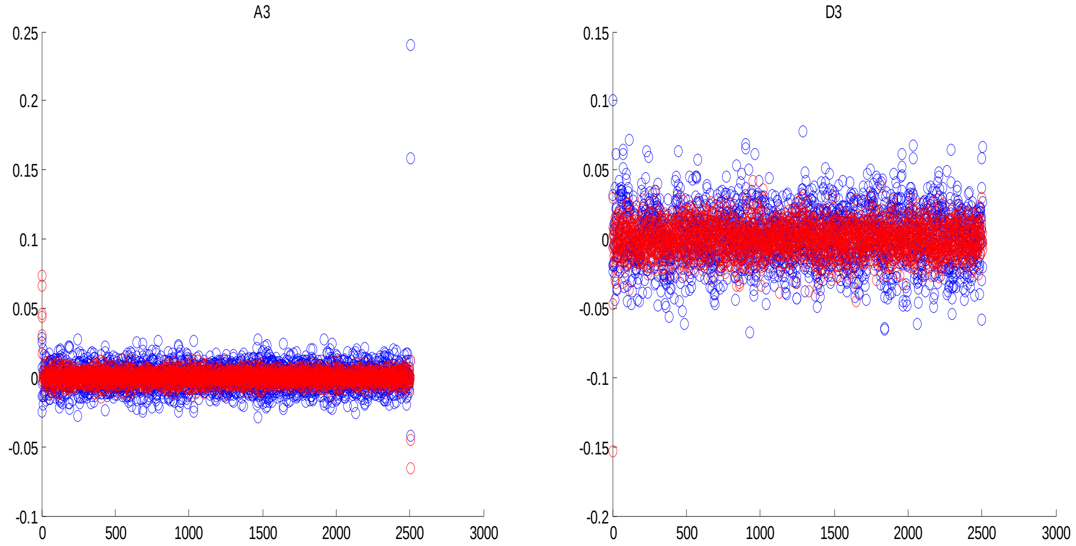

Figure 5.20 Plot of Coefficients at $3^{rd}$ level i.e. A3 , D3

In Figure 5.20 comparison of variance of coefficients at Third level are plotted for good and faulty(bad) signals. In the approximation the bad signals are around -0.0125 to 0.0125 and good signals are scattered in the vicinity -0.025 to 0.025.While in the detail band the bad signal are lying in the region -0.025 to 0.025 and good signals are around -0.054 to 0.05.

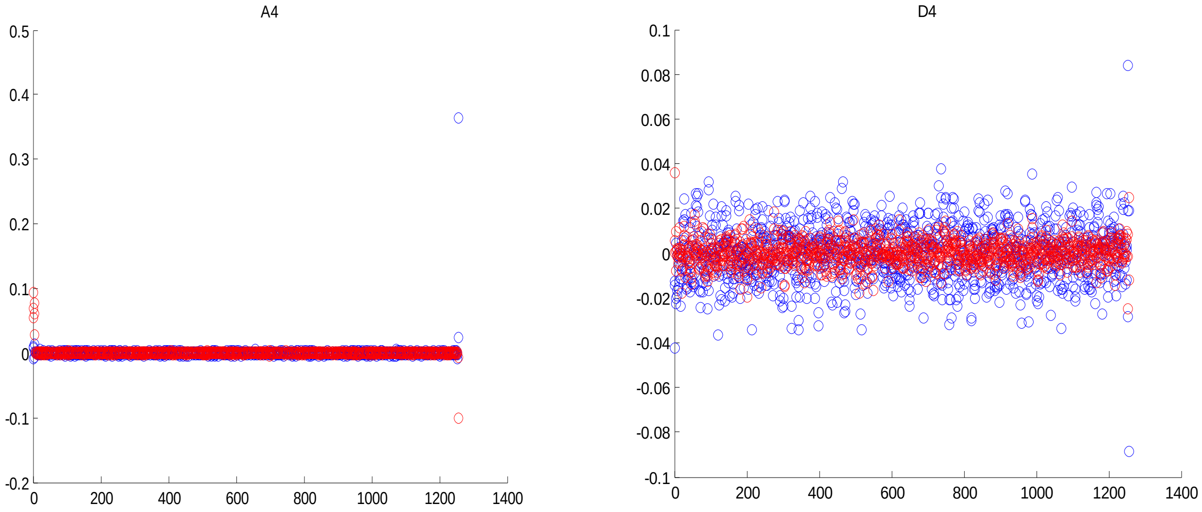

Figure 5.21 Plot of Coefficients at $4^{th}$ level i.e. A4 , D4

In Figure 5.21 comparison of variance of coefficients at Fourth level are plotted for good and faulty(bad) signals. In the approximation the bad signals are around centre -0.01 to

0.01 and good signals are just above the bad signal .While in the detail band the bad signal are lying in the region -0.01 to 0.01 and good signals are around -0.02 to 0.02.

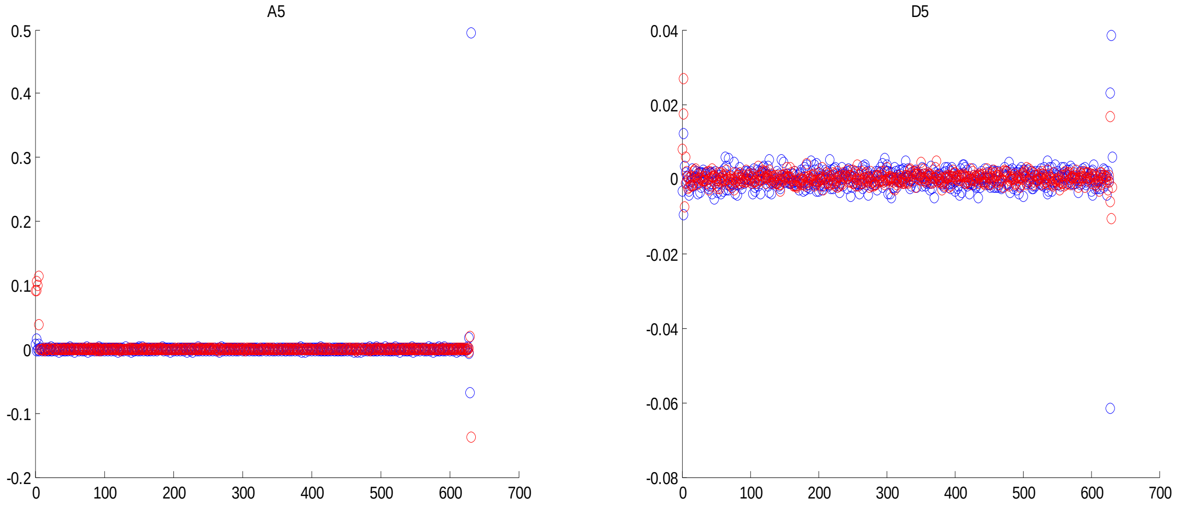

Figure 5.22 Plot of coefficients at $5^{th}$ level, i.e. A5, D5

In Figure 5.22 comparison of variance of coefficients at Fifth level are plotted for good and faulty(bad) signals. In the approximation the bad signals are around almost ± 0 and good signals are just overlapping on bad signals. While in the detail band the bad signal are lying in the region -0.005 to 0.005 and good signals are scattered along in the vicinity of bad signal.

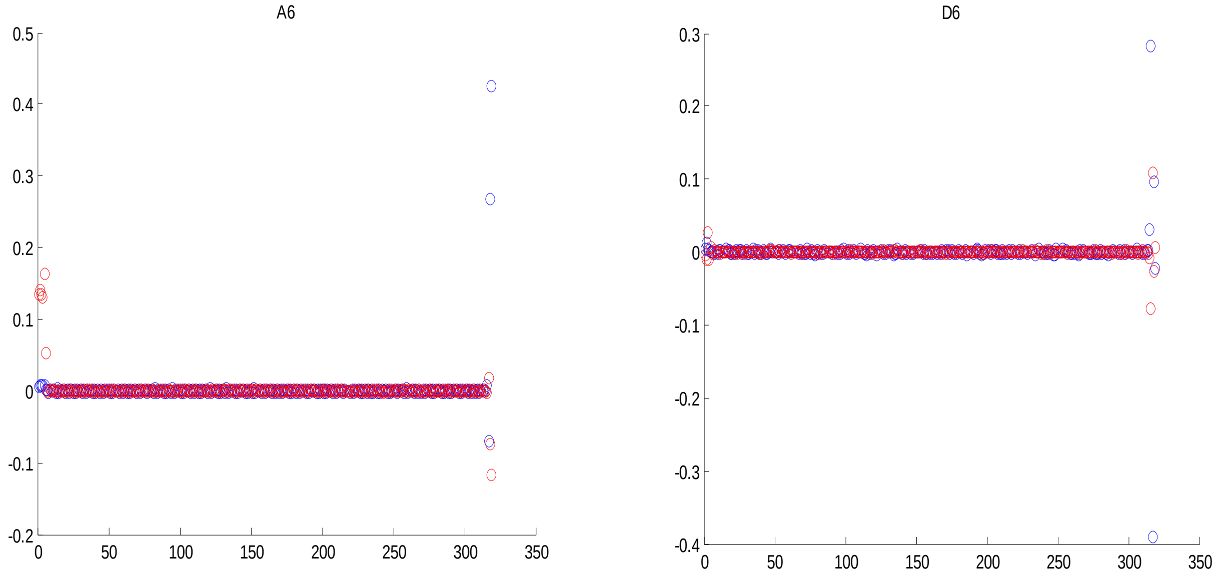

Figure 5.23 Plot of Coefficients at $6^{th}$ level i.e. A6, D6

In Figure 5.23 comparison of variance of coefficients at Sixth level are plotted for good and faulty(bad) signals. In the approximation the bad signals are around ±0 and good signals are very few around the bad signals. Similarly in the detail band the bad signal are lying in the region ±0 and good signals are around very negligible.

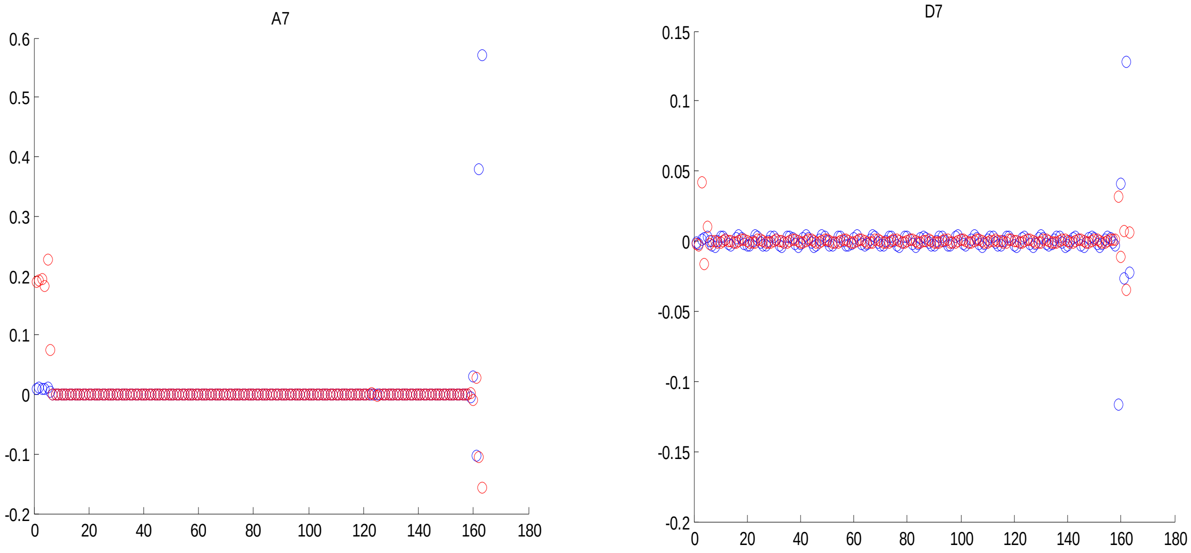

Figure 5.24 Plot of Coefficients at $7^{th}$ level i.e. A7, D7

In Figure 5.24 comparison of variance of coefficients at Seventh level are plotted for good and faulty (bad) signals. In the approximation very few coefficients of good are present whereas the faulty signal coefficients are much more and centred around ±0.While in the detail band the bad signal are lying in the region ±0 and good signals are just scattered around in the vicinity of bad.

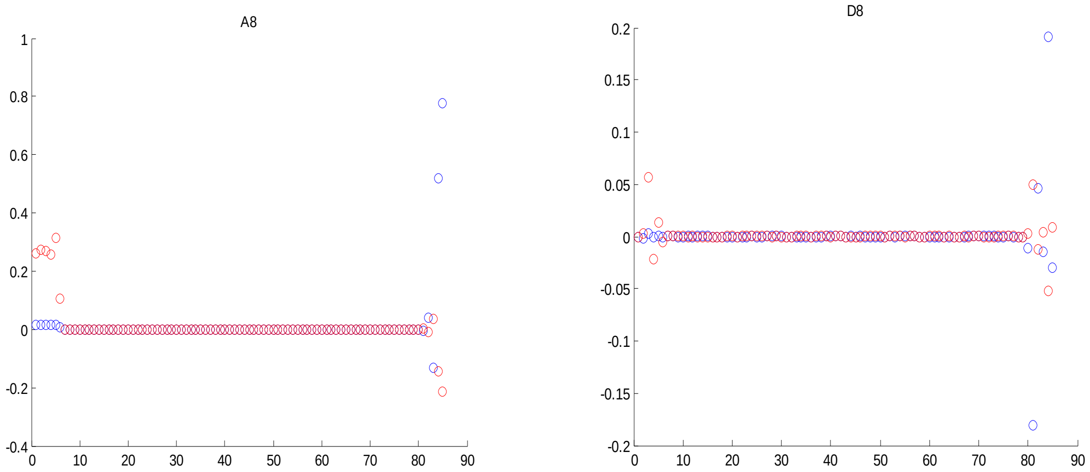

Figure 5.25 Plot of Coefficients at $8^{th}$ level i.e. A8, D8

In Figure 5.25 comparison of variance of coefficients at $8^{th}$ level are plotted for good and faulty(bad) signals. In the approximation very few coefficients of good are present in the beginning whereas the faulty signal coefficients are much more and centred around ±0.While in the detail band the bad signal are lying in the region ±0 and good signals are just scattered around in the vicinity of bad. In the detail part some coefficients are distributed around 80Hz which indicates present of a particular fault.

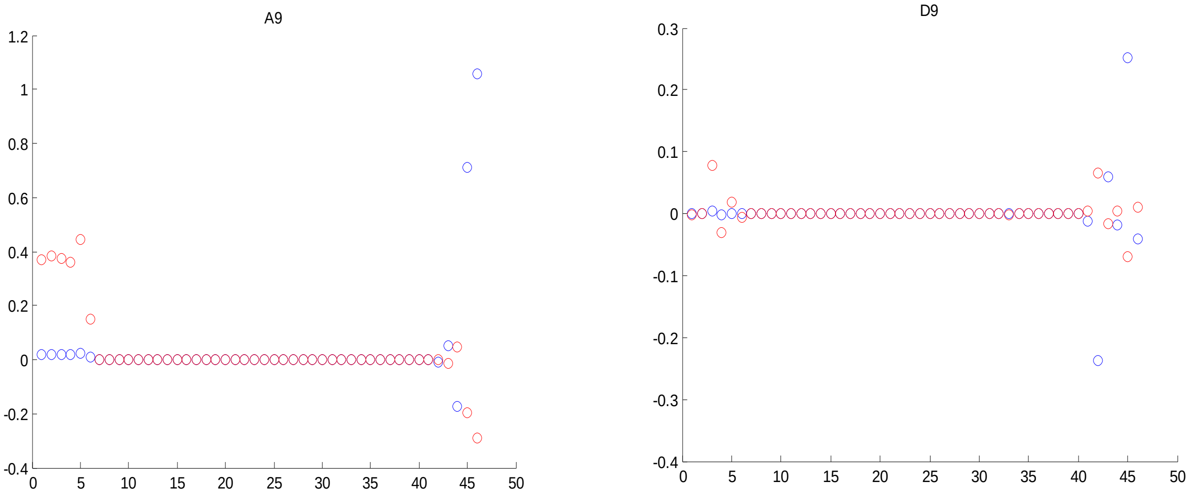

Figure 5.26 Plot of Coefficients at $9^{th}$ level i.e. A9, D9

In Figure 5.26 comparison of variance of coefficients at $9^{th}$ level are plotted for good and faulty(bad) signals. In the approximation very few coefficients of good are present in the beginning whereas the faulty signal coefficients are much more and centred around ±0.While in the detail band the bad signal are lying in the region ±0 and good signals are just scattered around in the vicinity of bad. In the detail part some coefficients are distributed around 45Hz which indicates present of a particular fault.

Table 5.3 Calculated Variance at different levels

| Levels | Good condition | | Faulty Condition | |
|---|---|---|---|---|
| | Variance($\sigma^2$) of Approx. Coefficients | Variance($\sigma^2$) of Details Coefficients | Variance($\sigma^2$) of Approx. Coefficients | Variance($\sigma^2$) of Details Coefficients |
| Level 1 | 0.134 | 0.1123 | 0.0016 | 0.0492 |
| Level 2 | 0.0446 | 0.0266 | 0.0502 | 0.0031 |
| Level 3 | 0.0200 | 0.0719 | 0.0157 | 0.0238 |
| Level 4 | 0.0200 | 0.0293 | 0.0207 | 0.0207 |
| Level 5 | 0.0733 | 0.009 | 0.0206 | 0.0101 |
| Level 6 | 0.1479 | 0.1405 | 0.0695 | 0.0417 |
| Level 7 | 0.0029 | 0.0381 | 0.0014 | 0.0190 |
| Level 8 | 0.0103 | 0.1560 | 0.0052 | 0.0201 |
| Level 9 | 0.0346 | 0.0027 | 0.0183 | 0.0674 |

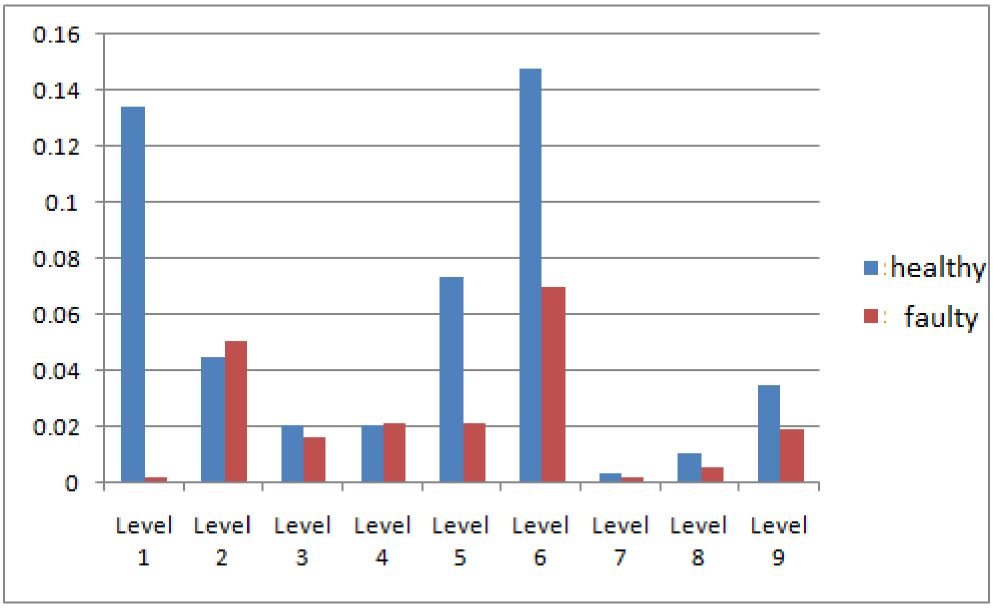

Figure 5.27 Plot for Approximation coefficients at different levels

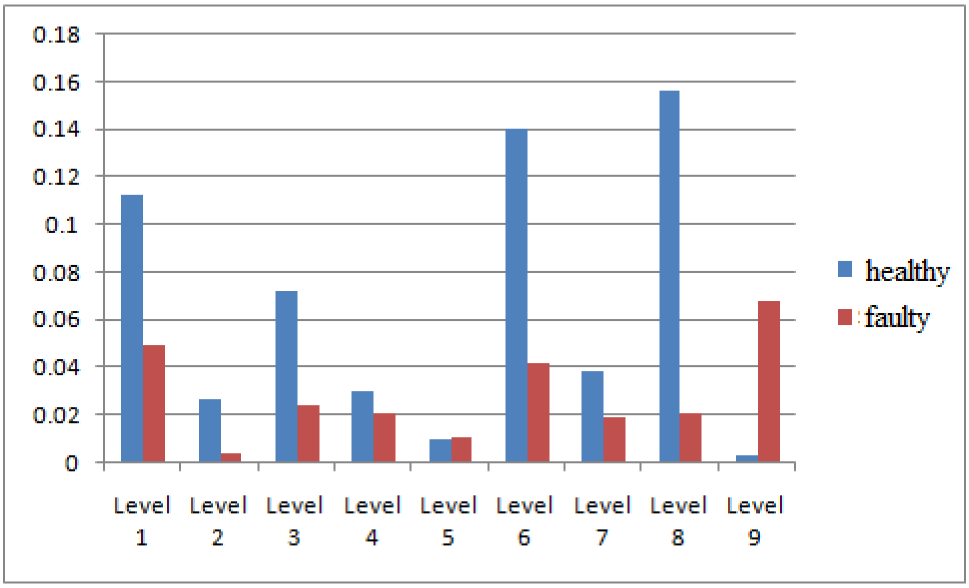

Figure 5.28 Plot for details coefficients at different levels

The graph of variance of approximation and detail coefficients has been plotted which clearly states that the fault exists at the lower level between the healthy and faulty signals , hence we can conclude that the fault exits at those particular corresponding frequencies as described in the plots.

## 5.3 Detection of fault related to Stator current

The objective of this section is to propose a scheme to detect the abnormalities related to stator current. The stator current contains the unique fault frequency component that can be used for the stator related fault detection. Since a motor failure due to stator fault may result in the shut down of the generating or production unit. Early detection of stator short winding during motor operation may eliminate consequent damage to adjacent coils. A stator current signal contains potential fault information. The most suitable measurements for diagnosing the faults under consideration, in term of easy accessibility, reliability, and sensitivity, are the stator current amplitudes $I_a, I_b, I_c$.

The proposed method allow early detection of stator related fault if it exists in the system, so that the excessive damage can be avoided. Thus this method may be used for continuous monitoring of induction motor health also.

### 5.3.1 Fuzzy Logic based diagnosis approach

Fuzzy systems rely on a set of rules. These rules, while superficially similar, allow the input to be fuzzy, i.e. more like the natural way that humans express knowledge. Thus, a engineer might refer to an electrical machine as “partially secure” or a “little overloaded”. This linguistic input can be expressed directly by a fuzzy system. Therefore, the natural format greatly eases the interface between the engineer knowledge and the domain expert.

As stated, the induction motor stator condition can be deduced by observing the stator current amplitudes. Interpretation of results is difficult as relationships between the motor condition and the current amplitudes are vague. Therefore, using fuzzy logic, numerical data are represented as linguistic information.

In our fault detection system, the stator current amplitudes $I_a, I_b, I_c$ are considered as the input variables to the fuzzy system. The stator condition, CM, is chosen as the output variable. All the system inputs and outputs are defined using fuzzy set theory. The fuzzy membership functions are obtained for the stator current and its condition monitoring (CM). The membership functions for stator current are highlighted in the Figure 5.29 and 5.30. Similarly the fuzzy membership function for the stator condition (CM) is shown in Figure 5.31 and 5.32. [5.2]

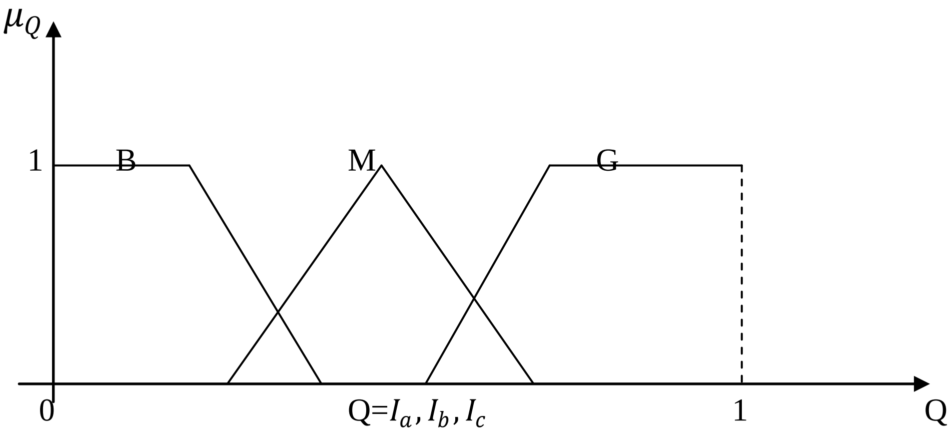

Figure 5.29 Fuzzy membership functions for stator current

(B= bad, M=medium, G=good)

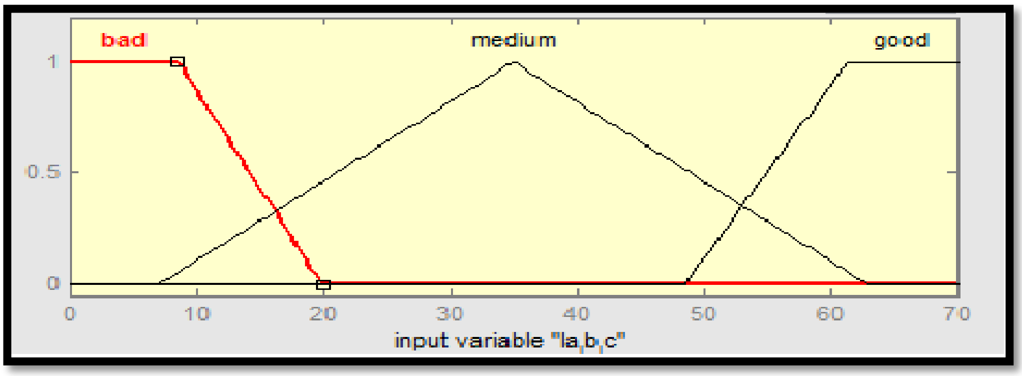

Figure 5.30 Actual Fuzzy membership function obtained

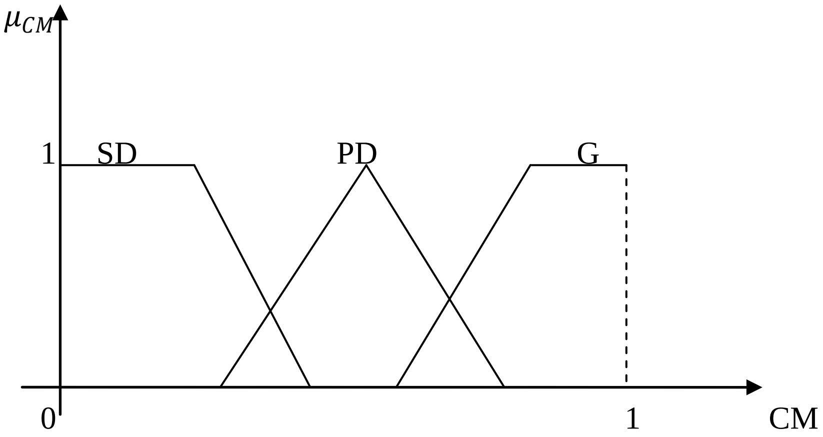

Figure 5.31 Fuzzy membership function for stator current(CM)

(SD=seriously damage, PD=partially damage, G=good)

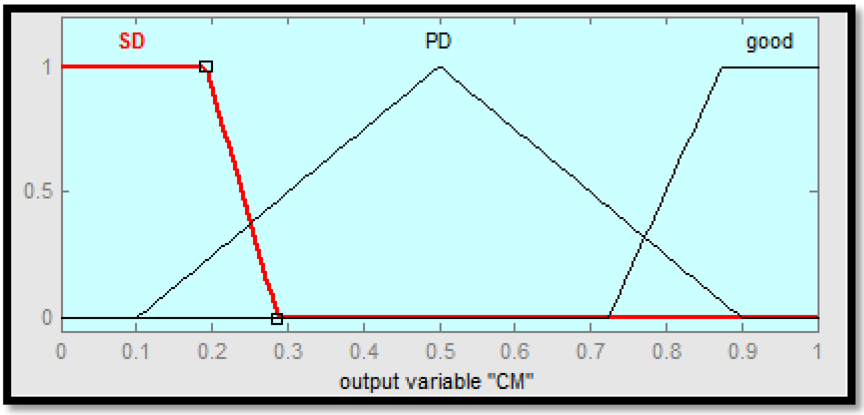

Figure 5.32 Actual fuzzy membership function obtained for CM

These fuzzy rules have been optimised so as to cover all the healthy and faulty cases. For our fault detection case, we have obtained the following 14 if then rules.

Rule (1) If $I_a$ is bad and $I_b$ is bad and $I_c$ is bad Then CM is SD

Rule (2) If $I_a$ is bad and $I_b$ is medium and $I_c$ is bad Then CM is SD

Rule (3) If $I_a$ is bad and $I_b$ is bad and $I_c$ is medium Then CM is SD

Rule (4) If $I_a$ is bad and $I_b$ is bad and $I_c$ is good Then CM is SD

Rule (5) If $I_a$ is medium and $I_b$ is medium and $I_c$ is bad Then CM is PD

Rule (6) If $I_a$ is good and $I_b$ is medium and $I_c$ is bad Then CM is PD

Rule (7) If $I_a$ is good and $I_b$ is medium and $I_c$ is medium Then CM is PD

Rule (8) If $I_a$ is good and $I_b$ is good and $I_c$ is bad Then CM is Good

Rule (9) If $I_a$ is medium and $I_b$ is good and $I_c$ is good Then CM is Good

Rule (10) If $I_a$ is good and $I_b$ is good and $I_c$ is good Then CM is Good

Rule (11) If $I_a$ is good and $I_b$ is good and $I_c$ is medium Then CM is Good

Rule (12) If $I_a$ is medium and $I_b$ medium and $I_c$ is medium Then CM is PD

Rule (13) If $I_a$ medium and $I_b$ is medium and $I_c$ is good Then CM is Good

Rule (14) If $I_a$ is bad and $I_b$ is good and $I_c$ is medium Then CM is PD

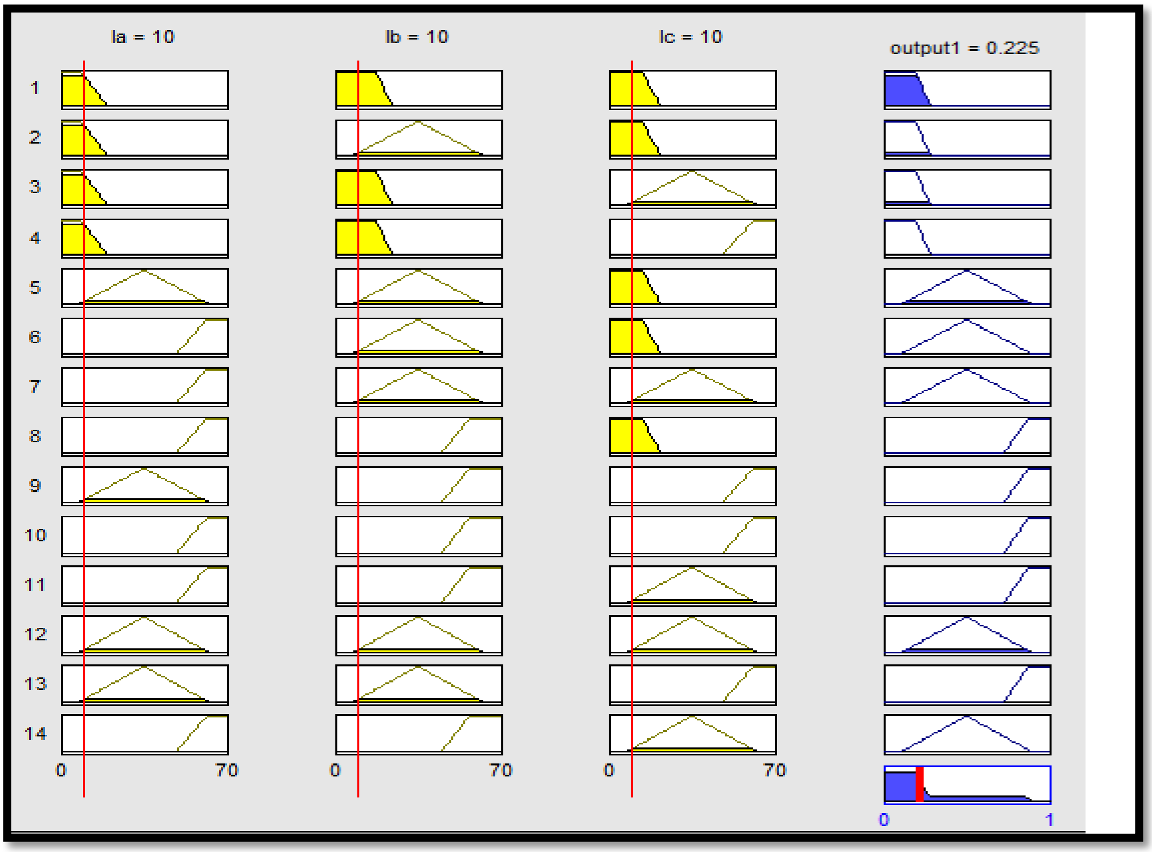

Figure 5.33 Fuzzy inference diagram for Seriously damaged motor

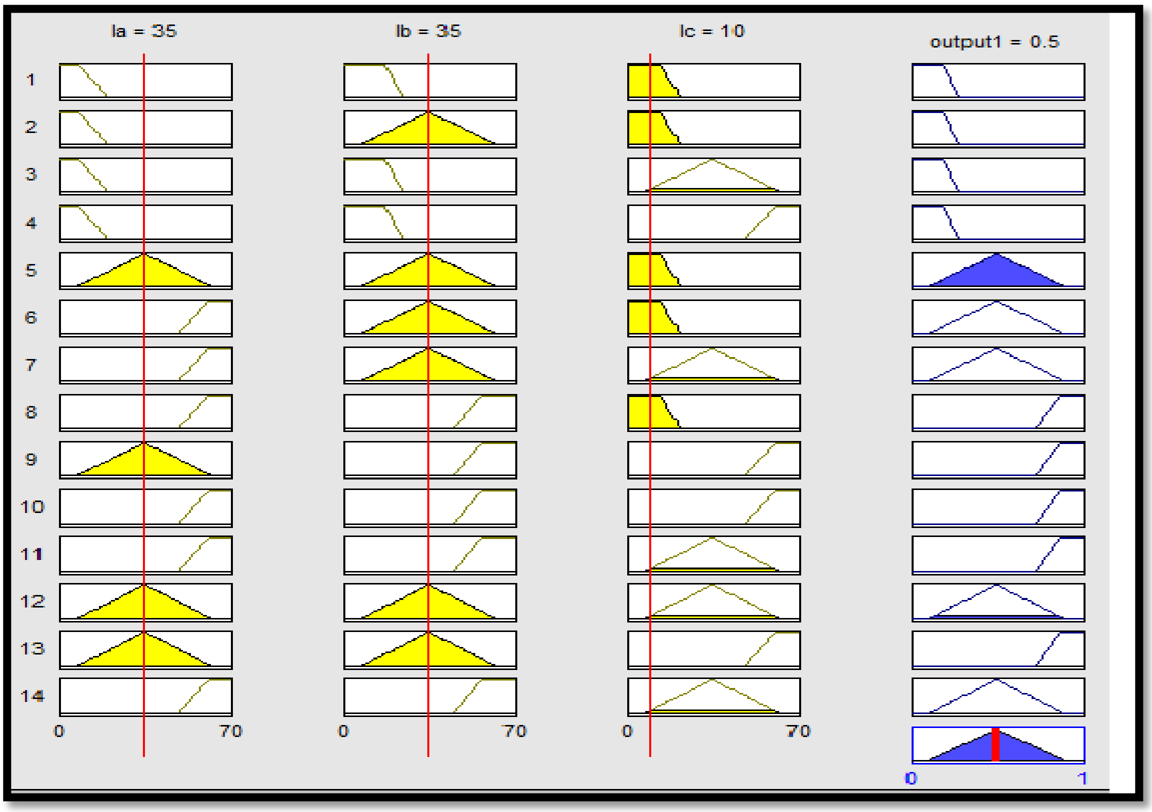

Figure 5.34 Fuzzy inference diagram for Partially damaged motor

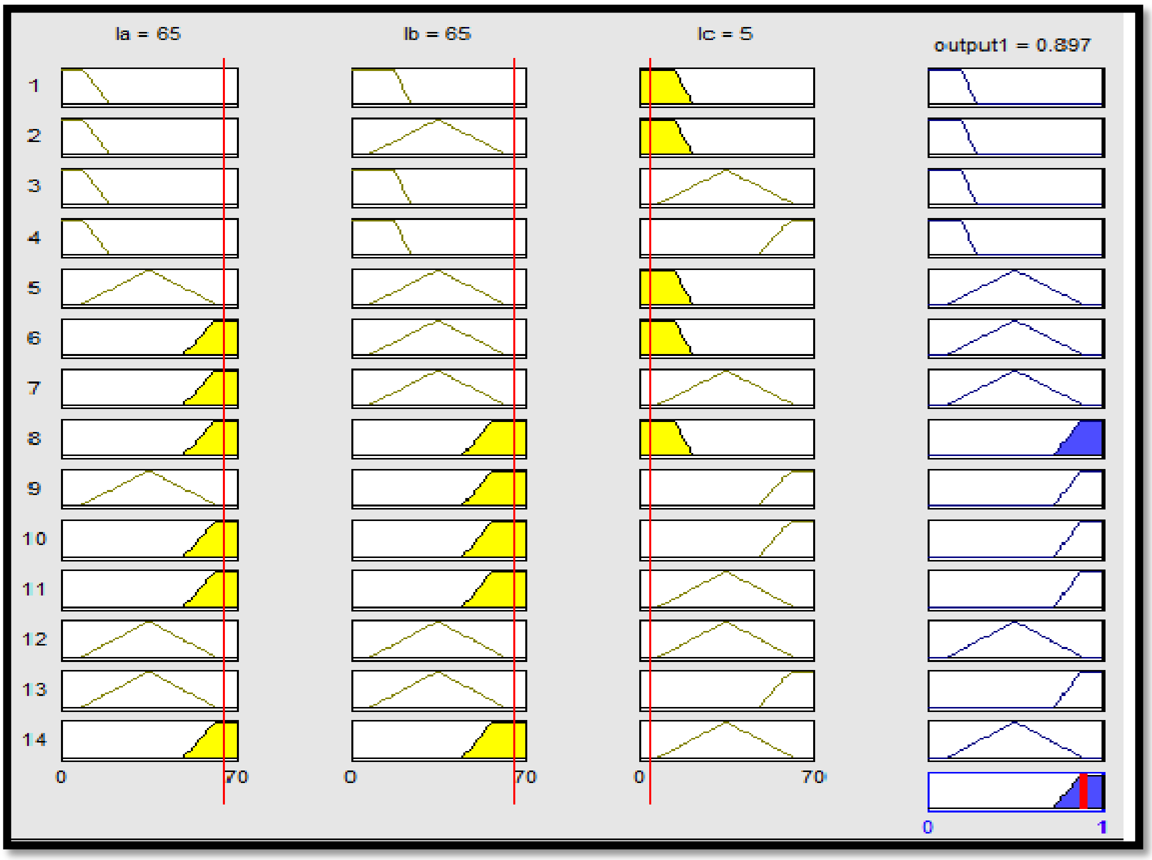

Figure 5.35 Fuzzy inference diagram for Healthy motor

### 5.3.2 Conclusion

By using the FIS technique the stator current condition is analysed for different cases by using if then rules. In the beginning as much as 27 rules are made but finally these are minimised to 14. For Figure 5.33 it is rule (1) that is solicited, in fact $I_a = I_b = I_c = 10$ are bad (small). The motor is this case is supposed to be seriously damaged (CM=0.225) since the amplitude of current is defined by linguistic terms “Bad”. Similarly in the Figure 5.34 it is rule (5) that is solicited, in fact $I_a = I_b = 35$ are “Medium” and $I_c = 10$ are “Bad”. The motor is this case is Partially Damaged (CM=0.5).Finally for Figure 5.35 it is rule (8) that is solicited when $I_a = 65$, $I_b = 65$ are “Good” and $I_c = 10$ are “Bad”. The motor is this case is Healthy (CM=0.897).

## 5.4 Chapter Summary

In the presented chapter the detection of particular fault frequency related to bearing fault has been done by applying the different signal processing techniques on the faulty and healthy samples. The stator current fault detection has been done by using the FIS strategy. This information from both these two parameters (bearing fault & stator current) is now used for the fusion process.

# References

[5.1] for all the data related to good bearing and bad bearing (vibration) http://www.wiley.com//legacy/wileychi//shin_hammond/

[5.2] M. Zeraoulia , A. Mamoune , H. Mangel ,M.E.H. Benbouzid “A Simple Fuzzy Logic Approach for Induction Motors Stator Condition Monitoring” , J. Electrical Systems 1-1 (2005) pp15-25

# Chapter VI

# Multi Sensor Fusion for Condition Monitoring: An Overview

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## 6.1 Fusion using FIS

In chapter V, bearing fault and stator current fault was detected using signal processing techniques and fuzzy logic. In this chapter a multi-sensor data fusion algorithm for condition monitoring using fuzzy logic for event detection application is proposed. In the proposed method, a hybrid algorithm is developed in the MATLAB environment. The use of more than one sensor provides additional information on the condition of induction motor. The processing and fusion of data from different sensors are carried out using proposed fuzzy rule based system. In multi sensor data fusion raw data or processed data are fused together to and processed so that a decision can be made regarding the condition of the machine. This chapter proposes a hybrid algorithm develop in the MATLAB environment, which combines feature level fusion and decision level fusion to make a final decision on the condition of the machine. The final fusion result indicates the probability of motor being fault based on the input.

First of all different features are selected based on the no. of input available(in our case vibration and stator current). The fixed no. of data samples are taken from the available input. Since the data/samples available are having larger difference so normalize data of each feature quantity by using some normalization techniques. The redundant feature vectors are removed in the time series. After the removal of redundant features, the remaining features are fuzzified and each feature is assigned a membership function. After this the fuzzy rule based system is applied to fused the two normalized feature samples. Based on the input parameters the samples are fused and the result of fusion indicates the probability of motor being faulted. The block diagram of multi sensor fusion using fuzzy rule based is shown in figure6.1. [6.1]

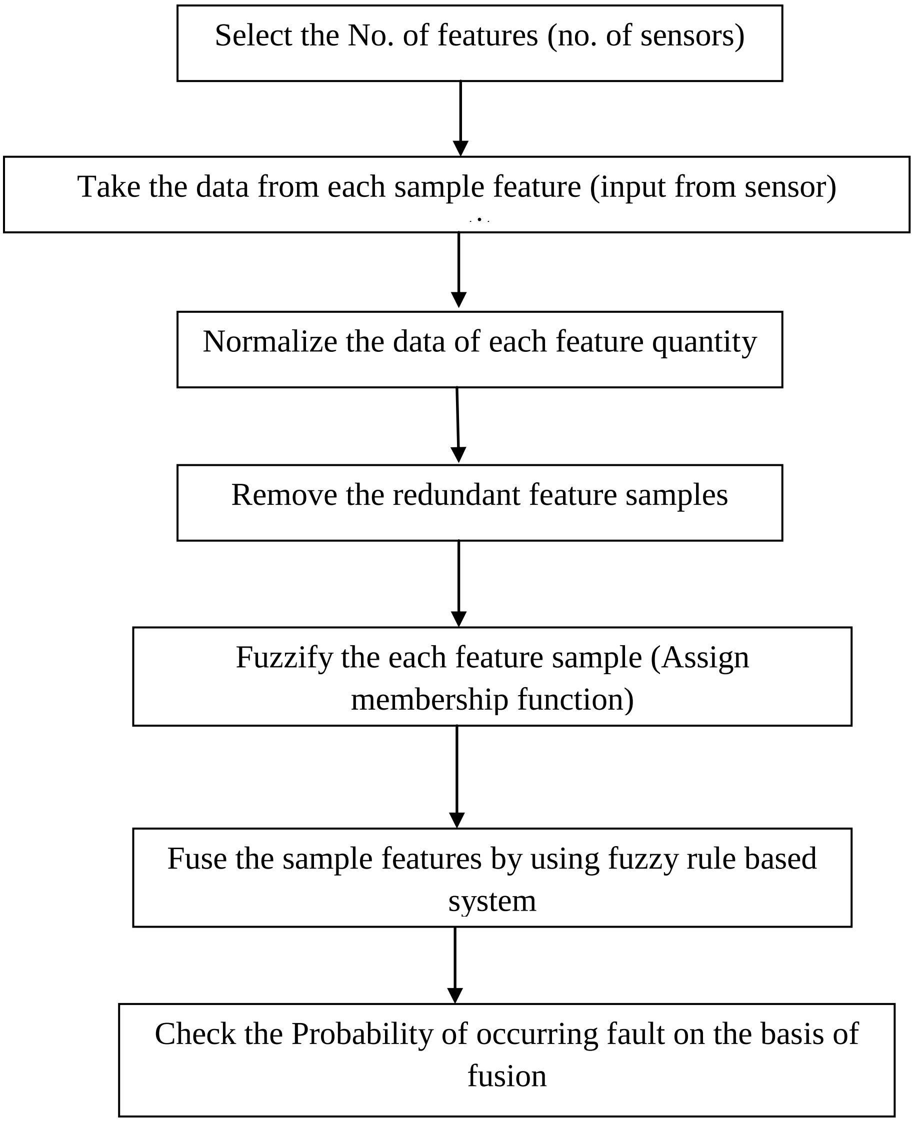

Figure 6.1 Flowchart for the multi sensor fusion

## 6.2 Results and Discussions

The results of fusion using different sets of stator current and vibration are shown in this section. For easy classification of motor being faulted the stator current are categorised as good current, bad current and very bad current. Similarly the vibration data is categorised as healthy vibration and faulty vibration. The membership function is assigned for each current component $(I_a, I_b, I_c)$ as well as vibration shown in figure 6.2. The fuzzy inference system are shown from the figure 6.3 – 6.8. Based on these fuzzy inferences the final fusion discussion is carried out in the form of table 6.1 which shows the probability of motor being faulted based on the different combination of current and vibration samples after they are fused.

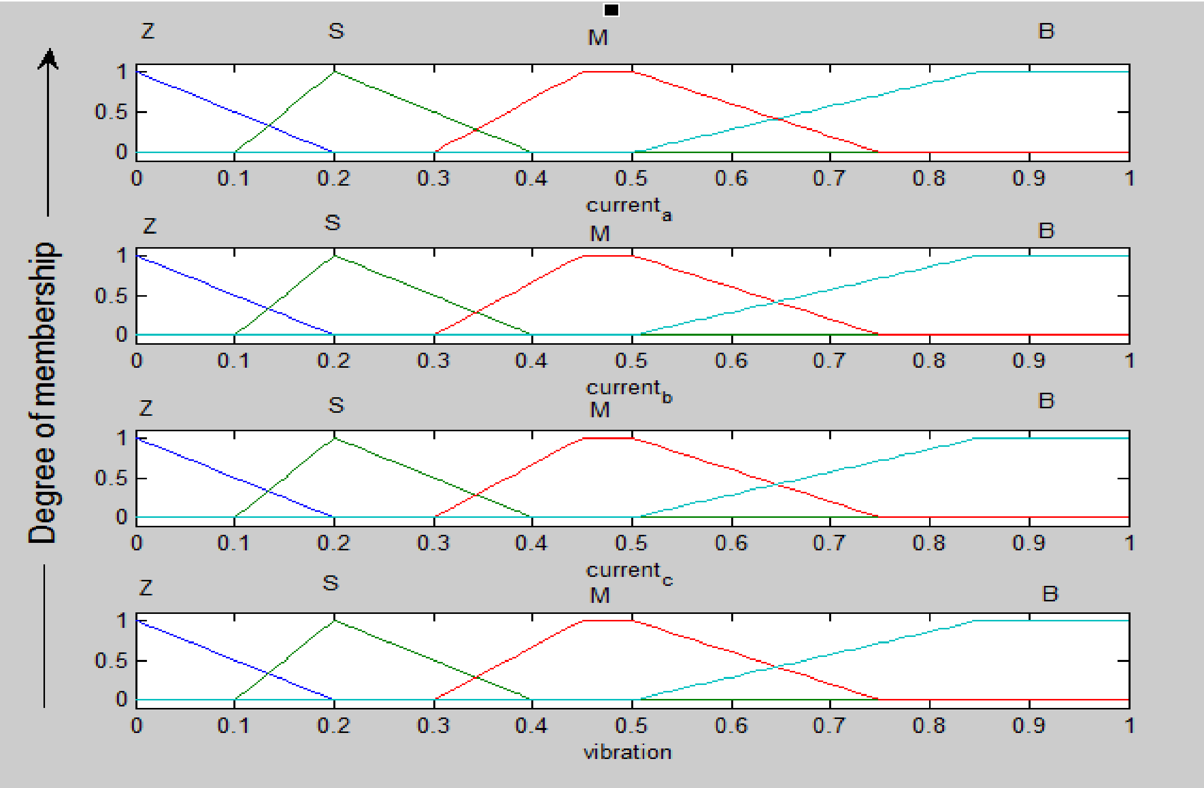

Figure 6.2 Membership function for Stator current (Ia,Ib,Ic) and vibration

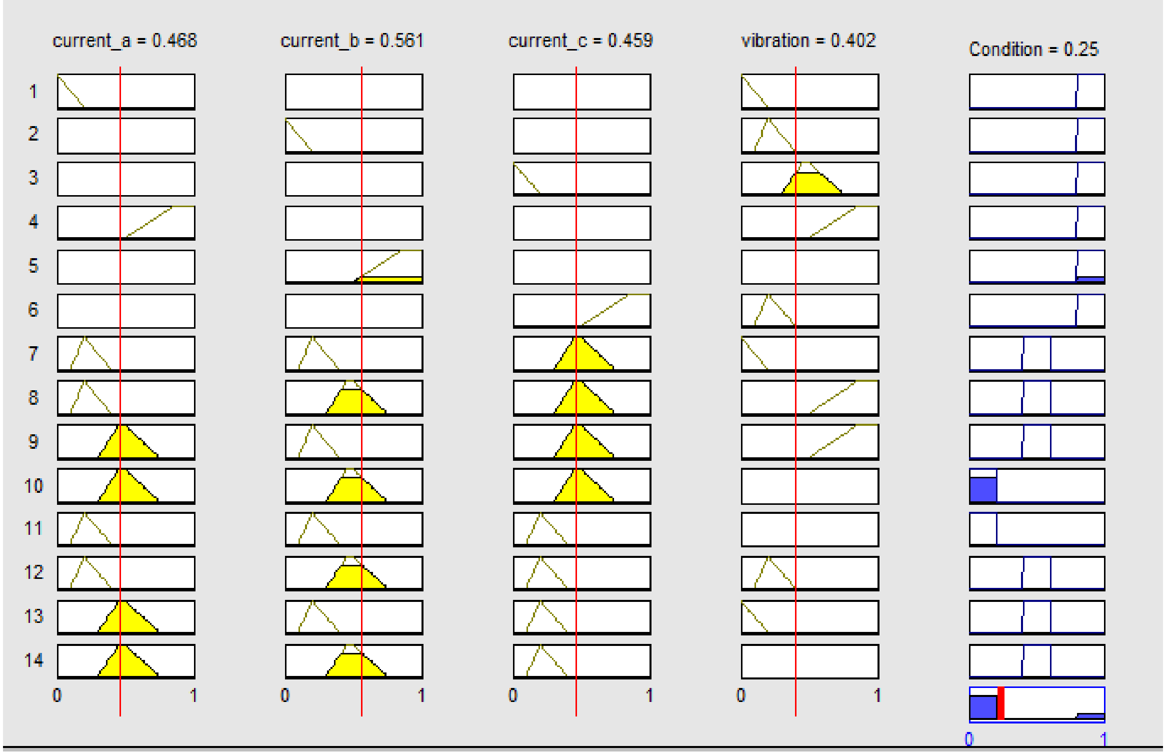

Figure 6.3 Fuzzy inference diagram for good current and healthy vibration

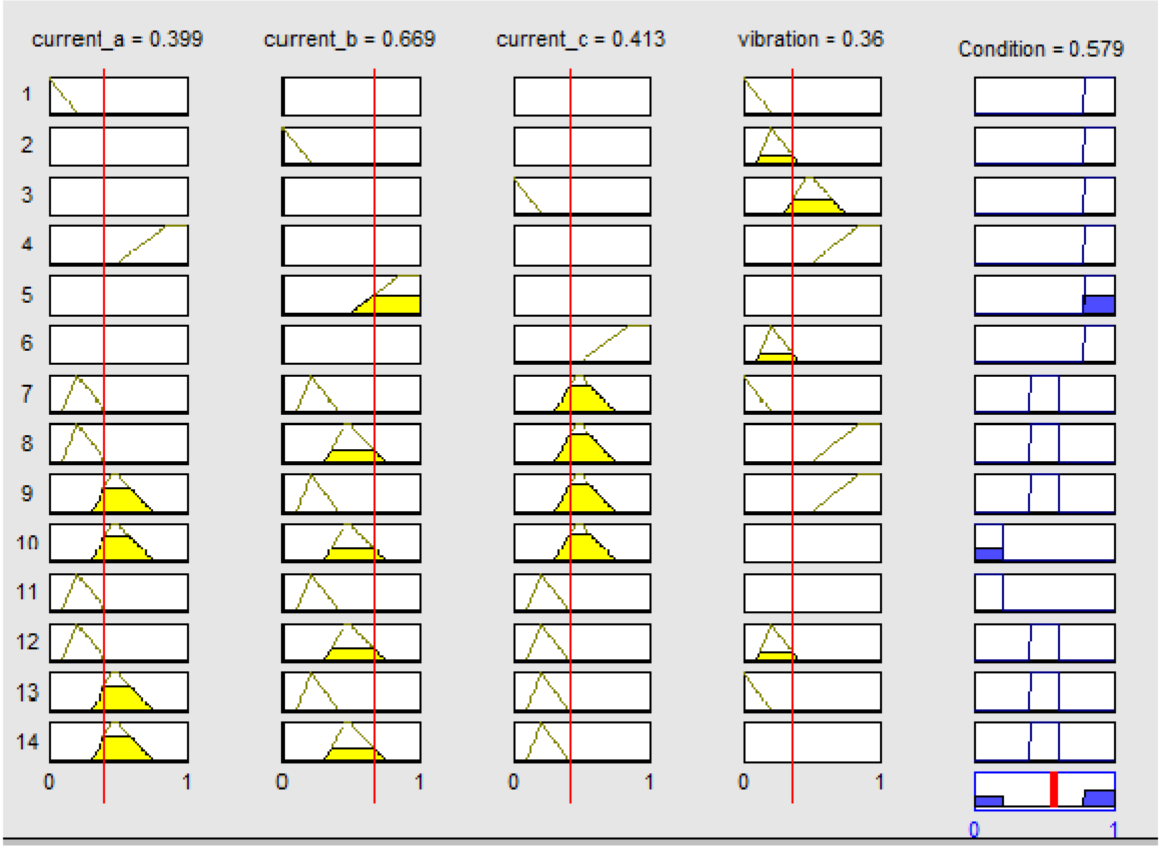

Figure6.4 Fuzzy inference diagram for bad current and healthy vibration

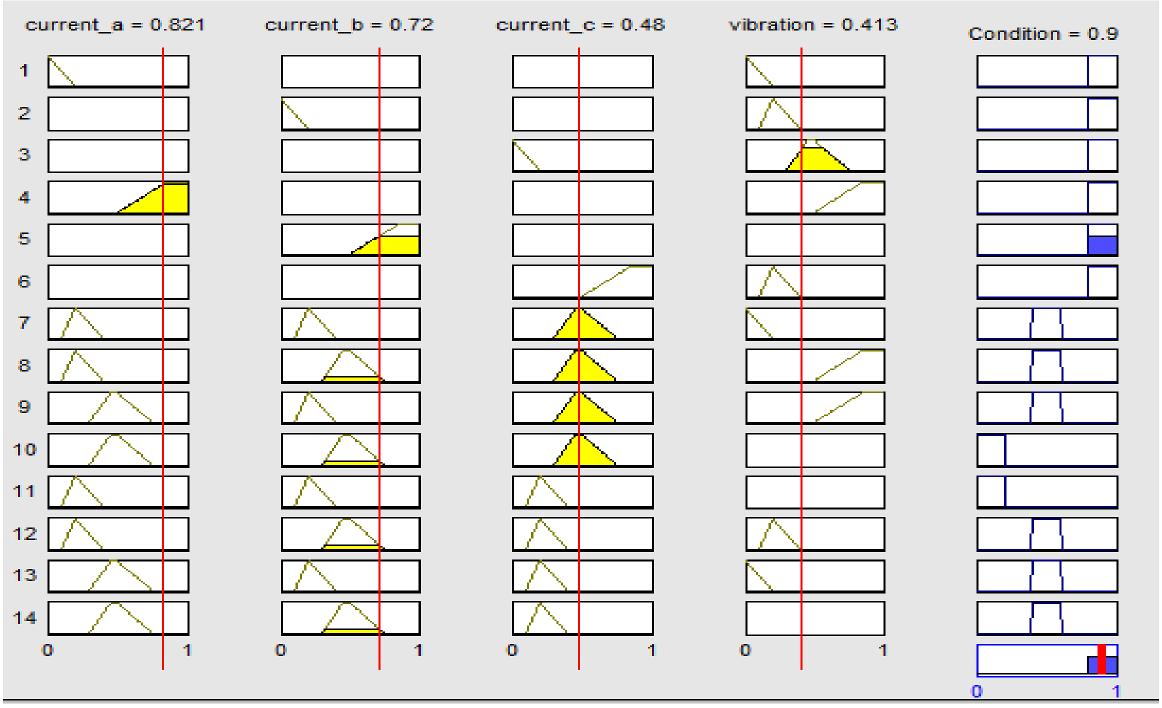

Figure 6.5 Fuzzy inference diagram for very bad current and healthy vibration

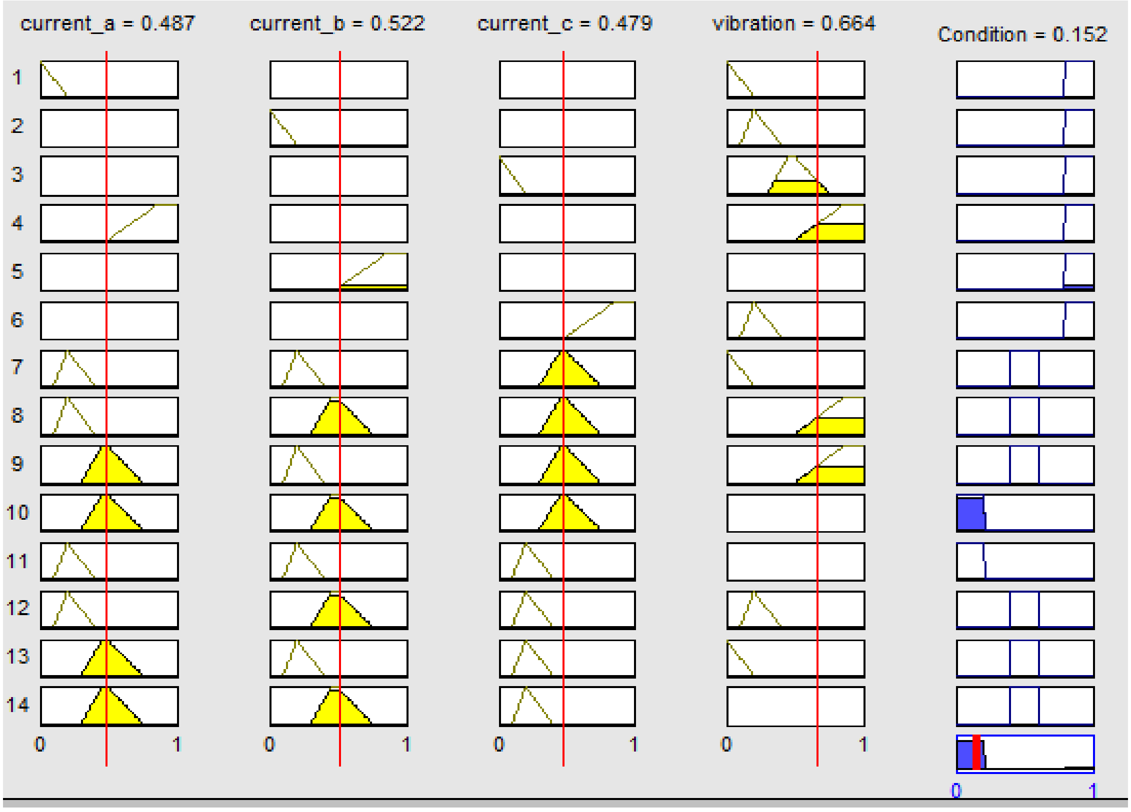

Figure 6.6 Fuzzy inference diagram for good current and faulty vibration

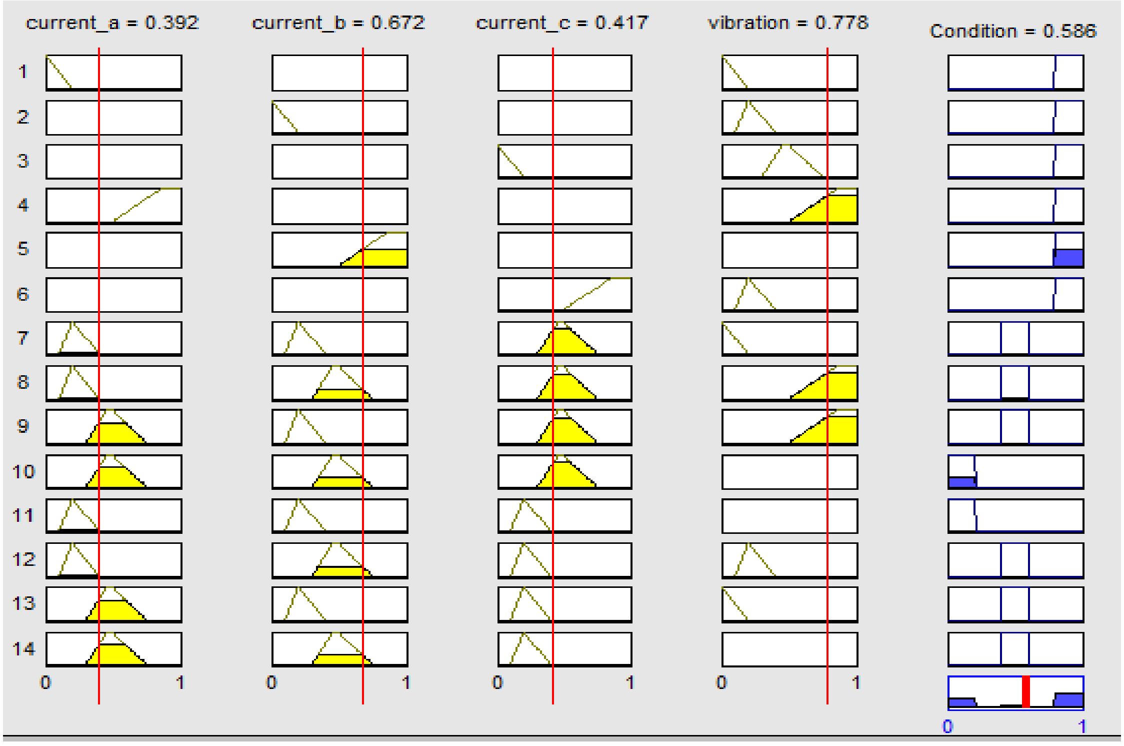

Figure 6.7 Fuzzy inference diagram for bad current and faulty vibration

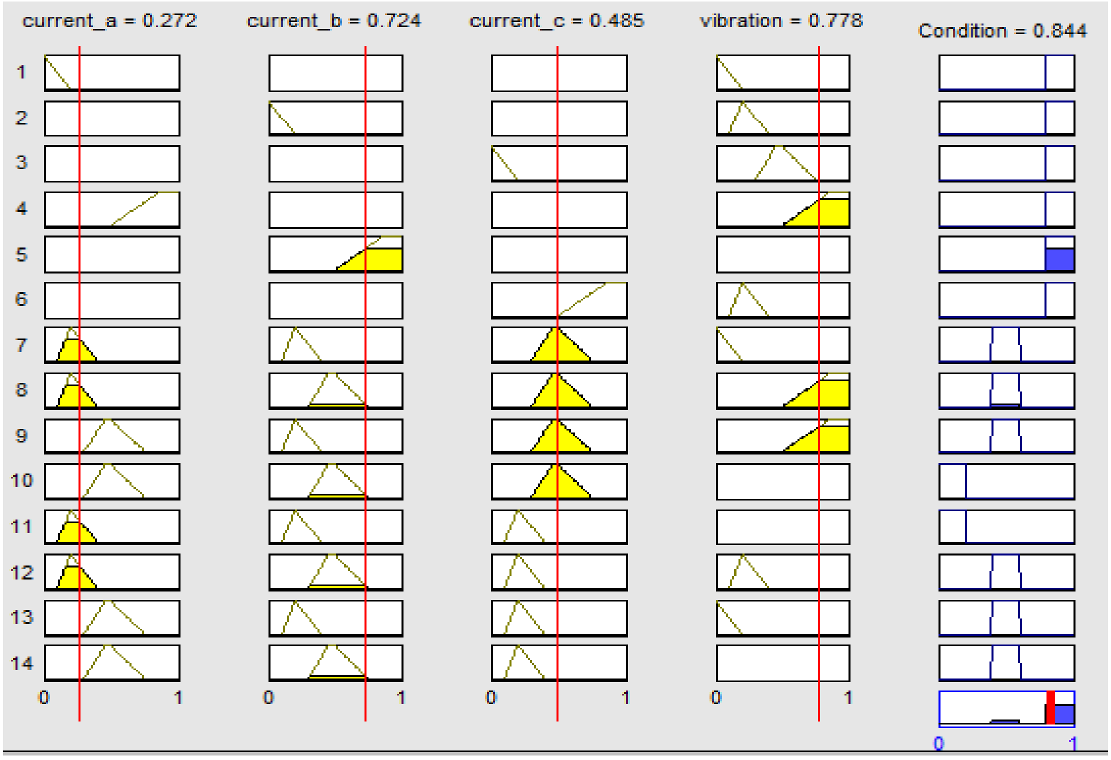

Figure 6.8 Fuzzy inference diagram for very bad current and faulty vibration

Table 6.1 Probability of motor being faulted based on fusion

| S.No | Stator Current | | | Vibration | Probability of motor being faulty |
|---|---|---|---|---|---|
| | Ia | Ib | Ic | | |
| 1. | 0.4675 | 0.5609 | 0.4594 | 0.4024 | 0.2495 |
| 2. | 0.3994 | 0.6690 | 0.4132 | 0.3605 | 0.5786 |
| 3. | 0.8213 | 0.7200 | 0.4802 | 0.4134 | 0.8359 |
| 4. | 0.4869 | 0.5223 | 0.4786 | 0.6640 | 0.1522 |
| 5. | 0.3919 | 0.6722 | 0.4174 | 0.7785 | 0.5858 |
| 6. | 0.2722 | 0.7239 | 0.4854 | 0.7785 | 0.8440 |

From the first row of table 6.1 it can be seen that if the stator current is good and healthy vibration (Figure 6.3) then probability of fault is 0.24(24%). From the second row it can be seen that if the stator current is bad and healthy vibration(Figure 6.4) the probability of fault is 0.57(57%). From the third row it can be seen that if stator current is very bad and healthy vibration (Figure 6.5)then probability of fault is 0.83(83%). From the fourth row it can be easily seen that when the stator current is good and faulty vibration(Figure

6.6) then probability of fault is 0.152(15.2%).Similarly from the fifth row it can be seen that when the stator current is bad and faulty vibration(Figure 6.7) then the probability of fault is 0.58(58%).Finally from the last row it can be easily observed that if the stator current is very bad and vibration is also faulty(Figure 6.8) then the probability of fault is 0.84(84%).

## 6.3 Chapter Summary

In the presented chapter a hybrid fusion algorithm is develop in the MATLAB environment, which combines feature level fusion and decision level fusion to make a final decision on the condition of the machine. The fusion is done by using the FIS strategy. The output of the fusion process indicates the probability of the fault occurring in the motor.

## Reference

[6.1] P. Manjunatha, A.K. Verma and A. Srividya, “Multi-Sensor Data Fusion in Cluster based Wireless Sensor Networks Using Fuzzy Logic Method” , IEEE Region 10 Colloquium and the Third ICIIS, Kharagpur, INDIA 2008 Dec 8-10.

# Chapter VII

## Conclusion & Future Scope

This dissertation gives a novel approach for the condition monitoring of induction motor by using the concept of multisensor fusion based strategy. The data collected from the different sources are processed under different headings and inference can be drawn based on the faults which are detected using different techniques. In the later stage of this work a hybrid fusion algorithm is develop in the MATLAB environment, which combines feature level fusion and decision level fusion to make a final decision on the condition of the machine. The common type of faults occurring in the induction motor is studied in this dissertation and a comparative studied has been made based on the existing literature available. The various types of current based monitoring and different fault diagnosis techniques are revived in this work and a brief literature review is presented to summarize the work done by other researchers in the same field.

The fast growth in applications of induction motor in delicate areas such as nuclear power plants, offshore petroleum industry, oil refineries etc has enhanced the need of day to day reckoning of motors. Therefore, diagnostic of various faults related to motor such as bearing faults, stator current are highlighted in this dissertation by the means of some advance signal processing techniques.

This approach shows that the condition monitoring of induction motor using multi sensor fusion is a promising system for fault detection. The proposed fuzzy logic approach for fusion effectively handles the uncertainty and vagueness present in the induction motor’s current and vibration data. More accurate, useful and comprehensive information regarding fault detection can be gathered by extracting more features. The rules can be easily adjusted and modified based on the input available to the system.

In **future scope** of the dissertation the optimal rule based FIS technique and genetic algorithm can be used to identify the bearing faults and stator current faults when N number of systems (sensors) are operating together, by using more number of sensors the accuracy and sensitivity of the system can be enhanced. This concept can be used in the number of applications like defence equipments, robotics environment where no. of movements are required to operate the robots, and systems where more than one features are required to make decision.