COMPARATIVE STUDY OF VIBRATION AND CURRENT SIGNATURE ANALYSIS FOR DETECTION OF BEARING FAULTS IN INDUCTION MOTOR

A DISSERTATION

Submitted in partial fulfillment of the
requirements for the award of the degree
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ELECTRICAL ENGINEERING
(With Specialization in Power Apparatus and Electric Drives)

by

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CANDIDATE'S DECLARATION

I hereby declare that the work that is being presented in this dissertation report entitled "COMPARATIVE STUDY OF VIBRATION AND CURRENT SIGNATURE ANALYSIS FOR DETECTION OF BEARING FAULTS IN INDUCTION MOTOR" submitted in partial fulfillment of the requirements for the award of the degree of Master of Technology with specialization in "Power Apparatus and Electric Drives", to the Department Of Electrical Engineering, Indian Institute Of Technology, Roorkee, is an authentic record of my own work carried out, under the guidance of, Dr. S. P. Gupta and Dr. Vinod Kumar, Professors, Department of Electrical Engineering.

I have not submitted the matter presented in this dissertation report for the Award of any other degree or diploma.

Date: 30-December-2006
Place: Roorkee

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ABSTRACT

In this work, a comparative study of stator current and vibration signal analysis has been done for detecting faults of outer and inner race in rolling bearings of induction motor. The investigation has been carried out on machines of different ratings at different load conditions.

Defective rolling element bearings generate eccentricity in the air-gap with mechanical vibrations. The air-gap eccentricities cause variations in the stator air-gap flux density that produces visible changes in the stator current spectrum. This is why we use MCSA to detect bearing faults along with vibration spectrum; in addition to this MCSA is a noninvasive method. In many industrial applications it becomes difficult to access vibration signal and hence MCSA greatly contributes for fault detection. Why because MCSA uses the induction motor as an efficient transducer.

In this work, wavelet packet decomposition technique is used for the current and vibration spectrums to get fine resolution; along with this auto-correlation is applied for both the signals to eliminate the randomly varying high frequency coefficients from the noise signals. This work indicates that detecting fault frequencies by motor current spectrum analysis is more difficult than the vibration spectrum analysis.

The analysis is carried out in two ways: one is on-line and the other one is off-line. For on-line analysis MATLAB® programming is used for data acquisition and for signal analysis; where as for off line analysis, LabVIEW™ is used for data acquisition and MATLAB is used for signal analysis. Efficient monitoring system has been used both for low (7.5 kw) and high ratings (400 kw and 600 kw) motors of laboratory model and of a steel rolling mill respectively.

CONTENTS

ORGANISATION OF THE THESIS

This thesis deals the condition monitoring of the induction motor for identification of various faults in the bearings of 7.5 kw, 400 kw and 600 kw rating machines. Both current and vibration extracts the fault features in the bearings and are useful to diagnose the induction motors.

The thesis is organized as follows:

CHAPTER 1 INTRODUCTION

This chapter deals with the concept of condition monitoring for electrical machines and gives application of the condition monitoring system. It highlights the literature review on the area of fault detection by utilizing different monitoring parameters and from which different analysis techniques are used to detect these faults.

CHAPTER 2 FAILURE MECHANISM OF DIFFERENT PARTS OF ROTATING ELECTRIC MACHINES AND THEIR EARLY DETECTION TECHNIQUES

This chapter describes the main parts of an induction motor and detects the various faults that occur in the machine. And further explores the suitable monitoring technique for fault detection at an incipient state.

CHAPTER 3 DEVELOPMENT OF MONITORING SYSTEM

This deals with the selection of the transducers which senses the current and vibration signals and through the hardware the signals flows to the DAQ card from which the data is transferred using the labVIEW software to the computer.

<u>CHAPTER 4</u> COMPARATIVE STUDY OF CURRENT AND VIBRATION SPECTRUMS FOR THE IDENTIFICATION OF BEARING FAULTS IN INDUCTION MOTOR

The signals attained in the previous chapter is stored in a data file, which is further used by applying wavelet packet decomposition technique analysis for detecting faults in the bearings of the above mentioned machines.

SUGGESTIONS FOR FUTURE WORK

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List of symbols

d_b ball diameter (mm);

p_d ball pitch diameter (mm);

f_b ball defect characteristic frequency (Hz);

f_{bng} harmonic component which indicates bearing fault in stator current;

f_c cage defect characteristic frequency (Hz);

f_e electrical supply frequency (Hz);

f_{ecc} eccentricity frequency (Hz);

fi inner race defect characteristic frequency (Hz);

f_o outer race defect characteristic frequency (Hz);

f_r relative revolutions per second between inner and outer races (Hz);

n_b number of balls;

p the number of machine pole pairs;

s slip (pu);

β contact angle of balls to inner and outer races;

f_1 supply frequency (Hz);

f_2 slip frequency of rotor currents (Hz);

f_{sb} side band frequency (Hz);

f_{st} frequency components in stator current that are a function of shorted turns(Hz);

f_v is one of the characteristic vibration frequencies;

f_{rm} is the frequency corresponding to rotor speed (mechanical) in(Hz);

CHAPTER 1

INTRODUCTION

This chapter reveals that what the condition monitoring is? It also gives a review of literature on fault detection in induction motor by using current and vibration spectrums.

1.1 GENERAL

Induction motors are a critical component of many industrial processes and are frequently integrated in commercially available equipment and industrial processes. Motor-driven equipment often provide core capabilities essential to business success and to safety of equipment and personnel. There are many published techniques and many commercially available tools to monitor induction motors to insure a high degree of reliability uptime. In spite of these tools, many companies are still faced with unexpected system failures and reduced motor lifetime. Environmental, duty, and installation issues may combine to accelerate motor failure far sooner than the designed motor lifetimes. Critical induction motor applications are found in all industries and include all motor horse powers. It has been found that many of the commercial products to monitor induction motors are not cost effective when deployed on typical low- to medium-horsepower induction motors. Advances in sensors, algorithms, and architectures should provide the necessary technologies for effective incipient failure detection.

Motor reliability studies have been performed by both General Electric and the IEEE Industry Application Society in order to evaluate the reliability of electric motors and identify design and operational characteristics that offer the potential to increase their reliability. The results of these studies show that bearing problems account for over 40% of all machine failures. Over the past several decades, rolling-element (ball and roller) bearings have been utilized in many electric machines while sleeve (fluid film) bearings are installed in only the largest industrial machines. In the case of induction motors, rolling-element bearings are overwhelmingly used to provide rotor support. So therefore, it is important that measures are taken to the state of the machine as and when it enters or about to enter into the fault mode.

1.2 NEED OF CONDITION MONITORING

Rotating electrical machines permeate all area of modern life at both domestic and industrial level. The average home will contain approximately 20 to 30 electrical motors in clocks, domestic appliances, toys and heating systems. Such motors will generally be rated in the 0 to 1 kw range [1].

A substantial proportion of the food we buy is kept fresh by chilling or air conditioning, using systems centered on electrical machinery. Many of the domestic products we use are made directly from, or are packaged in, by-products of the petrochemical industry. Process industries of this kind rely heavily on electrical machinery to transport and control the feed stocks and reactions required to produce the plastics and fibers.

The steel used to make car will have been rolled using large electrical machines, and at an early state still the furnaces will have been charged using yet more electrical machines. Without them our society would quickly cease to function. It is necessary to take care of electrical machines

1.3 FUNCTION OF CONDITION MONITORING

The notion of the schedule shutdown introduces one logically to the case that can be made on behalf of monitoring. By condition monitoring we mean the continuous evaluation of the health of plant and equipment throughout its serviceable life.

Monitoring should be designed so as to pre-empt faults, whereas protection is essentially retro-active. Condition monitoring can, in many cases, be extended to provide primary protection, but its real function must always be to attempt to recognize the development of fault at an early stage.

1.4 WHICH MACHINES AND WHAT PARAMETERS TO MONITOR

Larger electrical drives that support generating plant will benefit from monitoring although perhaps not continuous monitoring, if a high margin of spare capacity exists. One could include induced and forced draught boiler fan drives, boiler feed pump drives, and cooling water pump drives in power stations in this category. It must always be borne in mind; however that successful monitoring can allow a big reduction in the requirement for on-site spare capacity.

The parameters to be monitored are essentially those that will provide the operator and maintainer with sufficient details to make informed decisions on operation and maintenance scheduling, but which ensure security of plant operation. Automatic on-line monitoring has only recently begun to make an impact in the area of electrical machines. Traditional quantities such as line currents and voltages, core temperatures, bearing vibration levels have been measured and will continue to be used. Other specialist methods, involving the accurate measurement of rotational speed or the sensing of leakage fluxes are being developed in order to monitor a variety of fault conditions.

1.5 BENEFITS OF CONDITION MONITORING

Advanced warning is obviously desirable since it allows maintenance staff greater freedom to schedule outages in the most convenient manner, resulting in lower down time and lower capitalized losses. Continuous condition monitoring of certain critical items of plant can lead to significant benefits. These benefits occur as a result of greater plant efficiency, reduced capitalized losses due to breakdown and reduced replacement costs.

Condition monitoring should give information relevant to both the operational and maintenance functions. There is also the important additional consideration that better maintenance gives better safety.

1.6 LITERATURE REVIEW

From early stages of developing electrical machines, researchers have been engaged in developing methods for machine analysis, protection and maintenance. The use of advanced methods of technology increases the precision and accuracy of monitoring systems. The area of condition monitoring and fault diagnosis of electrical machines is essentially related to a number of subjects such as electrical machines, methods of monitoring, reliability and maintenance, instrumentation, signal processing and intelligent systems. In order to reveal the contribution of the researchers in area of condition monitoring outlines are selected in the presented literature survey.

1.6.1 CURRENT SIGNAL MONITORING

Modern measurement techniques in combination with advanced computerized data processing and acquisition show new ways in the field of induction machines monitoring by the way of spectral analysis of operational process parameters (e.g., temperature, pressure, steam flow, etc.).

In many situations, vibration monitoring methods were utilized for incipient fault detection [2]. However, stator current monitoring was found to provide the same indication with out requiring access to the motor. Recently stator current based condition monitoring of electrical machines got the attention of many researchers.

Izzet Y Onel, K Burka Dalci and Ibrahim Senol [3] have investigated the feasibility of detecting bearing faults using the spectrum of a single phase of the stator current of an induction machine. Defective rolling element bearings generate eccentricity in the air-gap with mechanical vibrations. The air-gap eccentricities cause variations in the air-gap flux density that produces visible changes in the stator current spectrum. Machine with outer race defects are used to verify the relationships between the vibrational and current frequencies. The experimental results clearly illustrate that the stator current signature can be used to identify the presence of a bearing fault. This research also indicates that detecting these fault frequencies in the motor current is significantly more difficult than detecting them in the motor vibration. Additionally, the act of installing or remounting a test bearing in a test motor can alter the current and vibration characteristics of the induction machine and conceal some fault frequencies; therefore, it is difficult to compare different bearings of the same type or even the same bearing in different installations.

A comparison of vibration and current monitoring technique is given by Benbouid et al [4]. The paper first reviewed the presence of vibration frequency components for known faults such as eccentricity and broken rotor bars, shaft speed oscillations, rotor asymmetry and bearing failure. It was mentioned that all of these faults produce asymmetry in the air gap length which causes variations in the air gap flux density. This affects the inductance of the machine and hence produces stator current harmonics with the known frequencies. However, in these paper only electrical faults such as voltage unbalance and single phasing of supply is considered for demonstration of high resolution technique such as MUSIC and ROOT-MUSIC by using stator current. It is cleared that the approximate complexity of these techniques is W, whereas classical spectral analysis is N (log2N). Where N is the number of samples.

M.E.H.Benbouzid [5] has presented the techniques used to extract the features from the motor's signature for prediction of its health. The harmonics content of motor currents and the instantaneous power is related to the machine health. The benefit of using bispectrum, high resolution spectrum and wavelet transform as a medium tool for motor fault detection is discussed. The paper gives guidelines for selecting the appropriate tool for motor diagnosis.

R.R. Schoent, T.G. Habet1er, F. Kamran, and R.G. Bartheld [6] have presented the feasibility of detecting bearing faults using a spectrum of a single phase of the stator current of an induction machine. Air gap eccentricities cause variations in the air gap flux density that produce visible changes in the stator current spectrum at predictable frequencies. Since rolling-element bearings support the rotor, a bearing defect also produces variations is the air gap length of the machine. These variations generate noticeable change in the stator current spectrum. The predictability of air gap eccentricities has been extended to include faults in rolling-element bearings that excite mechanical vibrations at fractional values of the rotational speed. Measured current and vibration spectrums were presented to verify this relationship.

S. Nandi, S. Ahmed, and H. A. Toliyat [7] have discussed a brief review of bearing, stator, rotor and eccentricity related faults and their diagnosis has been presented in this paper. It is clear from various literatures that non-invasive motor current signature analysis (MCSA) is by far the most preferred technique to diagnose fault. However, theoretical analysis and modeling of machine faults are indeed necessary to distinguish the relevant frequency components from the others that may be present due to time harmonics, machine saturation, etc. Other techniques for fault detection such as axial flux based measurements; vibration analysis, etc. have also been discussed. A section on automated fault detection has also been included.

Caryn M. Riley, Brian K. Lin, Thomas G. Habetler and Gerald B. Kliman [8] have presented initial study into the relationship between vibration and current harmonics of electric motors, including the effect of externally induced vibrations. Vibration spectral data and the current spectral data from a single stator phase current were employed to investigate the relationship between vibration and current harmonics. The rms vibration sum and the rms current sum were found to have a fairly monotonic relationship at a given frequency, and are tightly correlated. This high correlation implies that the current spectrum can be used to evaluate motor vibration. In addition, evaluation of internal vibrations demonstrated that stator current monitoring can also be used as a bearing health indicator in the absence of vibration probes.

Ramzy R. Obaid and Thomas G. Habetler [9] have proposed that Mechanical conditions in induction motors can be detected at any load condition, using the stator current, if the method used takes into account the abnormalities and the resonance caused by change of load. Mechanical vibration does not always decrease by increasing the load as anticipated. Sometimes, other factors may have stronger effect on the vibration than the load and cause it to increase.

Mechanical resonance does occur at certain speeds, and significantly affects both the motor vibration and stator current frequency spectra. This mechanical resonance is highly dependant on the motor-load setup. A motor with a disk (like that used for load unbalance) and a motor without a disk, have totally different resonance speeds and vibration spectra. Although the current is as good as the vibration in indicating the presence of a fault, the plot of the components of interest in the current versus load does not necessarily look like the plot of the components of interest in the vibration versus load. This is due to several reasons, but important, is that the vibration sensor measures the *absolute* movement (vibration or shaking) of the motor, while the current reflects a *relative* movement (displacement in the air-gap).

1.6.2 VIBRATION ANALYSIS

Many condition monitoring methods have been proposed for rotating machine using one or combination of mentioned parameters. In rotating electrical machinery, vibration signal is commonly used for fault diagnostic. This is because when machine or a structural component is in good condition, its vibration profile has the 'normal' characteristic shape and it will change as a fault begins to develop [10].

Forces produced in machine by shafts, gears and loads are usually transmitted though supporting bearings and therefore, most of the breakdowns in rotating machine are directly related to rolling element-bearing failure. Vibration reading taken on bearing housing can therefore provide a signature that contains information of the machine condition.

The bearing wear or defects occur in raceways and rolling elements and each particular defect of bearing generates its own vibration frequency obtained from the geometry of the bearing. Therefore, by identifying these frequencies in the vibration spectrum it is possible to monitor the bearing condition. Besides bearing defects, additional faults such as unbalanced shafts, misalignment, mechanical looseness bent shafts and damaged gear teeth and electrical faults such as unbalanced supply, broken rotor bar etc. can also be detected from vibration spectrum [11].

S. A. McInerny and Y. Dai [12] have described an instructional module on fault detection in rolling element bearings. After reviewing the basic operation of rolling element bearings and the characteristics of idealized bearing fault vibration signatures, the shortcomings of conventional spectral analysis were illustrated with a synthetic signal generated in MATLAB. The basis and effectiveness of envelope analysis forbearing fault analysis were then examined. Finally, a set of graphically driven procedures developed to illustrate bearing fault detection techniques was presented.

Hongmou Lao and Saleh Zein-Sabatto [13] have showed that neural network is high potential for bearing RUL prediction. The rotation frequency is the primary feature frequency for the unbalance failure. The vibration PSD analysis shows that the vibration features are in the low frequencies, normally within 300Hz. The frequency resolution in vibration signal analysis is sensitive to the effective feature extraction. This frequency resolution is constrained by the sample duration time, the higher the resolution the longer the sample duration time. The lower rotation frequency needs higher resolution. If the frequency spectrum resolution is fixed, there will be a lower limit to the rotation frequency we can diagnosis and prediction. When a specific fault is developing in bearing, its remaining useful life depends on the operating situation. The time-frequency properties of the vibration signal provide us with the information about its current situation by which we can estimate the RUL. The RUL can be classified to several levels: more than few days, in days, and in hours, gradually from rough prediction in longer time to more accurate prediction in a short time.

Jason R. Stack, Thomas G. Habetler, and Ronald G. Harley [14] have introduced the notion of categorizing bearing faults as either single-point defects or generalized roughness. This is important because it divides these faults according to the type of fault signatures they produce rather than the physical location of the fault. The benefit of this categorization is twofold. First, it ensures that the faults categorized as generalized roughness are not overlooked. The majority of bearing condition monitoring schemes in the literature focus on detection of single-point defects. While this is an important class of faults, a comprehensive and robust scheme must be able to detect both generalized roughness and single-point defect bearing faults. Second, grouping faults according to the type of fault signature they produce provides a clearer understanding of how these faults should be detected. This should provide improved insight into how bearing condition monitoring schemes should be designed and applied. Experimental results obtained from this research suggest generalized roughness faults produce unpredictable (and often broadband) changes in the machine vibration and stator current. This is in contrast to the predictable frequency components produced by single-point defects.

Tong-Xiao Zhanq, Xi-Jin Guo, Zhen Wang [15] have proposed a kind of rolling bearing fault diagnosis method based on the combination of envelope analysis and wavelet analysis. The method can pick up the fault frequencies effectively and enhance the capabilities of fault diagnosis under strong noise. In addition, the proposed method can be used to pick up other kinds of fault characteristics besides rolling bearing.

Jason R. Stack, Thomas G. Habetler, and Ronald G. Harley [16] have explained and experimentally illustrated how the location of a single-point defect with respect to the load zone can significantly affect fault-signature saliency. Because inner-race faults periodically rotate in and out of the load zone, a fault-signature model was developed to investigate and understand this interaction. This model showed the power spectrum of machine vibration from a bearing containing an inner-race defect to be comprised of groups of peaks separated by FIRF and peaks within the groups separated by Fs. This observation combined with the principle of phase coupling led to the development of a fault detector that searches for frequency components with phase-coupled sidebands whose spacing is predicted by the model. This detector was then applied to machine-vibration data, and the peaks it exhibited that were spaced by FIRF were counted and used as the fault index.

Giovanni Betta,Consolatina Liguori, Alfredo Paolillo, and Antonio Pietrosant [17] have described a DSP-based architecture for vibration analysis. It allows machine monitoring to be carried out on-line, with a consequent increase in the system and in environmental safety. The use of parametric unfault and fault models, estimated by extracting specific characteristics in the vibration spectrum, allows dealing with data strongly corrupted by noise, such as those typical in a real application. The integration of the traditional signal-processing algorithm with rule-based reasoning for fault detection and isolation presents many advantages, especially concerning the diagnostic performance of the system, with correct diagnosis in more than 99% of the situations. The emulation-based method used to estimate the vibration signal in the faulty condition proves to be very effective and can be easily extended to numerous application fields.

1.6.3 WAVELET TRANSFORM FOR MACHINE MONITORING

Wavelet analysis is a new development in the area of applied mathematics. They were first introduced in seismology to provide a time dimension in seismic analysis that Fourier analysis lacked. Fourier analysis is ideal for studying stationary signals (signals whose statistical properties are invariant over time) but is not well suited for non-stationary signal analysis. Wavelets were designed with such non-stationary signals in mind. Recently wavelet transform has found applications in different branches of science. Although, wavelet is a mature subject now, its application in machine monitoring and fault diagnosis is still at the beginning stage. Only few papers in this context are available in this literature.

Z.Hui, W.Shu-juan, Z.Qing-sen and Z.Guo-fu [18] have proposed two kinds of rolling bearing fault diagnosis methods based on WPT, which are autocorrelation method and cross-correlation method. The former is used when the fault frequency is unknown. The later is used when the fault frequency is known.

These two kinds of methods pick up the fault frequencies effectively and enhance the capabilities of fault diagnosis under strong noise. The proposed methods can be used to pick up other kinds of fault characteristics besides rolling element bearing.

Martin [19] has demonstrated the limitation of using Fourier Transform approach for bearing damage monitoring. The traditional treatment of vibration spectrum fluctuations is the averaging, which may lead to hide some features of short duration. The alternative approach to non-stationary vibration signal is the wavelet transform. The paper presented the application of wavelet transforms of vibration signals for diagnosing the bearing faults. Author present a comparison between both approaches in predicting bearing faults.

Yen and Lin [20] have employed wavelet packet for extracting useful information from vibration signal. Though, the measured vibration signal contains non-stationary part, Fourier transform can not provide sufficient information to detect some machine faults. Such that , wavelet packet is designed to analyze Such type of signals. The result of employing wavelet packets are used with the aid of statistical-based feature selection criteria to discard the feature components containing little discriminate information. The extracted reduced dimensional feature vector is then used as input to the neural network classifier. The results show improvement in neural network generalization capability and significant reduction in training time.

Schoen R R, Habetler T G, Kamran F, Barthled R G [21] have discussed different kinds of bearing damages and their detection in induction motor by using stator current signature from advanced signal processing techniques.

Zhongming, Bin Wu and Alireza Sadeghian [22] have introduced new feature coefficients for induction motor mechanical faults are obtained by WPD of the stator current. The feature coefficients differentiate the healthy and faulty conditions with an obvious difference. They can be used for the purpose of online noninvasive detection and diagnosis of such mechanical faults. One of the major advantages of this method is that it can be used for nonstationary signal analysis. As is well known, induction motors are commonly used together with the power electronics drives. The traditional FFT-based MCSA method is subject to not only the harmonics disturbance, but also frequent dynamics of the drives. This method can be used for such applications. Another advantage is that the feature coefficients obtained using the proposed method is of multiple frequency resolutions. The same frequency component can be represented with different frequency resolution. It is advantageous for fault detection and diagnosis. This method can also be extended to other MCSA-based fault detection applications.

Michael.J.Vevaney and Levent Eren [23] have revealed uncertainty is a pervasive and persistent quality of real-time systems. The total elimination of uncertainty is often impossible, however, because of the complex nature of the systems under control. But rather than admit defeat, a proactive approach to mitigating uncertainty is needed. This approach starts with acknowledging uncertainty's existence and then identifying its possible causes so that the mitigation strategy can be designed.

Vu Pu, Wen-Siieng Li, Guo-Jiua Xu [24] introduced The singularity with Lipschitz exponents obtained from wavelet transform which has been applied to the fault diagnosis of rolling element bearings. This research indicates that singularity measured by Lipschitz exponents can be an index that characterizes the bearing condition and has great potential to be a useful tool for the defect detection in rotating machinery. The study presented in this paper is of an exploratory character. Further investigations are required to fully establish the method.

1.6.4 OTHER MONITORING TECHNIQUES AND FAULT IDENTIFICATION

Different monitoring techniques have been developed by researches using different machine variables. Here we discus different monitoring methods [6]. However in this work focus is on stator current and vibration signal based monitoring also bird's-eye view on different faults diagnosis techniques in induction machine.

Induction machine fault identification based thermal parameters has been reported by Rajgopal and Seetaram [25].

Beguenane and Benbouzid [26] have presented thermal monitoring technique for induction motor using rotor resistance measurement.

Cho et al [27] have used stator current, stator voltage and rotor velocity to estimate the rotor resistance of cage induction motor for rotor bar fault identification.

Penman and Tavner [1] explained the importance of various monitoring techniques and uses of monitoring system.

1.7 OBJECTIVES OF PRESENT THESIS WORK

The main objective of the present work is to build an efficient diagnostic system for faults in induction motor. Effort has also been made to develop the diagnostic system by using advanced processing techniques such as wavelet analysis.

The methodology to achieve the objectives is as follows:

1) The development of condition monitoring system and real time data has been recorded from the motors in laboratory. This has also been done on large motors of a steel rolling mill.
2) The changes in vibration and current profiles are observed at different load conditions.
3) The features of the current and vibration signals are used for the fault diagnosis. Some features are extracted from these signals to identify the bearing faults in induction motors.

CHAPTER 2

FAILURE MECHANISM OF DIFFERENT PARTS OF ROTATING ELECTRIC MACHINES AND THEIR EARLY DETECTION TECHNIQUES

This chapter contains overview of common faults in induction motor and their early detection techniques, and also presents the causes of the failure of these parts

2.1 INTRODUCTION

The induction motor is considered as a robust and fault tolerant machine and is a popular choice in industrial drives. It is important that measures are taken to diagnose the state of the machine as and when it enters into fault mode. It is further necessary to do so on-line by continuously monitoring the machine variables.

The reason behind failures in rotating electrical machines lie in their design, manufacturing tolerance, assembly, installation, working environment, nature of load and schedule of maintenance. Induction motor like other rotating machines is subjected to both electromagnetic and mechanical forces. The design of motor is such that the interaction between these forces under normal condition leads to a stable operation with minimum noise and vibrations. When the fault takes place, the equilibrium between these forces is lost leading to further enhancement of fault.

2.2 FAULTS IN INDUCTION MOTOR PARTS

The motor faults can be categorized into two types: mechanical and electrical. Mechanical faults in the rotor are identified as eccentricity (static or dynamic) and misalignment, while stator eccentricity and core slacking are the main types of mechanical faults in the stator. Moreover, bearing fault, which may cause rotor eccentricity, is the common mechanical fault in the induction motors.

Here in this work main concentration is only on this fault. Other mechanical faults such as rotor rubbing to stator and rotor fatigue etc. are the consequences of the previous mentioned faults. Winding faults such as turn to turn, phase to phase and winding to earth (body) faults are the roots of the electrical faults in the rotor of the slip-ring induction motor. The roots for electrical faults in the squirrel cage rotor are bars crack, slacking of bars and bad connection with the end rings. In addition short circuit of rotor laminations is a common fault in both types of motors. Stator is subjected to some types of fault such as winding faults and core faults. Winding fault is due to turn to turn, phase to phase and winding to earth short circuit, while core faults is due to core slacking, laminations short circuit and rotor strike.

Failure surveys have reported that percentage failure by components in induction motors is typically [28]:

- Stator related: 38%
- Rotor related: 10%
- Bearing related: 40%
- Others: 12%.

2.3 SYMPTOMS PRODUCED BY FAULTS ON MACHINE PERFORMANCE

Of the above types of faults: 1) bearing; 2) the stator or armature faults; 3) the broken rotor bar and end ring faults of induction machines; and 4) the eccentricity-related faults are the most prevalent ones and, thus, demand special attention. These faults produce one or more of the symptoms as follow [28]:

- unbalanced air-gap voltages and line currents;
- increased torque pulsations;
- decreased average torque;
- increased losses and reduction in efficiency;
- excessive heating.

2.4 RELATIONSHIP BETWEEN MACHINE SPECIFICATIONS AND FAILURE MECHANISM

The specification of a machine must reflect the mechanical, electrical and environmental conditions in which the machine will work. These matters will have a bearing on the mechanism by which the machine may fail in service. The need for monitoring and the selection of the parameters to be monitored must be affected by these operational conditions. Table 2.1 sets out the operational conditions which are covered by a specification and which are relevant to monitoring. TABLE 2.1 Operational Conditions, Defined in the Specification, which affect the Machine Failure

Operational Condition	Nature of that Condition	Effects on failure Mechanism
Mechanical	Characteristics of the load or driving machine	Duty cycle: Successive overloads may cause overheating or bearing damage Pulsating load: May cause bearing damage Repeated starting: Repeated application of high starting forces may damage end windings and rotor windings Load or drive vibration: May be transmitted to machine causing bearing damage
Electrical	Characteristics of the electrical system and of the machine being connected to it	Slow voltage fluctuations: May cause loss of power and stalling of a motor Fast voltage fluctuations: May cause insulation failure in winding

Operational Condition	Nature of that Condition	Effects on failure Mechanism
Environmental	Characteristics of the process in which the machine is being used	Temperature: High temperature may cause insulation deterioration; low temperatures cause frosting
	Characteristics of the geographical location of the process	Humidity: High humidity may cause condensation and insulation failure; low humidity may cause dry out of solvents in insulation Cleanliness: Dirt from the environment may enter machine and contaminate insulation or mechanical components; dirt from the machine brush-gear may do the same

2.5 REQUIREMENTS OF THE MACHINE DESIGN

Mechanically, machines can exposed to periods of intermittent running, frequent starting and to arduous duty cycles, where the load varies frequently between no-load and full-load with occasional overloads. These can lead to slackening of windings, insulation degradation, bearing wear and vibration.

Similarly a machine driving a pulsating load such as a compressor is going to experience heavy bearing wear.

From electrical supply point of view a machine, by virtue of its location in a supply system or its task in a manufacturing process, may be subjected to a variety of transients at its supply terminals. These may be slow fluctuations in the supply voltage or even unbalance between the three phases which can cause operational problems; for example, if the machine does not have the thermal capacity to deal with the overheating that unbalance can lead to. More rapid transients in the supply voltage, however, can overstress the winding insulation because the electric stress is not uniformly distributed throughout the winding length. Modern interrupts produce very rapid voltage surges which have been known to break down the inter-turn insulation on the line end coils of motors. The most severe electrical transients a machine can receive, however are during starting or re-switching of the supply, and part of the duty of many machines in industrial processes is to be repeatedly started and run for short periods. This will cause overheating, slackening of winding systems, movement of electrical connections and overstressing of terminal boxes.

Environmentally there are thermal and contamination problems. The machine may run exceptionally hot because of cooling problems; ambient conditions or simply that machine is being operated to its rating limit. These can deteriorate its insulating materials. Also the machine may be operating in dirty environment because of industrial process in which it is operating. The cooling gas may also become damp because of ambient conditions, which leads to condensation of moisture on electrical insulation and connections giving a reduced insulation resistance.

Clearly a machine needs to be designed to meet mechanical, electrical and environmental disturbances it is likely to encounter during its life. But as monitoring system should be directed towards detecting this unwanted disturbance and hence prevents the machine from catastrophic failure.

2.6 FAILURE MECHANISM OF TYPICAL PARTS OF THE MACHINE AND SUITABLE MONITORING TECHNIQUE TO IDENTIFY IT

Any failure involves a route or mechanism, processing the initial defect to the failure itself. The time taken for such a progression will vary, depending on a wide range of circumstances. What is important; however, is that all faults will have early indicators of their presence and it is here that monitoring must seek to look and act. Also any fault is likely to have a number of possible causes and is likely to give rise to a number of early indications. A typical route to failure is shown in below figure 2.1.

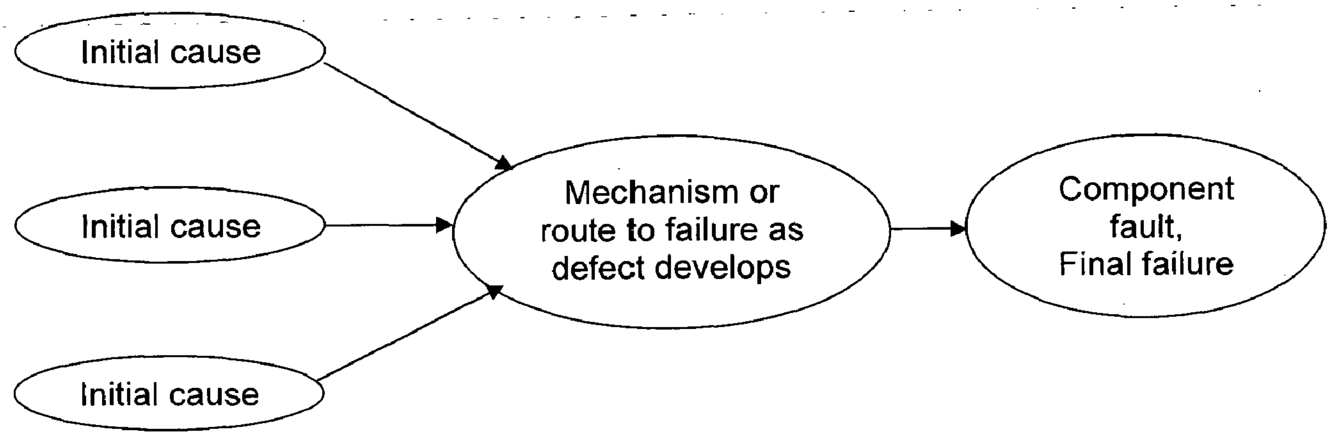


Figure 2.1: Typical route to failure in electrical machines

2.6.1 STATOR CORE DEFECTS

A core fault is a rare event which usually only occurs in the large machines where the laminated steel cores are sufficiently massive, and carry a sufficiently high magnetic flux density, that when shorting occurs between laminations potentially damaging currents can flow. Damage to the core may happen when rotor insertion or even in the manufacturing process itself. On smaller machines also stator core damage takes place. Here the damage may be the result of defects in manufacture but more often is caused by excessive vibration in the machine, leading to the fretting of the stator core laminations, or it may be due to an earlier bearing failure allowing the rotor to touch-down onto the stator and rub the laminations.

Early indications of the fault were the flow of large circulating current, high temperatures and the pyrolysing of insulation material.

2.6.2 WINDING INSULATION DEFECTS

It is clear that one of the intrinsically weakest components of an electrical machine both mechanically and electrically is the insulation system. In the early days insulation faults were excessively frequent. As the technology goes up this kind of faults are reduced. Insulation failure occurs due to ageing or the action of the isolated defect.

The early indication will be an increase in discharge active in the machine.

2.6.3 STATOR END WINDING FAULTS

Faults occur in the end winding when the bracing structure slackens, either as a result of a succession of unusual overloads or because of an extended period of continuous running. In some cases the end winding insulation becomes cracked, fretted or worn away. On the largest machines fatigue failure of conductors can occur when the winding becomes slack enough to permit a significant amount of conductor movement during normal operation or during the much larger forces of starting or re-switching. Where the end winding insulation is damaged by impact or eroded by debris worming into it under the action of electromagnetic forces.

The early indications of problems are an increase in end winding vibration and the possibility of electrical discharge activity to nearby earth planes.

2.6.4 ROTOR WINDING FAULTS

Defects on the rotor windings of induction motors have not been easy to detect because there is not always an electrical connection to the winding and it is difficult to measure the low frequency currents induced there. Although the rotor winding of a squirrel cage induction motor is exceptionally rugged, defects do occur particularly on the larger machines. These are usually associated with the high temperatures attained in the rotor, and the high centrifugal loadings on the end rings of the cage, particularly during starting. Faults may occur during manufacture, through defective casting in the case of die cast rotors, or poor jointing in the case of brazed or welded end rings. Such a defect results in high resistance which will overheat and at high temperature the strength of the cage will be impaired. It should be remembered that the bars must provide the braking and accelerating forces on the end ring when the motor changes speed. If the motor speed fluctuates, because of changing load or as a part of the normal duty cycle, then high cycle fatigue failures can occur at the joints between bars and ring. If the motor is repeatedly started then the exceptional starting forces may lead to low –cycle fatigue failure of the winding component.

The early indications of these faults are pulsations in the speed, supply current and stray leakage flux of the machine.

2.6.5 ROTOR BODY DEFECTS

A high centrifugal stresses in machine rotors can also lead to problems in the rotor body as well as the windings. The propagation of cracks from surface defects in the rotor material, or its associated components, due to high cycle fatigue under the action of the self-weight forces during rotation, has lead to catastrophic rotor failure. Excessive heating of the rotor can also weaken the rotor material. Eddy current losses in the rotor negative sequence in the supply has led to overheating and the initiation of serious fatigue cracking. Large transients on the electrical system to which a machine is connected can also impose sudden strains on its rotor. If a resonant condition exits between the machine and the system then sudden transients can excite torsional oscillations which can lead to rotor or coupling failure. Eccentricity of the rotor can lead to vibration due to unbalanced magnetic pull and this can be compounded when the asymmetric heating leads to thermal bending of the rotor.

The early indications of this type of fault are usually excessive transverse bearing vibrations although attention is being focused more recently on measuring the torsional oscillations of the shaft itself.

2.6.6 BEARING FAULTS

Rolling element bearings generally consist of two rings, an inner and an outer, between which a set of balls or rollers rotate in raceways. Under normal operating conditions of balanced load and good alignment, fatigue failure begins with small fissures, located between the surface of the raceway and the rolling elements, which gradually propagate to the surface generating detectable vibrations and increasing noise levels .Continued stress causes fragments of the material to break loose, producing a localized fatigue phenomena known as flaking or sapling .Once started, the affected area expands rapidly contaminating the lubricant and causing localized overloading over the entire circumference of the raceway .Eventually, the failure results in rough running of the bearing. While this is the normal mode of failure in rolling element bearings, there are many other conditions which reduce the time to bearing failure. These external sources include contamination, corrosion, improper lubrication, improper installation or brineling.

The early indications of this type of fault are usually excessive transverse bearing vibrations.

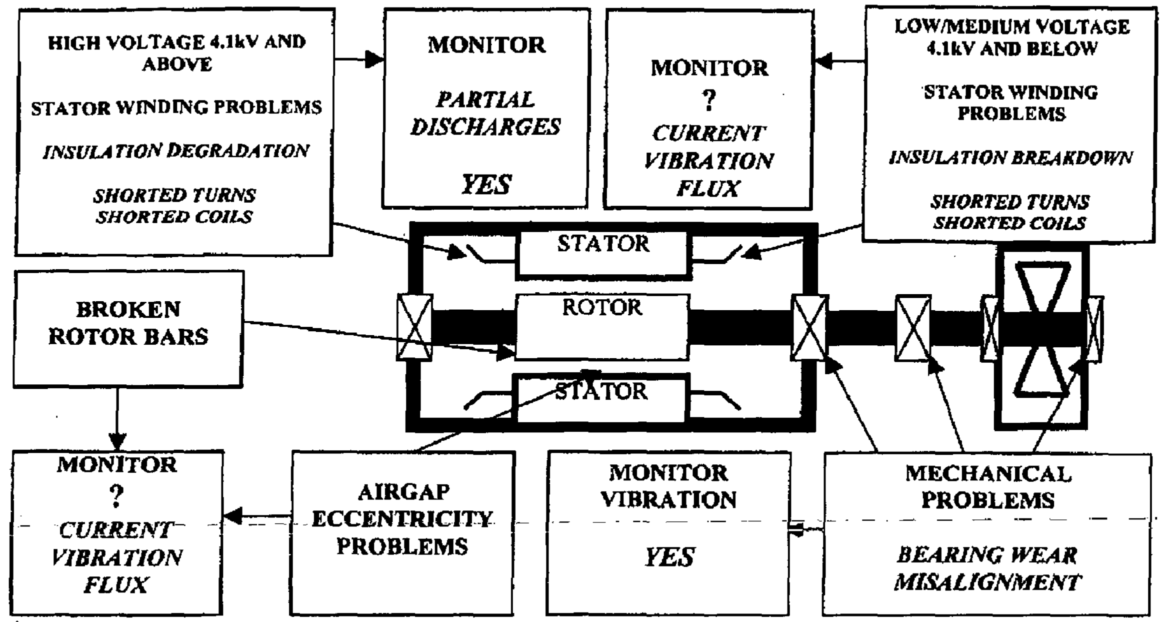


Figure 2.2: Problems, failures and possible on-line monitoring techniques for induction motor drives [5]

2.7 CONCLUSION

In this chapter various parts of the induction machine has been discussed and also how these parts subject to various problems is mentioned. The failure mechanism demonstrates how defects may be detected in their early stages by monitoring appropriate parameters. And also mention about the machine design to withstand for the abnormalities.

CHAPTER 3

DEVELOPMENT OF MONITORING SYSTEM

This chapter deals with the use of hardware and development of LABVIEW and MATLAB software for recording of the current and vibration signal under healthy and faulty conditions in the lab and in the steel rolling mill machines.

3.1 INTRODUCTION

There are a wide variety of monitoring systems starting from a very simple to a very complex one with advance and intelligent instrumentations [1, 29]. An example of simple monitoring system is an over-current relay connected with alarm; when the current exceeds a certain limit, the system gives a warning alarm. However, complex systems are used in very important and critical positions such as nuclear reactors, space rockets, submarines, airplanes etc.
Where accurate information about the parameters being monitored is needed. In general, economical and safety considerations play an important role in the selection of the monitoring system. In the present time, there are many monitoring systems available commercially Developed by multinational companies such as B&K, BBC, ABB, etc [1, 29]. These systems are developed for certain specific applications. The cost of such systems is very high and there is less flexibility in changing the system parameters.

For the purpose of monitoring and diagnosis of the machine condition, a computerized monitoring system is indigenously developed. The specifications of the monitoring system are high accuracy, fast, simple design with reliability and rugged construction.

3.2 MONITORING SYSTEM ELEMENTS

The basic elements of monitoring systems are sensors, signal conditioning, data acquisition and signal processing. Each element has many parameters with different specifications. In the present work, the monitoring system uses electrical variables current and their harmonics and vibration parameters to obtain the machine condition. The types of fault of our concern are bearing faults (both inner and outer race faults). From the above, the selection of the sensing elements depends on the limit of changes of the machine variables, accuracy of the obtained information and the monitoring method. Machine variables as three phase three phase stator currents, speed, vibration (radial and horizontal) that cover the entire requirement to recognize the expected types of faults, are selected for monitoring. Tachometer, piezoelectric accelerometer and ac current clamps are used to measure the mentioned machine variables.

However, most of the sensors provide outputs in the form of electrical signals (digital or analogue), the level of the output and the linearity with the input need to be conditioned. One machine analyzer also used for vibration signal analysis. Here we used BNC-2120 to connect analog signal to NI DAQ 6024E through a 68 line card. NI DAQ 6024E converts the analog signal into digital form on which we can do manipulations easily by using a PC. The speed of data acquisition system and the number of inputs to be scanned are controlled by the software. The schematic diagram of the developed monitoring system is shown in Figure 3.2. The details of each element of the system are described as below.

3.3 TRANSDUCERS

Transducer is the basic element in the monitoring system. It is used to sense the system quantities by actuating energy from one system and transmitting it in another form to a second system. Generally, there are two types of transducers; passive and active. The input of passive transducers is mostly a physical quantity such as vibration, speed, temperature, current etc, while the output is in the form of electrical energy. Since the electrical output is limited by the physical input, such transducers tend to have low energy output and thus requiring amplification [30]. Examples of these transducers are thermocouples and piezoelectric accelerometers. The active transducers have physical input, excitation, and electrical output such as strain gauge accelerometer and semiconductor temperature sensors.

In the present system, different transducers are used to measure current, speed and vibrations. The characteristics of these transducers are explained below with some details.

3.4 VARIOUS PARAMETERS FOR FAULT DIAGNOSIS

There are various parameters, which can be used for knowing the status of the machine. Most commonly used parameters for fault diagnosis in industry are:-

1. current measurement
2. vibration measurement
3. temperature measurement
4. voltage measurement
5. speed measurement

Here in this work current and vibration signals have been used for the detection of bearing faults in induction motors (both lab and steel industry machines). To measure vibration accelerometer is used and for the current signal measurement current clamp has been used.

3.5 ACCELEROMETER

Nowadays, however, velocity and displacement are commonly measured using accelerometers, the required parameter being derived by integration. Accelerometers produce an electrical output that is directly proportional to the acceleration to which they are subjected. In recent years the piezoelectric device has become almost universally accepted as the transducer to use for all but the most specialized of vibration measurements. It is physically much more robust than the velocity transducer and has a much superior frequency range. This has become more important as techniques involving frequencies well above 1 kHz have been adopted. The construction of a typical piezoelectric accelerometer is illustrated in Figure 3.1.

When it is subject to vibration, the seismic mass, which is held against the piezoelectric element, exerts a force upon it. This force is proportional to the acceleration. Under such conditions the piezoelectric element, which is usually a polarized ceramic material, generates a proportional electric charge across its faces. The output can then be conditioned using a charge amplifier and either velocity or displacement signals recovered by integration. The device has the obvious advantage of generating its output without an external electrical source being required. More recently integrated circuit piezoelectric devices have become available with the output signal conditioning resident in the accelerometer encapsulation.

There is an extremely wide range of piezoelectric accelerometers available today, from very small devices that will measure shocks of high acceleration, in excess of 10^6 ms-², to large devices with sensitivities greater than 1000 pC/ ms-². Highly sensitive devices, on the other hand, have to be physically large so as to accommodate the increased seismic mass required to generate the high output. In all cases, however, care must be taken when mounting accelerometers since they can be easily destroyed through over—tightening [1].

Here in this work Vibration pick-up has been used was: PU series, PU-601R its details are mentioned in Appendix A-1.

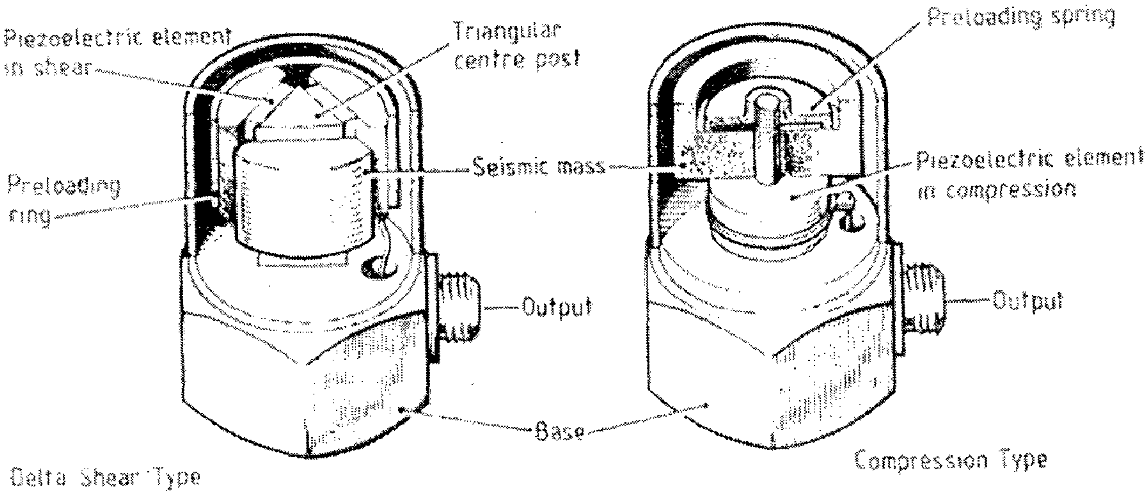


Figure 3.1 the piezoelectric accelerometer

3.6 i400s AC CURRENT CLAMP

It is nothing but the current transformer. The core of the transformer can be split with the help of a trigger switch and therefore core can be clamped around a live conductor to measure the current without breaking the circuit. That's why we can call MCSA as a non-invasive method to identify the faults in the machine. Here the operating principle of this transducer is this when the current passing through a conductor the magnetic field is produced around it, according to Faraday's law this varying magnetic flux is cut by the secondary winding which is on the core. Due to this action there is the voltage across the secondary winding which is in the order of 10 or 100mV/A. By using this sensor we can measure the range of current between 40-400A. Details of this sensor are clearly mentioned in appendix A-2. Here we can connect the out put of the sensor directly to the BNC 2120 as an analog input

3.7 SPEED MEASUREMENT

Here we measured the speed by using the tachometer. It's the general way of measuring the speed. But for more accurate results we go for the non-contacting type of measurement of the speed.

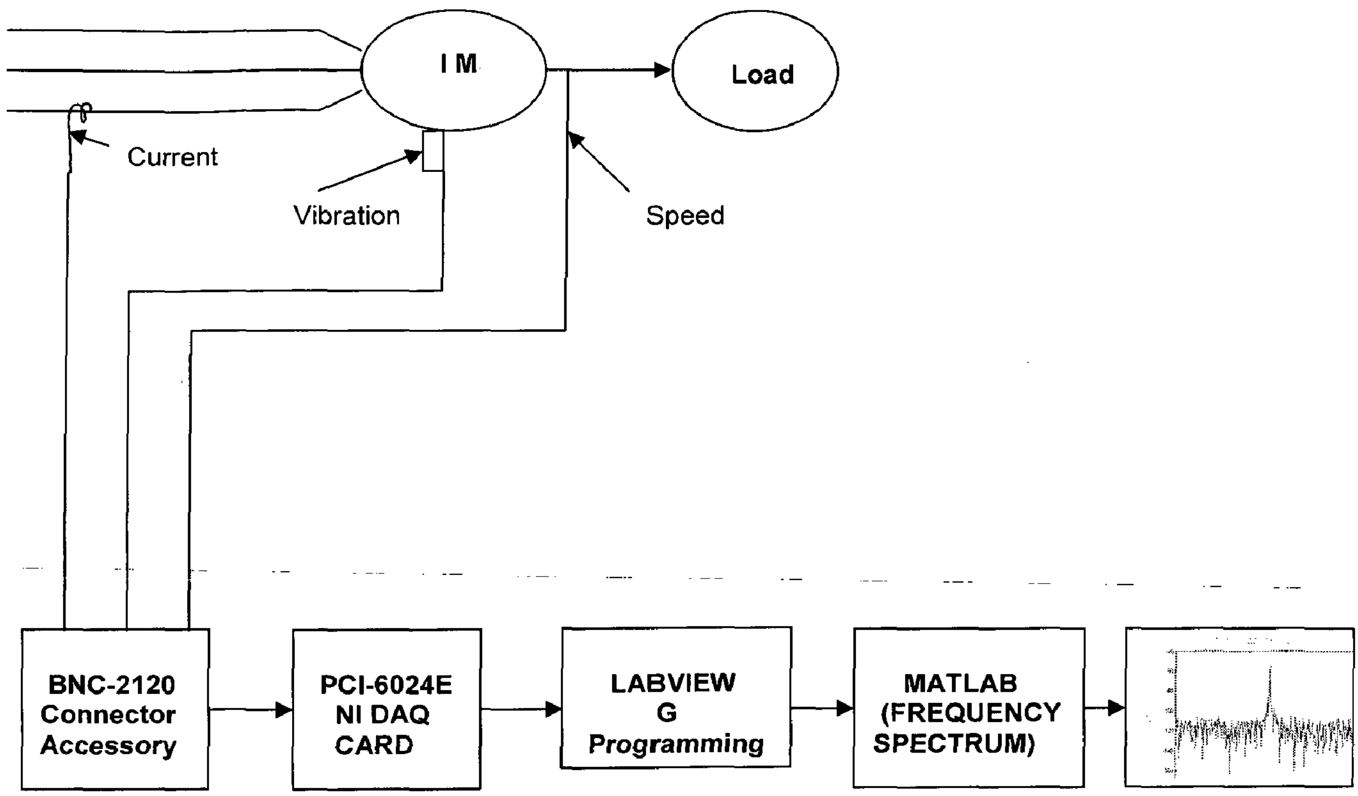


Figure 3.2 BASIC SCHEMATIC DIAGRAM OF THE WORK

3.8 BNC-2120 CONNECTOR ACCESSORY FOR E SERIES DEVICES

The BNC-2120 is a desktop or DIN rail-mountable accessory you can connect directly to E Series devices (like NI 602X E). The BNC-2120 has the following features [31]:

• Eight BNC connectors for analog input (AI) connection with an optional thermocouple connector, an optional temperature reference and optional resistor measurement screw terminals

• Two BNC connectors for analog output (AO) connection

• Screw terminals for digital input/output (DIO) connection with state indicators

• Two user-defined BNC connectors

• A function generator with a frequency-adjustable, TTL-compatible square wave, and a frequency- and amplitude-adjustable sine wave or triangle wave

• A quadrature encoder

Front panel diagram and its details are mentioned in appendix A-3.

3.9 PCI 6024E DEVICE

The 6023, 6024, and 6025 E Series boards are high-performance multifunction analog, digital, and timing I/O boards for PCI, PXI, PCMCIA, and Compact PCI bus computers. Supported functions include analog input, analog output, digital I/O, and timing I/O.

NI-DAQ refers to the NI-DAQ driver software for PC compatible computers unless otherwise noted.

PXI, PXI stands for PCI extensions for Instrumentation.

PXI is an open specification that builds off the Compact PCI specification by adding instrumentation-specific features.

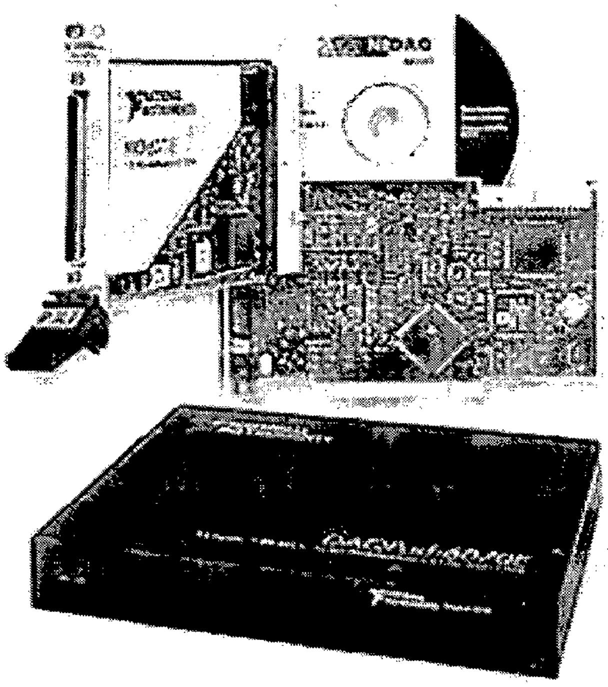


Figure 3.3 Multifunction DAQ

Using LabVIEW, Measurement Studio, or Virtual Bench software greatly reduces the development time for data acquisition and control application. Specifications and internal circuit of DAQ card is mentioned in Appendix A-4.

3.10 NI-DAQ DRIVER SOFTWARE

The NI-DAQ driver software shipped with 6023E/6024E/6025E is compatible with you device. It has an extensive library of functions that we can call from our application programming environment. These functions allow us to use all features of our 6023E/6024E/6025E [40].

NI-DAQ addresses many of the complex issues between the computer and the DAQ hardware such as programming interrupts. NI-DAQ maintains a consistent software interface among its different versions so that we can change platforms with minimal modifications to our code. Whether we are using LabVIEW, Measurement Studio, or other programming languages, our application uses the NI-DAQ driver software, as illustrated in Figure 3.4.

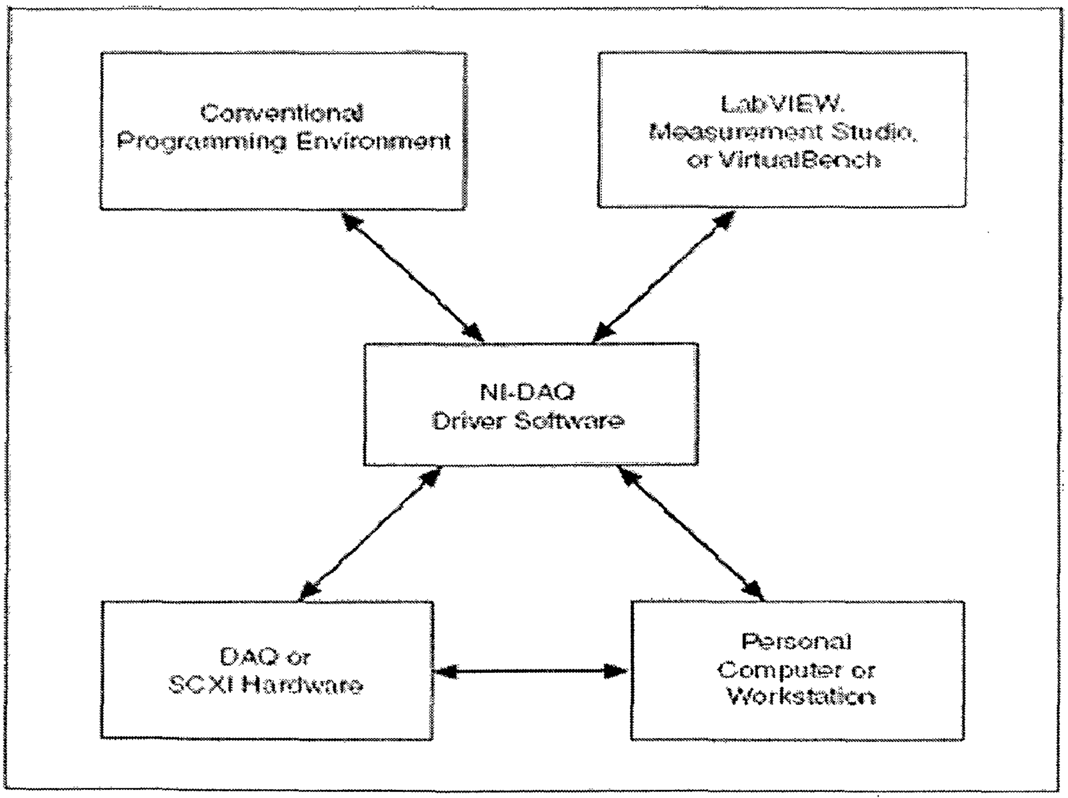


Figure 3.4 The Relationship between the Programming Environment, NI-DAQ and our Hardware

Here in this thesis work main function of the NI DAQ 6024E card is to acquire and convert the analog signal to digital form. The function of analog to digital conversion is clearly mentioned below.

3.11 ANALOG-TO-DIGITAL CONVERSION

Most signals of practical interest, such as speech, biological signals, seismic signals, radar signals, sonar signals, and various communications signals such as audio and video signals, are analog. To process analog signals by digital means, it is first necessary to convert them into digital form, that is, to convert them to a sequence of numbers having finite precision. This procedure is called analog-to-digital (A/D) conversion, and the corresponding devices are called A/D converters (AD Cs).

Conceptually, we view A/D conversion as a three-step process. This process is illustrated in Fig 3.5.

1. *Sampling.* This is the conversion of a continuous-time signal into a discrete-time signal obtained by taking "samples" of the continuous-time signal at discrete-time instants. Thus, if Xa (t) is the input to the sampler, the output is x (n T) x (n), where T is called the sampling interval.

2. *Quantization.* This is the conversion of a discrete-time continuous-valued signal into a discrete-time, discrete-valued (digital) signal. The value of each signal sample is represented by a value selected from a finite set of possible values. The difference between the unquantized sample x(n) and the quantized output xq(n) is called the quantization error.

3. *Coding.* In the coding process, each discrete value Xq (n) is represented by a b-bit binary sequence.

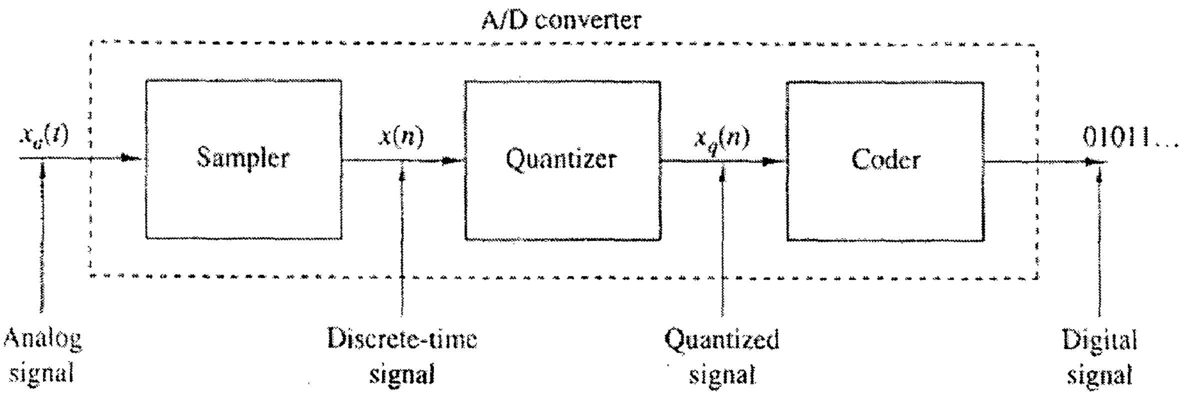


Figure 3.5 A/D Conversion Process

Although we model the A/D converter as a sampler followed by a quantizer and coder, in practice the AID conversion is performed by a single device that takes Xa(t) and produces a binary-coded number. The operations of sampling and quantization can be performed in either order but, in practice, sampling is always performed before quantization.

In particular, we demonstrate that sampling does not result in a loss of information, nor does it introduce distortion in the signal if the signal bandwidth is finite. In principle, the analog signal can be reconstructed from the samples, provided that the sampling rate is sufficiently high to avoid the problem commonly called On the other hand, quantization is a noninvertible or irreversible process that results in signal distortion. We shall show that amount of distortion dependent on the accuracy, as measured by the number of bits, in the A/D conversion process. The factors affecting the choice of the desired accuracy of the A/D converter are cost and sampling rate. In general, the cost increases with an increase in accuracy and/or sampling rate.

3.11.1 Sampling Theorem

If the highest frequency contained in an analog signal Xa(t) is F_{max} = B and the signal is sampled at a rate $F_s > 2F_{max}$ =2B, then Xa(t) can be exactly recovered from its sample values

3.11.2 Sampling of Analog Signals

There are many ways to sample an analog signal. We limit our discussion to periodic or uniform sampling, which is the type of sampling used most often in practice. This is described by the relation

$$x(n) = xa(nT), \quad -\alpha < n < \alpha$$

where x(n) is the discrete-time signal obtained by "taking samples" of the analog signal Xa(t) every T seconds. This procedure is illustrated in Fig. The time interval T between successive samples is called the sampling period or sample interval and its reciprocal 1/T = Fs is called the sampling rate (samples per second) or the sampling frequency (hertz).

Periodic sampling establishes a relationship between the time variables t and n of continuous-time and discrete-time signals, respectively. Indeed, these variables are linearly related through the sampling period T or, equivalently, through the sampling rate Fs = l/T, as t=nT=n/ Fs

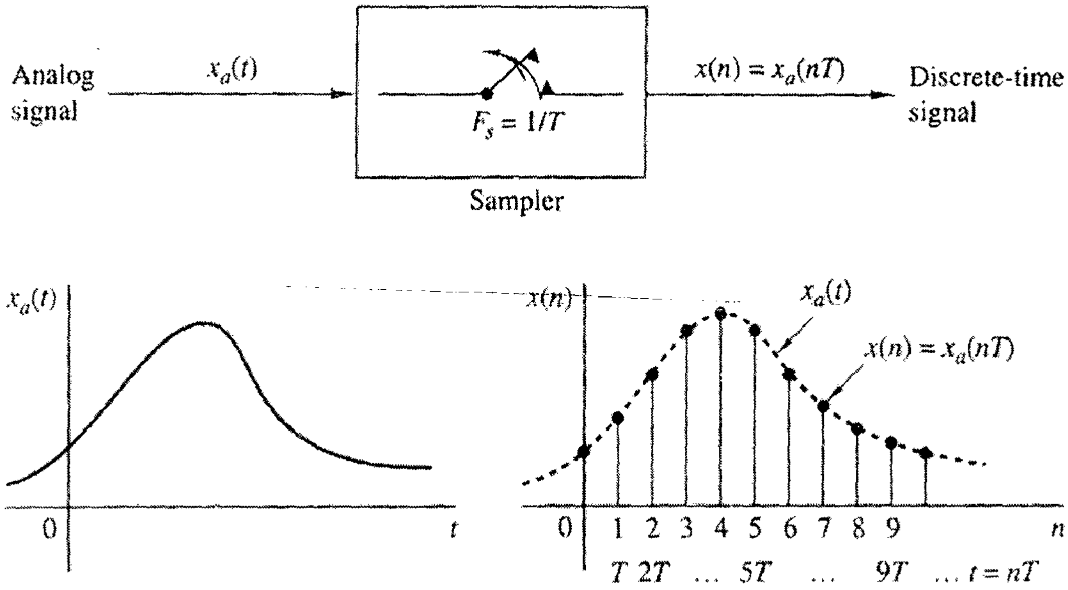


Figure 3.6 Periodic Sampling of an Analog Signal.

3.11.3 Quantization of Continuous-Amplitude Signals

As we have seen, a digital signal is a sequence of numbers (samples) in which each number is represented by a finite number of digits (finite precision). The process of converting a discrete-time continuous-amplitude signal into a digital signal by expressing each sample value as a finite (instead of an infinite) number of digits, is called quantization. The error introduced in representing the continuous-valued signal by a finite set of discrete value levels is called quantization error or quantization noise.

We denote the quantizer operation on the samples x(n) as Q[x(n)] and let Xq (n) denote the sequence of quantized samples at the output of the quantizer. Hence

$$xq(n) = Q[x(n)]$$

Then the quantization error is a sequence eq(n) defined as the difference between the quantized value and the actual sample value. Thus

$$eq(n) = xq(n) - x(n)$$

Theoretically, quantization of analog signals always results in a loss of information. This is a result of the ambiguity introduced by quantization. Indeed, quantization is an irreversible or noninvertible process (i.e., a many-to-one mapping) since all samples in a distance $\Delta/2$ about a certain quantization level are assigned the same value. This ambiguity makes the exact quantitative analysis of quantization extremely difficult.

3.11.4 Coding of Quantized Samples

The coding process in an A/D converter assigns a unique binary number to each quantization level. If we have L levels we need at least L different binary numbers. With a word length of b bits we can create 2^b different binary numbers. Hence we have $2^b >= L$, or equivalently, $b >= \log_2 L$. Thus the number of bits required in the coder is the smallest integer greater than or equal to $\log_2 L$ [32].

3.12 ABOUT LABVIEW

Lab VIEW is a program development environment, much like modern C or BASIC development environments. Other programming systems use text-based languages to create lines of code, while Lab VIEW uses a graphical programming language, 'G' to create programs in block diagram form.

Lab VIEW is a general purpose programming system like C, with extensive libraries of functions for any programming task. Lab VIEW includes libraries for data acquisition. GPIB and serial instrument control, data analysis, data presentation and data storage. These programs are called virtual instruments (VIs) because their appearance operation can imitate actual instruments. VIs are similar to the functions of conventional language programs.

To communicate with external devices Lab VIEW contains the drivers. These drivers are a set of Lab VIEW VIs that communicates with an instrument using standard VISA I/O functions. Each VI corresponding to a programmatic operation, such as configuring, reading from and writing to and triggering an instrument.

3 .13 CONCLUSIONS

The important requirements for the modern condition monitoring system in industry are on-line monitoring as well as off-line monitoring capability. We developed such industrial based system which is compact, flexible, and has fast acquisition of signals and same can also be used for small machines, with a very little hardware and of high accuracy .The National Instrument card was used to acquire the signal with a high sampling frequency rate.

The MATLAB and LabVIEW programs are compatibility with NI card was used for storing the current and vibration data collected from the industry and lab machines. This is to study the machine behavior at different operating conditions and to relate the change in the machine parameter with different fault phenomena. The efficiency of the monitoring system depends upon the accuracy of the information obtained using different types of sensing elements from the monitored machine. Selected machine parameters are considered for monitoring to achieve quality-monitoring system and to incorporate with industry environmental. The hardware along with the software allows the user to effectively monitor, store, analyze machine parameters, and trend current and vibration signals. The software was designed to conduct on-line analysis on the machine and off-line using the stored database.

The success of the monitoring system was proven by comparing the picked up waveforms of vibration signals from the accelerometer with the waveforms obtained using standard instruments i.e. MK-500D. The monitoring system comprises, of three i400s current clamps for current measurement, digital plus-tachometer for speed measurement, and an accelerometer. The data is transferred to the computer using 12-bit AID converter. The sampling frequency has been selected to get the higher resolution or the frequency collected. The sampling frequency is adjusted to 2 kHz.

CHAPTER 4

COMPARATIVE STUDY OF CURRENT AND VIBRATION SPECTRUMS FOR THE IDENTIFICATION OF FAULTS OF BEARINGS IN THE INDUCTION MOTOR

This chapter presents the condition monitoring of the machines by using current and vibration signals. Both spectrums show the unique fault features in the machines. Finally this chapter gives the important conclusions based on the experimental results

4.1 INTRODUCTION

Both the current and vibration signals carry a great deal of information about the health of the machine. Any kind of fault [inner race, outer race, cage or ball defect] present in the bearing may causes to induce some characteristic harmonic components in both the spectrums. These characteristic components are dynamically reveals the status of the machine. Here the dynamically means we will know the condition of the machine by on-line itself. We can also use this method to identify the condition of different parts of the machine i.e for broken rotor bars, stator core and stator winding etc. here in this work current and vibration signals are used to study on lab and steel industry machines for various fault conditions in the bearings only.

4.2 MOTOR CURRENT SIGNATURE ANALYSIS

Since 1985, current signature analysis has been growing as a preferred predictive maintenance tool to identify damaged rotors and air-gap anomalies in induction motors. MCSA is based on the observations that variances in the stator-rotor air gap are reflected back into the motor's current signature through the air gap flux affecting the counter electromotive force. These changes in CEMF then modulate the running current turning an induction motor into an efficient transducer. Newly developed methods of extracting information from the line current supplied to a motor have uncovered information on both the electrical and mechanical health of the equipment. Now in this work MCSA is used to identify the mechanical faults such as bearing faults in the machine.

4.2.1 DEFINITION OF MCSA

What is MCSA?

Motor current signature analysis (MCSA) is a system used for analyzing or trending dynamic, energized systems. Proper analysis of MCSA results will assist the technician in identifying [33]:

1) Incoming winding health
2) Stator winding health
3) Rotor winding health
4) Air gap static and dynamic eccentricity
5) Coupling health, including direct, belted and geared systems
6) Load issues
7) System efficiency
8) Bearing health etc.

Here in this work MCSA is used to identify the bearing faults in induction motor (both on lab and steel industry machines)

4.2.2 BEARING FAULTS

Induction motors are frequently used in industrial applications in a wide range of operating areas, due to their simple and robust structure and low production cost. The reliability of an induction motor is of paramount importance in industrial, commercial, aerospace and military applications. Bearings play an important role in the reliability and performance of all motor systems. 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, most faults arising in motors are often linked to bearing faults. The result of many studies show that bearing problems account for over 40% of all machine failures.

In many situations, vibration monitoring methods are utilized to detect the presence of an incipient bearing failure. Vibration monitoring is a reliable tool for detecting bearing failures [3]. Vibration data typically contain fault signatures and salient fault features because of direct measurement of the critical signal and placement of the vibration sensor. However, placing a sensing device on the motor might not be possible or practical in many applications, especially for a facility that employs a large number of electrical machines. In military and aerospace areas, large electromechanical systems are often equipped with mechanical sensors, primarily vibration sensors based on proximity probes. These are delicate, and too expensive for industrial systems, and can cause heavy loss to the customer. This is why, in spite of the existence of vibration methods, it has been suggested that stator current monitoring can provide the same information without requiring access to the motor body.

4.2.3 BEARING STRUCTURAL DEFECTS AND CAUSES OF FAULTS

Rolling element bearings generally consist of two rings, an inner and an outer, between which a set of balls or rollers rotate in raceways. Under normal operating conditions of balanced load and good alignment, fatigue failure begins with small fissures, located between the surface of the raceway and the rolling elements, which gradually propagate to the surface generating detectable vibrations and increasing noise levels .Continued stress causes fragments of the material to break loose, producing a localized fatigue phenomena known as flaking or sapling .Once started, the affected area expands rapidly contaminating the lubricant and causing localized overloading over the entire circumference of the raceway .Eventually, the failure results in rough running of the bearing. While this is the normal mode of failure in rolling element bearings, there are many other conditions which reduce the time to bearing failure. These external sources include contamination, corrosion, improper lubrication, improper installation or brineling.

Contamination and corrosion frequently accelerate bearing failure because of the harsh environments present in most industrial settings. Dirt and other foreign matter that is commonly present often contaminate the bearing lubrication. The abrasive nature of this minute particles, whose hardness can vary from relatively soft the diamond like, cause pitting and sanding actions that give way to measurable wear of the balls and raceways.

Bearing corrosion is produced by the presence of water, acids, deteriorated lubrication and even perspiration from careless handling during installations. Once the chemical reaction has advanced sufficiently, particles are worn-off resulting in the same abrasive action produced by bearing contamination. Improper lubrication includes both under- and over-lubrication. In either case, the rolling elements are not allowed to rotate on the designed oil film causing increased levels of heating. The excessive heating causes the grease to break down, which reduces its ability to lubricate the bearing elements and accelerates the failure process.

Installation problems are often caused by improperly forcing the bearing onto the shaft or in the housing. This produces physical damage in the form of brinelling or false brinelling of the raceways which leads to premature failure. Misalignment of the bearing, which occurs in the four ways depicted in figure, is also a common result of defective bearing installation. The most common of these is caused by tilted races.

Brinelling is the formation of indentations in the raceways as a result of deformation caused by static overloading. While this form of damage is rare, a form of "false brinelling" occurs more often. In this case, the bearing is exposed to vibrations while even though lightly loaded bearings are less susceptible, false brinelling still happens and has even occurred during the transportation of uninstalled bearings.

Regardless of the failure mechanism, defective rolling element bearings generate mechanical vibrations at the rotational speeds of each component. These characteristic frequencies, which are related to the raceways and the balls or rollers, can be calculated from the bearing dimensions and the rotational speed of the machine. Mechanical vibration analysis techniques are commonly used to monitor these frequencies in order to determine the condition of the bearing [3].

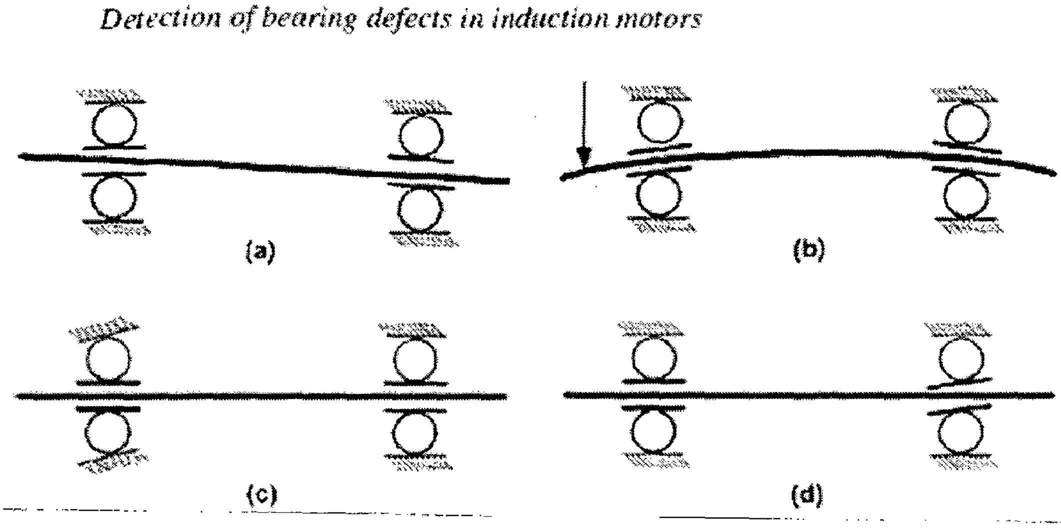


Fig 4.1 **(a)** Misalignment (out-of-line), **(b)** Shaft deflection, **(c)** crooked or tilted outer race, **(d)** crooked or tilted inner race.

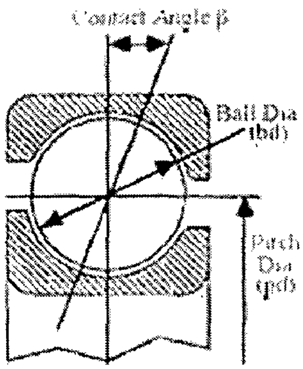


Fig 4.2 Ball bearing dimensions.

4.3 STATOR CURRENT ANALYSIS

The relationship of the bearing vibration to the stator current spectrum can be determined by remembering that any air-gap eccentricity produces anomalies in the air-gap flux density. In the case of a dynamic eccentricity that varies with rotor position, the oscillation in the air-gap.

Table 4.1 Fault frequencies for bearing damage [3]

Cage fault	$f_c = \frac{1}{2} f_r \left(1 - \frac{d_b \cos\beta}{p_d}\right)$
Outer raceway fault	$f_o = \frac{n_b}{2} f_r \left(1 - \frac{d_b \cos\beta}{p_d}\right)$
Inner raceway fault	$f_i = \frac{n_b}{2} f_r \left(1 + \frac{d_b \cos\beta}{p_d}\right)$
Ball fault	$f_b = \frac{p_d}{2 d_b} f_r \left(1 - \frac{d_b^2 \cos^2\beta}{p_d^2}\right)$

p_d = *pitch diameter*
d_b = *ball diameter*
n_b = *no of balls*
f_r = *rotational frequency*

length causes variations in the air-gap flux density. This variation affects the inductance of the machine producing stator current harmonics with frequencies predicted by

$$fecc = fe\,[1 \pm k((1 - s)/(p/2))],\quad fecc = |fe \pm k \cdot frm|, \qquad \text{4(a)}$$

where *fe* is the electrical supply frequency,

k = 1, 2, 3, . . . ,

s is the per unit slip,

p is the number of machine pole pairs and

frm is the mechanical rotor speed in hertz.

Since ball bearings support the rotor, any bearing defect produces a radial motion between the rotor and the stator of the machine. The cause of air-gap eccentricity, these variations generate harmonic stator currents at predictable frequencies, related to the vibrational and electrical supply frequencies by

$$fbng = |fe \pm m \cdot fv|, \quad \ldots\ldots\ldots\ldots\ldots \quad 4(b)$$

where m = 1, 2, 3, . . . and fv is one of the characteristic vibration frequencies. These fault frequencies are given in table 1, where Nb is the number of balls, d_b is the ball diameter, p_d is the ball pitch diameter, β is the ball contact angle (typically equals 0°) and fr is relative revolution per second between inner and outer races. These equations, shown in table 4.1 require specific information concerning the bearing construction to calculate the exact characteristic frequencies.

In the case of bearings with between six and twelve rolling elements, the fundamental inner and outer race frequencies, fi and fo, can be calculated approximately by,

$$fi = 0{\cdot}6 \cdot n_b \cdot frm, \; fo = 0{\cdot}4 \cdot n_b \cdot frm. \quad \ldots\ldots\ldots\ldots\ldots \quad 4(c)$$

In this way it is possible to determine the bearing race frequencies for all seven ball combinations without having explicit knowledge of the bearing construction. This allows determination of the important frequency components in the stator current and these frequency values are defined as $(fe \pm 0{\cdot}4 \cdot n_b \cdot frm)$ and $(fe \pm 0{\cdot}6 \cdot n_b \cdot frm)$, where n_b = 6, 7, . . . , 12 .

4.4 VIBRATION SIGNAL ANALYSIS

An electrical machine, its associated support structure and the load to which it is coupled form a complex mechanical system. It is free to vibrate at its own natural frequency, or can be forced at many different frequencies. The result may be a level of noise that is unacceptably high, or a progressive degree of mechanical damage that ends in a total machine failure.

The principal areas of vibration in electrical machines are:

a) the stator core response to the attractive force developed between rotor and stator;

b) the response of the stator end windings to the electromagnetic forces on the conductors;
c) the dynamic behaviour of the rotor;
d) the response of the shaft bearings to vibration transmitted from the rotor.

These four areas are obviously inter-related; for example bearing misalignment or wear can quite easily result in eccentric running which will in turn stimulate the vibrational modes of the stator.

Out of these four types concentration in this thesis is only on the response of the shaft bearings to vibration transmitted from the rotor.

4.4.1 MACHINE VIBRATION

It has been observed that there is a relationship between the mechanical vibration measurable at the surface of the electrical machine and source of defect inside the machine. Table 4.2 indicates that for induction motor, almost all types of faults can be identified just by analyzing the vibration signal collected from the machine surface.

Table 4.2 Failure Mechanism of Induction Motor

S.No	Fault	Cause	Early indication of fault
1	Frame vibration	Defective assembly Defective installation Excessive mechanical vibration	Vibration
2	Earth fault	Abrasion of Insulation	Vibration
3	Broken rotor bars	Defective design Defective manufacture Thermal cycling due to excessive starting	Vibration Distorted air-gap flux Pulsating speed Supply current
4	Mechanical unbalance	Movement of end rings Asymmetric blocking of cooling ducts shorted rotor bars	Vibration

S.No	Fault	Cause	Early indication of fault
5	Mechanical misalignment	Defective installation Failure of bearing	Vibration Distorted air-gap flux Overheating
6	Bearing misalignment	Incorrect bearing clearance Incorrect bearing loading	Vibration Debris in lubricating oil
7	Loss of bearing lubrication	Contamination of lubricating oil Excessive bearing clearance	Vibration Debris in lubricating oil

The sources of the vibration in rotating electric machines may be divided into two groups: forces due to mechanical origin and the forces due to magnetic origin. These forces produce vibration directly on the machine structure. The relative importance of each type of source depends on the type and size of the machine.

4.4.2 VIBRATION DUE TO THE MECHANICAL FORCES

The vibration due to the mechanical forces may be either from surrounding environment or produced from the machine itself. For most machines, the vibrations due to the machine itself are produced by dynamic rotor imbalance, stator and rotor rubbing, and rolling motion in the bearing; which depend on the condition of the machine for a given operating mode. These forces may often be reduced to insignificant proportions by dynamically balancing the rotor accurately. When a machine has been in use for some time, the rotor balance may change owing to slight winding movement or bending of the shaft, so that this type of vibration may become greater as the machine ages.

Bearings are essential mechanical elements in rotating electrical machines to provide relative displacement between stator and rotor. They transmit some of the rotor forces to the stator. It is important to measure the vibrations at the bearings due to these forces as well as the vibration generated by the bearings themselves. The noise and vibration due to the response of the shaft bearing depend upon many factors, such as, type of bearing, size of the machine.

In bearing manufacturing, slight error in the geometric shape and dimensions and deviation in the properties of the material are unavoidable. All these factors make even new bearing to generate its own vibration. The degree of vibration depends upon material, tolerance, and assembly of the bearings.

Also, rolling elements as spheres or cylinders are deformed under the influence of high forces. The ball resonance frequency due to elastic deformation is increased with the decrease of the ball radius. The elastic deformation of the ball produces vibrations of high frequency.

In addition to these factors, the level and frequency of vibration can be significant to the working environment, such as temperature, dirtiness, lubrication, loading, speed, and mode of fittings.

4.4.3 VIBRATION DUE TO THE MAGNETIC FORCE

The radial force due to the air-gap field is the main source of the magnetic vibration of the electrical machines. In actual machines, when a three phases, sinusoidal currents displaced 120 degrees in time, flows in the machine winding, pulsating magnetic field by each coil with fundamental and harmonics are produced. The space harmonics of the three phase winding mmf create revolving fields that interact with the air gap permeance. The air gap permeance is not uniform due to the effect of slots, saturation and eccentricity. This interaction induce further flux density waves of pole number and frequency equal to the sum and difference of the corresponding orders of the stator mmf and permeance waves. Hence, the flux density wave along with its harmonics pass through the air gap and act on the rotor winding and induce voltage having a same order of harmonics.

Due to the closed circuit of the rotor, the current will flow in the rotor winding having same voltage harmonics plus another harmonics due to the rotor slotting, saturation and rotor motion. The mmf wave established due to the rotor current interacts with air gap permeance and produces a new set of flux density wave. The rotor current produces a torque similar to the current harmonics with different number of poles and with lower synchronous speeds. When the number of poles of the harmonic field present in the air gap is multiple of two, unbalanced radial magnetic forces and consequently radial vibration of the rotor as a whole are produced. Also, symmetrical radial forces of high frequency are produced by superposition of rotating magnetic fields of different pole numbers. These forces create stator noise and vibration. [Alger]

4.4.4 VIBRATIONS OF FAULTY INDUCTION MACHINE AND FREQUENCY COMPONENTS

Every rotating machine vibrates. These vibrations are due to the presence of electrical and mechanical forces. Additionally, interaction of these forces makes identification of root cause elusive. The induction motor is also subjected to various types of electrical and mechanical faults. The effect of these faults is to distort air gap flux of the machine. The degree of distortion depends upon the type and the degree of fault. This perturbation in flux produces machine vibrations. Although, the induced harmonics affected the whole frequency components of the vibration only some of these harmonics have a dominant value in the vibration spectrum. These frequency components can be used to detect the presence of the machine faults. Some of the electrical fault mechanisms are discussed here under along with frequency chart and vibration standard chart

4.4.4. a) ONE-TIME LINE FREQUENCY VIBRATION

Unbalanced magnetic pull may result in vibration at line frequency. This line frequency vibration is normally very small or nonexistent, but if the stator or rotor system has a resonance at or near line frequency the vibration may be large.

4.4.4. b)TWICE-LINE FREQUENCY VIBRATIONS

The power supply produces an electromagnetic attracting force between the stator and rotor which is maximum at a point on the stator when the magnetizing current flowing in the stator is at maximum, (either positive or negative). As a result there will be two peak forces during each cycle of the voltage or current wave, reducing to zero at the point in time when the current and fundamental flux wave pass through zero. This will result in a frequency of vibration equal to 2* the frequency of the power source. This particular vibration is extremely sensitive to the motor's frame. It is also influenced by the eccentricity of the rotor.

4.4.4. c) ROTOR BAR PASSING FREQUENCY VIBRATIONS

The electrical current in the rotor bars creates a magnetic field around the bars. This field applies an attracting force to the stator teeth and this force creates the vibration al the frequency RBPF given by

RBPF = RPM * Numberofrotorslots/60

As load increases, vibration frequencies also appears at RBPF plus side bands at $\pm$ 2f, $\pm$4f and $\pm$6f Hz where f is supply frequency.

The frequency of this source of vibration can be picked up from the motor frame and bearing housings, but due to higher value, these frequencies will not be seen between shaft and bearing defect frequencies. For this reason, vibration specification requirements do not require these frequencies to be included in overall vibration.

4.5 BROKEN ROTOR BAR

If a bar is broken or open braze joint exits, no current will flow in the rotor bar. As a result, the field in the rotor around that particular bar will not exist. Therefore, the force applied to that side of the rotor would different from that on the other side of the rotor, again creating unbalanced magnetic force that rotates at one times rotational speed and modulates at a frequency equal to slip frequency times the number of poles.

4.6 BEARING RELATED VIBRATIONS

Bearing related vibrations are common to all types of rotating equipment Rolling-element bearing generally consists of two rings, an inner and outer, between which a set of balls or rollers rotate. Brief description about this is given in section 4.1.2

4.6.1 BEARING RESPONSE

General

A considerable proportion of the rotor force is transmitted to the stator via the bearings. Therefore it is important to be able to gauge the vibrational responses of the bearings to these external forces so that they may not be confused with vibrational frequencies generated by defects in the bearings themselves. External forces will result in a relative vibration of the rotor with respect to the housing and an absolute vibration of the complete bearing housing.

This action must be considered for both rolling element bearings and oil-lubricated sleeve bearings. But here in this work consideration is only for rolling-element (both ball and roller) bearings. Here the ball bearings are used and diagnosed for lab machine and the roller-bearings are used for steel industry machines.

4.6.2 ROLLING ELEMENT BEARING

A schematic view of a typical rolling element bearing is shown in fig. The failure of bearings such as these is the commonest form of malfunction associated with smaller machines.

Because of their construction rolling element bearings produce very precisely identifiable vibrational frequencies. Also since the oil film is very thin the relative motion between the housing and the shaft is small. It is therefore possible to detect the vibrations associated with the bearings using an accelerometer mounted directly on the bearing house. The characteristic frequencies like as shown in table 4.1 of such bearings depend on the geometrical size of the various elements.

Besides the frequencies given in table 4.1 there will also be higher frequencies generated by elastic deformation of the rolling elements themselves, and the excitation of the natural modes of the rings that comprise the inner and outer races. These effects will, however, be secondary to the principal components mentioned here.

The magnitudes of the components given in table 4.1 are often lost in the general noise background when the degree of damage is small, but because of their precise nature they present an effective route for monitoring progressive bearing detection. A simple instrument can be devised using an accelerometer mounted on the bearing housing to detect the amplitude of vibration at these characteristic frequencies. Once the characteristic frequencies have been calculated it is possible to enhance the performance of the instrument by the use of highly selective filters and weighting functions, so as to be able to identify bearing faults at an earlier stage.

When monitoring the vibration due to rolling-element bearings it is always prudent to try and achieve good base-line data. This is because once the bearings becomes significantly worn by any one of these reasons (i.e flaking or sapling, contamination, corrosion, improper lubrication, improper installation or brineling) the spectrum of vibration it emits becomes more random again, although at a much higher level than the base value for a good bearing. Clearly if no base line is available and no history has been built up, it is possible for specific defects to be masked by the increase in general background level.

Machinery may also exhibit a small degree of unbalance; this will tend to modulate the characteristic frequencies of the bearings and produce side bands at the rotational frequency. This feature is clearly shown in the results.

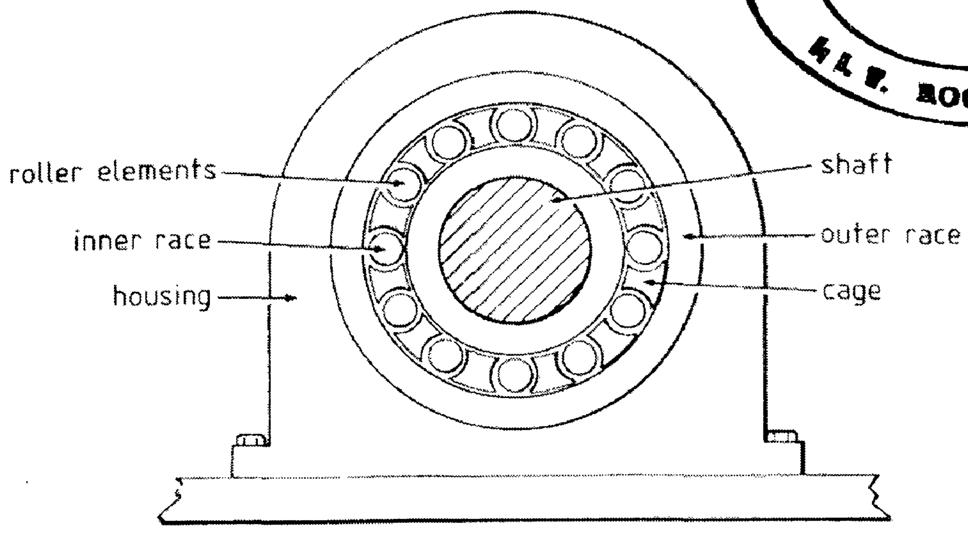


Fig 4.3 Rolling element bearing assembly

4.7 FEATURE SELECTION AND EXTRACTION

Feature selection and extraction is an important part of the diagnostic scheme. A number of parameters can be used to characterize the current and vibration signal. It is important that these parameters reflect those features that change with fault. Not all the parameters have proved useful due to variety of factors such as assessment, implementation and most importantly, their diagnostic utility. Precise definitions of these parameters become more important with computer aided analysis. Therefore the next step is to extract the features from the current and vibration signals for healthy machines and the machines having various fault conditions. Time and frequency domain analyses are the two methods used in this condition monitoring applications. The differences in the current and vibration signals of healthy and unhealthy machine are investigated by employing these two methods.

4.8 TIME DOMAIN ANALYSIS:

Statistical Parameters

Several statistical parameters, calculated in the time domain, are generally used to denote average properties of machine data. These statistical parameters may be used to perform a quick check of the changes in the statistical behavior of a signal.

For a given data set (xi), its statistical character can be obtained by calculating the moments. The concept of moment is of great significance in statistical work. With the help of moments the central tendency of the set of observation i.e. they're variability, their asymmetry and the height of the peak can be measured [11, 34].

As applied to statistics, Pearson first used the term moment in his 1893 letter to Nature where he suggested that the moments about the mean could be used to measure the asymmetry of a curve. The moments about the mean provide quantitative indices to describe deviations of empirical distributions from the normal distribution. The mean value, standard deviation, skewness, and kurtosis, complexity, third order cumulant are some of parameters used for such purpose. The sample mean and PDF (probability distribution function) summarize two aspects of a set of numbers: location and spread. Two other values that are sometimes computed from a set of numbers are the skewness and the kurtosis. The skewness is meant to summarize how asymmetric a data set is. That is, rather than having the symmetrical mount shape, the data is more spread out on one side of the median than the other. Kurtosis is meant to capture the presence of "extreme" values relative to the bulk of the data. The definition of these parameters is given as under:

4.8.1 Mean value

For discrete time signal (xi) the mean value is obtained by using following equation:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i \quad \text{.......................4(d)}$$

where N is the number of the data points.

4.8.2 RMS value

The simplest and more common approach to vibration monitoring is to measure the overall intensity of an unfiltered vibration signal. This is normally achieved with the estimate o Root Mean Square (RMS) level of the time record. The RMS of the discrete time signal is calculated as.

$$rms = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2} \quad \text{.............4(e)}$$

4.8.3 Peak value: Measure of Maximum Amplitude of Signal in a window width

4.8.4 Crest factor

The crest factor yields the measure of the spikiness of a signal. It is meaningful where the peak values are reasonably uniform and repeatable from one cycle to another cycle.

Crest factor = Peak value/RMS value

4.8.5 Standard deviation

Standard deviation is a statistical term that provides a good indication of volatility. It measures how widely values are dispersed from the average.

$$\sigma=\sqrt{\frac{1}{N}\sum_{i=0}^{N-1}(x(n)-\overline{x(n)})^2} \quad ....4(f)$$

4.8.6 2nd Central Moment: Variance

The variance about the meant of the given data set is calculated as

$$\upsilon=\frac{1}{N}\sum(xi-\mu)^2 \quad ....4(g)$$

4.8.7 3rd Central Moment: Skew ness

Skew ness is a measure of symmetry, or more precisely, the lack of symmetryabout its mean. A distribution, or data set, is symmetric if it looks the same to the left and riglt of the center point. The skewness of normal distribution is zero, and any symmetric data should have a skewness near zero. Negative values for the skewness indicate data that are skewed left and positive values for the skewness indicate data that are skewed right. By skewed left, mean that the left tail is heavier than the right tail. Similarly, skewed right means that the right tail is heavier than the left tail.

$$c(skewness)=\frac{1}{N}\sum(xi-\mu)^3 \quad ....4(h)$$

4.8.8 4th central normalized moment: Kurtosis

A more recent development in the state of art of bearing fault detection is statistically based parameter called Kurtosis. It is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct crack near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. Positive kurtosis indicates a "peaked" distribution and negative kurtosis indicates a "flat" distribution

$$\kappa(kurtosis) = \frac{\frac{1}{N}\sum_{i=1}^{N}(xi-\mu)^4}{\sigma^4} \quad \ldots\ldots\ldots\ldots.4(i)$$

The Kurtosis technique has the major advantage that the calculated discriminate takes a value, which is independent of load or speed conditions. It has been found that the Kurtosis factor for undamaged bearing is 3. In general, the initial appearance of flaws is marked by an increase in the value of Kurtosis. As the damage becomes more severe, the values falling back towards 3 [35].

4.8.9 Cumulant Calculation

The measurement noise which often appears to be Gaussian disappears at the third or fourth order cumulant value.

It is defined with respect to moment the concept of moment is of great significance in statistical work. With the help of moments the central tendency of the set of observation i.e. their variability, their asymmetry and the height of the peak can be measured. [36].

Cumulant calculation:

1st Order Moment, $m_1 = \frac{1}{n}\sum(x-\overline{x})$ ....4(j)

2nd Order Moment, $m_2 = \frac{1}{n}\sum(x-\overline{x})^2$ ....4(k)

3rd Order Moment, $m_3 = \frac{1}{n}\sum(x-\overline{x})^3$ ....4(l)

4th Order Moment, $m_4 = \frac{1}{n}\sum(x-\overline{x})^4$ ....4(m)

1st Order Cumulant, $c_1 = m_1$ ....4(n)

2nd Order Cumulant, $c_2 = m_2 - m_1^2$ ....4(o)

3rd Order Cumulant, $c_3 = m_3 - 3m_2m_1 + 2m_1^3$ ....4(p)

4th Order Cumulant, $c_4 = m_4 + 4m_3m_1 - 3m_2^2 + 12m_2m_1^2 - 6m_1^4$ .....4(q)

4.9 FREQUENCY DOMAIN ANALYSIS

Another conventional approach used to process the current and vibration signals is the frequency domain. Frequency domain features of the current and vibration signals provided additional information in the assessment of condition monitoring of rotating electrical machines.

Frequency analysis of a signal highlights many important hidden features and extracts some useful information. The purpose of this analysis was to find out the frequency contents of the current and vibration data so that the relationship between the frequencies and the type of the fault is established. The simplest way to identify the multiple sinusoid signals was Fourier transform spectrum analysis. By this method the machinery condition is assessed by observing the presence of assumed stationary frequency components. But here both current and vibration signals are non-stationary ones that's why in this work wavelet packet decomposition has been used. Brief explanation about different transforms have been discussed in the below paragraphs.

4.9.1 Fourier Analysis

Signal analysts already have at their disposal an impressive arsenal of tools. Perhaps the most well known of these is *Fourier analysis*, which breaks down a signal into constituent sinusoids of different frequencies. Another way to think of Fourier analysis is as a mathematical technique for *transforming* our view of the signal from time-based to frequency-based.

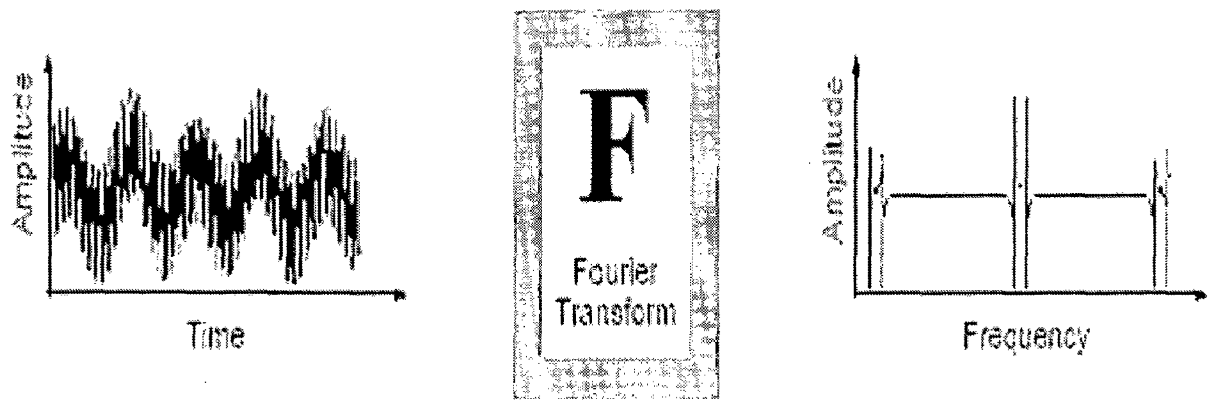


Fig 4.4 Representation of time and frequency domain

Although FT is probably the most popular transform being used (especially in electrical engineering), it is not the only one. There are many other transforms that are used quite often by engineers and mathematicians. Hilbert transform, short-time Fourier transform (more about this later), Wigner distributions, the Radon Transform, and of course our featured transformation, the wavelet transform, constitute only a small portion of a huge list of transforms that are available at engineer's and mathematician's disposal. Every transformation technique has its own area of application, with advantages and disadvantages, and the wavelet transform (WT) is no exception.

For a better understanding of the need for the WT we need to look at the FT more closely. No frequency information is available in the time-domain signal, and no time information is available in the Fourier transformed signal. The natural question that comes to mind is that is it necessary to have both the time and the frequency information at the same time?

As it can be seen subsequently, the answer depends on the particular application and the nature of the signal in hand. Recall that the FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. This information is not required when the signal is so-called stationary. It is required to take closer look at this stationary concept more closely, since it is of paramount importance in signal analysis. Signals

whose frequency content does not change in time are called stationary signals. In other words, the frequency content of stationary signals does not change in time. In this case, one does not need to know at what times frequency components exist since all frequency components exist at all times [36]

For example the following signal

x(t)=cos(2*pi* 1O*t)+cos(2*pi*25 *t)+cos(2*pi*50*t)+cos(2*pi* 100*t)...4(r)

is a stationary signal, because it has frequencies of 10, 25, 50, and 100 Hz at any given time instant. The signal can be plotted as shown in the below figure:

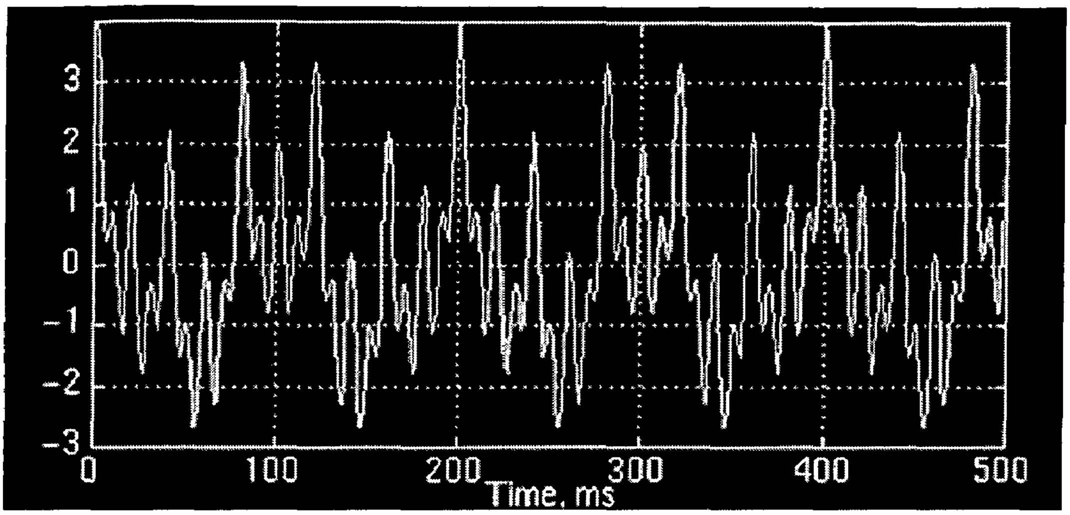


Fig 4.5 Plot of x(t)

And the following is its FT:

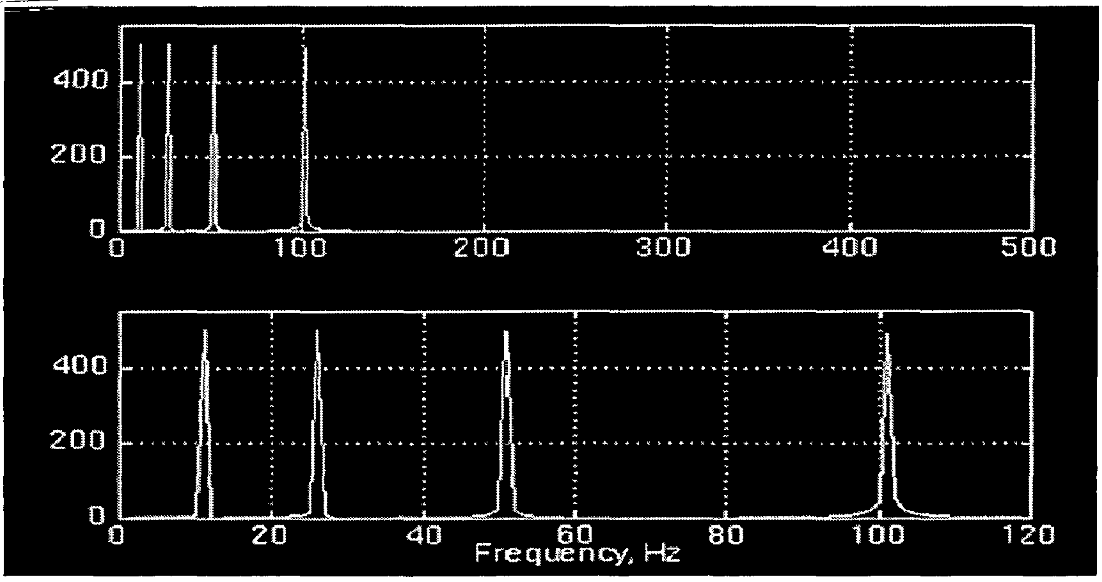


Fig 4.6 Fourier Transform of x(t)

The top plot *in figure* 4.6 is the (half of the symmetric) *frequency spectrum* of the signal in figure 4.5 The bottom plot is the zoomed version of the top plot, showing only the range of frequencies that are of interest to us. Note the four spectral components corresponding to the frequencies 10, 25, 50 and 100.

Contrary to the signal in Figure 4.5, the following signal is not stationary. Figure 4.7 plots a signal whose frequency constantly changes in time. This signal is known as the "chirp" signal. This is a non-stationary signal.

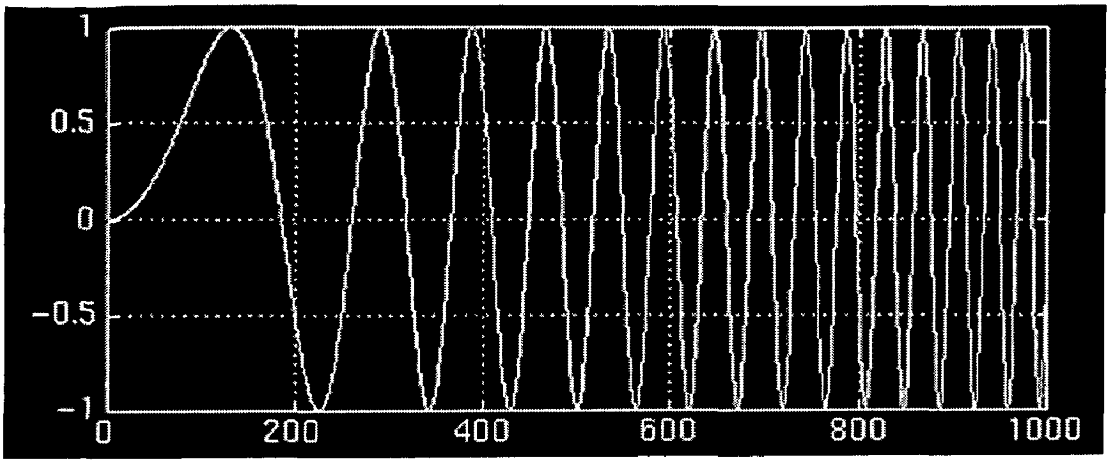


Fig 4.7 Non-stationary signal

The Figure 4.8 plots a signal with four different frequency components at four different time intervals, hence a non-stationary signal. The interval 0 to 300 ms has a 100 Hz sinusoid, the interval 300 to 600 ms has a 50 Hz sinusoid, the interval 600 to 800 ms has a 25 Hz sinusoid, and finally the interval 800 to 1000 ms has a 10 Hz sinusoid

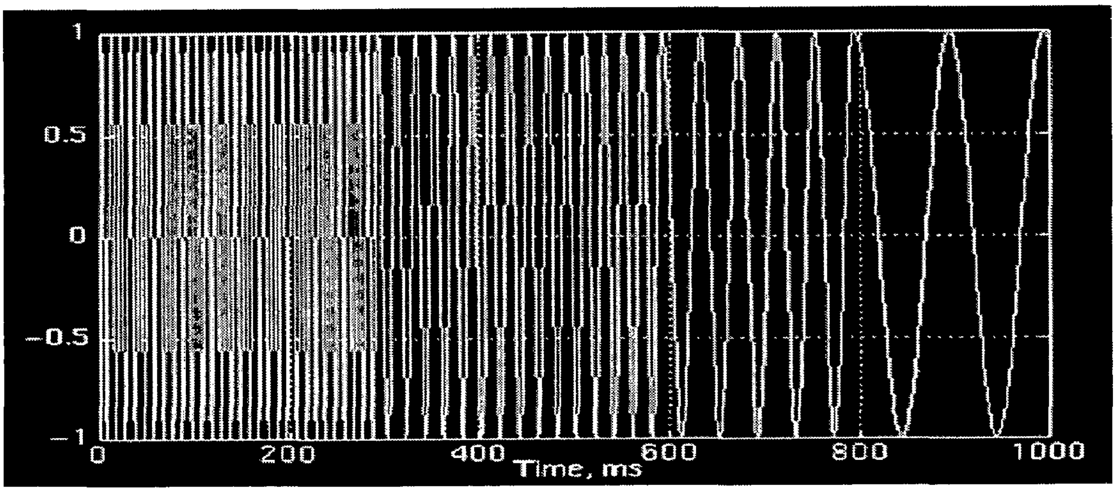


Fig 4.8 Non-stationary signal with different frequency components

And the following is its FT:

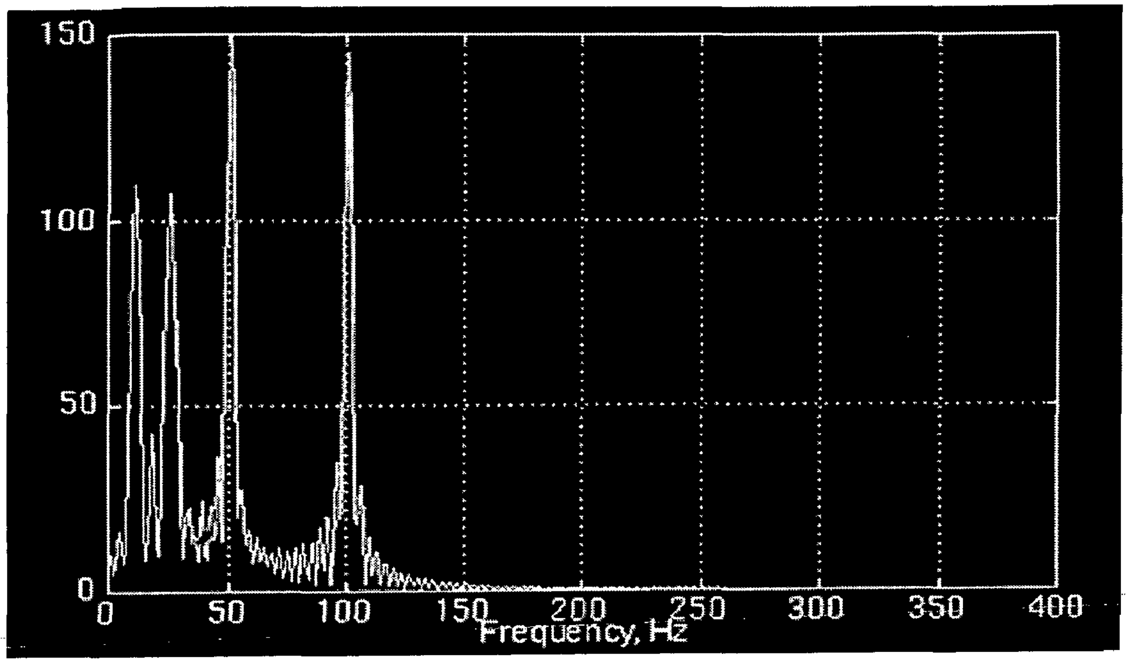


Fig 4.9 FT of non-stationary signal.

The little ripples at this time; they are due to sudden changes from one frequency component to another, which have no significance in this text. Note that the amplitudes of higher frequency components are higher than those of the lower frequency ones. This is due to fact that higher frequencies last longer (300 ms each) than the lower frequency components (200 ms each). Other than those ripples, everything seems to be right. The FT has four peaks, corresponding to four frequencies with reasonable amplitude.

For the first signal, plotted in figure 4.5, consider the following question i.e., "At what times (or time intervals), do these frequency components occur?" and the answer would be at all times. Therefore, in stationary signals, all frequency components that exist in the signal exist throughout the entire duration of the signal. There is 10 Hz at all times, there is 50 Hz at all times, and there is 100 Hz at all times. Now, consider the same question for the non-stationary signal in figure 4.7 or in figure 4.8, "At what times these frequency components occur?" For the signal in figure 4.7, we know that in the first interval we have the lowers frequency component. For the signal in figure 4.8, the frequency components change continuously. Therefore, for these signals the frequency components do not appear at all times.

Now, compare the Figures 4.6 and 4.9. The similarity between these two spectrums should be apparent. Both of them show four spectral components at exactly the same frequencies, i.e., at 10, 25, 50, and 100 Hz. Other than the ripples, and the difference in amplitude (which can always be normalized), the two spectrums are almost identical, although the corresponding time-domain signals are not even close to each other. Both of the signals involves the same frequency components, but the first one has these frequencies at all times, the second one has these frequencies at different intervals. So, how come the spectrums of two entirely different signals look very much alike? Recall that the FT gives the spectral content of the signal, but it gives no information regarding where in time those spectral components appear.

Therefore, FT is not a suitable technique for non-stationary signal, with one exception: FT can be used for non-stationary signals, if we are only interested in what spectral components exist in the signal, but not interested where these occur. However, if this information is needed, i.e., if we want to know, what spectral component occur at what time (interval) , then Fourier transform is not the right transform to use.

For practical purposes it is difficult to make the separation, since there are a lot of practical stationary signals, as well as non-stationary ones. Almost all biological signals, for example, are non-stationary. Some of the most famous ones are ECG (electrical activity of the heart, electrocardiograph), EEG (electrical activity of the brain, electroencephalograph), and EMG (electrical activity of the muscles, electromyogram).

"Therefore it can be inferred that, the FT gives what frequency components (spectral components) exist in the signal. Nothing more, nothing less ".

When the time localization of the spectral components is needed, a transform giving the time-frequency representation of the signal is needed. That's why we go for the following transformations.

4.9.2 Short time Fourier analysis

In an effort to correct this deficiency, Dennis Gabor adapted the Fourier transform to analyze only a small section of the signal at a time i.e., a technique called *windowing* the signal. Gabor's adaptation called Short-time Fourier Transform (STFT), maps a signal into a two-dimensional function of time and frequency, the same is depicted in figure 4.10

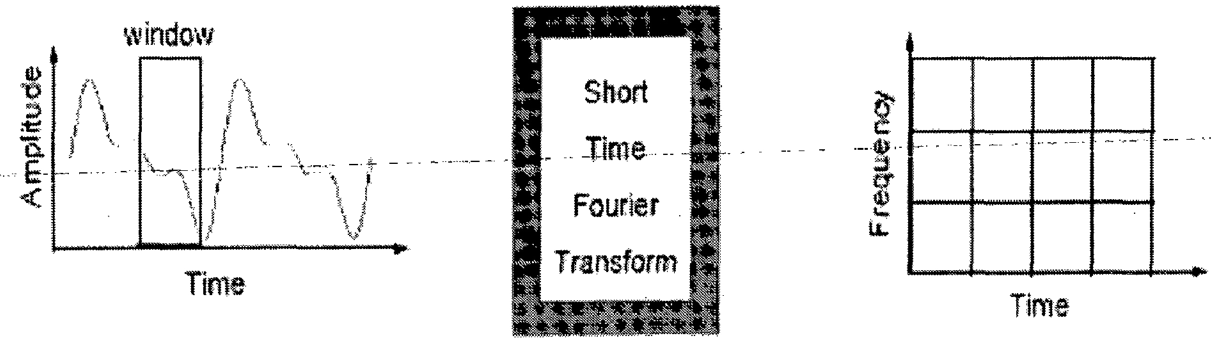


Fig 4.10 STFT representation of the signal

The STFT represents a sort of compromise between the time- and frequency-based views of a signal. It provides some information about both when and at what frequencies a signal event occurs. However, you can only obtain this information with limited precision, and that precision is determined by the size of the window.

While the STFT compromise between time and frequency information can be useful, the drawback is that once you choose a particular size for the time window, that window is the same for all frequencies. Many signals require a more flexible approach —one where we can vary the window size to determine more accurately either time or frequency. to understand why researches switched over to the development of WT from the existing STFT, prior knowledge of uncertainty principle and problem of resolution is a must.

The uncertainty principle, originally found and formulated by Heisenberg, states that "the momentum and the position of a moving particle cannot be known simultaneously." This applies to our above argument as follows:
The frequency and time information of a signal at some certain point in the time-frequency plane cannot be known. In other words, "we cannot know what spectral component exists at any given time instant. The best we can do is to investigate what spectral components exist at any given interval of time". This is a problem of resolution [37], and it is the main reason why researchers had switched over to WT from STFT.

STFT gives a fixed resolution at all times, whereas WT gives a variable resolution.

4.9.3 Wavelet Analysis [38]

A wavelet is a waveform of effectively limited duration that has an average value of zero.
Compare wavelets with sine waves, which are the basis of Fourier analysis.
Sinusoids do not have limited duration — they extend from minus to plus infinity.
And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric.

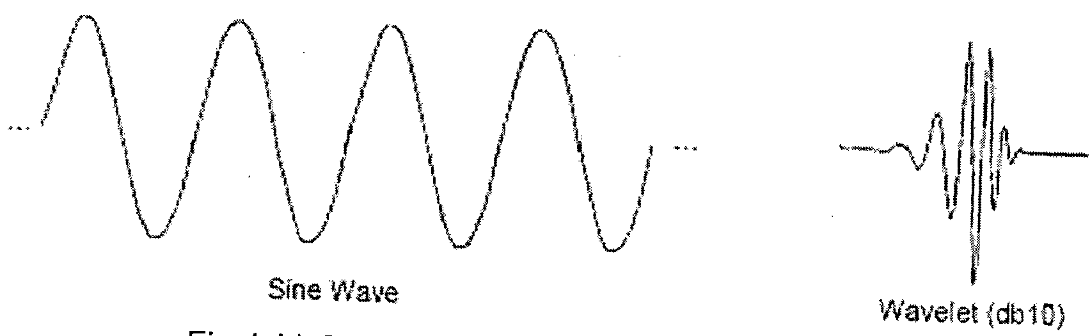


Fig 4.11 Comparison of the sine and wavelet function

Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or *mother*) wavelet.

Just looking at pictures of wavelets and sine waves, you can see intuitively that signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid.

4.9.3 a) Scaling

We've already alluded to the fact that wavelet analysis produces a time-scale view of a signal, and now we're talking about scaling and shifting wavelets. What exactly do we mean by *scale* in this context?

Scaling a wavelet simply means stretching (or compressing) it. To go beyond colloquial descriptions such as "stretching," we introduce the *scale factor*, often denoted by the letter a. If we're talking about sinusoids, for example, the effect of the scale factor is very easy to see:

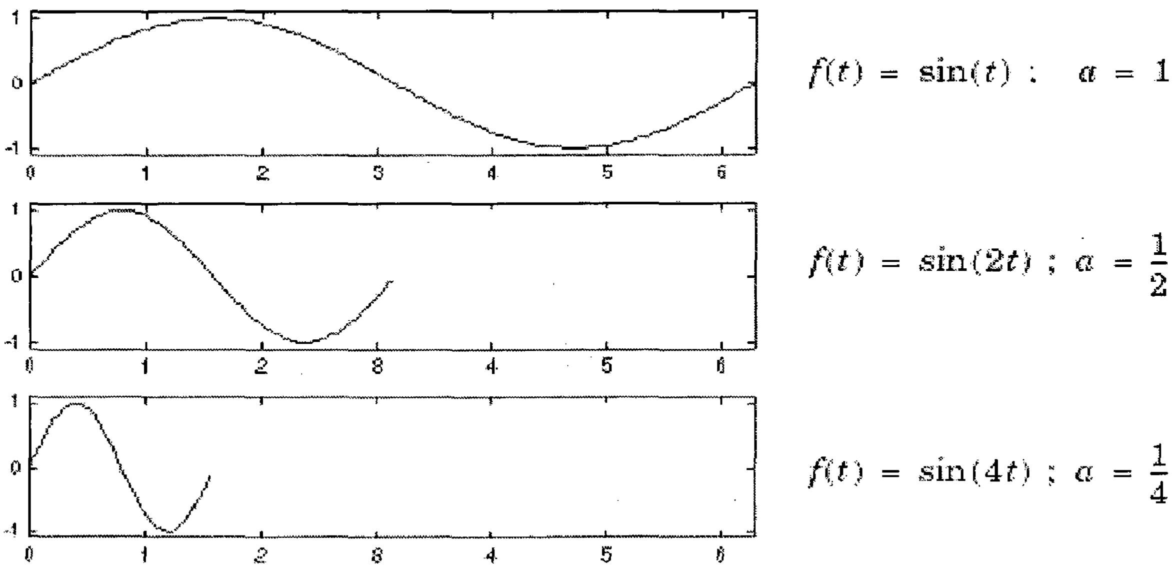
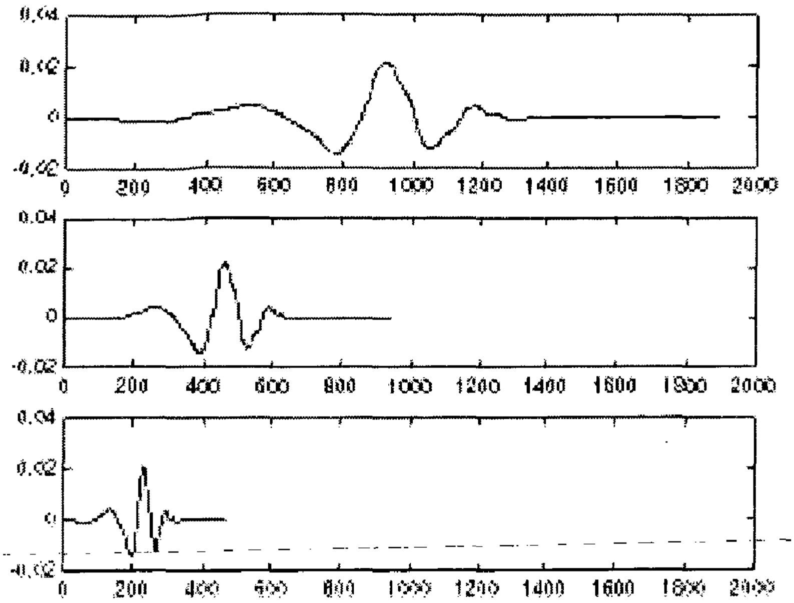


Fig 4.12 Explanation of scaling function of an ordinary wave

The scale factor works exactly the same with wavelets. The smaller the scale factor, the more "compressed" the wavelet.



$$f(t) = \psi(t) \quad ; \quad a = 1$$

$$f(t) = \psi(2t) \quad ; \quad a = \frac{1}{2}$$

$$f(t) = \psi(4t) \quad ; \quad a = \frac{1}{4}$$

Fig 4.13 Explanation of scaling function of a wavelet

It is clear from the diagrams that, for a sinusoid $\sin \omega t$, the scale factor is related (inversely) to the radian frequency ω. Similarly, with wavelet analysis, the scale is related to the frequency of the signal.

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.

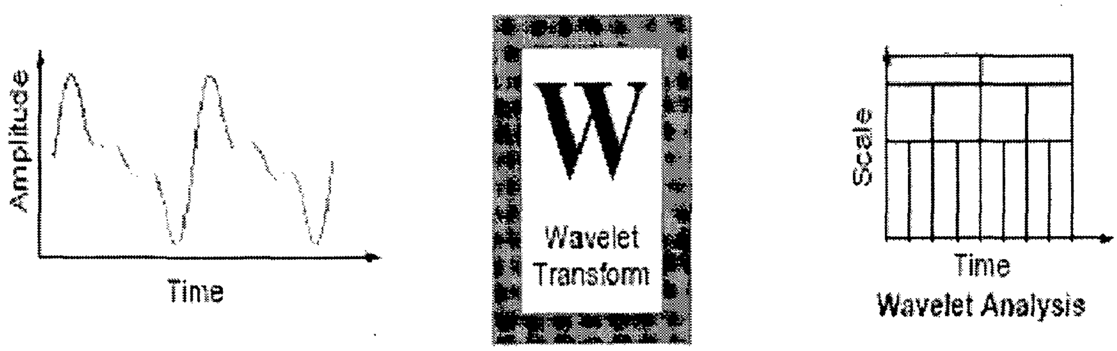


Fig 4.14 Time domain into time-scale domain

You may have noticed that wavelet analysis does not use a time-frequency region, but rather a time-scale region.

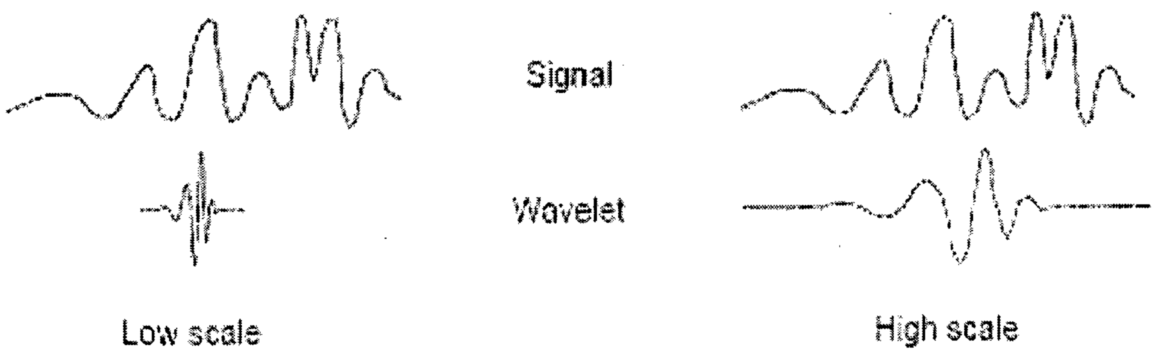


Fig 4.15 Scale-Frequency relation

Thus, there is a correspondence between wavelet scales and frequency as revealed by wavelet analysis:

• Low scale a $\Rightarrow$ compressed wavelet $\Rightarrow$ rapidly changing, details $\Rightarrow$ High Frequency ω

• High scale a $\Rightarrow$ Stretched wavelet $\Rightarrow$ slowly changing, coarse features $\Rightarrow$ Low Frequency ω

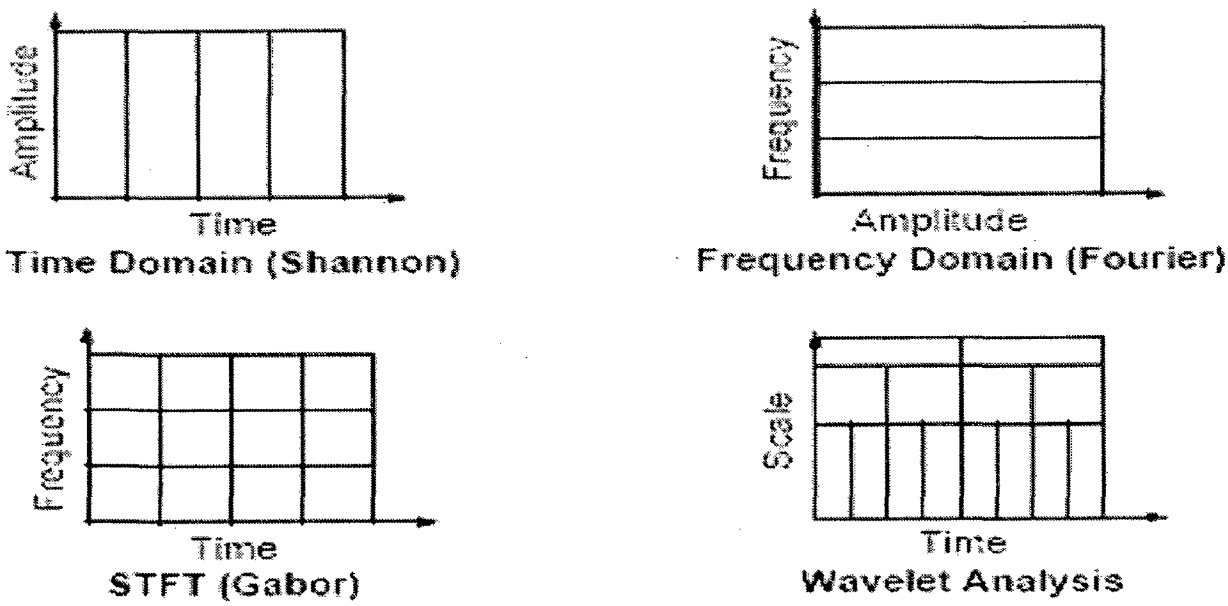


Fig 4.16 over all representation of all the four transformations

4.10 CORRELATION OF DISCRETE- TIME SIGNALS

It is a measure of the degree to which the two signals are similar and thus to extract some information that depends to a large extent on the application [32].

Here are two kinds 1. Cross-correlation

2. Auto-correlation

4.10.1 Cross-correlation: - Suppose that we have two real signal sequences x(n) and y(n) each of which has finite energy. The cross-correlation of x(n) and y(n) is a sequence $r_{xy}(l)$, which is defined as

$$r_{xy}(l)=\sum_{n=-\alpha}^{\alpha}x(n)y(n-l); \quad l=0,\pm1,\pm2,\ldots\ldots \quad 4(s)$$

Or equivalently as

$$r_{xy}(l)=\sum_{n=-\alpha}^{\alpha}x(n+l)y(n) \quad ; l=0,\pm1,\pm2,\ldots\ldots \quad 4(t)$$

l Where

l is the (time) shift (or lap) parameter and the subscripts xy on the cross-correlation sequence $r_{xy}(l)$ indicates the sequences being correlated.

4.10.2 Auto-correlation: - Instead of two signals here we correlate the same signal i.e x(n) . The auto-correlation of x(n) is $r_{xx}(l)$ is

$$r_{xx}(l)=\sum_{n=-\alpha}^{\alpha}x(n)x(n-l) \quad ; l=0,\pm1,\pm2,\ldots\ldots \quad 4(u)$$

In some practical applications, correlation is used to identify periodicities in an observed physical signal which may be corrupted by random interference.
Here in this work auto-correlation is used to eliminate the noise present in the signals.

Specifications of Laboratory motor (induction motor):-

1. 7.5 kw
2. 10 A
3. 415 V
4. 1440 rpm
5. connection Δ
6. bearing type (NBC 6308)
7. Rotor squirrel cage

Table 4.3 The Magnitude of Key Frequencies for the Bearing used in the Test Motor

Bearing Type (NBC 6308),	d_b =15mm,	p_d =65mm,	$n = 7$,	$\beta = 0^0$
Vibration Frequency	f_o	f_i	f_b	f_c
Magnitude (Hz)	64.5	103.4	49.3	9.2

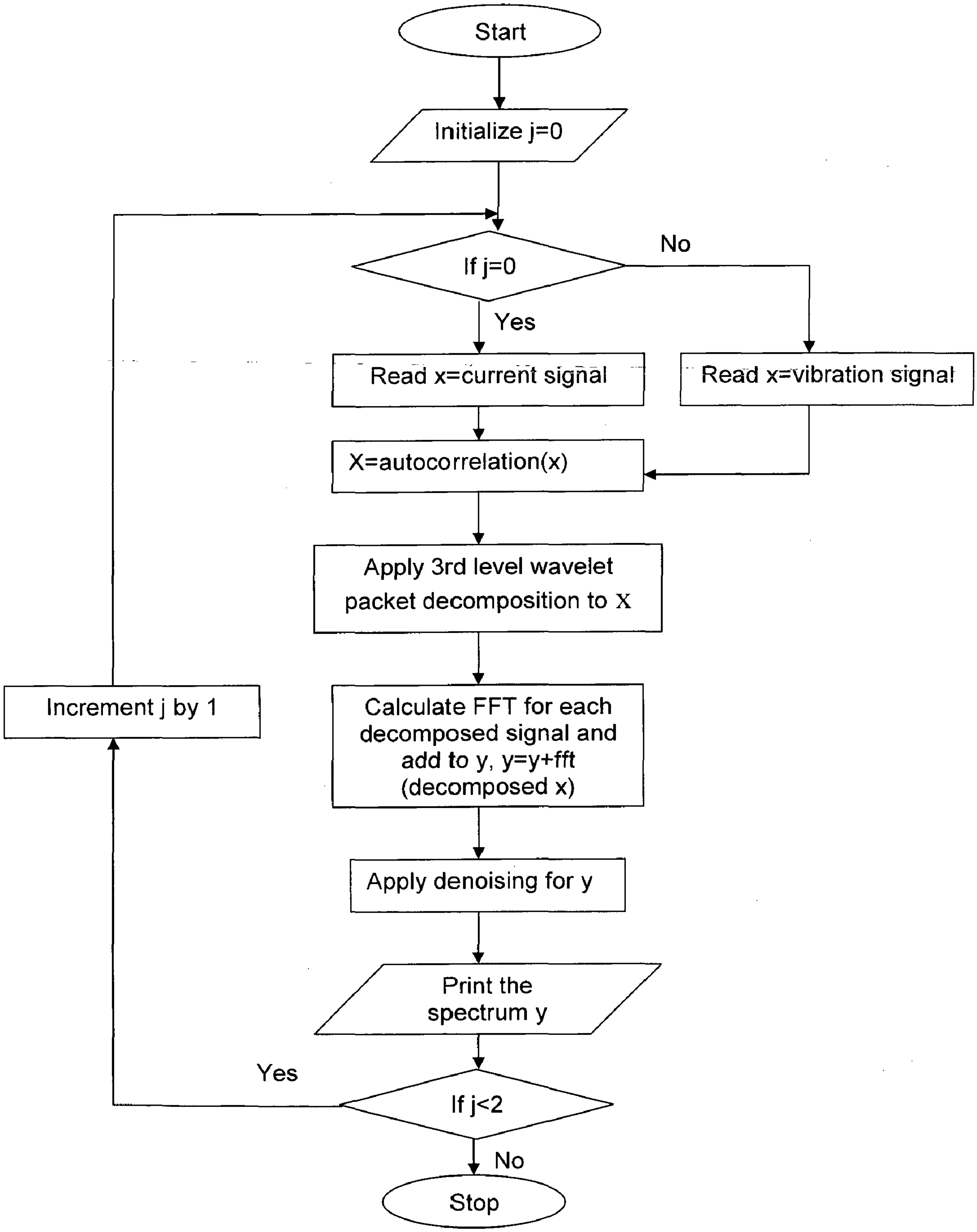
Specifications of the steel rolling mill Motors (Both are Induction Motors)

	Machine 1	Machine 2
1.	400 kw	600 kw
2.	705 A	1057 A
3.	415 V	415 V
4.	738 rpm	742 rpm
5.	connection Δ	connection Δ
6.	bearing type NU 326	bearing type NU 326
7.	rotor slip-ring	rotor slip-ring

Table 4.4 The Magnitude of Key Frequencies for the Bearing used in the Test Motor

Bearing Type (NU 326), d_b =40 mm, p_d =207 mm, $n = 13$, $\beta = 0^0$				
Vibration Frequency	f_o	f_i	f_b	f_c
Magnitude (Hz)	64.3	95.2	30.5	4.9

4.11 FLOW CHART OF THE PROGRAM



4.12 EXPERIMENTAL RESULTS AND COMMENTS ON MOTORS OF STEEL ROLLING MILL

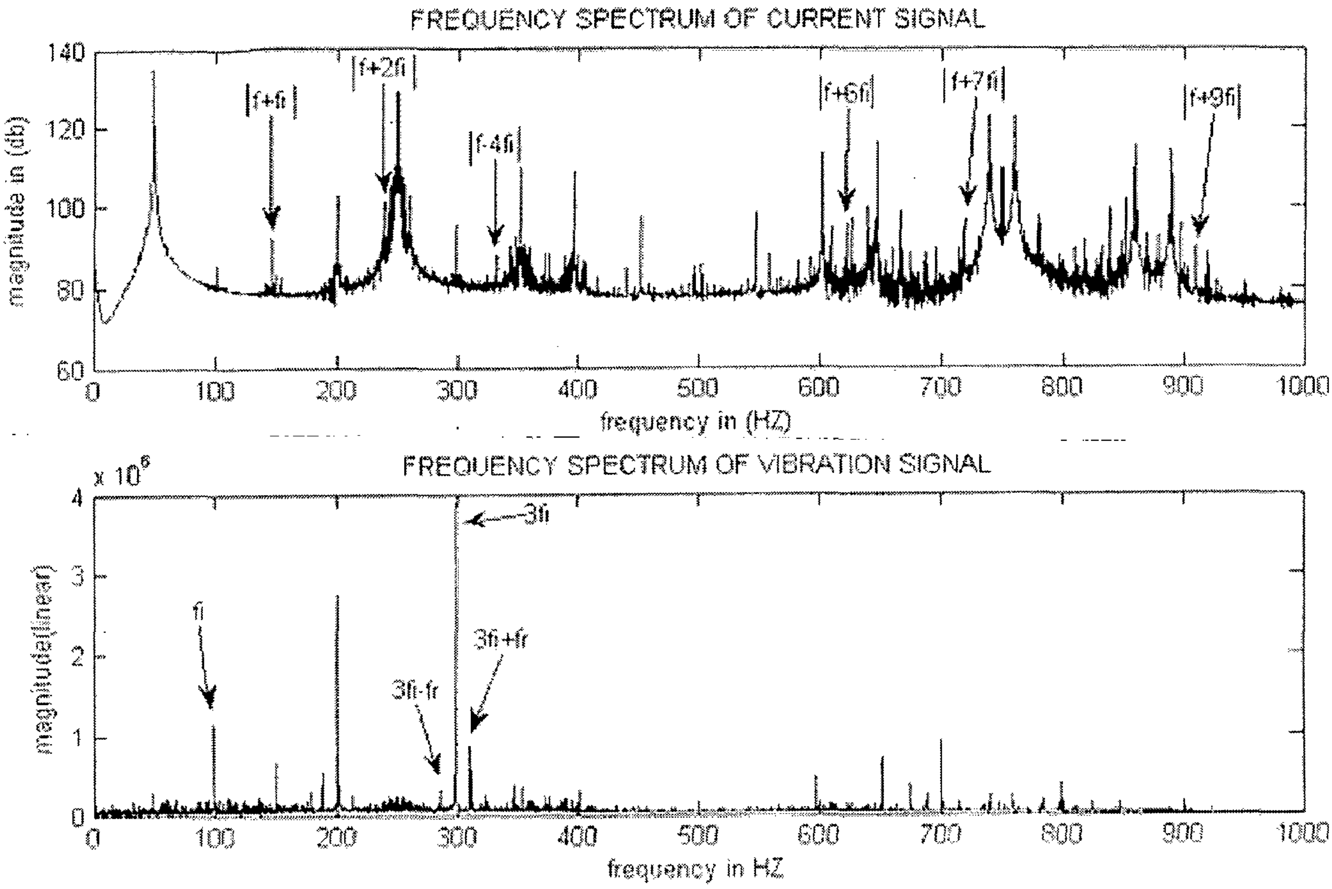


Figure 4.17 Current and Vibration Spectrums of Machine 1(Shaft End Bearing)

Here both the spectrums are clearly showing the inner race (f_i) fault frequencies. In addition to this we can observe the side band components with rotational frequency, which indicates the eccentricity in the alignment of the load and the motor shaft.

Here the signals are sampled at 10000sam/sec. After down sampling, Sampling frequency of the signals are 2000Hz, and are analyzed by using 3rd level wavelet packet decomposition.

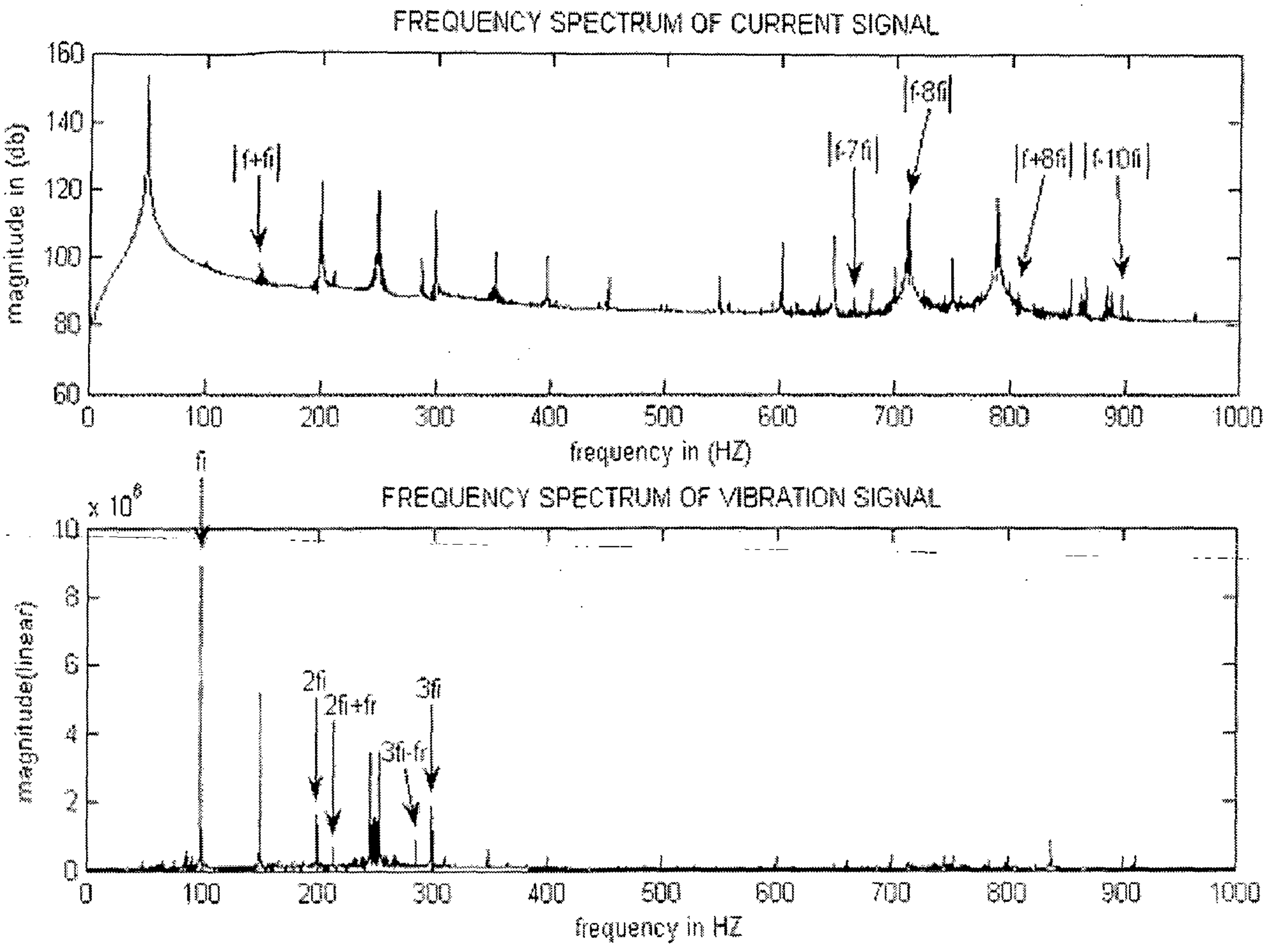


Figure 4.18 Current and Vibration Spectrums of Machine 1(Load End Bearing)

Load end bearing also have the inner race fault (f_i) why because in the vibration spectrum we can observe a great peak at the frequency f_i. This peak indicating the severity of the fault condition. If we observe the current spectrum it is also showing the inner race fault frequencies. But attention should pay to identify these fault frequency components.

Here also the signals are sampled at 10000sam/sec. After down sampling, Sampling frequency of the signals are 2000Hz, and are analyzed by using 3rd level wavelet packet decomposition.

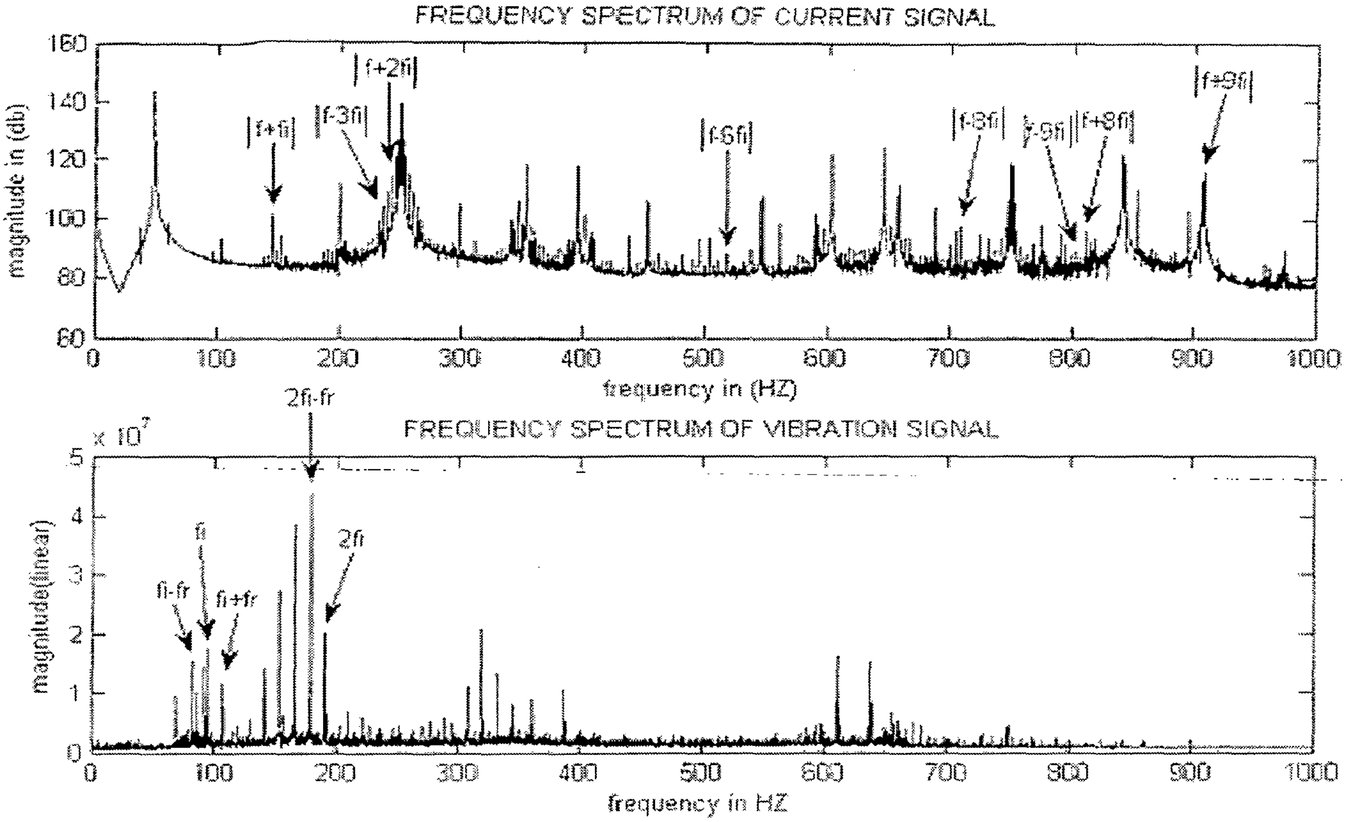


Figure 4.19 Current and Vibration Spectrums of Machine 1(Load Coupling Bearing)

Both current and vibration spectrums are showing inner race (f_i) frequency components, in addition to that both are showing small degree of unbalance between stator to rotor alignment that's why we can observe rotational frequency components as side band to f_i, as well as to the supply frequency f of the current signal.

Here also the signals are sampled at 10000sam/sec. After down sampling, Sampling frequency of the signals are 2000Hz, and are analyzed by using 3rd level wavelet packet decomposition

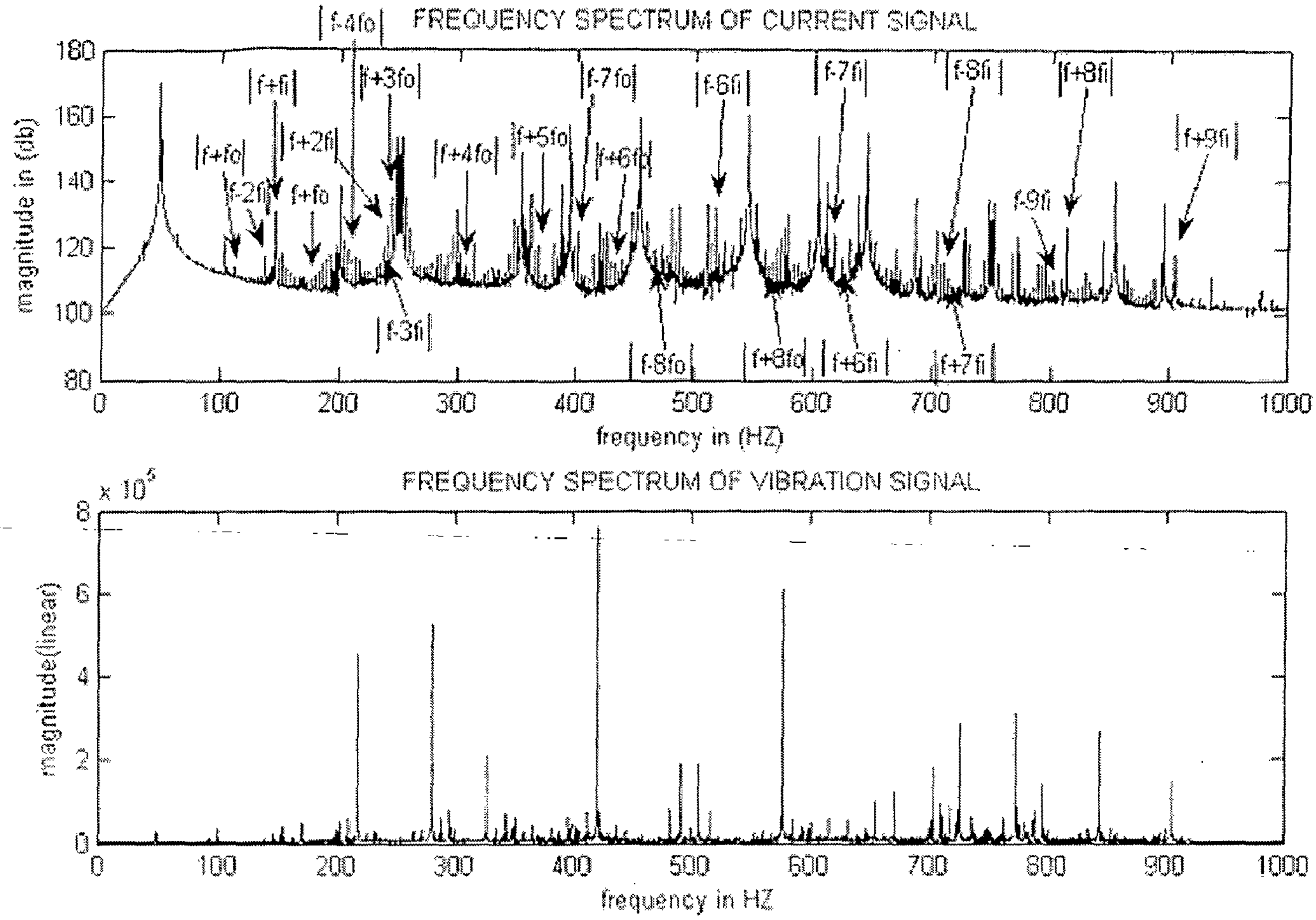


Figure 4.20 Current and Vibration Spectrums of Machine 2 (Shaft End Bearing)

Here current spectrum is showing both inner (f_i) and outer race (f_o) fault frequency components. But vibration spectrum is not showing either of these faults. And one important observation is that the peaks of inner race fault components are higher than to outer race components in the current spectrum.

One important conclusion from this spectrum, we can't say exactly in which bearing the fault occurred but we can say whether the fault is present or not in the bearings of the machine by using this current spectrum, but by using the vibration spectrum we can say on which bearing the fault is present. Why because we place the sensor directly on the location itself.

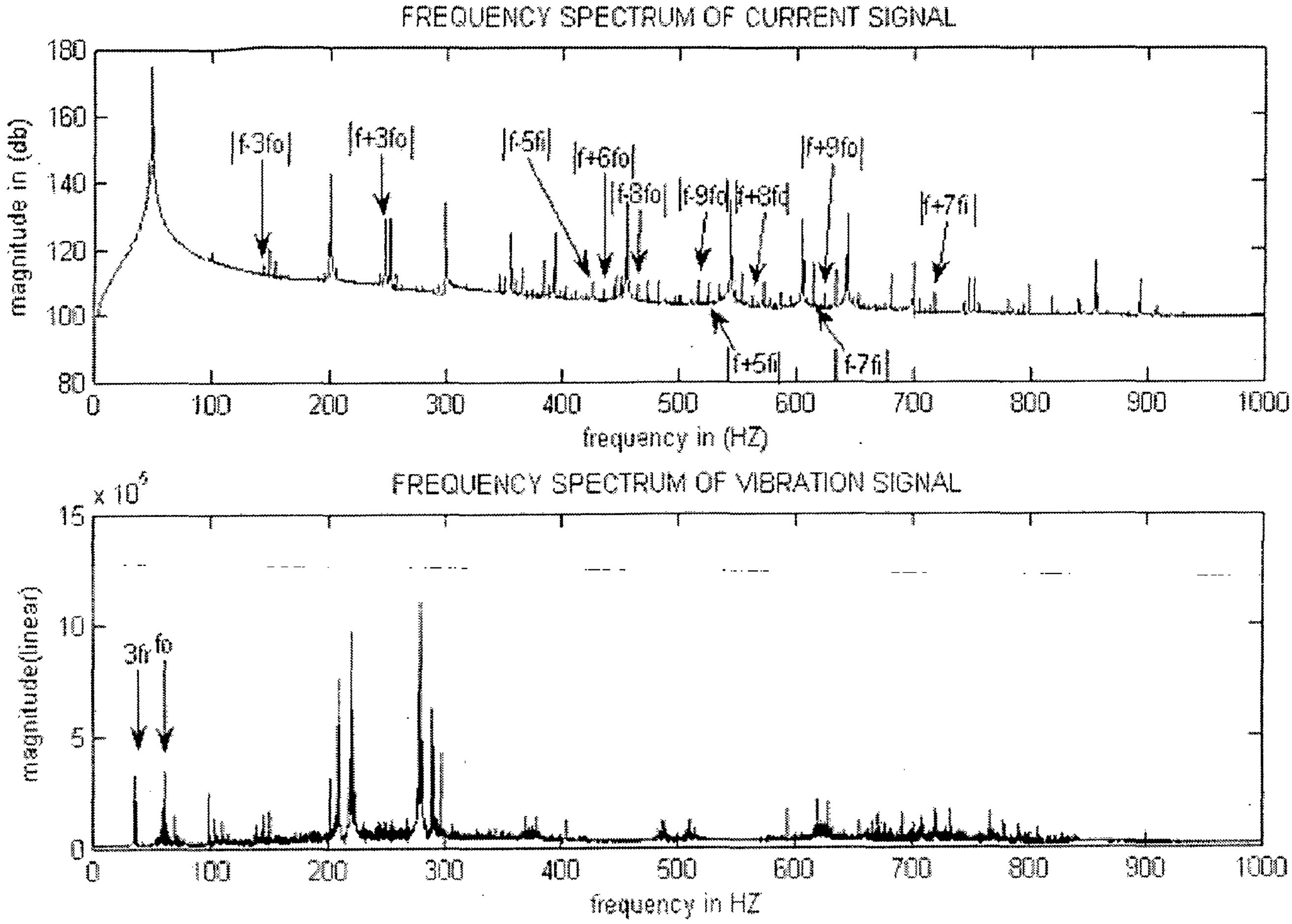


Figure 4.21 Current and Vibration Spectrums of Machine 2 (Load End Bearing)

Here vibration spectrum is clearly showing the outer race fault frequency component (f_o). In addition to that it is also showing the multiples of the rotational frequency component ($3fr$).

But here in current spectrum we can observe both inner and outer race fault frequency components. Why this current spectrum showing the both faults? this is because load end bearing has outer race fault and the load coupling bearing has the inner race fault.

Here also the signals are sampled at 10000sam/sec. After down sampling, Sampling frequency of the signals are 2000Hz, and are analyzed by using 3rd level wavelet packet decomposition.

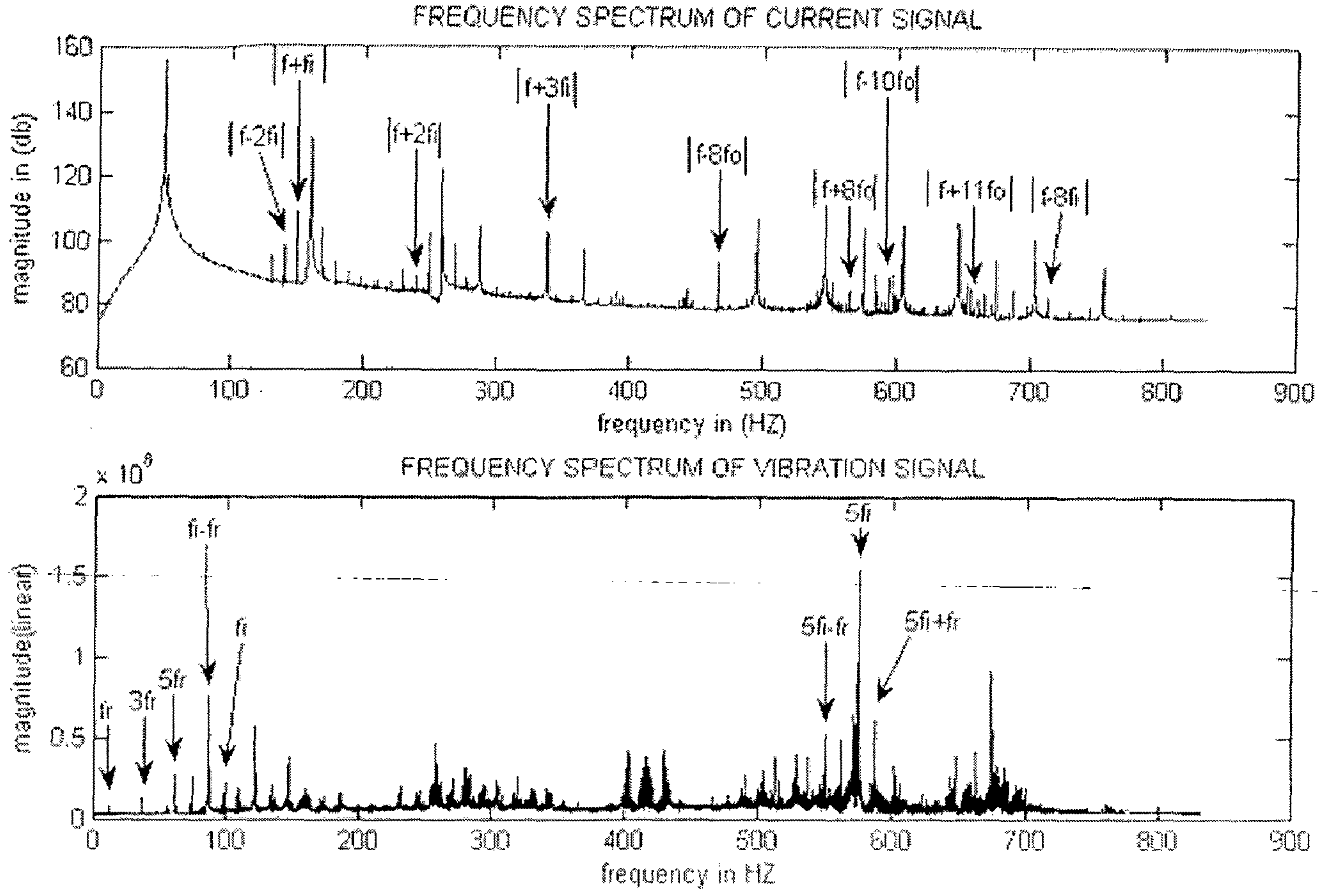


Figure 4.21 Current and Vibration Spectrums of Machine 2 (Load Coupling Bearing)

Here both current and vibration spectrums are showing inner race fault components. In vibration spectrum we can observe multiples of the rotational frequency component as well as multiples of the fault components.

In current spectrum we can observe the outer race fault components this is because of the load end bearing fault.

Here also the signals are sampled at 10000sam/sec. After down sampling, Sampling frequency of the signals are 1666 Hz, and are analyzed by using 3rd level wavelet packet decomposition.

4.13 EXPERIMENTAL RESULTS AND COMMENTS ON LABORARORY MACHINES

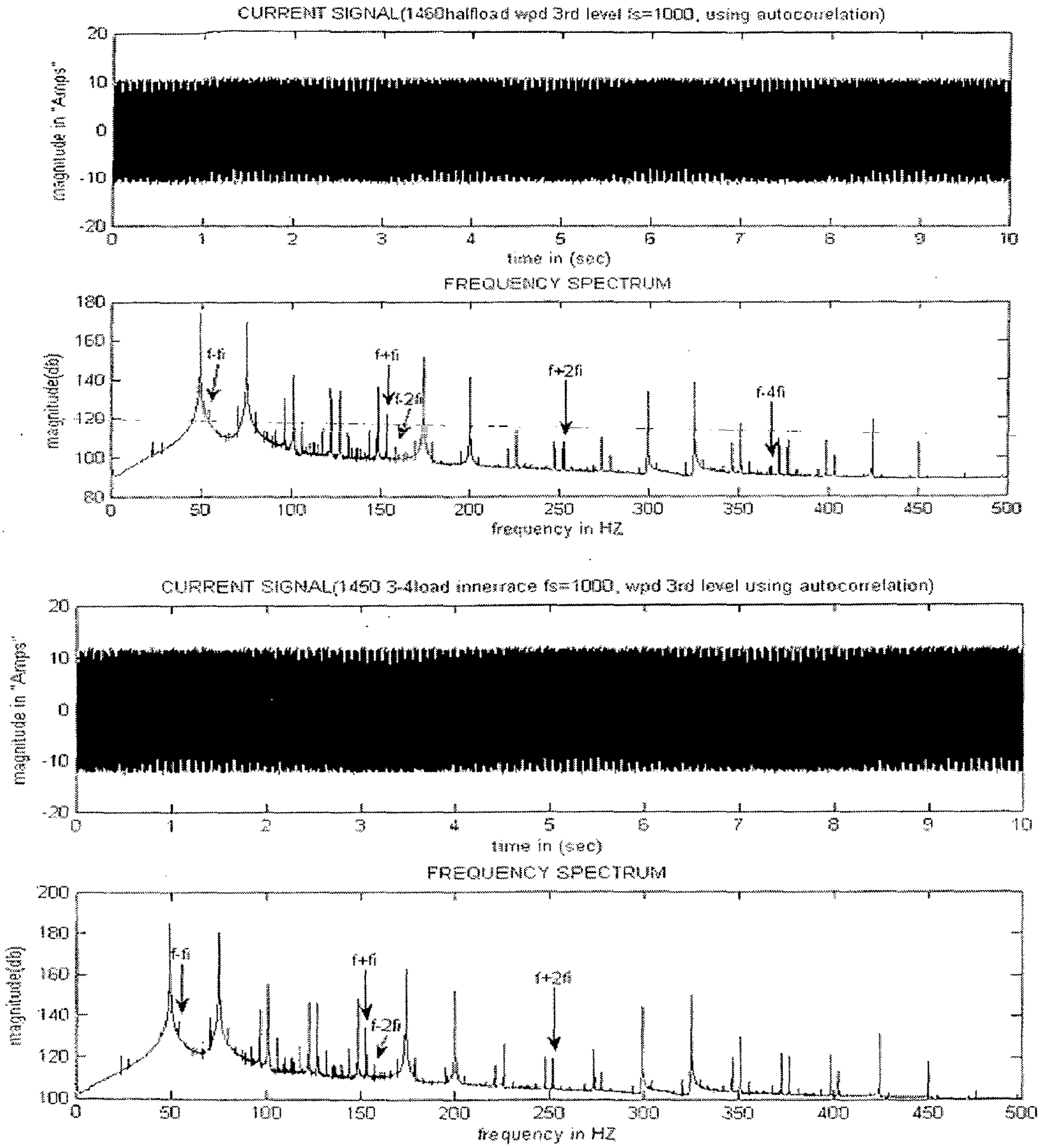


Figure 4.22 current spectrums at two different load conditions (above on at half load and below one is at 3-4 load)

Both the spectrums are showing inner race fault components. Only the magnitudes have been changed at two different loads but the same components are present in the two cases.

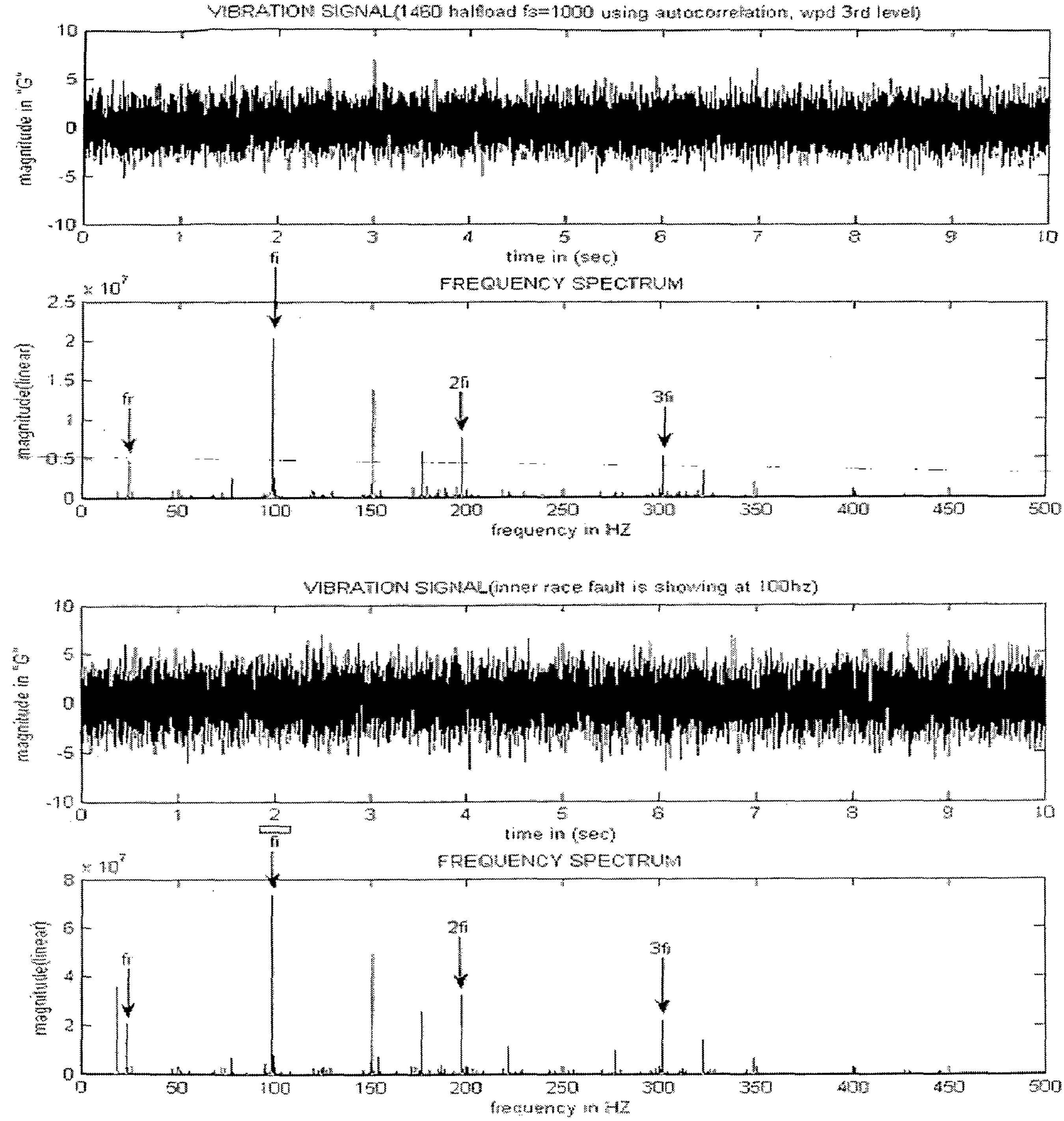
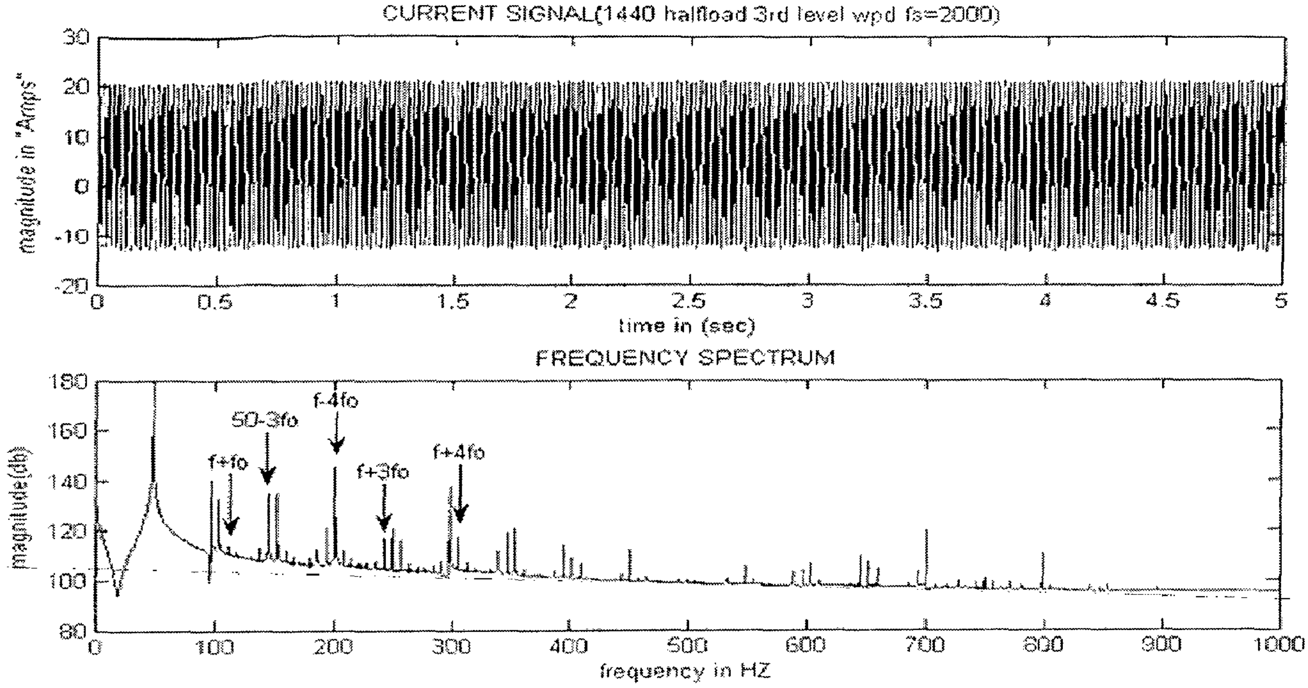


Figure 4.23 vibration spectrums at two different load conditions (above on at half load and below one is at 3-4 load)

Vibration spectrum on both load conditions showing inner race fault components, only difference is on the magnitude of the spectrum peaks on higher loads its strength is high. Here we can observe multiples of fault components. The signal is acquired at the rate of 1000 sap/sec.



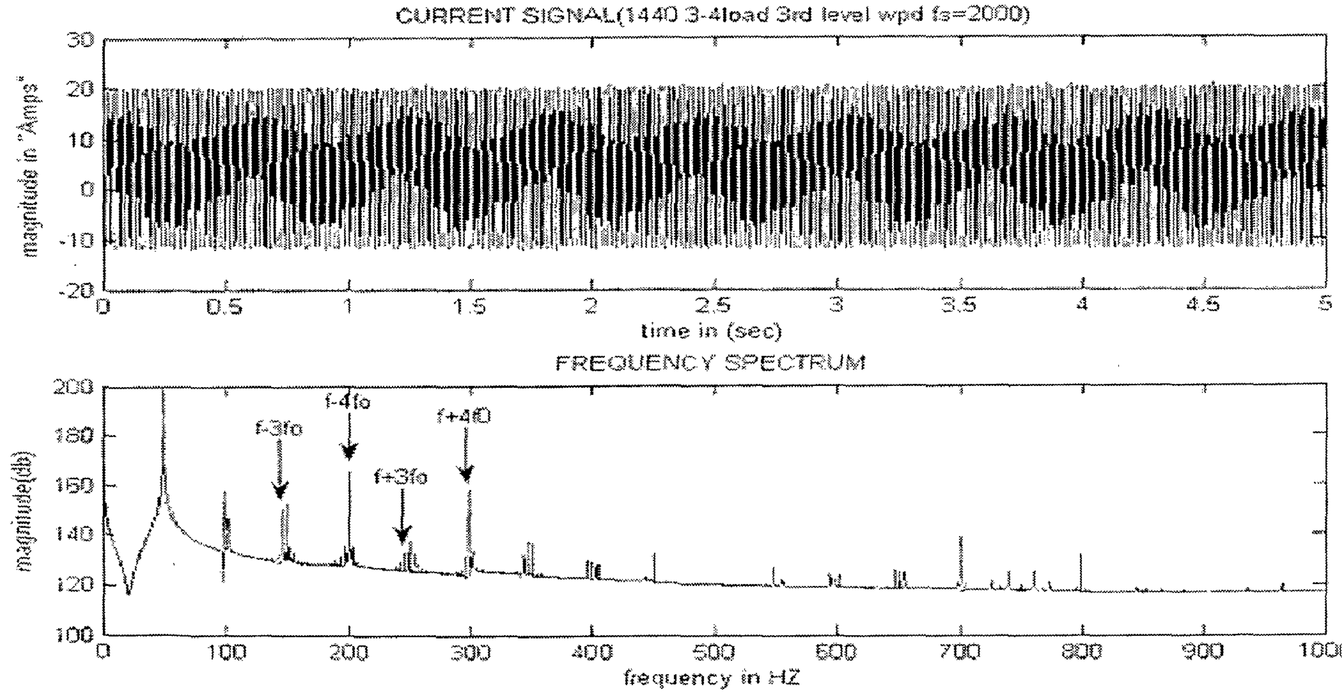


Figure 4.24 current spectrums at two different load conditions (above on at half load and below one is at 3-4 load)

There are no changes in the two spectrums and are showing outer race components at two different loads but only some extra components are added at lower load.

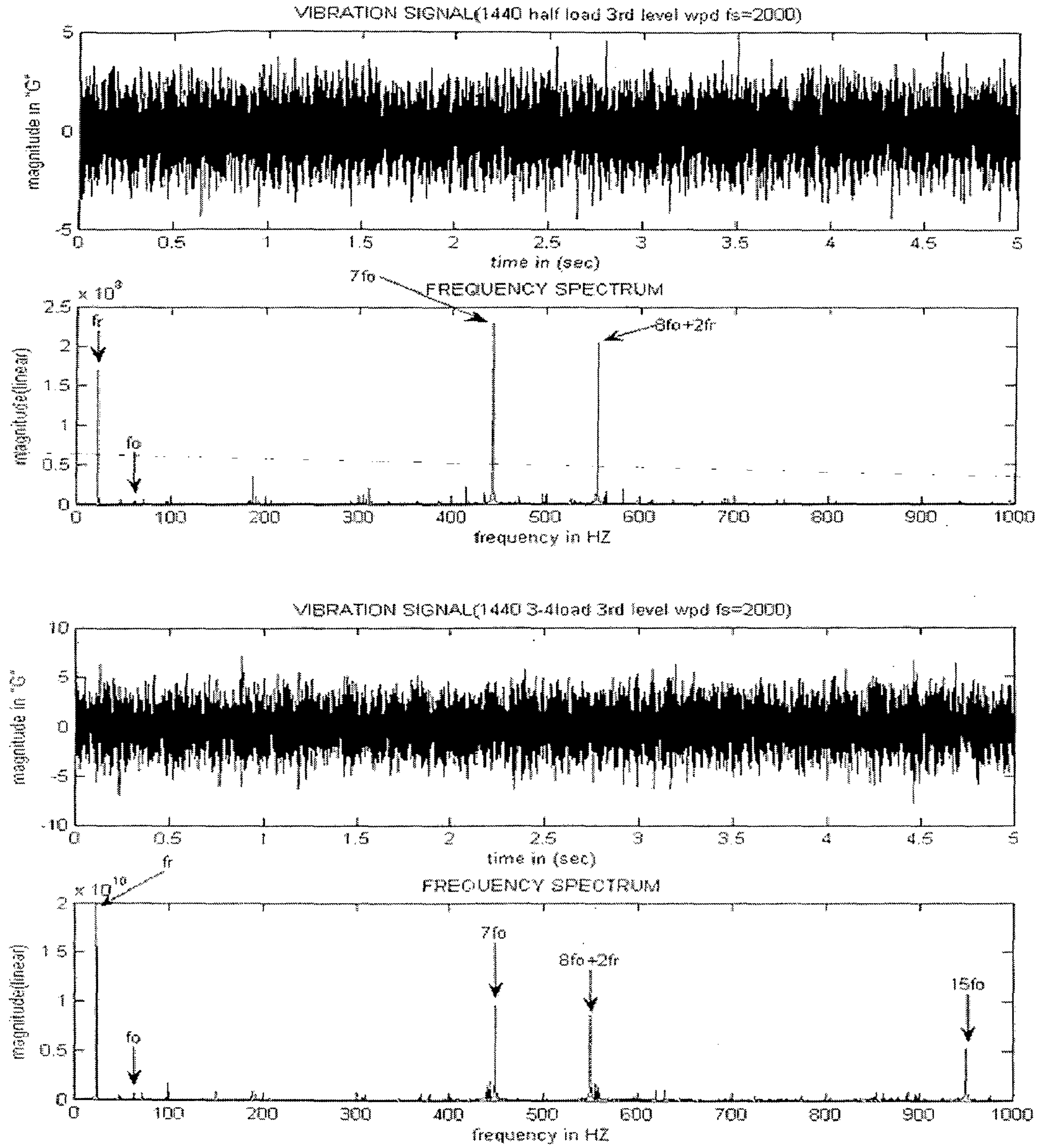


Figure 4.25 vibration spectrums at two different load conditions (above on at half load and below one is at 3-4 load)

Here both spectrums are showing outer race fault components but the severity of the fault is very less that's why these are showing small peaks. Here the signal is collected at 2000sam/sec. And we can observe strong peak at rotational frequency

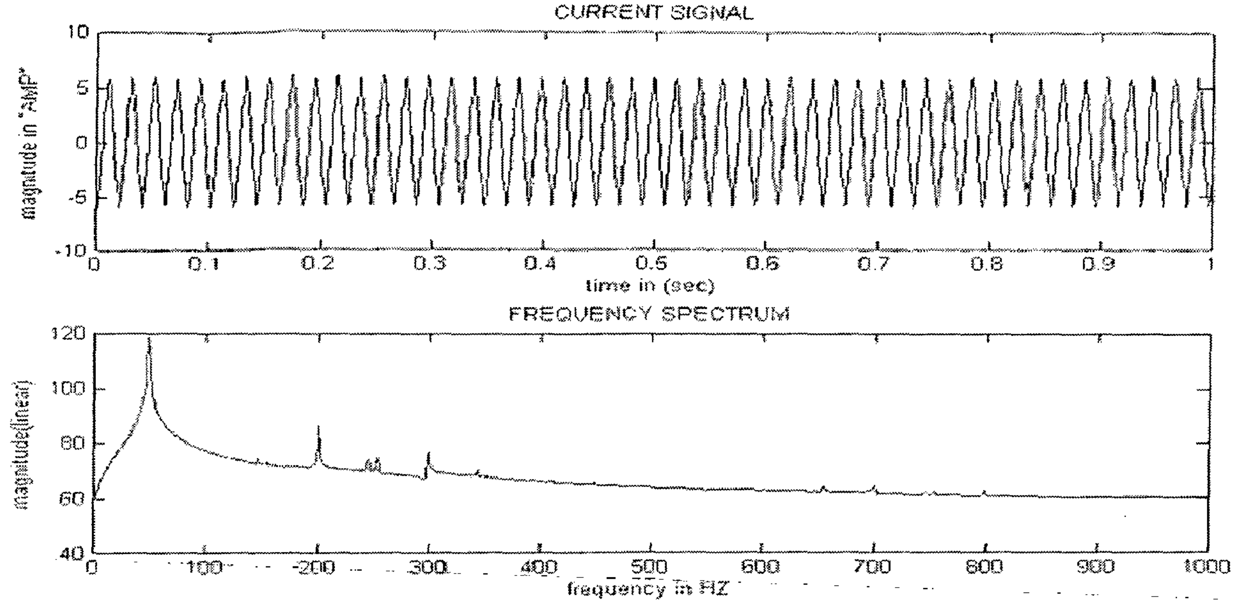


Figure 4.26 current spectrum of healthy bearing

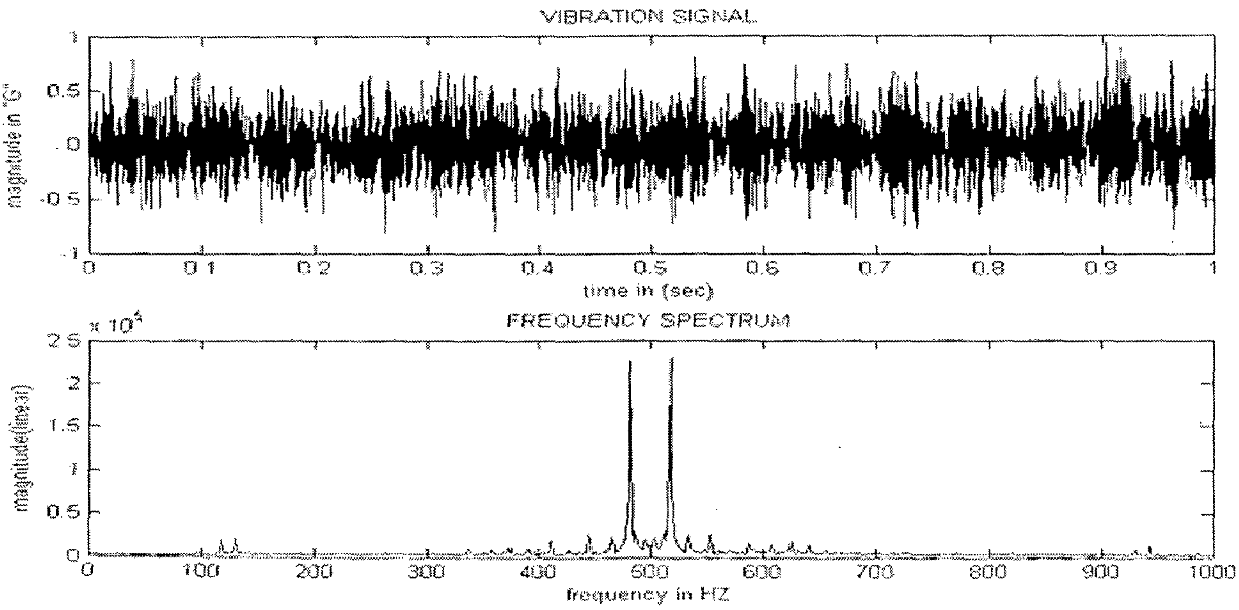


Figure 4.27 vibration spectrum of healthy bearing

Both the above figures are showing nothing regarding fault, so the bearing is the healthy one.

4.14 CONCLUSIONS

The main aim of the work in this thesis is condition monitoring of the induction motors (both lab and steel industry motors). Changes in various frequency components are observed to detect various faults of motor roller bearing. Both current and vibration signals are used in this work for analysis. It is observed that the magnitude of the frequency components are varied on different load conditions, but the same frequency components are always present irrespective of the load. As compared to vibration spectrum current spectrum needs more attention to identify the fault frequencies.

One major observation is we can not say exactly in which bearing the fault occurred by using the current spectrum analysis, but we can tell the fault in the bearing is present or not by using this current spectrum. We can say exactly in which bearing the fault is present by using vibration signal analysis, why because we directly place the transducer on the location itself.

SUGGESTIONS FOR FUTURE WORK

The area of condition monitoring is wide and include in many topics. It is suggested to make some improvement in the present monitoring system by use of the following.

1. Perform the condition monitoring of induction motors (both lab and steel industry machines) by using the parameters such as voltage, sound and temperature and correlate them to current, vibration parameter results.

2. Use multiwavelets instead of using one fixed function to translate and dilate for making basis functions i.e. use a finite number of wavelet functions [39].

3. Instead of doing on-line analysis try to implement continuous condition monitoring of induction motor.

4. Employ expert system for fault diagnosis of induction motor using rule based weight obtained from neural network. This combination of ANN and expert knowledge may enhance the monitoring system for diagnosis

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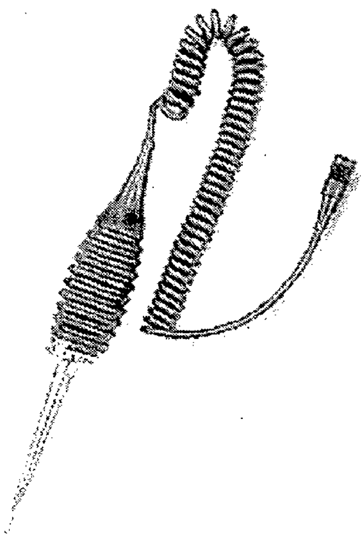
APPENDIX A-1

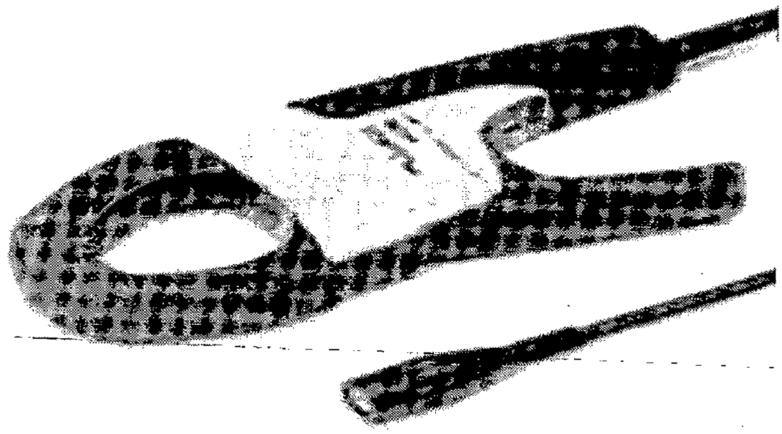
Vibration pick-up: PU series **PU-601R**



Form	Holdings	Attaching screw	M6×6L
Feature	General purpose	Case material	Hard rubber
Response to voltage	5.1mV/(m/s2) (50mV/G)	Attachment cable	Cirque cord/code
Frequency range (±3dB)	5~5,000Hz (screw stop)	Cable length	1m
Maximum measurement acceleration	490m/s2 (50G)	Cable protection (Option)	
Maximum approved acceleration	9,800m/s2 (1000G)	Pre-amp	Built-in
Resonance frequency	Above 25kHz (screw stop)	Insulation	Case iso rate
Operating temperature limit	-10～60℃	Mass	170g

APPENDIX A-2

Fluke i400s High safety AC current clamp with BNC output



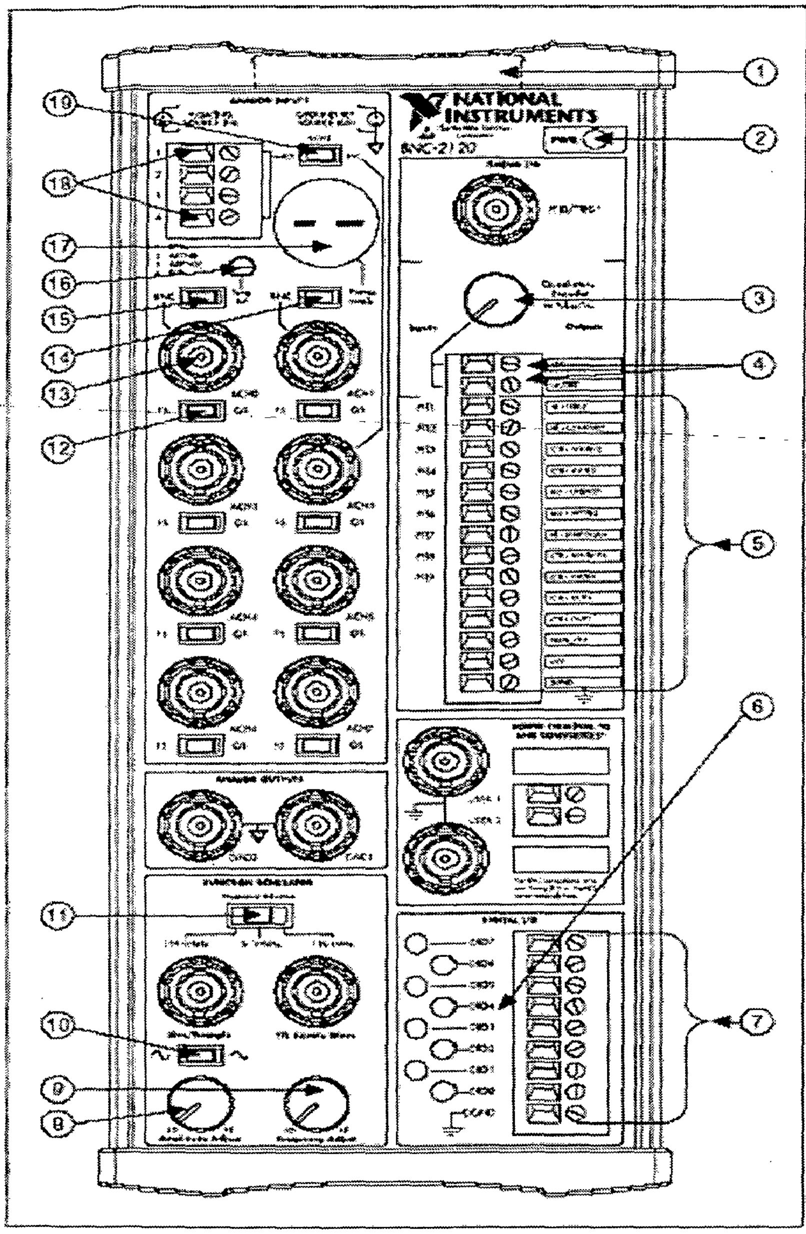
Specifications		
Nominal current range:	40 A Range 400 A Range	0.5 A to 40 A 5 A to 400 A
Basic accuracy:	40 A Range 400 A Range	2% + 0.015 A (45-400 Hz) 2% + 0.04 A (45-400 Hz)
Typical Bandwidth:	40 A Range 400 A Range	5 Hz - 10 kHz 5 Hz - 10 kHz
Output level(s):	40 A Range 400 A Range	10 mV/A 1 mV/A

Safety Specifications	
Safety	CAT IV 600 V, CAT III, 1000 V
Maximum Non-Destructive Current	1000 V AC

FEATURES

- Companion to our scope or power quality meter to measure up to 400 A AC.
- Only current clamp available with a CAT IV 600 V / CAT III 1000 V safety rating. Specially designed to offer maximum utility in a compact shape.
- Take accurate current readings without breaking the circuit.
- Soft non-slippery over mold handle, Max. conductor Ø 32 mm
- Optional PM9081/001 BNC/Banana adapter for DMM's.
- Two ranges: 40 A & 400 A, 10 or 100 mV/Amp output.

APPENDIX A-3



1 68-Position I/O Connector
2 Power LED Indicator
3 Quadrature Encoder Knob
4 Quadrature Encoder Output Screw Terminals
5 TIO Screw Terminals
6 DIO LED State Indicators
7 DIO Screw Terminals
8 Function Generator Amplitude Adjust Knob
9 Function Generator Frequency Adjust Knob
10 Sine/Triangle Waveform Selection Switch
11 Frequency Range Selection Switch
12 Floating Source (FS)/ Ground-Referenced Source (GS) Switch
13 BNC Connector
14 BNC/Thermocouple Selection Switch
15 BNC/Temperature Reference Selection Switch
16 Temperature Reference
17 Thermocouple Input Connector
18 Resistor Measurement Screw Terminals
19 Resistor/BNC Selection Switch

BNC 2120 FRONT PANNEL

Specifications

This section lists the specifications of the BNC-2120. These specifications are typical at 25 ° C unless otherwise specified.

Analog Input

Number of channels (default) ....Eight differential
Field connections (default) ....Eight BNC connectors
Protection...No additional protection provided.

Optional connections
Thermocouple ....Uncompensated miniature connector, mates with 2-prong or sub-miniature connector
Resistor ....Two screw terminals
Resistor measurement range .... 100 Ω to 1 MΩ
Resistor measurement error ≤5%

Power Requirement

+5 VDC (±5%)..................................... 200 mA, sourced from the E Series device

Power available
at +5 V screw terminal .... E Series power, less power consumed at +5 VDC (±5%)

Environment

Operating temperature........................... 0 to 50 ° C
Storage temperature .... –55 to 125 ° C
Relative humidity................................. 5 to 90% noncondensing

SPECIFICATIONS

Analog Input

Number of channels .... 16 single-ended or 8 differential (software-selectable per channe)

Type of ADC.. Successive approximation

Resolution .... 12 bits, 1 in 4,096

Sampling rate .... 200 kS/s guaranteed

Input signal ranges .... Bipolar only

Input coupling ....DC

Max working voltage
(Signal + common mode) .... Each input should remain within ±11 V of ground

Analog Output Characteristics

Number of channels...................................2 voltage

Resolution..12 bits, 1 in 4,096

Max update rate

DMA...10 kHz, system dependent

Interrupts..1 kHz, system dependent

Type of DAC ....Double buffered, multiplying

Digital I/O

Number of channels

6025E.. 32 input/output

6023E and 6024E...................................... 8 input/output

Compatibility .... TTL/CMOS

Digital logic levels

Input low voltage: min 0v max 0.8v

Input high voltage: min 2v max 5v

Input low current (Vin= 0 V) : min (-) max -320μA

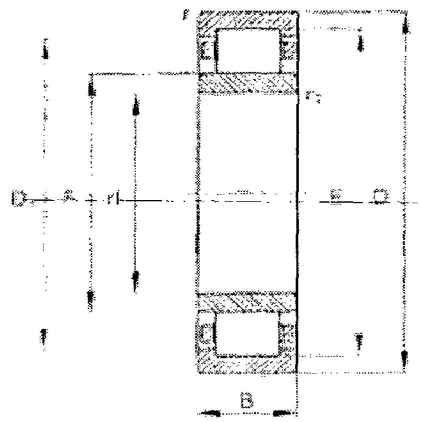
Input high current (Vin= 5 V) :min(-) max 10 μA

Power-on state ....Input (High-Z), 50 kΩ pull up to +5 VDC

Data transfers ....Programmed I/O

FAG Cylindrical roller bearings NU326-E-TVP2

main dimensions to DIN 5412-1, non-locating bearing, can be dismantled, with cage



d	130	mm	
D	280	mm	
B	58	mm	
D_1	235,2	mm	
$D_{a\ max}$	263	mm	
$d_{a\ max}$	164	mm	
$d_{a\ min}$	147	mm	
$d_{b\ min}$	169	mm	
E	247	mm	
F	167	mm	
$r_{1\ min}$	4	mm	
$r_{a\ max}$	3	mm	
$r_{a1\ max}$	3	mm	
r_{min}	4	mm	
s	3,5	mm	Axial displacement facility from central positio
m	16,2	kg	Mass
C_r	680000	N	Basic dynamic load rating, radial
C_{0r}	670000	N	Basic static load rating, radial
n_G	2600	1/min	Limiting speed
n_B	2400	1/min	Reference speed
C_{ur}	79000	N	Fatigue limit load, radial