DETECTION OF BEARING FAULTS IN INDUCTION MOTOR ELECTRICAL ENGINEERING

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A PROJECT REPORT ON

DETECTION OF
BEARING FAULTS IN INDUCTION MOTOR

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THE REQUIRMENT FOR THE DEGREE OF

BACHELOR OF TECHNOLOGY

In

ELECTRICAL ENGINEERING

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CERTIFICATE

It is hereby certified that the project entitled "ANALYSIS OF TECHNIQUES TO DETECT BEARING FAULTS IN INDUCTION MOTOR" is the original work carried out by students under my supervision and guidance. This report has been prepared and submitted by:

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In the partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Electrical Engineering at Faculty of Engineering, Dayalbagh Educational Institute, Agra.

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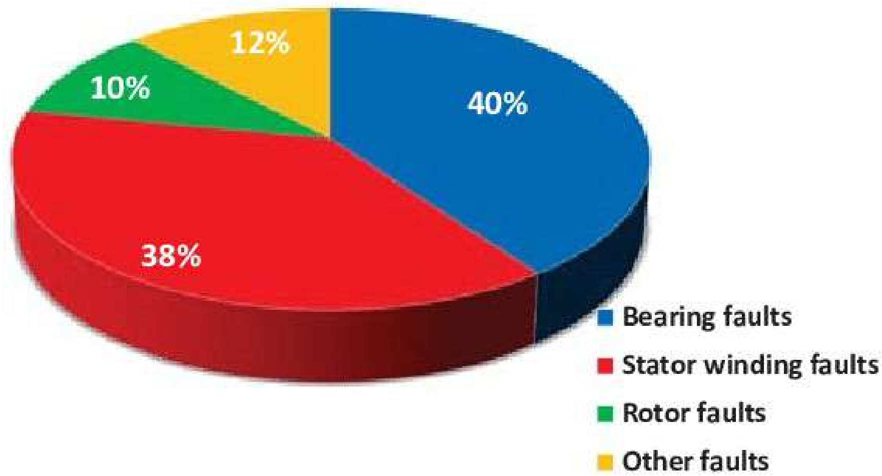
LITERATURE SURVEY

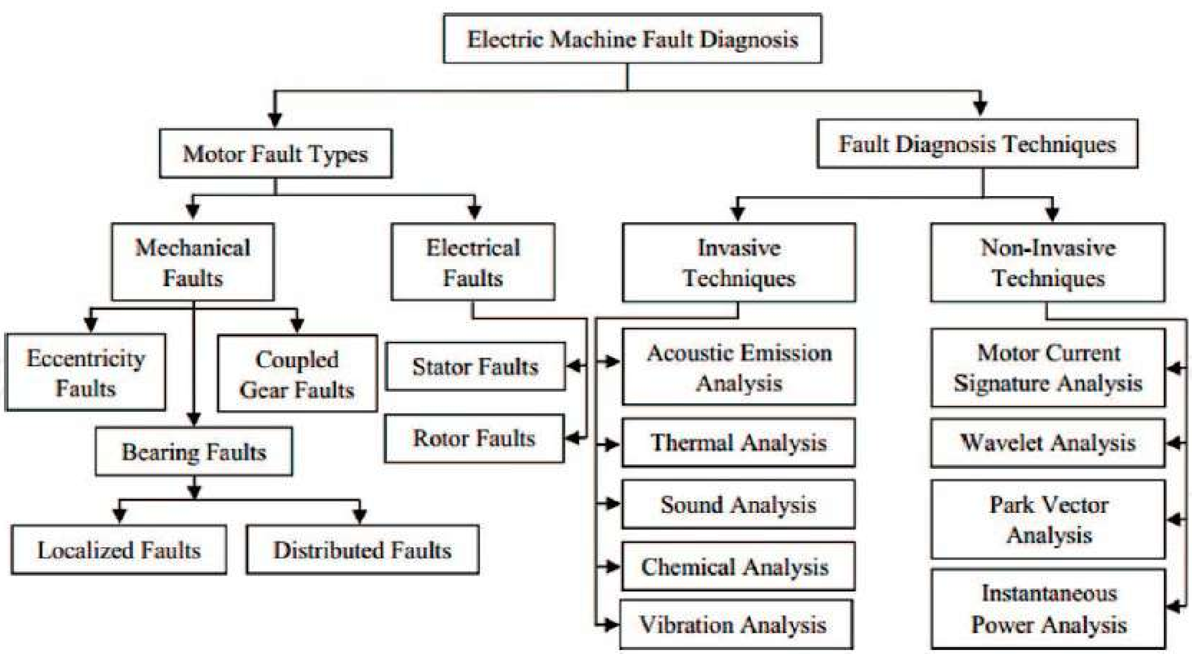
EPRI- ELECTRIC POWER RESEARCH INSTITUTE

In Industries about 90% of the machines are induction motor. And as per most of the survey bearing faults are the most occurring faults about 40 %(EPRI Survey Report) in AC machines in Industries. Bearing is a complex system which consist of two rings and a set of rolling elements running in the track between the rings. These rolling elements may be balls, cylindrical rollers, tapered rollers, needles, or barrel rollers, encased in a cage that provides equal spacing and prevents internal strikes.



The bearing signal is usually non-stationary in nature due to the slippage occurring between the mating components (e.g., rolling elements and ring raceways). Each bearing rotary component generates vibratory signals, and each component can experience damage. Bearing defects can be categorized into distributed and localized faults [2]. Typical distributed bearing defects include surface roughness, waviness, misaligned races, and off-size rolling elements, which are usually caused by design and manufacturing errors, improper mounting, wear, and corrosion. Localized bearing defects include cracks, pits, and spalls on the rolling surfaces, which are usually caused by plastic deformation, brinelling, and material fatigue. Both distributed and localized bearing faults increase the noise and vibration levels, and can cause machinery malfunction. From the health condition monitoring standpoint, localized bearing fault diagnostics are more important, because the spalling of races or rolling elements is the dominant style of the failure of rolling element bearings in real-world applications, and also many distributed faults originate from localized spallings. Bearing condition monitoring usually involves two sequential processes: feature extraction and fault diagnosis. Feature extraction is a process in which health condition related features are extracted by approximate signal processing techniques, whereas fault diagnosis is a decision-making process to estimate bearing health conditions based on the extracted representative features. Therefore, feature extraction plays the key role for bearing health condition monitoring, whereas non-robust features may lead to false alarms (i.e., an alarm is triggered by some noise instead of a real bearing fault) or missed alarms (i.e., the monitoring tool cannot recognize the existence of a bearing defect) in diagnostic operations. A number of are available for bearing fault detection. Based on the type of signals, they can be classified into acoustic signal analysis, temperature measurement, lubricant analysis, electrical current analysis, and vibration measurement, motor current signature analysis, sound analysis. An effective acoustic-based bearing health monitoring is acoustic emission, which is a phenomenon of transient elastic wave generation due to a rapid release of strain energy caused by a structural alteration in a solid material under mechanical and/or thermal stresses. Generation and propagation of cracks are among the primary sources of acoustic emission, and hence this technique can be used as a tool for the bearing fault detection. High bearing temperature is another reason for bearing failure, and bearing temperature should not exceed certain levels at rated conditions; therefore, monitoring the temperature of a bearing housing or lubricant provides another method for fault detection in rotary machines. In wear debris analysis, the presence of metallic particles in the lubricant can be detected by appropriate sensors. Furthermore, the analysis of the different metallic elements in the lubricant may facilitate the recognition of the locations of bearing faults. The health conditions of a machine may also be monitored by investigating the spectrum of the motor current. Usually, the changes in the electric signals are associated with the changes in the mechanical components of the machine; therefore, bearing faults can be detected via motor current analysis by using appropriate signal processing techniques. Bearing act as a source of vibration due to either varying compliance or the presence of defects in it, and vibration analysis is believed to be the most widely used approach in industries for machine fault diagnosis.

In the literature, BF has been studied, and researches proposed techniques to detect it. In one hand, techniques as Vibration Signals Analysis, Thermography Images Analysis, Motor Voltage Analysis, or MCSA have accomplished to detect this fault. In the other hand, spectral analysis as Fourier Transform (FT), Wavelet Transform, or techniques as Empirical Mode Decomposition (in occasions used at the same time) have demonstrated to be a good



The structure representing various motor faults and fault diagnosis techniques.

approach to extract the features from signals for later processing. As demands on running accuracy and speed are increased, dynamic analysis of roller bearings are becoming more and more important. Roller bearings have attracted substantial attention because of their nonlinearity effects due to the Hertzian force deformation relationship, radial clearance. Condition monitoring and fault diagnosis of induction motors based on the vibration analysis technique are widely used in modern industry. Accuracy of the machinery diagnosis made using vibration analysis depends on the ability to correctly analyze vibration data, especially frequency spectra. The temperature sensing for bearing cage temperature is based on thermal-induced shift in resonant frequency of an inductive coil and a temperature-sensitive capacitor mounted on a bearing cage. This shift is detected remotely by placing an interrogator coil in close proximity to the sensor coil and the bearing cage. Bearing cage vibrations result in change in the coupling factor between the sensor and interrogator coils along the bearing's axial direction. This leads to amplitude modulation of excitation frequency by a signal proportional to bearing cage vibration. In this article the author present bearing cage temperature is measured for different rpm. The corresponding vibration frequencies at each speed are measured and compared with theoretical values calculated using standard bearing frequency equations. A good agreement between measurement and theory is observed for various vibration components such as ball spin, fundamental train and ball pass-outer race frequencies with average variation of 2.8%.

INTRODUCTION TO BEARING

Bearings are mechanical assemblies that consist of rolling elements and usually inner and outer races which are used for rotating or linear shaft applications, and there are several different types of bearings, including ball and roller bearings, linear bearings, as well as mounted versions that may use either rolling element bearings or plain bearings. Ball bearings have spherical rolling elements and are used for lower load applications, while roller bearings use cylindrical rolling elements for heavier load carrying requirements. Linear bearings are used for linear movements along shafts and may also have rotational capabilities. Mounted bearings are assemblies in which the bearings are pre-assembled in mountings that, in turn, are bolted to frames, stanchions, etc., and are used for supporting the ends of shafts, conveyor rollers, etc. In addition to ball and roller bearings in their radial, linear, and mounted forms, bearings include those for civil engineering applications, which are called slide bearings; those used in small instruments and the like, known as jewel bearings; and very specialized bearings known collectively as frictionless bearings which includes air and magnetic varieties. Sleeve bearings, journal bearings, and other fluid-film bearings are addressed in the Bushings family.

Fig. BALL BEARING

Main purpose of bearing is to provide a low friction link between a moving part and a stationary part.

Its basic tasks are:

1. Reducing Friction: Primary objective of bearing is to minimize the friction between two relatively moving objects. So that lesser amount of heat is produced and also reduces wear & tear of parts.

2. Supporting the load: Bearing supports the load in all directions. As shaft always try to push bearing in the direction where load is moving, it becomes very necessary that bearing withstand that stress or sudden forces applied on it.

TYPES OF BEARING

1. ## ROLLING ELEMENT BEARING:

In these bearings rolling elements placed between the turning and stationary races prevent sliding friction. There are two main types:

Ball Bearings

Ball Bearings are mechanical assemblies that consist of rolling spherical elements that are captured between circular inner and outer races. They provide a means of supporting rotating shafts and minimizing friction between shafts and stationary machine members. Ball bearings are used primarily in machinery that has shafts requiring support for low friction rotation. There are several configurations, most notably shielded or sealed. Ball bearings are standardized to permit interchangeability. Ball bearings are also known as rolling element bearings or anti-friction bearings. Considerations include

- First choice for high speeds or high precision apps
- Large range of standardized forms
- Handle radial and axial loads with specific configurations

Roller Bearings

Roller Bearings are mechanical assemblies that consist of cylindrical or tapered rolling elements usually captured between inner and outer races. They provide a means of supporting rotating shafts and minimizing friction between shafts and stationary machine members. Roller bearings are used primarily in machinery with rotating shafts that require the support of heavier loads than ball bearings provide. Tapered roller bearings are often used to accommodate higher thrust loads in addition to the radial loads. Types range from cylindrical to spherical rollers. Roller bearings are standardized like ball bearings, albeit to a lesser degree. Considerations include

- Higher load capacities than ball bearings
- Can withstand high axial loads

2. ## MOUNTED BEARING:

Mounted Bearings are mechanical assemblies that consist of bearings housed within bolt-on or threaded mounting components and include pillow blocks, flanged units, etc. They provide means of supporting rotating shafts and minimizing friction between shafts and stationary machine members. Mounted bearings are used primarily in machinery with exposed rotating shafting. They are used as take-up devices on the ends of conveyors and as flanged units along intermediate points. The bearings can be rolling element or journal bearing configurations. Mounted bearings are designed for bolt-on mounting and ease of replacement. Other varieties of mounted bearings include rod end bearings and cam followers. Considerations include

- Housed units reduce mounting concerns, protection issues

- Cartridge designs ease replacement
- Shafts usually held in place with set screws
- Allow adjustment of the supported components
- Mainly used for low/mid speed applications

3. LINEAR BEARING:

Linear Bearings are mechanical assemblies that consist of ball or roller elements captured in housings and used to provide linear movement along shafts. Linear bearings are used primarily in machinery that requires linear movement and positioning along shafts. They also may have secondary rotational features depending on the design. Considerations include

- Lower friction and higher accuracies compared with bushings
- Costlier and more complex than bushings

4. SLIDE BEARING:

Slide bearings are mechanical assemblies designed to provide free motion in one dimension between structural elements. Slide bearings are used primarily in the structural support of bridges as well as commercial and industrial buildings. These parts accommodate thermal movement, allow for end-beam rotation, and isolate components of the structure against vibration, noise, and shock. Other types of slide bearings include those used on truss base plates, heat exchangers, and process equipment.

5. JEWEL BEARINGS:

Jewel bearings are mechanical devices used in light rotating applications such as watches, meter movements, gyroscopes, etc. where loads are small and the supported rotating shafts are tiny. Jewel bearings are constructed from a range of synthetics, with ruby and sapphire being particularly common.

6. FRICTIONLESS BEARING:

Frictionless bearings are mechanical or electro-mechanical alternatives to conventional bearings that provide controllable shaft support through air, magnetic fields, etc. for critical, high precision applications

CLASSIFICATION OF ROLLING ELEMENT BEARING

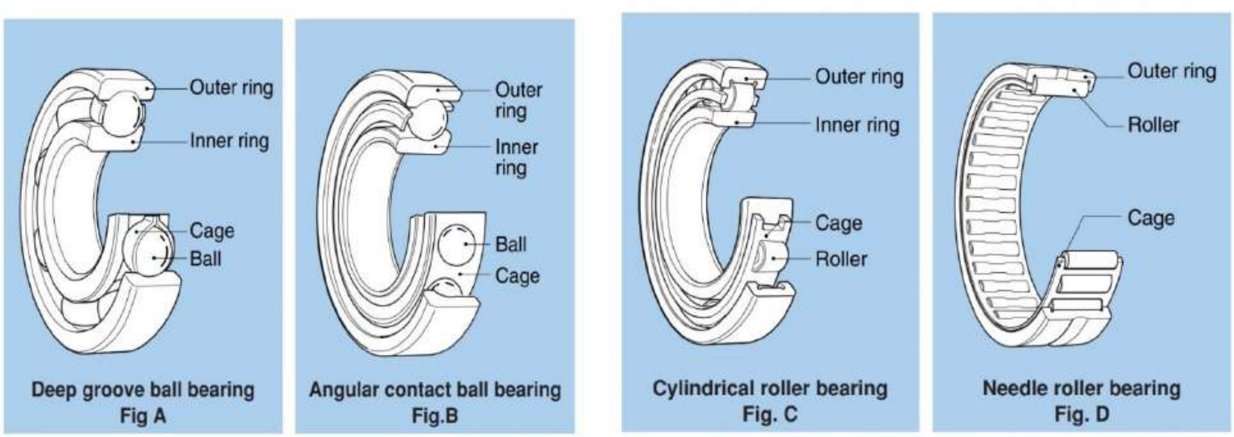
As, in this project report we only focused on the ROLLING ELEMENT BEARING.

ROLLING BEARING CONSTRUCTION:

Most rolling bearings consist of rings with raceway (inner ring and outer ring), rolling elements (either balls or rollers) and cage. The cage separates the rolling elements at regular intervals, holds them in place within the inner and outer raceways, and allows them to rotate freely. **Raceway (inner ring and outer ring) or raceway washer**: The surface on which rolling elements roll is called the "raceway surface". The load placed on the bearing is supported by this contact surface. Generally the inner ring fits on the axle or shaft and the outer ring on the housing.

Rolling elements: Rolling elements classify in two types: balls and rollers. Rollers come in four types: cylindrical, needle, tapered, and spherical. Balls geometrically contact with the raceway surfaces of the inner and outer rings at "points", while the contact surface of rollers is a "line" contact. Theoretically, rolling bearings are so constructed as to allow the rolling elements to rotate orbitally while also rotating on their own axes at the same time.

Cages: Cages function to maintain rolling elements at a uniform pitch so load is never applied directly to the cage and to prevent the rolling elements from falling out when handling the bearing. Types of cages differ according to way they are manufactured, and include pressed, machined and formed cages



Deep groove ball bearing Fig A

Angular contact ball bearing Fig.B

Cylindrical roller bearing Fig. C

Needle roller bearing Fig. D

Fig. ROLLING ELEMENT BEARING

ROLLING BEARING CLASSIFICATION

Rolling bearings divide into two main classifications: **ball bearings and roller bearings**. Ball bearings are classified according to their bearing ring configurations: deep groove type and angular contact type. Roller bearings on the other hand are classified according to the shape of the rollers: cylindrical, needle, tapered and spherical.

Rolling bearings can be further classified according to the direction in which the load is applied; radial bearings carry radial loads and thrust bearings carry axial loads.

Other classification methods include: 1) number of rolling rows (single, double, or 4-row), 2) separable and non-separable, in which either the inner ring or the outer ring can be detached.

There are also bearings designed for special applications, such as: railway car journal roller bearings, ball screw support bearings, turntable bearings, as well as linear motion bearings (linear ball bearings, linear roller bearings and linear flat roller bearings).Types of rolling bearings

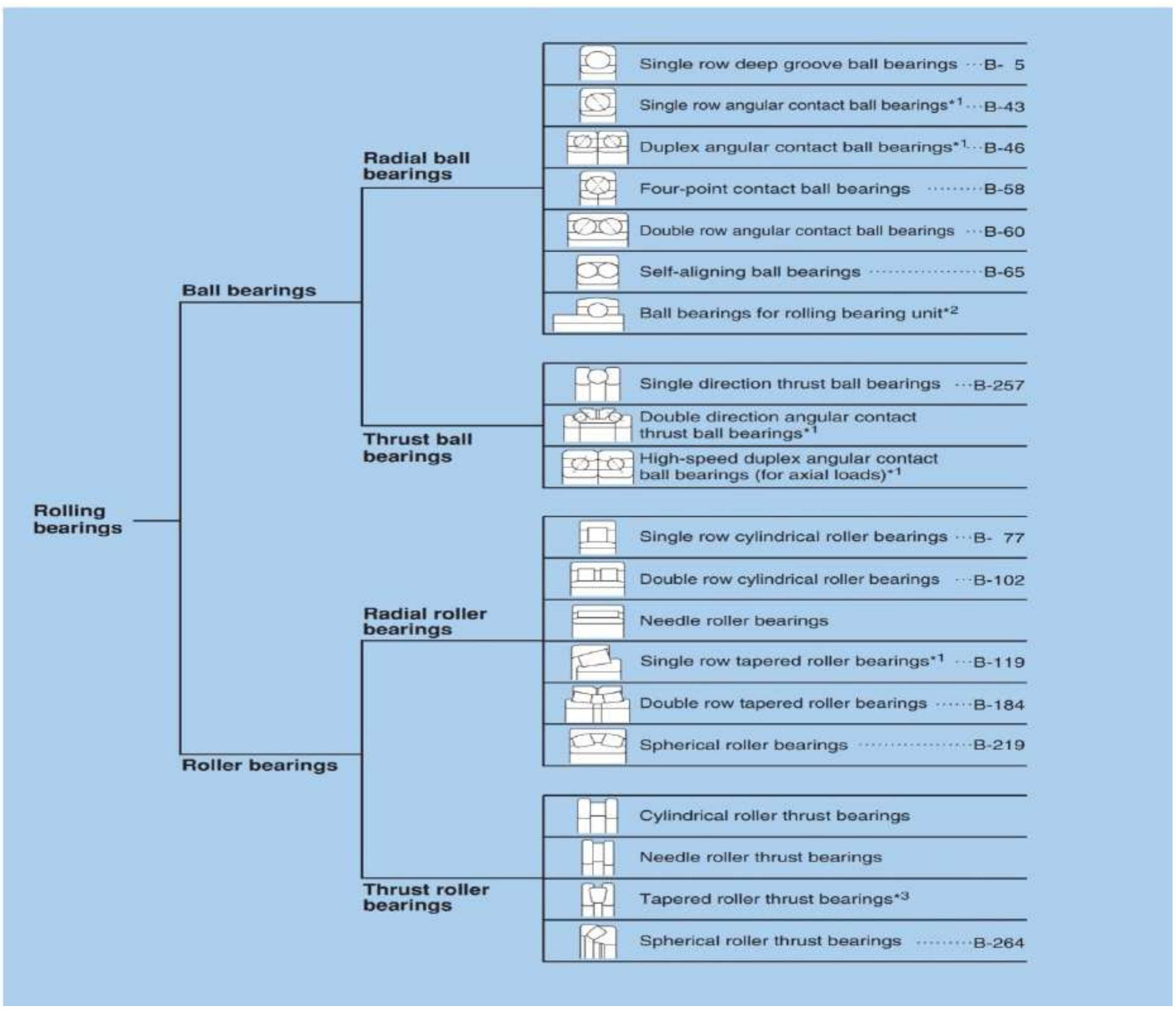
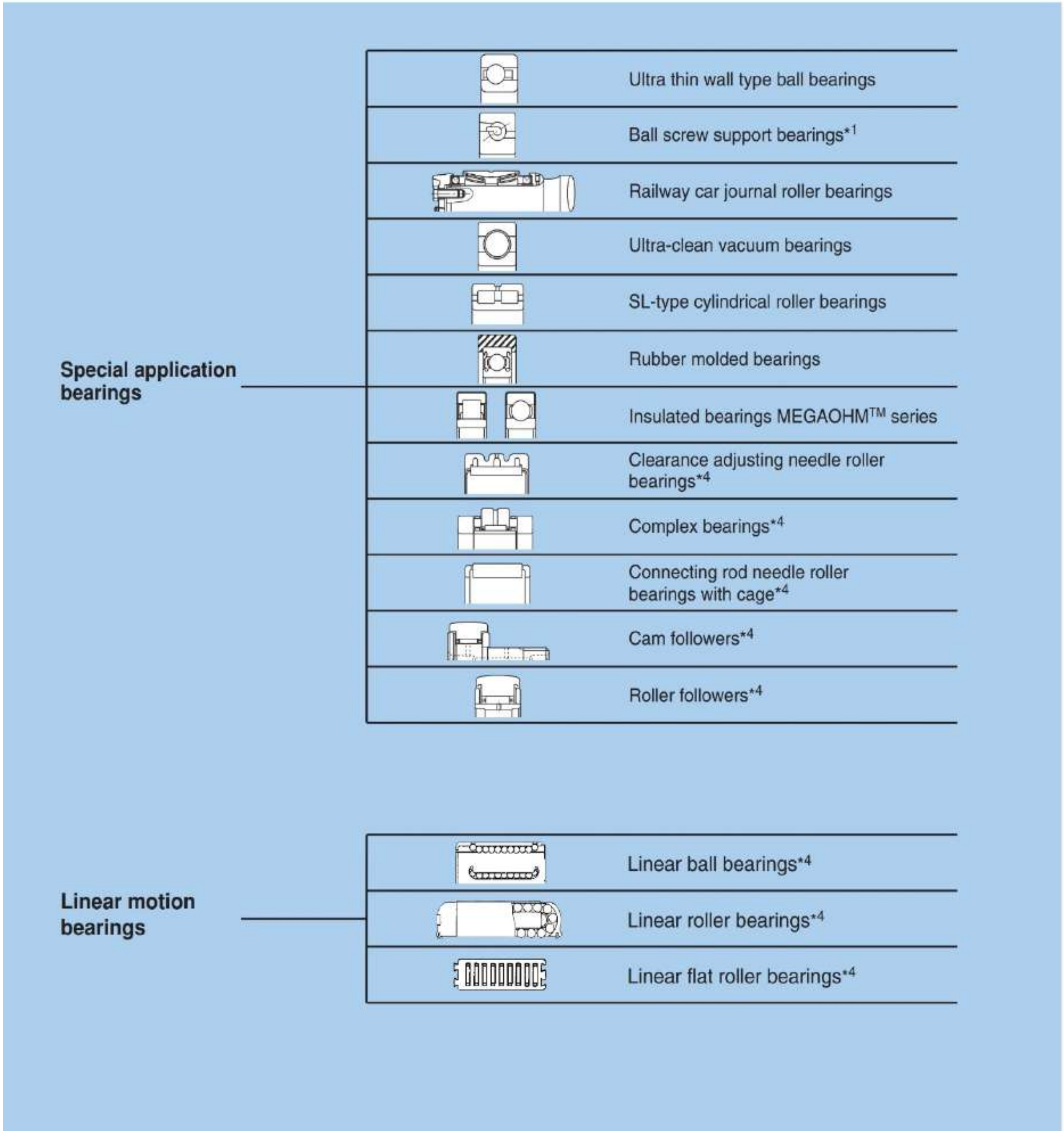


FIG. CLASSIFICATION OF BEARING



However, when compared with sliding bearings, rolling bearing have the following advantages:

(1) The starting friction coefficient is lower and there is little difference between this and the dynamic friction coefficient.

(2) They are internationally standardized, interchangeable and readily obtainable.

(3) They are easy to lubricate and consume less lubricant.

(4) As a general rule, one bearing can carry both radial and axial loads at the same time.

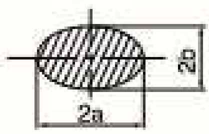
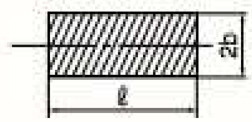
(5) May be used in either high or low temperature applications.

BALL BEARING

In this project report we mainly focused in the BALL BEARING, which is the type of the rolling element bearing

Ball Bearings are mechanical assemblies that consist of rolling spherical elements that are captured between circular inner and outer races. They provide a means of supporting rotating shafts and minimizing friction between shafts and stationary machine members. Ball bearings are used primarily in machinery that has shafts requiring support for low friction rotation. There are several configurations, most notably shielded or sealed. Ball bearings are standardized to permit interchange ability. Ball bearings are also known as rolling element bearings or anti-friction bearings.

COMPARISION BETWEEN BALL BEARING AND ROLLER BAERING

	Ball bearings	Roller bearings
Contact with raceway	 **Point contact** Contact surface is oval when load is applied.	 **Linear contact** Contact surface is generally rectangular when load is applied.
Characteristics	Because of point contact there is little rolling resistance, ball bearings are suitable for low torque and high-speed applications. They also have superior acoustic characteristics.	Because of linear contact, rotational torque is higher for roller bearings than for ball bearings, but rigidity is also higher.
Load capacity	Load capacity is lower for ball bearings, but radial bearings are capable of bearing loads in both the radial and axial direction.	Load capacity is higher for rolling bearings. Cylindrical roller bearings equipped with a lip can bear slight radial loads. Combining tapered roller bearings in pairs enables the bearings to bear an axial load in both directions.

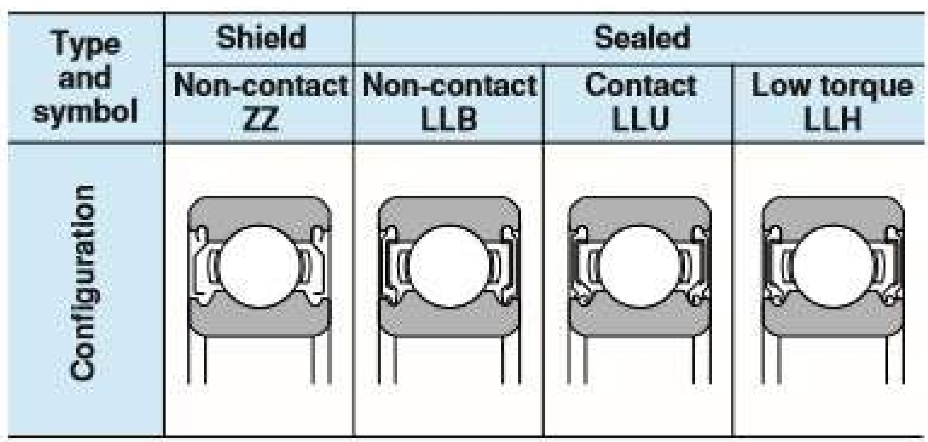
TYPES OF BALL BEARING

DEEP GROOVE BALL BEARING:

The most common type of bearing, deep groove ball bearings are widely used in a variety of fields. Deep groove ball bearings include shield bearings and sealed bearings with grease make them easier to use. Deep groove ball bearings also include bearings with a locating snap-ring to facilitate positioning when mounting the outer ring, expansion compensating bearings which absorb dimension variation of the bearing fitting surface due to housing temperature, and TAB bearings that are able to withstand contamination in the lubricating oil.

In a ball bearing, the load is transmitted from the outer race to the ball and from the ball to the inner race. Since the ball is a sphere, it only contacts the inner and outer race at a very small point, which helps it to spin very smoothly. The is also means that there is not very much contact area holding the load, so if the bearing is overloaded, the balls can deform, ruining the bearing.

CONFIGURATION OFSEALED BALL BEARING

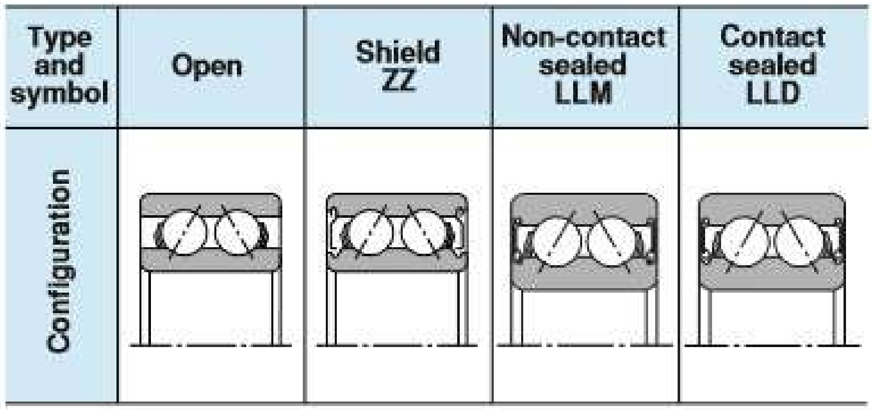


ANGULAR CONTACT BALL BEARING:

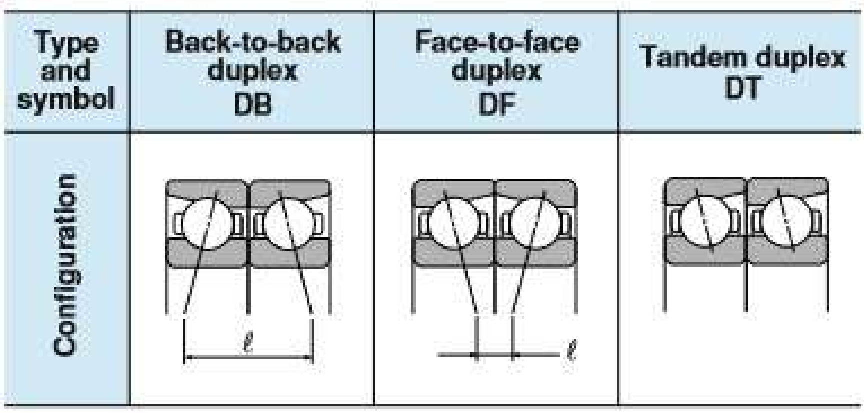
The line that unites point of contact of the inner ring, ball and outer ring runs at a certain angle (contact angle) in the radial direction. Bearings are generally designed with three contact angles. Angular contact ball bearings can support an axial load, but cannot be used by single bearing because of the contact angle. They must instead be used in pairs or in combinations. Angular contact ball bearings include double row angular contact ball bearings for which the inner and outer rings are combined as a single unit. The contact angle of double row angular contact ball bearings is 25˚. There are also four-point contact bearings that can support an axial load in both directions by themselves. These bearings however require caution because problems such as excessive temperature rise and wearing could occur depending on the load condition.

Angular Contact ball bearings have raceways in the inner and outer rings which are displaced with respect to each other in the direction of the bearing axis. This means that they are suitable for the accommodation of combined loads such as simultaneously acting radial and axial loads in vertical machines.

Configuration of double row angular contact ball bearings



Combinations of duplex angular contact ball bearings

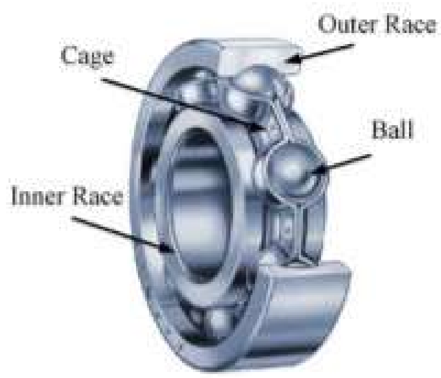


THRUST BEARING

There are many types of thrust bearings that differ according to shape of rolling element and application. Allowable rotational speed is generally low and special attention must be paid to lubrication. In addition to the ones given below, there are various types of thrust bearings for special application.

BEARING FAULTS

The bearing consists mainly of the outer and inner raceway, the balls and the cage which assures equidistance between the balls. The different faults occurring in a rolling-element bearing can be classified according to the affected element: **1. outer raceway defect 2. inner raceway defect 3. ball defect or roller defect 4. Cage defect**



BEARING DAMAGE SEVERITY LEVEL

When making a spectral diagnosis of a bearing problem the following considerations must be taken into account:

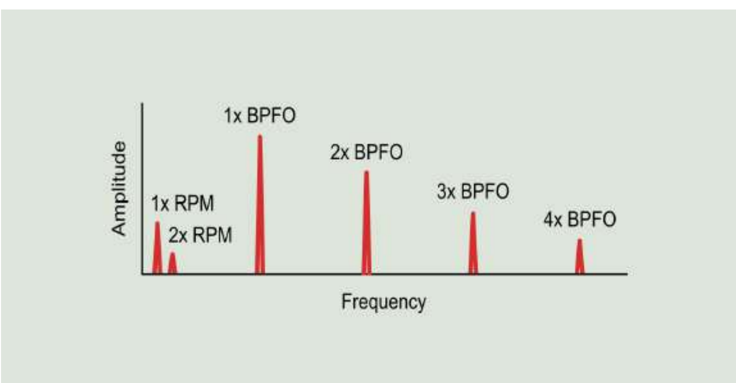
- The most frequent bearing component faults usually happen in the following order**:** ***outer race, inner race, rolling elements and finally in the cage.*** This will be the case as long as the bearing has been correctly mounted.
- It is really important to know if the bearing has a defect in the inner race or in the outer race. The importance of identifying the defect type lies in the need to estimate the useful remaining life of the bearing. Bearings with defects in the outer race generally have a longer expected life than bearings with defects in the inner race.
- Identical defects in the two bearing races are characterized by the fact that the amplitudes of the inner race fault frequencies will be lower than the amplitudes of the outer race fault frequencies. The reason for this is related to the bearing structure and the path the vibration needs to travel to arrive to the sensor. If we place the sensor close to the bearing load zone, where most of the outer race defects occur, the transmission of the vibration energy to the sensor occurs through the outer race and the casing. This is a transmission path that provides a reliable measurement of the vibration due to the defect. If the fault is located in an area of the inner race, which is the one that rotates in most cases, the vibration energy is transmitted this time from the inner race to the sensor through the balls or rollers, the cage, the outer race and the casing, so that the transmission is usually weaker. In addition, it has to be taken into account that the inner race is turning and is often outside the load zone, which implies significantly lower amplitude of impacts. It is important to make sure that the data sampling of each measurement takes at least the time corresponding to one shaft revolution, since if the data is taken very quickly it can happen that the signal coming from the impacts produced when the defect passes through the load zone is not acquired.

- High-frequency vibration readings are the first indicator of the beginning of bearing deterioration, since the impacts due to a small defect tend to excite the races natural frequencies (at high frequency). These measurements are made in acceleration units in the band between 1 and 20 kHz.
- During the initial phase of bearing race deterioration high frequency low amplitude harmonics usually appear in the spectra. Its identification will allow us to detect the initial phase of bearing deterioration and to be able to monitor its evolution, allowing us to plan for a replacement well in advance. As the damage progresses, the amplitudes of the initially identified fault frequencies will increase and intermediate harmonics of those fault frequencies will appear, until at the final stage of highest damage severity level the first harmonics of the fault frequencies will clearly appear.
- The occurrence of new bearing failure frequencies will indicate a greater defect severity.
- The bearing race failing frequencies is sometimes accompanied by side bands whose frequency difference with respect to the fundamental coincides with the shaft rotating frequency. Another frequency that can modulate bearing race failing frequencies is the FTF or bearing cage failing frequency, indicating a greater bearing damage. The increase in the number and amplitude of these sidebands will indicate the progression of the damage.
- When there is significant bearing damage, individual frequencies may disappear and significant energy bands may appear, often indicating changes in bearing geometry.
- If the lubrication is not adequate, bearing deterioration will accelerate, so it is good practice that when the damage is identified, the bearing properly lubricated to try to prolong its life.
- Time waveform analysis can be helpful for bearing diagnosis. For deteriorated bearings it will be characterized by high impacts in acceleration and a frequency difference between peaks that roughly coincide with one of the failing frequencies

Typical bearing defects and spectral identification

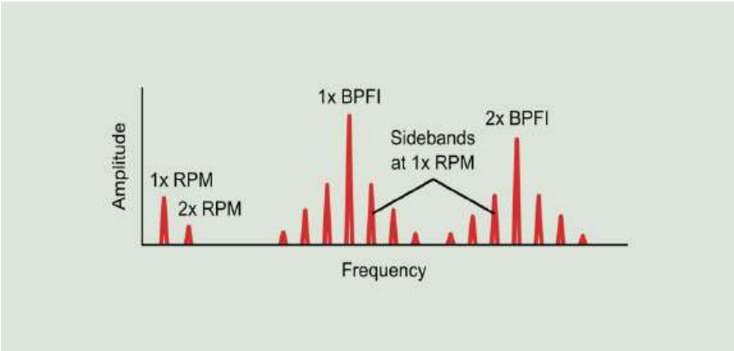
Below are the most typical bearing defects and their identification in the frequency spectrum:

- **Outer race defects:** the spectrum is characterized by the presence of harmonic peaks of the outer race failing frequency (between 8 and 10 harmonics of the BPFO).



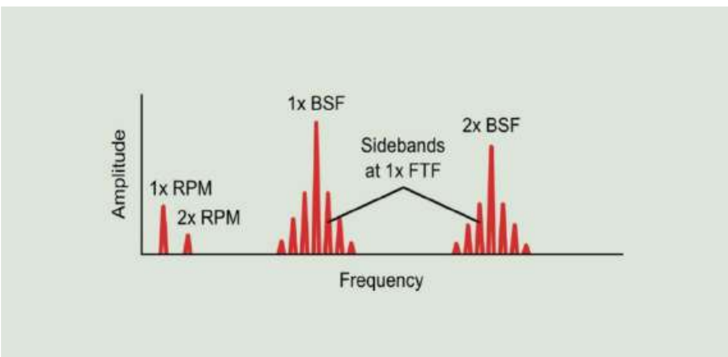
OUTER RACE DEFECT

- **Inner race defects:** the spectrum shows several harmonic peaks of the inner race failing frequency (usually between 8 and 10 BPFI harmonics) modulated by sidebands at 1x RPM.



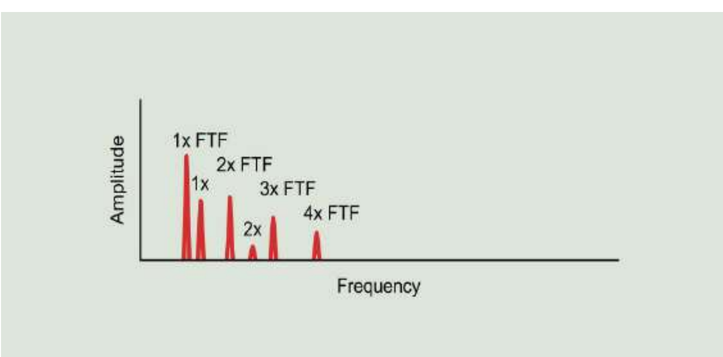
NNER RACE DEFECT

- **Ball or roller defects: they are characterized by the presence in the spectrum** of harmonics of the rolling element deterioration frequency (BSF). In most cases, the harmonic of greater amplitude usually indicates the number of deteriorated balls or rollers. They are usually accompanied by defects on the races.



BALL- ROLLER DEFECT

- **Cage defects:** are characterized by the presence in the spectrum of the cage failing frequency (FTF) and its harmonics. Generally, a defect in the cage is accompanied by defects in the races and the FTF usually modulates one of these race failure frequencies leading to sums and/or differences of frequencies.



CAGE DEFECT

- Defects of multiple components: it is quite common to find bearings with multiple deteriorated components, and in such case multiple failing frequencies and their corresponding harmonics will appear.
- **Looseness:** we can distinguish the following types:

  1. **Excessive bearing internal clearance:** Usually features a spectral signature characterized by the presence of synchronous vibration (rotating speed harmonics), sub-synchronous vibration (0.5x RPM) and non-synchronous (1.5x RPM, 2.5xRPM, 3.5x RPM, etc.) . These frequencies sometimes can be modulated by the FTF.

  2. **Looseness between bearing and shaft:** Several rotation frequency harmonics appear and normally the dominant one is the 3x RPM.

  3. **Looseness between bearing and casing:** It presents several harmonics of the rotating frequency, being the peaks at 1x and 4x RPM the ones with higher amplitudes.

- **Bearing misalignment:** as already mentioned in the chapter about misalignment, spectral signatures are characterized by the presence of vibration at various harmonics of the rotating frequency, with the amplitude being the most significant at N_B x RPM, where N_B is the number of rolling elements in the bearing.
- **Inadequate lubrication:** lubrication problems are characterized by high frequency vibration (between 1 kHz and 20 kHz), with bands of peaks spaced apart from each other, due to the excitation of the resonance frequencies of the bearings in these frequency ranges.

Frequency bands for the analysis of bearing condition

The possibility of splitting the spectrum overall value into multiple frequency bands allows us to know in advance the areas in which the most typical problems are usually manifested and help us to identify them even before we can visualize the spectrum in frequencies and wave in the time. For typical machines where the aim is monitor low and medium frequency issues (unbalance, misalignment, looseness, etc.) and high frequency issues (bearings) we recommend to use the frequency bands indicated in the following table.

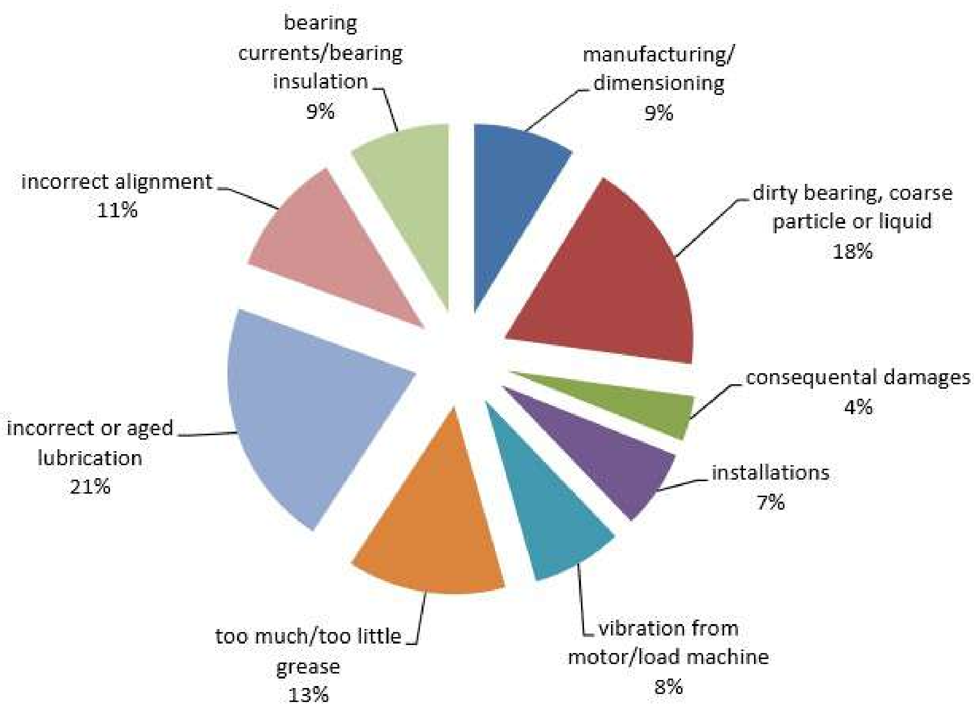
Spectral parameter	Bandwidth
Imbalance, missalignment, looseness, rub and belt wear.	1.5 to 2.5x RPM
Missalignment and looseness.	1.5x to 2.5x RPM
Looseness, missalignment and BSF.	2.5 to 4.5x RPM
First harmonics of the bearing fault frequencies BPFO, BPFI and BSF.	4.5 to 20.5x RPM
Higher bearing fault frequencies harmonics and presence of frequencies related to electrical issues.	20.5 to 50x RPM
High frequency spectral band, in units of acceleration (G's). Alarm parameter in case of early bearing deterioration stage, presence of cavitation or lack of lubrication.	1 to 20 kHz

Spectral bands for the detection of rolling element bearing problems

BEARING FAILURES

Now we will discuss about bearing failure which occurs in the bearing used in induction motor. Reasons of faults or failure can be different sometimes more than one reason cause failure of bearing in induction motor. If we know the possible causes of bearing failure then it can become easy for us to detect any failure in bearing and correct it before any unwanted situation occurs.

The main factors behind bearing faults are dust and corrosion. Induction motors are often operated in hard conditions. That is why foreign materials, water, acid, and humidity are the main reasons for bearing deteriorations. Contamination and corrosion frequently accelerate bearing failures because of the harsh environments present in most industrial settings. Dirt and other foreign matters that are commonly present often contaminate the bearing lubrication. The abrasive nature of these minute particles, whose hardness can vary from relatively soft to diamond-like, causes pitting and sanding that lead 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 installation. Once, the chemical reaction has advanced sufficiently, particles are worn off resulting in the same abrasive effect produced by bearing contamination. Improper lubrication includes both under and over lubrication



BEARING COMMON FAILURE

Some common failures are:

1. OVER HEATING:

Symptoms are discoloration of the rings, balls, and cages from gold to blue. Temperatures in excess of 400°F can anneal the ring and ball materials. The resulting loss in hardness reduces the bearing capacity causing early failure. In extreme cases, balls and rings will deform. The temperature rise can also degrade or destroy lubricant Common culprits are heavy electrical heat loads, inadequate heat paths and insufficient cooling or lubrication when loads and speeds are excessive. Thermal or overload controls, adequate heat paths, and supplemental cooling are effective cures

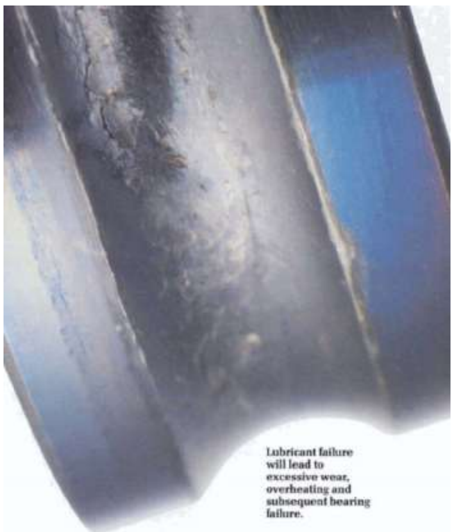
OVER HEATING

2. NORMAL FATIGUE FAILURE:

Fatigue failure-usually referred to as spalling is the fracture of the running surfaces and subsequent removal of small discrete particles of material. Spalling can occur on the inner ring, outer ring, or balls. This type of failure is progressive and once initiated will spread as a result of further operation. It will always be accompanied by a marked increase in vibration, indicating an abnormality. The remedy is to replace the bearing or consider redesigning to use a bearing having a greater calculated fatigue life.

3. LUBRICANT FALIURE:

Discoloured (blue and brown) ball LUBRICANT tracks and balls are symptoms of lubricant failure. Excessive wear of balls, ring and cages will follow, result in a in over heating and subsequent catastrophic failure. Ball bearings depend on the continuous presence-of a very thin-millionths of an inch-film of lubricant between balls and races, and between the cage, bearing rings, and balls. Failures are typically caused by restricted lubricant flow or excessive temperatures that degrade the lubricant's properties. Barden engineers can advise users on the most suitable lubricant 9 e and quantity to use. Refer to lubricant section of Barden C-10 dog for more information. Also, i any steps taken to correct improper 1 fit control preload better, and cool I the shafts and housings will reduce bearing temperatures and improve lubricant life.



4. CORRISION:

Red and brown areas on balls, race- ways, cages, or bands of ball bearings are symptoms of corrosion. This condition results from exposing bearings to corrosive fluids or a corrosive atmosphere. The usual result is increased vibration followed by wear, with subsequent increase in radial clearance or loss of preload. In extreme cases, corrosion can initiate early fatigue failures. Correct by diverting corrosive fluids away from bearing areas and use integrally sealed bearings when- ever possible. If the environment is particularly hostile, the use of external seals in addition to integral seals should be considered. The use of stainless steel bearings is also helpful

5. VIBRATION:

Ball bearings are easily damaged from vibration when the motor is not running, so the rotor is locked during transportation. Ball bearings can sustain more vibration than roller bearings when not running. Both types can only withstand single and infrequent shocks of 2-3g without sustaining damage; shocks of greater magnitude should obviously be avoided. Sleeve bearings can sustain single and infrequent shocks of 3-5g. Again, the rotor is fixed axially during transportation: don't forget to unlock it before energizing the motor Vibration in motors is normally caused by

• Unbalanced loads, like fans mounted on unstable base frames, can provoke heavy vibration

• Operating equipment near resonance points, especially when adjustable speed drives are used,can provoke heavy vibration

• Lack of uniformity in the magnetic field

6. TIGHT FITS:

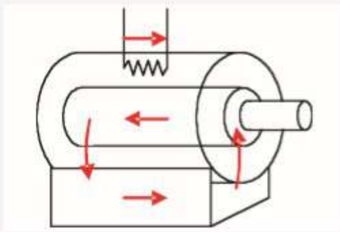
A heavy ball wear path in the bottom of the raceway around the entire circumference of the inner ring and outer ring indicates a tight fit. Where interference fits exceed the radii clearance at operating temperature, the balls will become excessively loaded. ?his will result in a rapid temperature rise accompanied by high torque. Continued operation can lead to rapid wear and fatigue. Corrective action includes a decrease in total interference- better matching of bearings to shafts and housings-taking into consideration the differences in materials and operating temperatures. Increased radii1 clearance will also increase bearing life under the above conditions

7. BEARING CURRENT:

Bearing currents have been recognised for a long time. In this, currents were a consequence of asymmetrical stator windings. As the fabrication of windings and motors improved, these currents became less and less significant, and today are no longer important. On the other hand, in recent times, the growing use of frequency converters with PWM technology has brought back the bearing current discussion again. Modern AC Converters have as their motor output, a high du/dt (voltage gradient) combined with a high switching frequency. This results in the sum of the three-phase voltages not being zero any more, as it is in a three-phase network. The so-called common voltage depends on the intermediate circuit DC voltage and the switching frequency. Without considering counter measures for these effects, a motor bearing can be destroyed within a few months of operation. If such a common mode voltage is present, there might be different dominant root causes. This voltage always tries to generate a current flow

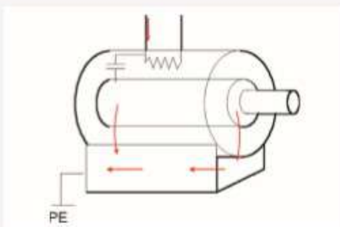
Bearing currents in a nutshell

There are three main types of current, which can be classified as follows:



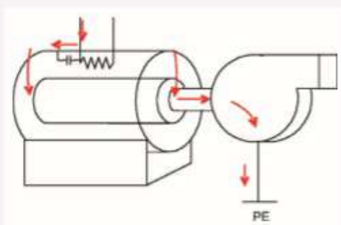
High frequency circulation current

- Risk in medium and high power motors, frame sizes IEC 315 and up, PN >100 kW.
- High du/dt and high switching frequency increase the risk.
- Problem in > 95 % of cases



Capacitive discharge current

- Special cases with small motors
- Motor frame grounded
- Shaft is not grounded via machinery



High Frequency shaft grounding currents

- Asymmetric, unshielded motor cabling
- Incidental grounding of the motor shaft through the gearbox or driven machinery
- Poor stator grounding

8. False Brinelling

Rapid movement of the balls in a raceway while equipment is idle wears away at the lubrication. In addition, a lack of rotation in the bearing does not allow fresh lubricant to return to the spot. Both of these conditions result in false brinelling. We may see linear wear marks in the axial direction at the rolling-element pitch or no raised edges as opposed to marks due to incorrect mounting.

9. Contamination

Contamination is caused by foreign substances getting into bearing lubricants or cleaning solutions. These include dirt, abrasive grit, dust, steel chips from contaminated work areas and dirty hands or tools. Watch for denting of rolling elements and raceways that cause vibration.

Summary of reasons for bearing failures

Impending bearing problems are preceded by a change in its behaviour. Early indications for potential problems are increases in temperature, vibration levels or noise levels of the motorIn a correct installation, and under adequate supervision, the temperature and the vibration can be easily visualised by trend logs. Th e noise level, however, can only be detected by the maintenance staff during routine checks. If potential problems are not recognised and analysed promptly, or if incorrect diagnoses of the problems are made, sooner or later it will lead to a bearing problem.

Deterioration stages

- **Stage 1**: In this stage, the bearing is in perfect condition so that in the spectrum only the rotating frequency and possibly some of its harmonics are visible.

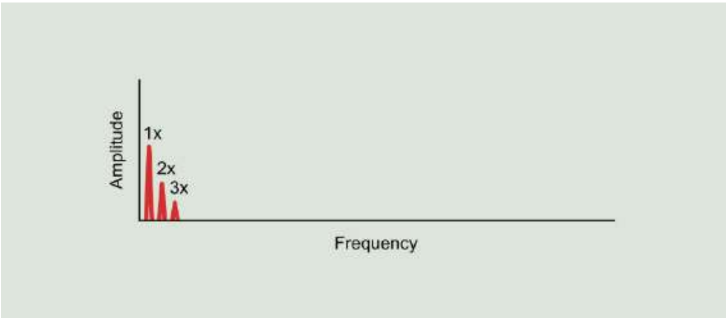


Figure: Stage 1 of bearing deterioration

- **Stage 2**: Vibration readings occur at high frequency, and they are the first symptom of the beginning of the deterioration of a bearing. These readings are due to impacts, caused by a small defect, which tend to excite the high-frequency natural frequencies of the bearing races. These measurements are taken from the acceleration spectrum in a band between 1 kHz and 20 kHz.

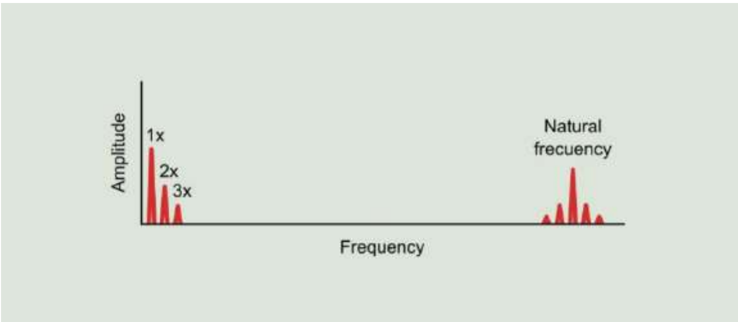


Figure: Stage 2 of bearing deterioration

- **Stage 3**: The characteristic fault frequencies and their harmonics appear. As the damage progresses, it increases both the amplitude of the fault frequencies and their harmonics as well as the high frequency vibration in acceleration. Monitoring their evolution allows us to plan for a replacement well in advance.

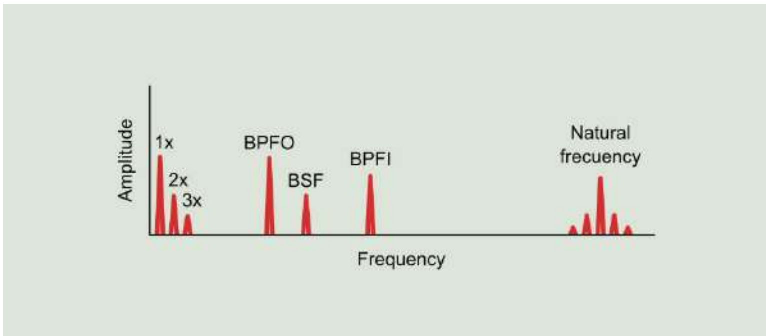


Figure: Stage 3 of bearing deterioration

- **Stage 4**: This is the final stage of the bearing. When it is considerably damaged, there are similar symptoms to looseness and friction. There is also a background noise clearly visible in acceleration at high frequency. It increases the amplitude of 1x RPM and its harmonics and decrease or disappear the amplitude of the fault frequencies as they become masked in the background noise.

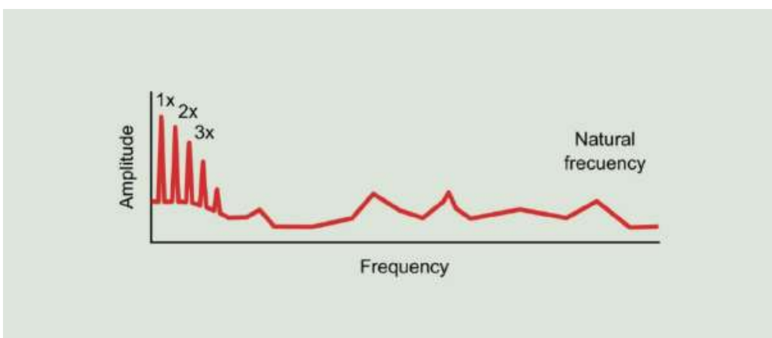


Figure: Stage 4 of bearing deterioration

The four possible bearing failing frequencies are:

- **BPFO (Ball Pass Frequency Outer**) or outer race failing frequency. Corresponds physically to the number of balls or rollers that pass through a given point of the outer race each time the shaft makes a complete turn.
- **BPFI (Ball Pass Frequency Inner)** or inner race failing frequency. Corresponds physically to the number of balls or rollers that pass through a given point of the inner track each time the shaft makes a complete turn.
- **BSF (Ball Spin Frequency)** or rolling element failing frequency. Corresponds physically to the number of turns that a bearing ball or roller makes each time the shaft makes a complete turn.
- **FTF (Fundamental Train Frequency)** or cage failing frequency. Corresponds physically to the number of turns that makes the bearing cage each time the shaft makes a complete turn.

TECHNIQUES TO DETECT BEARING FAULTS IN INDUCTION MOTOR

1. INFRARED THERMOGRAPHY

INTRODUCTION

Infrared thermography has been extensively applied over decades to areas such as maintenance of electrical installations. Its use in electrical machines has been mainly circumscribed to the detection of faults in static machines, such as power transformers. However, with regard to the predictive maintenance of rotating electrical machines, its use has been much more limited. In spite of this fact, the potential of this tool, together with the progressive decrease in the price of infrared cameras, make this technique a very interesting option to, at least complement, the diagnosis provided by other well-known techniques, such as current or vibration data analysis. In this context, infrared thermography has recently shown potential for the detection of motor faults including misalignments, cooling problems, bearing damages or connection defects. This work presents several industrial cases that help to illustrate the effectiveness of this technique for the detection of a wide range of faults in field induction motors. The data obtained with this technique made it possible to detect the presence of faults of diverse nature (electrical, mechanical, thermal and environmental); these data were very useful to either diagnose or to complement the diagnosis provided by other tools.

INFRARED thermography is a well-known technique in the electrical engineering area. Over decades, it has been a very useful tool for regular inspections of electrical installations and distribution lines [1-4]; for instance, infrared cameras have been applied to the detection of defects in electrical panel boards, power cables, electric switchgear or power meters, among many others. In the area of electrical machines condition monitoring, infrared thermography has been a preferred option for the detection of eventual faults in power transformers operating in substations, power plants and industrial facilities. Indeed, intelligent fault diagnosis methods based on image processing have been proposed in the literature, based on the analysis of infrared images of transformers. The application of infrared thermography to the electric motors condition monitoring area is much more limited. In D.C. machines, infrared thermography is a useful tool to detect possible defects in the commutator as well as in the brushes system, which are weak points under a maintenance point of view. In wound rotor induction machines and in synchronous motors and generators, infrared data analysis can provide very interesting information about the condition of the slip rings-brushes system, indicating possible asymmetries or defective contacts. For most of these machines, infrared thermography is commonly used in standard off-line tests, as the core ring test (or loop test) to detect core inter-laminar insulation failures. However, in general terms, the application of this technique has been often circumscribed to the detection of defective connections, usually external to the machine itself.

In spite of the previous facts, infrared thermography seems a very interesting option taking into consideration that most of the motor faults usually lead to temperature rises (either general or located in specific regions) that may be detected via infrared data analysis. On the other hand, despite infrared cameras came with excessively high costs only a few years ago, today there are infrared data acquisition devices with very affordable prices and with advanced features (such as high image resolution or possibility of acquiring images during transient regimes).These facts confer this technique with a huge potential, since it can easily become an excellent informational source for the condition monitoring of rotating electric machines. In the case of induction motors, the technique may be very useful, especially for large induction motors, the cost of which can easily amount to $1-2 million and whose unexpected failures can entail losses of several million $. In these machines, the infrared thermography may play an excellent role to diagnose certain failures or to complement the diagnostic conclusions obtained with other techniques as vibration or current data analysis. As a matter of fact, recent works have proposed the combination of infrared data analysis with the analysis of currents (both in steady-state and in transient regime) in order to reach a more reliable conclusion about the condition of certain parts of the machine [20]. In these works, it was proven, via laboratory tests, that the infrared thermography technique could be especially useful for the complementary diagnosis of bearing failures or cooling problems, among others.

This project report presents several case studies referred to the application of the infrared thermography technique to field motors operating in a petrochemical plant. The results included here are a part of a more general study that was intended to diagnose the condition of a set of motors with different sizes and operating conditions; in twenty of them, the infrared technique was showing evidences of diverse anomalies. The interesting conclusions of the study revealed that the infrared technique was able to diagnose or provide very useful information for the diagnosis of faults of very different nature as bearing lubrication problems, incorrect belt tightening, deficient cooling, damaged bearings or defective connections, among others.

Bearing wear can have many potential causes. It can be caused by contamination (penetration of fine abrasive particles in the bearing), lack of lubrication or vibration, among other. Indentations are usually linked to deficient mounting, periodic overloads or penetration of external particles. With regard to smearing, it is usually caused by an inadequate lubrication of two surfaces that, when sliding against each other under load, provokes the transfer of material from one surface to the other. When smearing occurs, the corresponding surfaces become with a ‘torn’ appearance. Smearing often leads to very high temperatures in the material so that rehardening takes place. This can cause flaking and even cracking. On the other hand, when the lubricant film is too thin, surface distress may appear due to the contact between the surface imperfections of balls and races. The exposure to enough amounts of moisture or water so that the lubricant film does not correctly protect the material surfaces, may lead to corrosion of the bearings. Finally the circulation of currents through the bearing (i.e. current flows from one ring to the other via the bearing element) provokes very high rises in the temperature of the material (from tempering to melting levels). This leads to the appearance of discolored areas as well as to the formation of fluting (corrugation in bearing raceways). This is an important problem in inverter-fed motors.

METHOD OF INFRARED THERMOGRAPHY

Basically, the infrared thermography technique allows the visualization of the superficial temperatures of an object with high resolution and in a non-invasive way, i.e., not needing any contact with the object [20]. The physical basis of the method relies on converting infrared radiation measurements into temperature measurements. This is carried out by measuring the radiation emitted by the object surface within the infrared portion of the electromagnetic spectrum and by subsequently translating these measurements into electrical signals. The measurement device is an infrared camera, which measures the superficial temperature gradients by means of its infrared sensors, by capturing high quality images [20]. According to the energy source over which the infrared inspection is carried out, two possible infrared readings exist: direct and indirect. Direct readings are obtained when measuring the radiation from the main energy source point while indirect readings are those that are done in neighboring or close points, where the heat has been transmitted via conduction, radiation or convection. Some authors define direct readings as those where there is little or no thermal insulation between the infrared camera and the energy source, while indirect readings are those where there is a considerable thermal insulation between both elements.

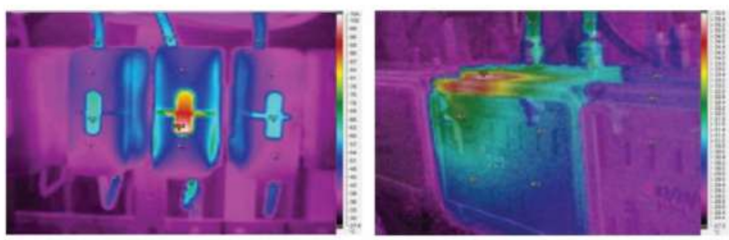


FIG. Direct (a) versus indirect (b) infrared reading

In general, dynamic equipment or components, as motors, bearings, gear reducers, etc… are analyzed via indirect infrared readings since the fault is started inside the equipment. Hence, it is necessary to assess them by taking into consideration both constructive, environmental and operational aspects in order to determine incorrect temperatures or heat transfer trends or patterns that would inform about the presence of developing failures. Fig. b shows an example of the evolution of the measured temperature values (weekly intervals) by means of direct and indirect infrared readings for the same fault. In general, indirect infrared readings have fault indicators that show exponential evolutions, so if the time intervals between successive measurements are too long, the fault can develop before it is detected.

In spite of this fact, note that, in many cases, the temperature distribution of the surface -thermal pattern- gives us a very important clue; hence, it becomes advisable to analyze the thermal gradients despite the fact that temperature thresholds are not surpassed.

TABLE: GENERAL ALARM THRESHOLDS ADOPTED FOR DIFFERENT DIAGNOSED COMPONENTS

Element	Temperature Threshold
Motor frame	>70 ºC
Gears (reducers, multipliers, etc..)	>80 ºC
Bearings	>70 ºC
Couplings	>80 ºC
Belt transmissions	>90 ºC

THERMAL IMAGING SPECIFICATION

Three main specifications are critical in the process of selecting a thermal imager: temperature range, thermal sensitivity (NETD), and resolution.

Temperature Range:

When selecting a thermal imager, evaluate the temperature range that will be suitable for your applications. For industrial applications, the temperature range is the number one specification to consider. Industrial thermal imagers feature a wider temperature range to accommodate facilities that have high-temperature equipment such as boilers and steam systems.

Thermal Sensitivity (NETD):

Thermal sensitivity, or Noise-Equivalent Temperature Difference (NETD), measures the smallest temperature difference that a thermal imaging camera can detect in the presence of electronic circuit noise. Cameras with a low NETD will detect smaller temperature differences and provide higher resolution images with increased accuracy. Thermal sensitivity is measured in milli-Kelvins (mK). Cameras are more sensitive with values at the low end of the scale. For example, cameras with 50 mK are about 4 times as sensitive as a camera with 200 mK. The more sensitive (50 mK) cameras provide a wider temperature difference, resulting in more colors on the thermal display.

Resolution:

Higher resolutions provide precise and reliable measurements of smaller targets from further distances, creating sharper thermal images. The higher the detector resolution, the more accurate the camera. When evaluating between detector resolution and display resolution, be aware that the quality of the thermal image and its data is always determined by the detector resolution. For example, if the built-in screen has a resolution of 307,200 pixels (640 x 480) but the thermal detector resolution is only 19,200 pixels (160 x 120), the thermal image can only be measured by the resolution of the thermal detector. The examples at right show that as the thermal detector resolution increases, the image detail becomes clearer and the temperature at a single point is more accurate.

TABLE: SPECIFICATION OF INDUCTION MOTOR AND THERMAL CAMERA

Machine /Equipment	**Specification**	**Machine /Equipment**
Induction Motor	Power Supply : 3 Phase 440V, 0.75A, 50Hz Power-: 0.5 HP Speed: 1440 rpm	Induction Motor
Thermal Camera	spectral range: 7.5–13 μm (Uncooled microbolometer) pixels : 320 × 240 temperature range of Storage: – 40°C to +70°C temperature range (Operating) –15°C to +50°C Relative humidity : +25°C to +40°C / 2 cycles	Thermal Camera

APPLICATION:

The infrared thermography technique was applied to a set of induction motors that were operating in a petrochemical plant. These motors were involved in different processes within the plant. Different anomalies were detected in twenty of theaforementioned motors. Twelve of them had malfunctions that were finally attributed to mechanical problems (deficient bearing lubrication, damaged bearings, deficient belt tightening and operational overload). The infrared data were acquired with a Fluke Ti-100 camera; the room temperature was registered in each measurement so that the measured data could be properly normalized.

2. <u>SOUND ANALYSIS</u>

Induction motors are one of the most commonly used electrical machines in industry because of various technical and economic reasons. The bearings are common elements of induction machine. The performance of bearing is influential on the performance of induction machine. The presence of bearing defects causes, a reduction in the efficiency of the machine or severe damage in induction machine. Therefore, this diagnosis is an intensively investigated field of research. Recently, many research activities were focused on the diagnosis of bearing faults using current signals and vibration signals. In this project report, **the sound of electric motors is analyzed** in order to obtain information for the detection of faults. Significant sound spectrum differences between healthy motor and motors with bearing faults are observed. The signal processing techniques that are being currently used for the analysis of sound signals of different induction motors.

INTRODUCTION

Early diagnosis of faults in induction machines is an extensively investigated field for cost and maintenance savings. In fact, induction motors are still the most important rotating electric machines in industry mainly because of 1) their low price; 2) ruggedness; 3) efficiency; and 4) reliability.

Many project reports can be found in the literature concerning the general condition monitoring of induction machines where the different fault types are analyzed. The distribution of failures within the machine subassemblies is reported in many reliability survey project reports. A rough classification identifies four classes: 1) bearings faults; 2) stator-related faults; 3) rotor-related faults; and 4) other faults (cooling, connection, terminal boxes). Depending on the type and size of the machine, bearing faults distribution vary from about 40% to about 90% from large to small machines. This project report reviews the various bearing defects present in rolling element bearing and the reasons for the defects. This method based on sound analysis technique is contribute to limiting the problems and the cost induced by the failure of a motor in an industrial process. In this study, we take into consideration the electric and mechanical faults. These are revealed in some sidebands of the specific frequencies. It is a known fact that induction motor parameters will change because of the motors' faults. Hence these parameters have to be monitored to prevent/reduce breakdowns.

When a mechanical part of the motor either wears or breaks up, a frequency component of the spectrum will change. In fact, each fault in a rotating machine produces vibrations and noise with distinctive characteristics that can be measured and compared with reference ones in order to perform the fault detection and diagnosis.

TYPES OF DEFECT

BEARING FAILURE MECHANISMS

Failure Mechanisms	**Reason for damage**
Mechanical Damage	Permanent indentation created by rolling element overload
Crack damage	Manufacturing defect or operating stress due to overload
Faulty Installation	Excessive preloading, misalignment, loose fit, excessive force used in mounting the bearing
Incorrect Design	Poor choice of bearing type or size for required operation
Wear damage	Gradual deterioration or abrasive particle entrained
Corrosion	Humid ambient subjected to surface oxidation

The defect in the bearing may arise due to improper mounting, improper operation, and overloading. The defects may be classified into distributed and localized defects. Surface roughness, waviness, and misaligned races are included into the class of distributed defects. The localized defects include cracks, pits, and spall caused by fracture on the rolling surface. Some of the reasons for the cause of the defect are discussed above in table-1.

Sound is an important parameter for the condition monitoring of machines and their elements. In a machine under operation, sound is always present. The levels of sound usually increase with deterioration in the condition of the machine. Sound amplitude is normally measured. Sound can be extracted using microphone

FAULT DETECTION TECHNIQUE

There are several techniques that can be employed to predict the condition of bearing, these include: Vibration monitoring, Current Signature Analysis, etc.

Condition monitoring based on measuring and analyzing of machine vibration signals is one of the oldest monitoring techniques and widely used to detect motor faults especially mechanical faults. However, vibration of machines is defined as a result of dynamic forces in machines which have moving parts and in structures which are connected to the machine. The major disadvantage of vibration monitoring is cost. For example, a regular vibration sensor costs several hundred dollars.

The current signature analysis is used for detecting the bearing fault in electric machine. This method requires the operating motors input current and frequency for analysing/detecting the fault in the bearing.

Monitoring Bearing Fault in Induction Motor using Sound Spectrum

The analysis of the bearing noise in electrical machines shows that the forces that occur in the rolling element bearings create the high frequency components of vibrations. In normally working rolling element bearings, the main types of high frequency oscillating forces are friction forces. When a defect develops in the bearing, shock pulses can also be found due to the breaks in the lubrication layer between the friction surfaces.

This method of diagnosing rolling element bearings through analysis of high frequency noise has many advantages. It makes it possible to locate the defective bearing easier because the noise signal does not contain any components from other units of the machine.

When a defect of wear of rolling surfaces appears, the friction forces are not uniform. They depend on the rotation angle of the rotating surfaces in the bearing causing the friction forces to be modulated by a periodic process. Periodic shock pulses appear if cavities or cracks appear in the bearing. It is possible to detect the presence of the friction forces modulation and of the periodic shock pulses by the spectral analysis of the envelope of the random noise produced by these processes. When the friction forces are modulated by a periodic process the harmonic component of the frequency will be found in the measured envelope spectrum. The frequency is determined by the period of the modulating process.

The analysis of sound spectrum is used for the detection of bearing faults. The faults detection will be done by comparing two values: the amplitudes of the harmonic components obtained from monitoring the sound spectrum at different frequencies and the amplitudes of the harmonic components at the same frequencies obtained from the reference sound spectrum.

ARCHITECTURE OF FAULT DETECTION SYSTEM

The architecture of fault detection system is shown in flow diagram of Fig. 1.

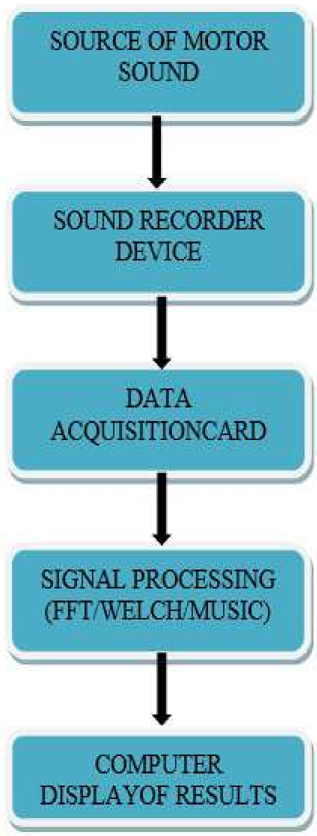


Fig. 1: Architecture of sound signal analysis

1. Source of Motor Sound

Different parts of the motor like bearing, air gap distance between stator and rotor due to rotating action and design of the motor structure give rise to different sounds with variation in amplitude and/or frequency.

2. Sound Recorder Device

For detecting the sound many devices are available, example microphone, sound meter and any electronic recording devices. In our research for sound recording we have used microphone in laptop. The recorded sound is in “wav” format.

3. Data Acquisition Card

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems (abbreviated with the acronym DAS or DAQ) typically convert analog waveforms into digital values for processing. The components of data acquisition systems include:

- Sensors that convert physical parameters to electrical signals.
- Signal conditioning circuitry to convert sensor signals into a form that can be converted to digital values.
- Analog-to-digital converters, which convert conditioned sensor signals to digital values. The software in the Data Acquisition toolbox allows MATLAB to acquire data from sensors and to send out electrical signals that can be used to control or drive external devices. We will be using this toolbox with two different pieces of hardware. One is the sound card built into our laptop, the microphone and speaker will serve as the data acquisition (and output) devices

4. Signal Processing

In signal processing we are going to analyse the sound signal for different transformation methods using SP tool box of MATLAB. SP tool is a graphical user interface (GUI) that manages a suite of four other GUIs: Signal Browser, Filter Design and Analysis Tool, FV Tool, and Spectrum Viewer. These GUIs provide access to many of the signal, filter, and spectral analysis functions in the toolbox

5. Computer Display of Results

The results of sound signal of normal and faulty signal will be displayed in display window

METHODS OF SOUND SIGNAL ANALYSIS

WELCH

In this, a novel fault diagnosis method is proposed, that is radial basis function neural network with power spectrum of Welch method. This fault diagnosis model adopts the way of end-to-end operating mode. It takes the original vibration signal (time-domain signal) as input, and Welch method transforms the data from time-domain signals to power spectrums and suppresses high strength noise. Then the results of Welch method are classified by radial basis function neural network. To test the performance of radial basis function neural network with power spectrum of Welch method, the method is compared with some advanced fault diagnosis methods, and the limit performance test for radial basis function neural network with power spectrum of Welch method is carried out to obtain its ultimate diagnosis ability. The results show that the proposed method can realize the high diagnostic precision without the complex feature extraction from the signal

Welch syntax is given by, [Pxx,w] = pwelch(x)

[Pxx,w] = pwelch(x) estimates the power spectral density Pxx of the input signal vector x using Welch's method. Welch's method splits the data into overlapping segments, computes modified period grams of the overlapping segments, and averages the resulting periodograms to produce the power spectral density estimate.

The vector x is segmented into eight sections of equal length, each with 50% overlap. Any remaining (trailing) entries in x that cannot be included in the eight segments of equal length are discarded.

HAMMING:

w = hamming(L) returns an L-point symmetric Hamming window in the column vector w. L should be a positive integer. The coefficients of a Hamming window are computed from the following equation.

$$W(n)=0.54-.46\cos\left(2\pi\frac{n}{N}\right),\ 0 \leq n \geq N$$

Window length L=N+1 w = hamming(L,'sflag') returns an L-point Hamming window using the window sampling specified by 'sflag', which can be either 'periodic' or 'symmetric' (the default). The 'periodic' flag is useful for DFT/FFT purposes, such as in spectral analysis. The DFT/FFT contains an implicit periodic extension and the periodic flag enables a signal windowed with a periodic window to have perfect periodic extension. When 'periodic' is specified, hamming computes a length L+1 window and returns the first L points.

MUSIC

The name MUSIC is an acronym for MUltiple SIgnal Classification. The MUSIC algorithm estimates the pseudo spectrum from a signal or a correlation matrix using Schmidt's Eigen space analysis method. The algorithm performs Eigen space analysis of the signal's correlation matrix in order to estimate the signal's frequency content. This algorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise.The revolution in music distribution and storage brought about by personal digital technology has simultaneously fueled tremendous interest in and attention to the ways that information technology can be applied to this kind of content. From browsing personal collections, to discovering new artists, to managing and protecting the rights of music creators, computers are now deeply involved inevery aspect of music. The eigenvalues and eigenvectors of the signal's correlation matrix are estimated if you don't supply the correlation matrix.

The MUSIC pseudo spectrum estimate is given by

$$P_{music}(f) = \frac{1}{e^H(f)\left(\sum_{k=p+1}^{N} V_k V_k^H\right)e(f)} = \frac{1}{\sum_{k=p+1}^{N} |V_k^H e(f)|^2}$$

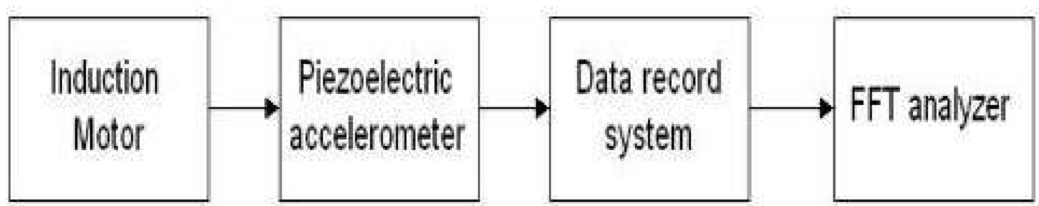
where N is the dimension of the eigenvectors and Vk is the k-th eigenvector of the correlation matrix. The integer p is the dimension of the signal subspace, so the eigenvectors Vk used in the sum correspond to the smallest eigenvalues and also span the noise subspace. The vector e(f) consists of complex exponentials, so the inner product amounts to a Fourier transform. This is used for computation of the pseudo spectrum estimate. The FFT is computed for each Vk and then the squared magnitudes are summed

3. VIBRATIONAL ANALYSIS

INTRODUCTION

Vibration Analysis refers to the process of measuring the vibration levels and frequencies of industrial machinery, and using that information to determine the “health” of the machine, and its components.

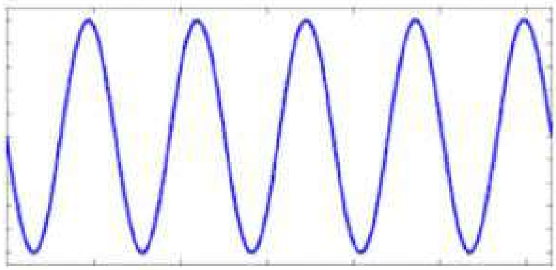
The forces occurring in the rolling element bearing in electrical machines create high frequency components of vibration. During normal conditions, these high frequency components are mainly because of friction but in case of a defect in bearings shock pulses can also be found due to breaks in lubrication layer between the friction surfaces. This method analyses the vibration spectrum of an induction machine using piezoelectric accelerometer which works on Fast Fourier Transform to extract from a time domain signal the frequency domain representation.



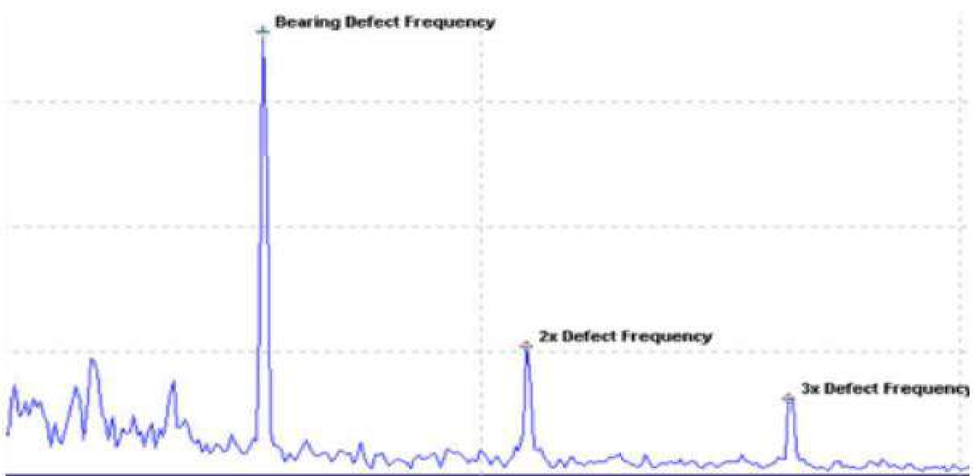
Schematic vibration measurement equipment.

When an industrial machine (such as a fan or induction motor) is operated, it generates vibration. This vibration can be measured, using a device called an accelerometer. An accelerometer generates a voltage signal, proportional to the amount of vibration, as well as the frequency of vibration, or how many times per second or minutes the vibration takes place. This voltage signal from the accelerometer is fed into a data collector, which records this signal as either a time waveform (amplitude vs. time), as a Fast Fourier Transform (amplitude vs. frequency), or as both. This signal can then be analyzed by a trained vibration analyst, or by the use of a “smart” computer program algorithm. The analyzed data is then used to determine the “health” of the machine, and identify any impending problems in the machine, such as misalignment, unbalance, a bearing or lubrication problem, looseness, and more As an example, if we took a general industrial fan, removed one of the fan blades, and started the fan up, we could expect the fan to vibrate, due to an unbalanced fan wheel. This unbalance force would occur one time per revolution of the fan.

If we re-installed the fan blade, this vibration would be reduced.



In another example, if a bearing on this fan had a spall (a portion of the bearing race gets damaged, much like a “pot hole” on a highway), each time one of the bearing’s roller contacted this spall, it would generate a vibration.
If 3.2 rollers “hit” the spall per revolution, we should expect to see a vibration signal of 3.2 times the running speed of the fan.



The use of vibration analysis can determine problems caused due to improper installation, machining errors, insufficient lubrication, improper shaft or sheave alignment, loose bolting, bent shafts, and much more. It can, in most cases, detect these problems long before the damage can be seen by maintenance, and long before it damages other machine components. The use of vibration analysis, condition monitoring, or predictive maintenance has made great strides increasing the usable life of machinery.

Vibration Frequency Spectrum

Vibration frequency spectrum contains fundamental frequencies, their harmonics and sidebands given by both, mechanical and electrical properties of the machine.

1. Twice line frequency

Twice line frequency (2fL) is caused by radial magnetic forces acting on the stator teeth and core. Values of these forces are derived from the air gap flux density distribution and vary in space and time.

$$p(\alpha,t) = \frac{B^2(\alpha,t)}{2\mu_0}$$

In p is the specific magnetic force in the particular time instant t and angular position around stator circumference α , B is the corresponding flux density and 0 μ is permeability of free space. Considering sinusoidal magnetizing current the resulting force has two peak values in each current period – if the current is at the positive and the negative maximum value. This means that vibrations caused by this force have frequency equal to twice the frequency of the supplying current.

2. Rotational speed frequency

Vibrations at the rotational speed frequency are characteristic for different kinds of faults. Besides rotor eccentricity, vibrations at this frequency can occur for example in case of unbalanced rotor, coupling misalignment or broken rotor bar. In order to true source of vibrations identification some other tests should be carried out. Among these tests belongs stator current frequency spectrum analysis or coastdown of the machine. Since the origin of these vibrations is electromagnetic, they should disappear immediately when the power supply is disconnected. Rotor eccentricity leads to the non-uniform air gap length around the stator circumference. That results in greater magnetic force acting in the direction of minimal air gap – unbalanced magnetic pull (UMP). Since the position of theminimal air gap is changing with revolving rotor UMP excites the vibration at the rotor speed frequency.

$$f_{1x} = \frac{RPM}{60}$$

3. Rotor bar passing frequency

Rotor bar passing frequency vibrations are caused by magnetic field around the rotor bars. This magnetic field is generated by the current induced into the bars. The forces caused by this magnetic field act on stator teeth and excite vibrations in the stator teeth and core. The amplitude of the vibrations increases with load. Frequency (4) of these vibrations is usually higher than 1 kHz and is out of the standard vibration diagnostics measurement range.

$$f_{Qr} = \frac{RPM \cdot Q_r}{60}$$

In Qris the number of rotor slots. Rotor bar passing frequency has also sidebands at + or – 2fl ,4fl,6fl.These vibrations are the main sources of high frequency noise in electrical machines, but do not cause any structural damage [2].

4. Higher eccentricity related frequencies

These frequencies are given by stator MMF harmonics and rotor slotting. They slightly change for different faults and can appear even in vibration frequency spectrum of healthy machine. The frequency values for the case of eccentricity according to [3] are given by:

$$f_{ecc} = \left[(iQ_r \pm k_e) \frac{1-s}{p} \pm n \right] f_1$$

ANALYSIS METHOD

1. Envelope Analysis (EA)

The envelope Analysis is an important signal processing technique which used to extract the fault features from modulation signals. The envelope Analysis can be decomposed into three steps; signal filtering, envelope extraction of the filtered signal by the application of Hilbert transform (HT), and the determination of the spectrum of the envelope by the applying the Fast Fourier transform (FFT).

The Hilbert Transform in time domain, for a given signal x(t), is given by:-

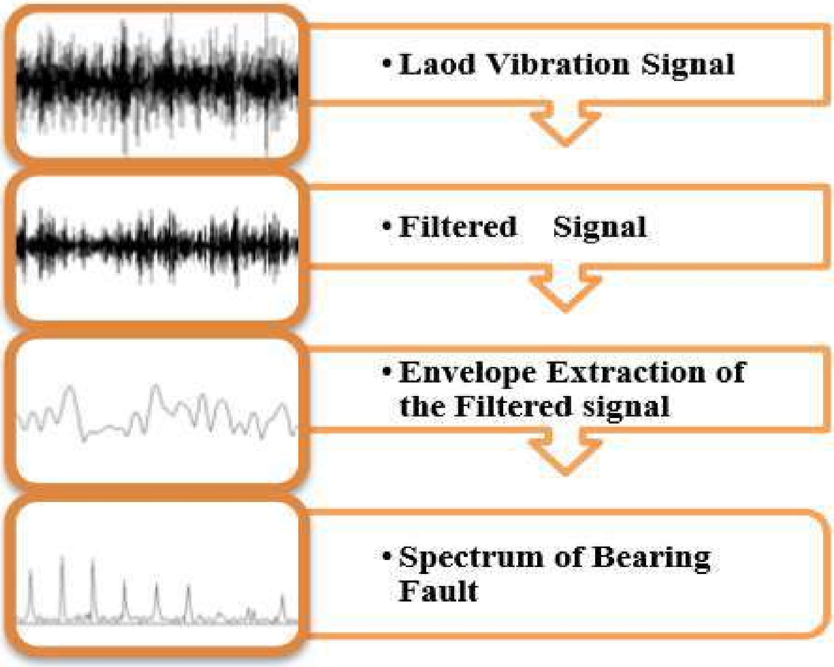
$$x(t)=\frac{1}{\pi}\int_{-\infty}^{+\infty} x(\tau)\,\frac{1}{t-\tau}\,d\tau$$

It is defined as the convolution of the signal x(t) with function 1/πt, which is the impulse response function of the Hilbert Transformer. The phase shifted and original signals are summed up to obtain an analytic signal x+(t) defined as follows ;

$X_+(t) = X(t) + jX(t)$

And,

$v(t)=\sqrt{[X_+(t)^2 + X(t)^2]}$



Procedure for Envelop Analysis (EA)

2. Short-Time Fourier Transform (STFT)

Short-Time Fourier Transform (STFT) or windowed Fourier transform (WFT) is the most widely used tool for time frequency (TF) analysis of non-stationary signals. The idea of STFT is to analyze the signal into segment by segment (or window by window). It uses a window function to slide on the signal studied and then divide it into several equal length segments (or window). The inside signal of the segments is supposed to be stationary. After that Fourier transform is applied in each segment to find out the frequencies contained in that segment.
Hence, the signal will be represented by two elements of: time and frequency shown inthe figure given below:-

For a signal x(t), its short time Fourier transform is defined as follows;

$STFT_x^{w}(\tau, f) = \int x(t).w*(t-\tau).e^{-i2\pi ft}dt$ Where:

W (t): is the window of width T which centered at τ

τ: is the parameter of temporal location of the window g

.

w *(t): is the conjugate of the complex function w (t).

The identification of the bearing faults is possible by using STFT. However, the problem with STFT is that it provides constant resolution for all frequencies since it uses the same window for the entire signal. Therefore, once the window function is chosen, the time and frequency resolution are fixed. So there is a trade-off to choose a proper window function between the time resolution and the frequency resolution: a longer window will lead to a higher frequency resolution with a lower time frequency and vice versa.

3. Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition (EMD) is an adaptive time-frequency technique for analyzing nonlinear and non-stationary signals, which can decompose the time domain signal into a set of oscillatory functions in the time-domain, called intrinsic mode functions (IMF). The nonlinear signal (i) is then decomposed into M intrinsic modes and a residue R_M.

$$i(n) = \sum_{m=1}^{M} imf_m(n) + R_M(n)$$

Empirical Mode Decomposition (EMD) is an excellent tool for bearing fault diagnosis. Unfortunately, there are two problems in EMD, which are the selection of the suitable decomposition level and its intrinsic mode functions (IMF) which contains the necessary information for faults diagnosis.

4. MCSA AND STATOR CURRENT

INTRODUCTION

Bearings are one of the critical components in rotating machinery. The need of an easy and effective fault diagnosis technique has led to the increasing use of motor current signature analysis (MCSA). Bearing faults in the mechanical system run by an induction motor causes change in its stator current spectrum. The faults in the bearings cause variations of load irregularities in the magnetic field which in turn change the mutual and self inductance causing side bands across the line frequency. The objective of this project report is to detect bearing faults (outer race fault) in a mechanical system using motor current signature. Fast Fourier Transform (FFT) is initially employed for a first comparison between a healthy and a defective bearing. Six wavelets are considered out of which three are real valued and remaining three are complex valued. Base wavelet has been selected on the basis of wavelet selection criteria - Maximum Relative wavelet energy.
With MCSA, the frequency spectrum of the measured stator current is obtained to perform analyses. In that spectrum, specific current components could be related to some electrical and mechanical errors. Besides the technical difficulties, it is plausible and relatively straightforward that electric stator (e.g. winding breakdown), electric rotor (e.g. broken rotor bar) or electric bearing problems (e.g. bearing currents) are detectable in the measured current. This is described and elucidated extensively by other authors. Detecting mechanical faults is only possible due to the radial rotor displacement excited by the fault (e.g. rotor eccentricity, bearing inner/outer race faults). The radial movement implies an air-gap variation (varying space between rotor and stator). The air-gap variation means electricity - wise a change of reluctance and flux linkage, which is detectable in the stator current. The mechanical fault frequencies are very similar to the formulas for vibration analysis but are modulated on the fundamental current frequency, due to the rotor movement-inductance variation transmission. Some fault frequencies could overlap in the frequency spectra. MCSA relies specifically on the induction machine as a sensor. The radial movement of the rotor in the stator leads to a change in the magnetic field which is detectable in the motor current. Theoretically, all faults that affect this radial movement result in a specific current signature. Therefore, MCSA is the designated technology to detect not only bearing defect but all kinds of faults in the machine

In STATOR CURRENT,

Different wavelength transform techniques are compared to find out the bearing faults in the induction machine, using the current frequency spectral subtraction. The various techniques that we perform on this test are as: Discrete wavelength transform (DWT), Stationary wavelength transform (SWT), Wavelet packet decomposition (WDP) and compared analysis to detect the fault in the bearing. In this work, the spectral subtraction is used to cancel the pre fault components in the stator current and also reduce the impact of noise. The stator current under healthy condition is modelled and decomposed into wavelet coefficients using DWT, SWT, and WPD. After that, the healthy stator current acquired from the induction motor is also decomposed into wavelet coefficient with same technique and after that the resultant coefficients are used to reconstruct a signal which is used to estimate the fault component

METHODS

STATOR CURRENT

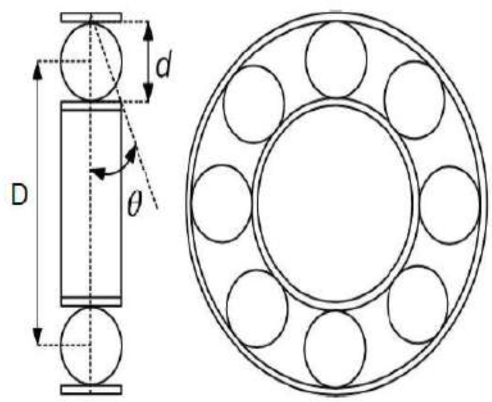
ELECTRICAL machines are virtually in all industrial plants today. A commonly used propulsion system device is an induction motor. The simplicity of the construction of this engine makes its bearing the most damageable elements. Statistical studies clearly show, that almost half (40%) of engine failures is caused by damage to the bearings. Detection of bearing fault depends on the extraction of a deterministic signal and its analysis to localize the fault. In the case of a fault localized on the inner or outer race, whenever a rolling element passes through the fault surface, a disturbance is generated. This disturbance is almost periodic series of impulses represent characteristics that vary with bearing geometry and fault localization; and also it produces resonance in the bearing and also in machine as a whole.
Since this series of generated impulse (disturbance) get amplitude modified when fault passes the load zone and these can be collected through sensors. Generation of this impulse varies with: the fault position (inner race, outer race, and cage), the bearing dimensions, and the machine shaft speed (fr). Therefore we can estimate the bearing characteristic frequencies, i.e., ball pass frequency of the outer race (BPFO), ball pass frequency of the inner race (BPFI), fundamental train frequency (FTF), which is related to cage speed rotation, and ball spin frequency (BSF).
The following equations represent these frequencies:

$$\text{BPFO} = \frac{n f_r}{2}\left(1 - \frac{d}{D}\cos\alpha\right)$$

$$\text{BPFI} = \frac{n f_r}{2}\left(1 + \frac{d}{D}\cos\alpha\right)$$

$$\text{FTF} = \frac{f_r}{2}\left(1 - \frac{d}{D}\cos\alpha\right)$$

$$\text{BSF} = \frac{D}{2d}\left[1 - \left(\frac{d}{D}\cos\alpha\right)^2\right]$$



Where, f_{bpfo} : outer race fault frequency,
f_{bpfi} : inner race fault frequency,
f_{rf} : rolling element fault frequency,
f_{cf} : cage fault frequency,
n_b : no. of rolling elements,
f : rotational frequency,
d : diameter of rolling element,
D : pitch diameter of rolling element bearing,
θ : contact angle.

When such characteristics frequencies occur we can say that bearing fault has occurred and can find its location. However, it is very difficult to extract these components, since they have low amplitude and are merged with other spectral components and background noise. Therefore fault detection of bearing using this technique is very difficult specially in industries where low signal-to-noise ratio of the characteristic frequency components associated with these faults, even though several studies have shown promising results in this area. On the other hand, in many situations, motor current signature analysis (MCSA) becomes a useful alternative to traditional fault detection methods, e.g., vibration analysis, particularly considering the sensor installation, risks, costs associated with process, and degree of criticality of the system or machine under analysis.

MCSA

MCSA is one of the most commonly used techniques to fault detection in induction motors, since it allows identifying electrical and mechanical faults. It performs a spectral analysis of stator electrical current, which is usually monitored at one of three power supply phases. In case of bearing faults, we consider that machines inductances varies due to rotating eccentricities at bearing characteristic frequencies f_C, i.e., BPFO, BPFI, etc., which produces a stator current modulation, described by

$$f_E = f_s \pm k \cdot f_C$$

where f_E is the frequency related to a bearing fault; f_s is the power supply frequency; and $k = 1, 2, 3, \ldots$ is the harmonic number. Thus, f_C appears in the current spectrum as sidebands. In this context, it is import to observe that rotor inertia and winding inductances produce an electromechanical filtering effect in stator current, such that, this current is mainly affected by low frequency components.

Using another approach we can model the effect of localized bearing fault in stator current as air gap eccentricity. In this case, a magnetic flux density variation affects stator current as a function of the fault location. Thus, frequencies related to the bearing faults are expressed by:

$$f_{E\,\text{outer race}} = f_s \pm k \cdot \text{BPFO}$$
$$f_{E\,\text{inner race}} = f_s \pm f_r \pm k \cdot \text{BPFI}$$
$$f_{E\,\text{ball}} = f_s \pm \text{FTF} \pm k \cdot \text{BSF}$$

where f_E *outer race*, f_E *inner race*, and f_E *ball* are the frequencies related to a fault in outer race, inner race, and ball respectively, which correspond to an amplitude modulation of the fundamental

power supply frequency (f_s). The current spectrum is not only corrupted by noise, but also by numerous harmonic components resulting from the regular magnetic behaviour of an induction machine. The biggest challenge for the practical implementation of MCSA is to measure and distinguish the fault frequencies from the other components and noise, located very close to and even faded with each other. However, by using an accurate frequency/magnitude resolution and the right signal processing methods, mechanical faults are detectable.

PRACTICAL IMPLEMENTATION OF MCSA

In order to obtain an accurate frequency spectrum of the stator current, primary and important part is measuring the current. The bearings in which the faults are to be detected using MCSA are installed in the mechanical system. The faults in the bearings installed in the mechanical system can be created artificially by electrical discharge machining. We must know all the specifications of ball bearing we are going to use in experimental setup like:

1. Number of balls
2. Shaft Speed
3. Ball Diameter
4. Pitch Diameter
5. Contact angle of bearing

For measuring the input current waveform of the three phases of the induction motor, three Tektronix A622 Hall Effect current probes can be used. Vibration monitoring can be done with an IMI make accelerometer, 608A11 (sensitivity of 100 mV/g).The outputs from the accelerometer and current probes can be recorded in a 4-channel data acquisition system of National Instruments (NI 9234 card and NI cDAQ -9174 chassis) attached with a PC with NI Lab View software. Raw signal data from the sensors are stored for future processing. The rotation speed of the motor can be measured with a built-in tachometer with LCD display and analog output. A belt and pulley arrangement mounted on the free end of the shaft for mechanical loading the test rig bearings.

Or we can use commercially available current clamps with a well defined range, accuracy and bandwidth as per requirement and budget. If a digital analysing program is desired (e.g. Matlab, Labview), a discrete sampling is needed (analog to digital transformation). Therefore, data acquisition cards are used to accomplish the discrete sampling. With the use of those cards, the data-import in mathematical software to perform the analysing algorithms is very convenient. The loss of data due to the analog-digital transformation (accuracy, bandwidth and quantization step) is neglected in relation to the properties of the current clamps.

Bounded to a discrete time sampling of the current, only a discrete frequency spectrum can be calculated. One of the possible tool for this is DFT(Discrete Fourier Transform) described by:

$$I_k = \sum_{n=0}^{N-1} i_n e^{-i2\pi kn/N}$$

with the sequence I_k of N complex numbers, the discrete stator current in and k the frequency per N samples (N is the number of samples).

The most obvious execution tool to perform a DFT is the Fast Fourier Transform (FFT), which is the most efficient way to perform a DFT. However, using a discrete frequency analysis implies some important consequences to the spectra and the analysis of it. Terms such as *aliasing* and l*eakage* are introduced and heavily disturb the spectral results. Although, using the correct sample rate, measurement time and a proper defined window minimizes the interference of these effects on the results. Greater the number of samples we take higher is our resolution.

KOLMOGOROV-SMIRNOV TEST

Applications of statistics are concerned about the question of whether two sets of data come from the same distribution function. For example, to test whether two distributions of gray intensities have the same distribution. This kind of test is called a goodness-of-fit test, K-S Test is an example of that kind of test. Let (x1, x2, ..., xn) be independent random variable, the distribution function (also called cumulative distribution function, CDF) is described as

$F(x) = P(X \leq x)$

where $x \in R$, $X \in R^n$, P(•) is a counter of the values that satisfy the • condition. The K-S Test is used to quantify the distance between the CDFs of two independent samples (or vectors) and determines if they arose from the same distribution. Let a sample X = {x1, x2, ..., xm} has a CDF $F_m(x)$ and a second sample Y = {y1, y2, ..., yn} has a CDF $G_n(x)$ and be two current distribution. Then, the distance between $F_m(x)$ and $G_n(x)$ can be calculated as follow

$$\hat{D}_{mn} = \max |F_m(x) - G_n(x)|$$

The value is used to calculate a threshold value $Q_{KS}(\lambda)$ described in below equation:

$$Q_{KS}(\lambda) = 2\sum_{j=1}^{\infty}(-1)^{j-1}e^{-2j^2\lambda^2}$$

where $\lambda = \hat{D}[\sqrt{J}+0.11/\sqrt{J}+0.12]$ and $J = \frac{mn}{m+n}$The value of $Q_{KS}(\lambda)$ may be treated as the p-value of the K-S Test. On this way, if a distance $\hat{D}_{mn}$ separates two current vectors and $\alpha_{0.05} \geq Q_{KS}(\lambda)$, then it can be said that the two current vector do not arise from the same distribution with a 5% of error.

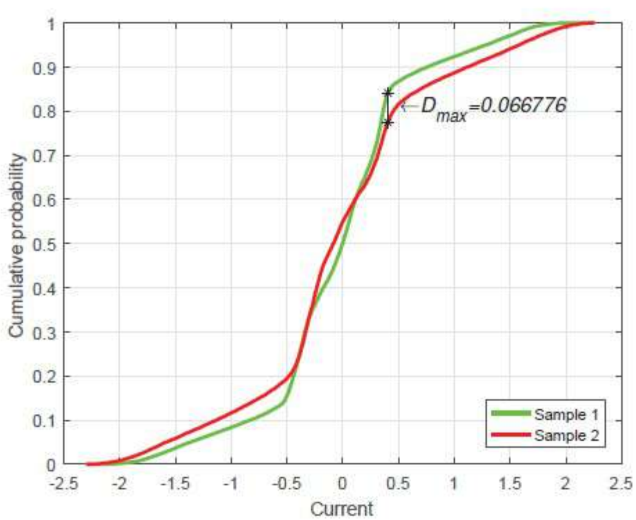
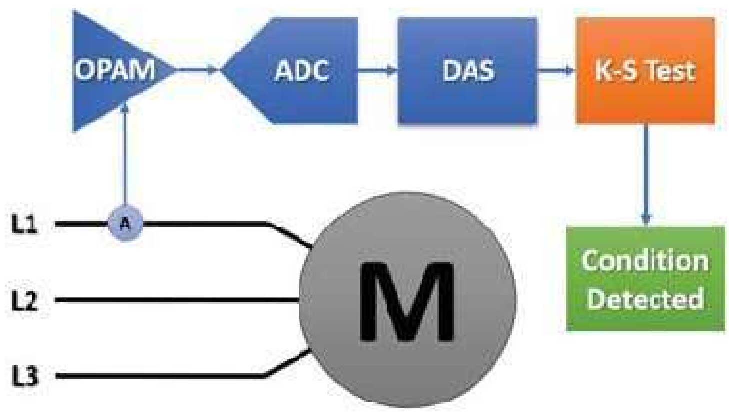


Fig. The Kolmogorov-Smirnov distance for two current samples.

METHODOLOGY

This methodology proposed consists on to obtain signals from a current sensor installed in a phase of the IM. Then, each signal is fitted by Instrumentation Amplifiers, and a Data Acquisition System (DAS) is used to capture and manage the data. The signals can be transmitted to a computer for labeling and saving. Later, the proposed technique is to be applied. The first step of this methodology consists of measuring current signals from ND and BF condition and featuring them. The featuring process comprises in to calculate the CDF of each signal. Then, the CDFs are compared with the CDF baseline of each condition to determine the maximum distance between a signal regarding a particular reference. From the maximum distance, a reference p-value is calculated to determine if the signal comes from one of the two motor conditions with a confidence value of $\alpha = 0.05$.



Experimental Setup: Thermography Method To Detect Bearing Fault:

A. TEST SETUP

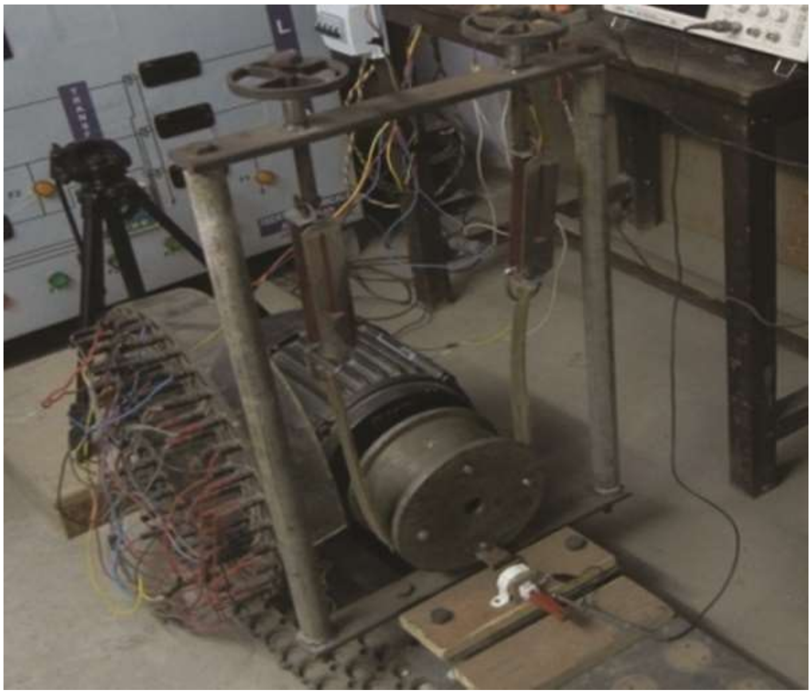


Figure 1

The experimentation is done in Electrical Engineering lab at Dayalbagh Educational Institute (Deemed University) Agra, India. The experiment setup is consisting of one induction motor having a healthy cooling system with the arrangement through which fault in the cooling system can be created. The specification of the motor are three phase Squirrel cage induction motor 230V, 50Hz, 3HP, inbuilt fan type cooling. A voltage –current-frequency (VIF) meter, one infrared thermal imaging camera with a proper fixed camera stand and one computer with MATLAB software installed. The real time image is acquired with the help of infrared thermal imaging camera for both healthy and faulty condition of the cooling system at different load conditions. For both the condition data are sent to computer. MATLAB imports these signals and graphs are drawn for all the parameters at faulty and healthy condition. Graphical analysis is also done for the final declaration of the health condition of the induction motor.Fig.1 shows the experimental setup of health monitoring system of induction motor using infrared thermal imaging camera.

B. Infrared Thermal Camera Specification

Used camera specification for the thermal imaging for experimental purpose of induction motor is shown as follow.

Image characteristics:

– Focus: Manual
– Field of view / min focus distance: 18° x 13° / 0.3m Thermal sensitivity: ≤ 0.1°C@30°C – spatial resolution (IFOV): 1.9 mrad Frame rate: 50/60 Hz
– Spectral range: 8 – 14µm
– Electronic zoom: 2X

Detector characteristics:

– Array size / format: 160 X 120
– Detector type: Uncoiled FPA microbolometer.

Image display:

– Temperature ranges : -20°C ~ + 350°C, optional up to +600°C or 1000°C
– LCD: Built-in-high resolution Color 2.5O LCD
– Measurement:
– Setup functions: Date / time, temperature unit, language
– Emissivity correction: Variable from 0.01 to 1.0
– Ambient temperature correction: Automatic correction according to user input
– Atmospheric transmission correction: Automatic correction according to user input object distance, relative humidity, ambient temperature.
– Accuracy: ± 2°C or ± 2 % of reading, whichever is greater.

Laser pointer:

Laser pointer: Class 2, 1mw / 635nm (red)

Image storage:

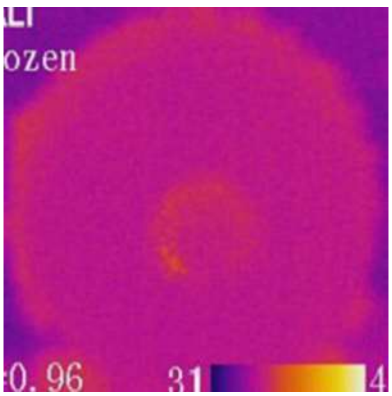
Storage mode: Automatic / manual single image saving
File format – thermal: PNG, 14 bit thermal image with measurement data

Experimentation:

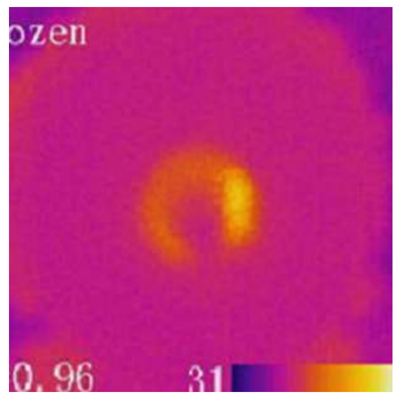
For the proposed method, we have a system i.e. one induction motor with the arrangement that we can create the fault in the cooling system of that motor easily. One digital camera is fixed on the stand to capture the infrared digital images. First we acquired the infrared thermal images of the motor from the healthy motor at different load conditions. Then we create the fault in the bearing of motor manually.

Then we acquired the infrared thermal images the faulty motor. All the images are taken from a fixed location from the camera stand. Then we crop particular part of the thermal images Firstly we divided our image into 9 equal parts then after selecting central part of the image we find RGB mean of that part for both reference image and test image and compare both means to detect fault in test image. For all the analysis we only used thermal images in MATLAB to find results.

Initial Images:



Initial Reference Image



Initial Test Image

MATLAB CODE

```
%%%%%%1.BEARING
%%%%%%2.SHAFT
%%%%%%3.WINDING


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%           BEARING CODE                      %%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%for bearing we create 2 mask instead of 1 for both REFERENCE and TEST
image%%%%%%%%%%%%%%%%
%%%%Bt01 IS FINAL REFERENCE IMAGE
%%%%FOR REFERENCE IMAGE%%%%%%%%%%%%%
%%%%creating mask 1%%%%%%%%%

%%%%%%t1 is just a white blank image%%%%%%%%%%
%%%%%%B01, Bt01 are images usede to create mask 1 image%%%%%%%%%%%

RefMASK1 = imread('C:\Users\hp\Desktop\major_project\ref1.png');
[rows, columns, numberOfColorChannels] = size(RefMASK1);
```

```
% Get the second image - should be the same size as rgbImage1.
RefIMAGE1 = imread('C:\Users\hp\Desktop\major_project\t1.png');
RefIMAGE1 = imresize(RefIMAGE1, [rows, columns]);


% Make the circle mask.
imageSize = size(RefMASK1);
ci = [165, 150, 55];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;


% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = RefMASK1(:, :, 1);
greenChannel1 = RefMASK1(:, :, 2);
blueChannel1 = RefMASK1(:, :, 3);


redChannel2 = RefIMAGE1(:,:,1);
greenChannel2 = RefIMAGE1(:,:, 2);
blueChannel2 = RefIMAGE1(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
RefIMAGE1 = cat(3, redChannel2, greenChannel2, blueChannel2);






%%%%%%%%%%%creating mask2%%%%%%%%%%%%

RefMASK2 = imread('C:\Users\hp\Desktop\major_project\t1.png');
[rows, columns, numberOfColorChannels] = size(RefMASK2);


% Get the second image - should be the same size as rgbImage1.
RefIMAGE2 = RefIMAGE1;
RefIMAGE2 = imresize(RefIMAGE2, [rows, columns]);


% Make the circle mask.
imageSize = size(RefMASK2);
ci = [165, 150, 25];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;
```

```
% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = RefMASK2(:, :, 1);
greenChannel1 = RefMASK2(:, :, 2);
blueChannel1 = RefMASK2(:, :, 3);


redChannel2 = RefIMAGE2(:,:,1);
greenChannel2 = RefIMAGE2(:,:, 2);
blueChannel2 = RefIMAGE2(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
RefIMAGE2 = cat(3, redChannel2, greenChannel2, blueChannel2);







%%%%%
%%%%%%%%%%%%%%%%%%%%FOR TEST IMAGE OF
BEARING%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%


%%%%%
%%%%%t1 is just a white blank image%%%%%%%%%

%%%%%%B03, Bt03 are images usede to create mask 1 image%%%%%%%%%%
TestMASK1 = imread('C:\Users\hp\Desktop\major_project\test1.png');
[rows, columns, numberOfColorChannels] = size(TestMASK1);


% Get the second image - should be the same size as rgbImage1.
TestIMAGE1 = imread('C:\Users\hp\Desktop\major_project\t1.png');
TestIMAGE1 = imresize(TestIMAGE1, [rows, columns]);


% Make the circle mask.
imageSize = size(TestMASK1);
ci = [165, 150, 55];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;


% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = TestMASK1(:, :, 1);
greenChannel1 = TestMASK1(:, :, 2);
blueChannel1 = TestMASK1(:, :, 3);
```

```
redChannel2 = TestIMAGE1(:,:,1);
greenChannel2 = TestIMAGE1(:,:, 2);
blueChannel2 = TestIMAGE1(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
TestIMAGE1 = cat(3, redChannel2, greenChannel2, blueChannel2);





%%%%%%%%%%%creating mask2%%%%%%%%%%%%
%%%%%%%%%%%B04, Bt04 are used to create mask2
TestMASK2 = imread('C:\Users\hp\Desktop\major_project\t1.png');
[rows, columns, numberOfColorChannels] = size(TestMASK2);


% Get the second image - should be the same size as rgbImage1.
TestIMAGE2 = TestIMAGE1;
TestIMAGE2 = imresize(TestIMAGE2, [rows, columns]);


% Make the circle mask.
imageSize = size(TestMASK2);
ci = [165, 150, 25];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;


% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = TestMASK2(:, :, 1);
greenChannel1 = TestMASK2(:, :, 2);
blueChannel1 = TestMASK2(:, :, 3);


redChannel2 = TestIMAGE2(:,:,1);
greenChannel2 = TestIMAGE2(:,:, 2);
blueChannel2 = TestIMAGE2(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
TestIMAGE2 = cat(3, redChannel2, greenChannel2, blueChannel2);
```

```
% Display final ref image

subplot(3, 2, 1);
imshow(RefIMAGE2);
axis('on', 'image');
title('FINAL REFERENCE IMAGE(BEARING)', 'FontSize', 10);


% Display final test image.
subplot(3, 2, 2);
imshow(TestIMAGE2);
axis('on', 'image');
title('FINAL TEST IMAGE(BEARING)', 'FontSize', 10);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%             CODE FOR DETECTING BEARING FAULT


b1 = RefIMAGE2;
b2 = TestIMAGE2;
[mb1,nb1,sb1] = size(b1);
[mb2,nb2,sb2] = size(b2);
flagB = true;

for i=1:sb1
 x = b1(:,:,i);
    % disp(x);
   sum = 0;
   [row,col] = size(x);
   m = uint16(row/3);
   n = uint16(col/3);
   %disp(row);
   %disp(col);
   counter=0;
        for a=n:2*n
             for b=m:2*m
               %disp(a);
               %disp(b);
               %disp(x(a,b));
               sum = sum + uint32(x(b,a));
               counter = counter +1;
             end
        end
   %disp(sum);
   mean_val1 = sum/counter;
   %disp(mean_val1);
    mean1 = mean_val1;
    disp(mean1);
 x = b2(:,:,i);
    % disp(x);
   sum = 0;
   [row,col] = size(x);
   m = uint16(row/3);
   n = uint16(col/3);
   %disp(row);
   %disp(col);
   counter=0;
        for a=n:2*n
             for b=m:2*m
               %disp(a);
```

```
                %disp(b);
                %disp(x(a,b));
                sum = sum + uint32(x(b,a));
                counter = counter +1;
              end
         end
    %disp(sum);
    mean_val2 = sum/counter;
    %disp(mean_val2);
     mean2 = mean_val2;
     disp(mean2);
     rat = double(mean1)/double(mean2);
     %disp(rat);
     if((rat>1.2) || (rat<0.8))
         flagB = false;
     end
end

if flagB==0
    disp('There is a fault in BEARING');
else
    disp('BEARING is healthy');
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%           SHAFT CODE                     %%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


%%%%%%%%%%%%%%%%%%REFERENCE image for shaft%%%%%%%%%%%%%%%




%S1, ST1 MAKES FINAL REFERENCE SHAFT IMAGE
S1 = imread('C:\Users\hp\Desktop\major_project\ref1.png');
[rows, columns, numberOfColorChannels] = size(S1);


% Get the second image - should be the same size as rgbImage1.
St1 = imread('C:\Users\hp\Desktop\major_project\t1.png');
St1 = imresize(St1, [rows, columns]);


% Make the circle mask.
imageSize = size(S1);
ci = [170, 150, 22];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;


% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = S1(:, :, 1);
greenChannel1 = S1(:, :, 2);
blueChannel1 = S1(:, :, 3);


redChannel2 = St1(:,:,1);
```

```
greenChannel2 = St1(:,:, 2);
blueChannel2 = St1(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
St1 = cat(3, redChannel2, greenChannel2, blueChannel2);






%%%%%%%%%%%%%%%%%%TEST image for shaft%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%




%S2, ST2 MAKES FINAL REFERENCE SHAFT IMAGE
S2 = imread('C:\Users\hp\Desktop\major_project\test1.png');
[rows, columns, numberOfColorChannels] = size(S2);


% Get the second image - should be the same size as rgbImage1.
St2 = imread('C:\Users\hp\Desktop\major_project\t1.png');
St2 = imresize(St2, [rows, columns]);


% Make the circle mask.
imageSize = size(S2);
ci = [170, 150, 22];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;


% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = S2(:, :, 1);
greenChannel1 = S2(:, :, 2);
blueChannel1 = S2(:, :, 3);


redChannel2 = St2(:,:,1);
greenChannel2 = St2(:,:, 2);
blueChannel2 = St2(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
St2 = cat(3, redChannel2, greenChannel2, blueChannel2);
```

```
subplot(3, 2, 3);
imshow(St1);
axis('on', 'image');
title('FINAL REFERENCE IMAGE(SHAFT)', 'FontSize',10);

subplot(3, 2, 4);
imshow(St2);
axis('on', 'image');
title('FINAL TEST IMAGE(SHAFT)', 'FontSize', 10);

%%%%%%%detecting fault in wdg%%%%%%%%%%%%%%%%%%%%%%%
sh1 = St1;
sh2 = St2;

[ms1,ns1,ss1] = size(sh1);
[ms2,ns2,ss2] = size(sh2);
flagS = true;


for i=1:ss1
 x = sh1(:,:,i);
    % disp(x);
   sum = 0;
   [row,col] = size(x);
   m = uint16(row/3);
   n = uint16(col/3);
   %disp(row);
   %disp(col);
   counter=0;
        for a=n:2*n
             for b=m:2*m
               %disp(a);
               %disp(b);
               %disp(x(a,b));
               sum = sum + uint32(x(b,a));
               counter = counter +1;
             end
        end
   %disp(sum);
   mean_val1 = sum/counter;
   %disp(mean_val1);
    mean1 = mean_val1;
    disp(mean1);
 x = sh2(:,:,i);
    % disp(x);
   sum = 0;
   [row,col] = size(x);
   m = uint16(row/3);
   n = uint16(col/3);
   %disp(row);
   %disp(col);
   counter=0;
        for a=n:2*n
             for b=m:2*m
               %disp(a);
               %disp(b);
               %disp(x(a,b));
```

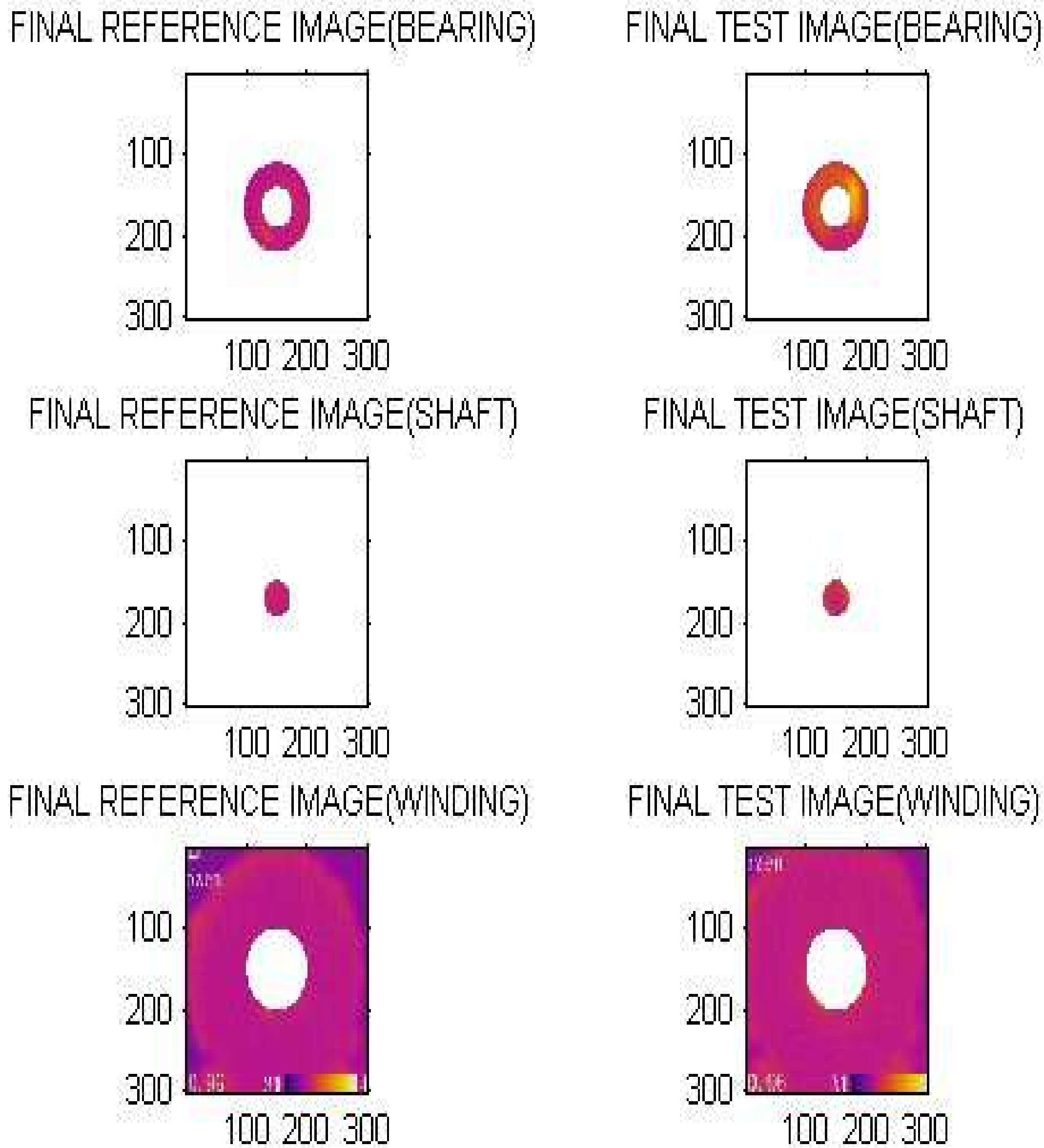
```
                sum = sum + uint32(x(b,a));
                counter = counter +1;
            end
        end
    %disp(sum);
    mean_val2 = sum/counter;
    %disp(mean_val2);
     mean2 = mean_val2;
     disp(mean2);
     rat = double(mean1)/double(mean2);
     %disp(rat);
     if((rat>1.2) || (rat<0.8))
         flagS = false;
     end
end

if flagS==0
    disp('THERE IS A PROBLEM IN SAHFT');
else
    disp('SHAFT IS HEALTHY');
end


%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%           WINDING CODE                     %%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%



%detecting wnding fault with 20% tolerance
%%%%%%%%%%%%%%%%%%ref image for wdg%%%%%%%%%%%%%%%%
%Read first image.

r1 = imread('C:\Users\hp\Desktop\major_project\t1.png');
[rows, columns, numberOfColorChannels] = size(r1);


% Get the second image - should be the same size as rgbImage1.
t1 = imread('C:\Users\hp\Desktop\major_project\ref1.png');
t1 = imresize(t1, [rows, columns]);


% Make the circle mask.
imageSize = size(r1);
ci = [150, 150, 50];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;


% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = r1(:, :, 1);
greenChannel1 = r1(:, :, 2);
blueChannel1 = r1(:, :, 3);


redChannel2 = t1(:,:,1);
```

```
greenChannel2 = t1(:,:, 2);
blueChannel2 = t1(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
t1 = cat(3, redChannel2, greenChannel2, blueChannel2);
% Display it.





%%%%%%%%%%%%%%%%%%test image for wdg%%%%%%%%%%%%%%%%%%%%%%%%%%%

r2 = imread('C:\Users\hp\Desktop\major_project\t1.png');
[rows, columns, numberOfColorChannels] = size(r2);


% Get the second image - should be the same size as rgbImage1.
t2 = imread('C:\Users\hp\Desktop\major_project\test1.png');
t2 = imresize(t2, [rows, columns]);


% Make the circle mask.
imageSize = size(r2);
ci = [150, 150, 50];     % center and radius of circle ([c_row, c_col, r])
[xx,yy] = ndgrid((1:imageSize(1))-ci(1),(1:imageSize(2))-ci(2));
mask = (xx.^2 + yy.^2) < ci(3)^2;


% Get the individual color channels
% Extract the individual red, green, and blue color channels.
redChannel1 = r2(:, :, 1);
greenChannel1 = r2(:, :, 2);
blueChannel1 = r2(:, :, 3);


redChannel2 = t2(:,:,1);
greenChannel2 = t2(:,:, 2);
blueChannel2 = t2(:,:, 3);


% Paste the image from the circle region of rgbImage1 onto rgbImage2 in
just the circle region.
redChannel2(mask) = redChannel1(mask);
greenChannel2(mask) = greenChannel1(mask);
blueChannel2(mask) = blueChannel1(mask);

% Recombine separate color channels into a single, true color RGB image.
t2 = cat(3, redChannel2, greenChannel2, blueChannel2);
% Display it.

subplot(3, 2, 5);
```

```
imshow(t1);
axis('on', 'image');
title('FINAL REFERENCE IMAGE(WINDING) ', 'FontSize', 10);

subplot(3, 2, 6);
imshow(t2);
axis('on', 'image');
title('FINAL TEST IMAGE(WINDING)', 'FontSize', 10);



%%%%%%%detecting fault in wdg%%%%%%%%%%%%%%%%%%%%%%%%
wdg1 = t1;
wdg2 = t2;

[mw1,nw1,sw1] = size(wdg1);
[mw2,nw2,sw2] = size(wdg2);
flagW = true;


for i=1:sw1
 x = wdg1(:,:,i);
    % disp(x);
   sum = 0;
   [row,col] = size(x);
   m = uint16(row);
   n = uint16(col);
   %disp(row);
   %disp(col);
   counter=0;
        for a=1:n
             for b=1:m
               %disp(a);
               %disp(b);
               %disp(x(a,b));
               sum = sum + uint32(x(b,a));
               counter = counter +1;
             end
        end
   %disp(sum);
   mean_val1 = sum/counter;
   %disp(mean_val1);
    mean1 = mean_val1;
    disp(mean1);
 x = wdg2(:,:,i);
    % disp(x);
   sum = 0;
   [row,col] = size(x);
   m = uint16(row);
   n = uint16(col);
   %disp(row);
   %disp(col);
   counter=0;
        for a=1:n
             for b=1:m
               %disp(a);
               %disp(b);
               %disp(x(a,b));
               sum = sum + uint32(x(b,a));
               counter = counter +1;
             end
```

```
        end
    %disp(sum);
    mean_val2 = sum/counter;
    %disp(mean_val2);
     mean2 = mean_val2;
     disp(mean2);
     rat = double(mean1)/double(mean2);
     %disp(rat);
     if((rat>1.2) || (rat<0.8))
         flagW = false;
     end
end

if flagW ==0
    disp('There is a fault in WINDING');
else
    disp('WINDING is healthy');
end
```

FINAL IMAGES PLOT ON WHICH MATAB CODE GIVE RESULT:



RESULT IN COMMAND WINDOW:

```
MATLAB Command Window

>> FINAL_CODE
   217

   229

   119

   149

   175

   130

There is a fault in BEARING
   246

   247

   222

   224

   234

   230

SHAFT IS HEALTHY
   187

   196

    49

    52

   143

   135

WINDING is healthy
```

RESULT IN WORKSAPCE:

MATLAB Workspace	Page 1
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Name	Value	Min	Max
a	300	300	300
b	300	300	300
b1	*300x300x3 uint8*	16	255
b2	*300x300x3 uint8*	0	255
blueChannel1	*300x300 uint8*	255	255
blueChannel2	*300x300 uint8*	0	255
ci	[150,150,50]	50	150
col	300	300	300
columns	300	300	300
counter	90000	90000	90000
flagB	0		
flagS	1		
flagW	1		
greenChannel1	*300x300 uint8*	255	255
greenChannel2	*300x300 uint8*	1	255
i	3	3	3
imageSize	[300,300,3]	3	300
m	300	300	300
mask	*300x300 logical*		
mb1	300	300	300
mb2	300	300	300
mean1	143	143	143
mean2	135	135	135
mean_val1	143	143	143
mean_val2	135	135	135
ms1	300	300	300
ms2	300	300	300
mw1	300	300	300
mw2	300	300	300
n	300	300	300
nb1	300	300	300
nb2	300	300	300
ns1	300	300	300
ns2	300	300	300
numberOfColorC...	3	3	3
nw1	300	300	300
nw2	300	300	300
r1	*300x300x3 uint8*	255	255

Name	Value	Min	Max
r2	*300x300x3 uint8*	255	255
rat	1.0593	1.0593	1.0593
redChannel1	*300x300 uint8*	255	255
redChannel2	*300x300 uint8*	22	255
RefIMAGE1	*300x300x3 uint8*	16	255
RefIMAGE2	*300x300x3 uint8*	16	255
RefMASK1	*300x300x3 uint8*	0	254
RefMASK2	*300x300x3 uint8*	255	255
row	300	300	300
rows	300	300	300
S1	*300x300x3 uint8*	0	254
S2	*300x300x3 uint8*	0	253
sb1	3	3	3
sb2	3	3	3
sh1	*300x300x3 uint8*	21	255
sh2	*300x300x3 uint8*	18	255
ss1	3	3	3
ss2	3	3	3
St1	*300x300x3 uint8*	21	255
St2	*300x300x3 uint8*	18	255
sum	12126086	12126...	12126...
sw1	3	3	3
sw2	3	3	3
t1	*300x300x3 uint8*	0	255
t2	*300x300x3 uint8*	0	255
TestIMAGE1	*300x300x3 uint8*	0	255
TestIMAGE2	*300x300x3 uint8*	0	255
TestMASK1	*300x300x3 uint8*	0	253
TestMASK2	*300x300x3 uint8*	255	255
wdg1	*300x300x3 uint8*	0	255
wdg2	*300x300x3 uint8*	0	255
x	*300x300 uint8*	0	255
xx	*300x300 double*	-149	150
yy	*300x300 double*	-149	150

We can use same code with a small change in loop to detect fault in induction motor in different parts.

Disadvantage of this technique is that it cannot tell exact bearing fault like outer race fault, inner race fault, ball defect etc. It just give us the information of possibility of fault in induction motor, but being an non invasive and cheap method as compared to other techniques we can definitely say that Thermal Imaging Technique is better and economical than other techniques to find bearing fault in Induction Motor.

Sound Analysis Method To Detect Bearing Fault:

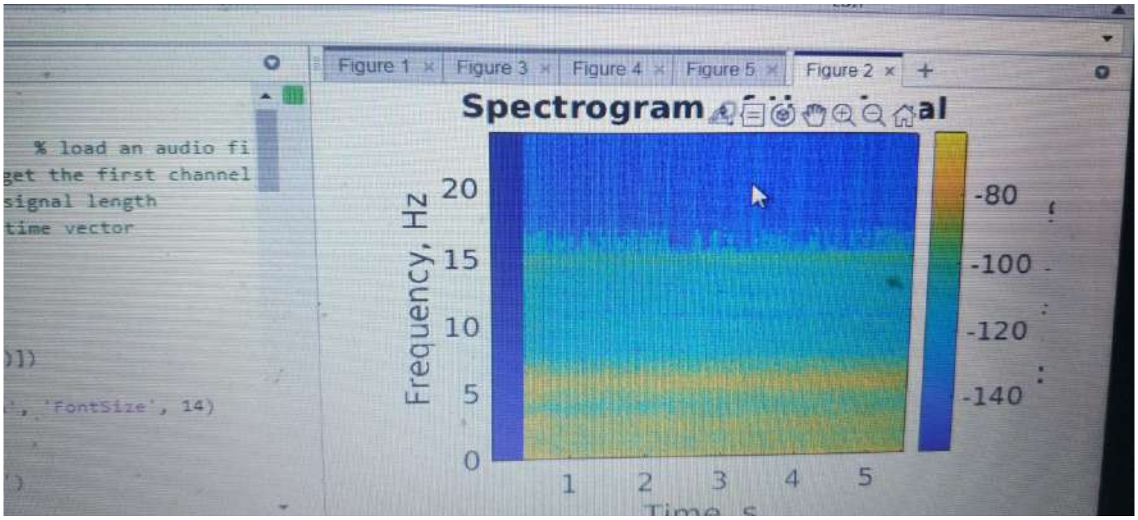
MATLAB CODE

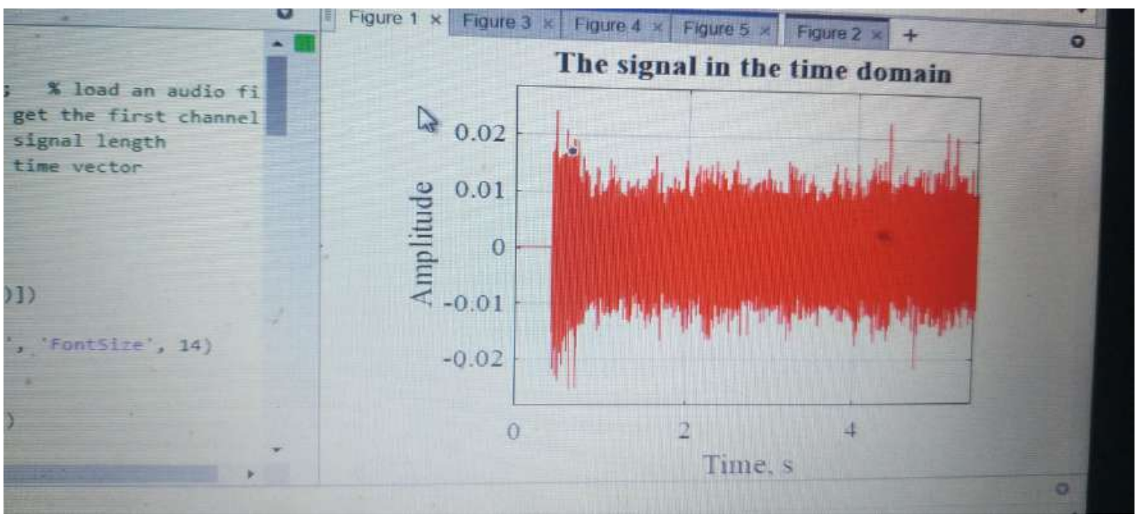
```
clear, clc, close all
% get a section of the sound file
[x, fs] = audioread('Healthyfan.wav'); % load an audio file
x = x(:, 1); % get the first channel
N = length(x); % signal length
t = (0:N-1)/fs; % time vector
% plot the signal waveform
figure(1)
plot(t, x, 'r')
xlim([0 max(t)])
ylim([-1.1*max(abs(x)) 1.1*max(abs(x))])
grid on
set(gca, 'FontName', 'Times New Roman', 'FontSize', 14)
xlabel('Time, s')
ylabel('Amplitude')
title('The signal in the time domain')
% plot the signal spectrogram
figure(2)
spectrogram(x, 1024, 3/4*1024, [], fs, 'yaxis')
box on
set(gca, 'FontName', 'Times New Roman', 'FontSize', 14)
xlabel('Time, s')
ylabel('Frequency, Hz')
title('Spectrogram of the signal')
h = colorbar;
set(h, 'FontName', 'Times New Roman', 'FontSize', 14)
ylabel(h, 'Magnitude, dB')
% spectral analysis
w = hanning(N, 'periodic');
[X, f] = periodogram(x, w, N, fs, 'power');
X = 20*log10(sqrt(X)*sqrt(2));
% plot the signal spectrum
figure(3)
semilogx(f, X, 'r')
xlim([0 max(f)])
grid on
set(gca, 'FontName', 'Times New Roman', 'FontSize', 14)
title('Amplitude spectrum of the signal')
xlabel('Frequency, Hz')
ylabel('Magnitude, dB')
% plot the signal histogram
figure(4)
histogram(x)
xlim([-1.1*max(abs(x)) 1.1*max(abs(x))])
grid on
set(gca, 'FontName', 'Times New Roman', 'FontSize', 14)
xlabel('Signal amplitude')
ylabel('Number of samples')
title('Probability distribution of the signal')
```

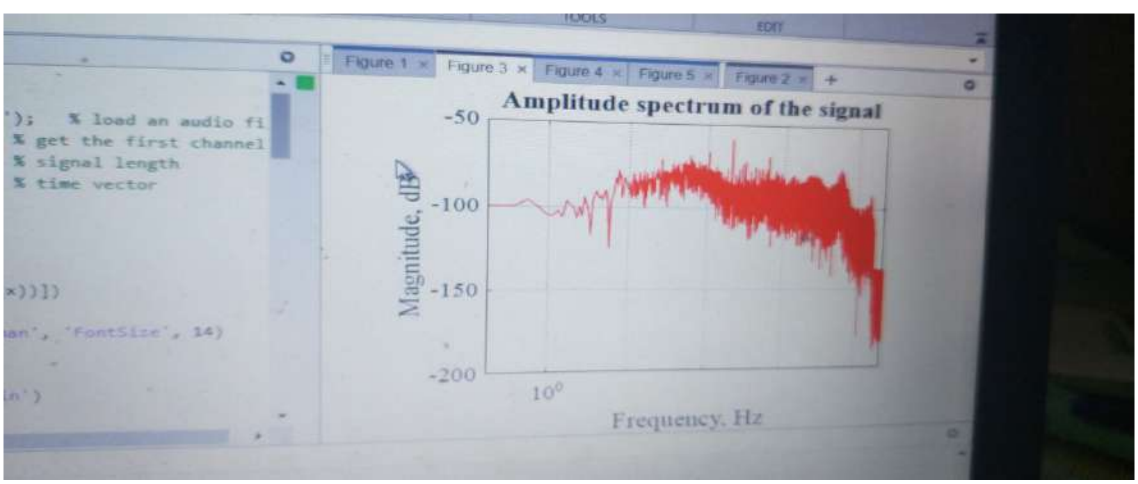
```
% autocorrelation function estimation
[Rx, lags] = xcorr(x, 'coeff');
d = lags/fs;
% plot the signal autocorrelation function
figure(5)
plot(d, Rx, 'r')
grid on
xlim([-max(d) max(d)])
set(gca, 'FontName', 'Times New Roman', 'FontSize', 14)
xlabel('Delay, s')
ylabel('Autocorrelation coefficient')
title('Autocorrelation of the signal')
line([-max(abs(d)) max(abs(d))], [0.05 0.05],...
    'Color', 'k', 'LineWidth', 2, 'LineStyle', '--')
% compute and display the minimum and maximum values
maxval = max(x);
minval = min(x);
disp(['Max value = ' num2str(maxval)])
disp(['Min value = ' num2str(minval)])

% compute and display the the DC and RMS values
u = mean(x);
s = std(x);
disp(['Mean value = ' num2str(u)])
disp(['RMS value = ' num2str(s)])
% compute and display the dynamic range
D = 20*log10(maxval/min(abs(nonzeros(x))));
disp(['Dynamic range D = ' num2str(D) ' dB'])
% compute and display the crest factor
Q = 20*log10(maxval/s);
disp(['Crest factor Q = ' num2str(Q) ' dB'])
% compute and display the autocorrelation time
ind = find(Rx>0.05, 1, 'last');
RT = (ind-N)/fs;
disp(['Autocorrelation time = ' num2str(RT) ' s'])
```

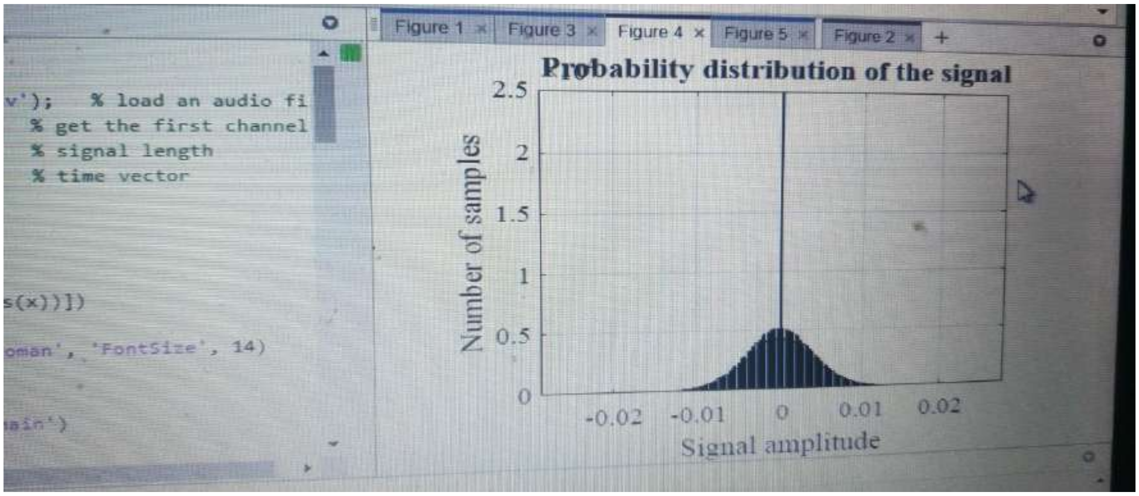
After getting result images for healthy sound file we will run the same code on faulty sound file and then compare result images to detect fault. Using this code we have find following images:

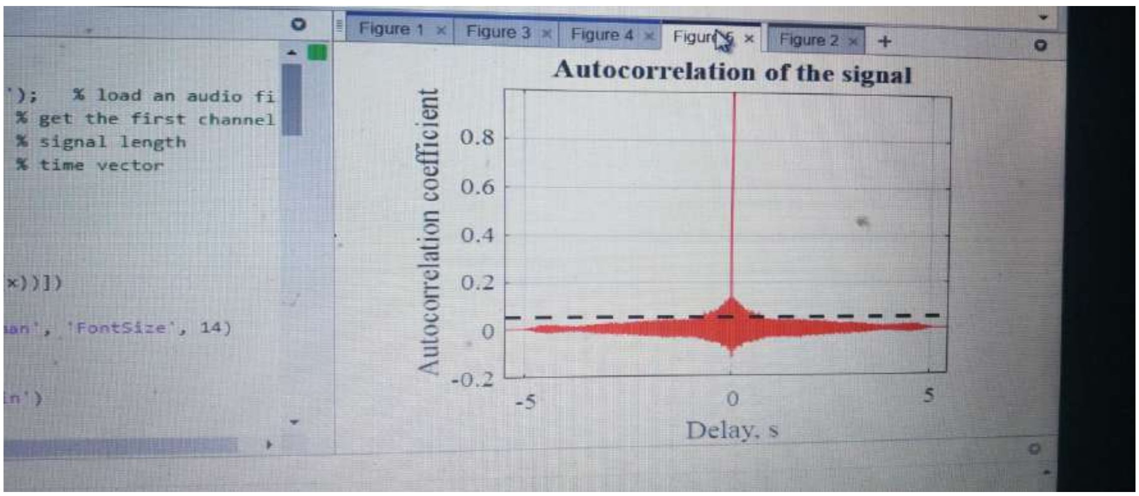
Images from Healthy motor sound file



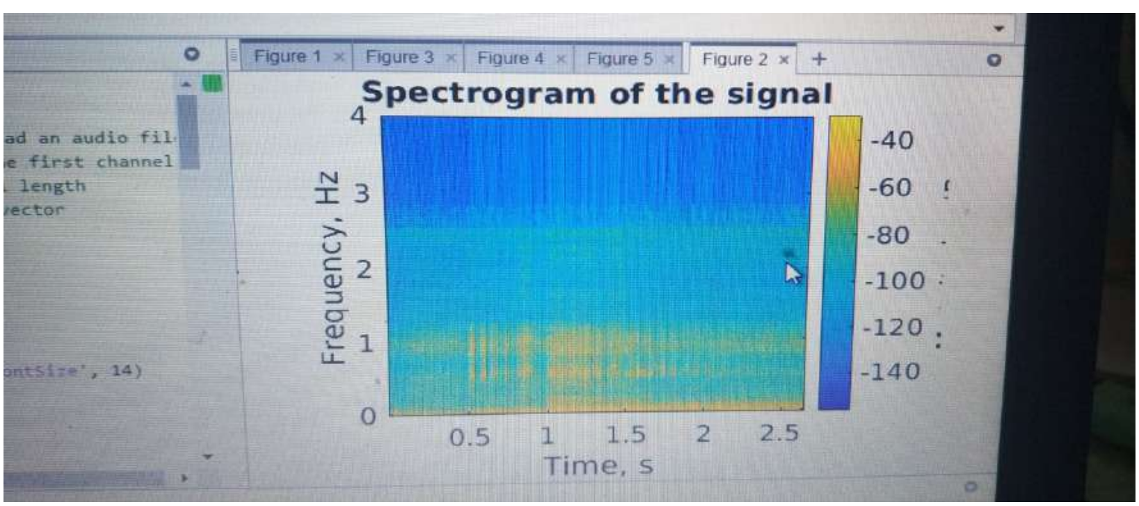








Images from Faulty motor sound file



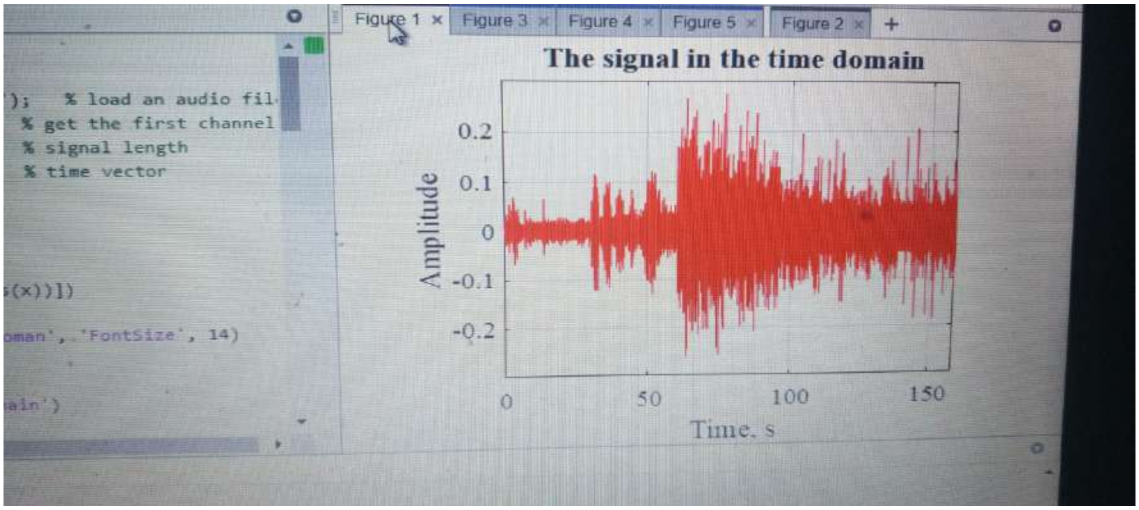


Figure 1
Figure 3
Figure 4
Figure 5
Figure 2
The signal in the time domain
Amplitude
Time, s
% load an audio fil
% get the first channel
% signal length
% time vector

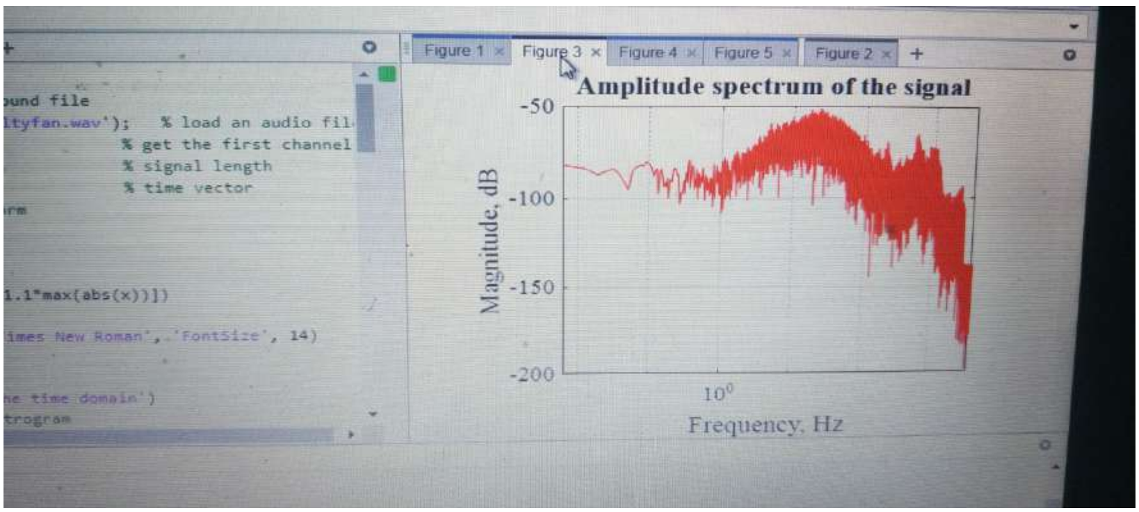


Figure 1
Figure 3
Figure 4
Figure 5
Figure 2
Amplitude spectrum of the signal
Magnitude, dB
Frequency, Hz
% load an audio fil
% get the first channel
% signal length
% time vector

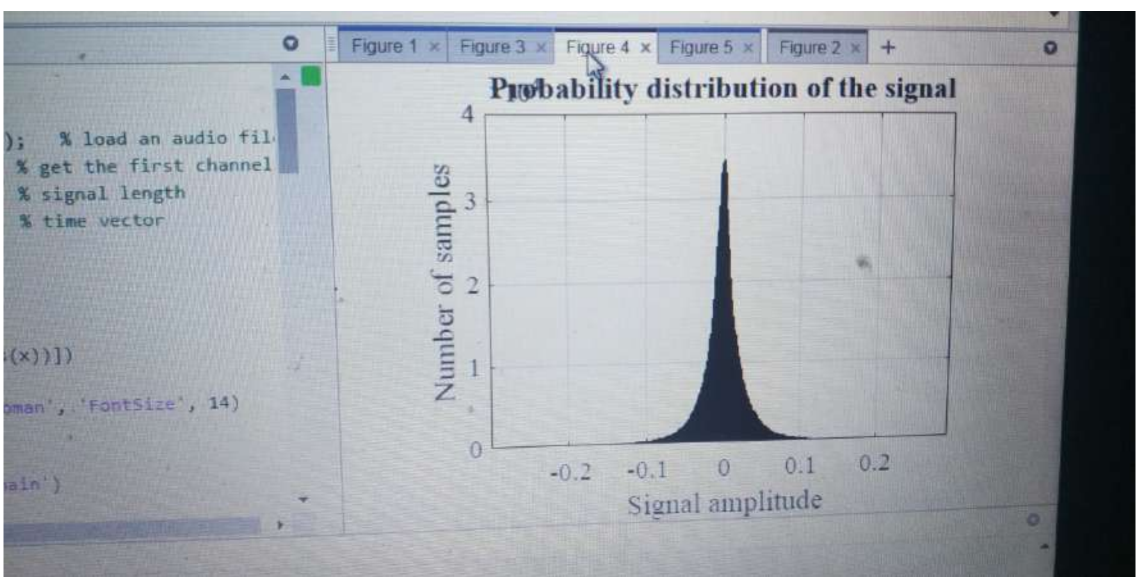


Figure 1
Figure 3
Figure 4
Figure 5
Figure 2
Probability distribution of the signal
Number of samples
Signal amplitude
% load an audio fil
% get the first channel
% signal length
% time vector

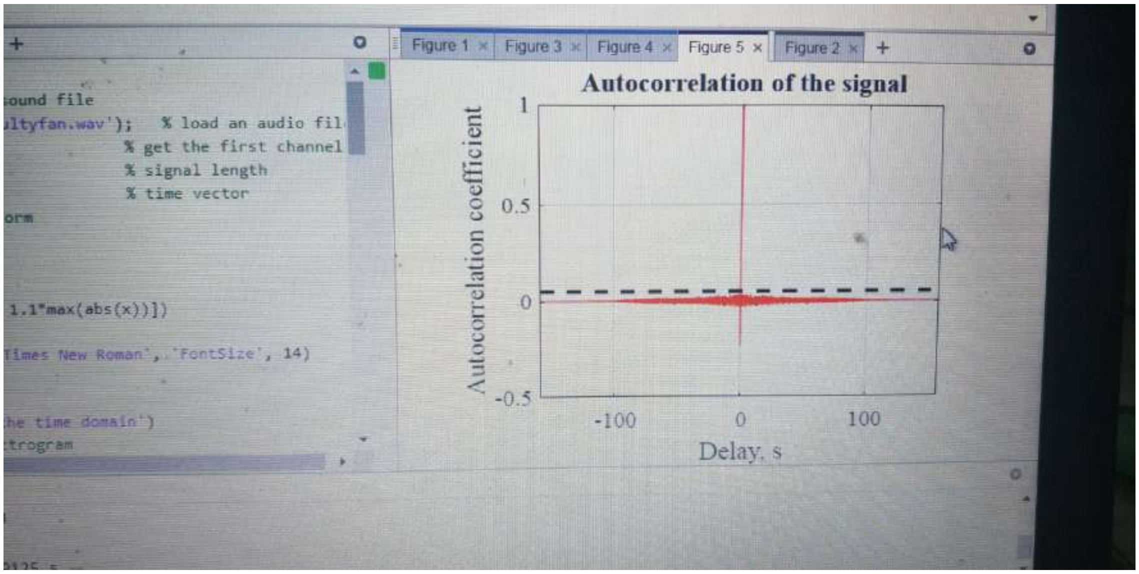


Figure 1
Figure 3
Figure 4
Figure 5
Figure 2
Autocorrelation of the signal
Autocorrelation coefficient
Delay, s
% load an audio fil
% get the first channel
% signal length
% time vector

SUMMARY OF VARIOUS TECHNIQUES

INFRARED THERMOGRAPHY

Mechanical faults are among the most frequent and the common failures in industrial induction motors. These types of faults includes bearing failures, rotor eccentricities, shaft misalignment and load-related faults unbalance, gearbox failures and transmission problems. In industry, the most prevailing technique for the diagnosis of mechanical faults relies upon the analysis of vibration data. Although vibration data analysis has some constraints which may even make the application of this technique impossible. For example, installing proper vibration sensors is a major requirement that doesn’t allow the application of this technique in some motors i.e. motors in special enclosures, submersible motors. On the other hand, vibration data analysis is not always effective for the discrimination between failures with mechanical and electrical origin, between motor faults and faults related to the load/transmission system or even between motor faults and non-fault related phenomena.

Infrared (IR) thermography has emerged as a suitable option for detection of mechanical failures and has been extensively over decades for maintenance of electrical installation. IR is a method, which detects infrared energy emitted from the object, converting it to temperature, and then displaying image of temperature distribution.The infrared thermography technique allows the visualisation of the temperatures of an object with high resolution without needing any contact with the object. This technique is quite useful for large induction motors. It is proven that IR thermography technique could be specially useful for diagnosis of bearing failures or cooling problems in induction motors.

Mechanical failures that can be easily detectable with infrared thermography include, shaft misalignment, transmission system problems (e.g. defective belts, couplings) and bearing faults leading to thermal emission (lubrication problems, damaged bearings).

Infrared thermography may be very useful to detect shaft misalignment due to the temperature increases that appear in the coupling region, showing important temperature gradients in that region.Problems in the transmission system may also lead to excessive heat dissipation that can be detected with infrared thermography.

A possible example is the deficient set up of a belt-based transmission system; a defective belt adjustment, an inadequate belt tightening or an incorrect system alignment can cause uneven belt wear, shorten belt life and can even provoke the mechanical failure of the system. An excessive tension may lead to stretch and weaken the belts and to excessive heat dissipation in the bearings, even if their lubrication is correct.Bearing faults that include primary faults like Bearing Wear, Indentations, Smearing, Surface Distress, Corrosion and secondary faults like flaking, cracks and cage damage can be easily detected using IR technique.

SOUND ANALYSIS

Detecting obvious faults by listening is easy task even if you're not expert on this field. But for machine task is more challenging. Normally in industrial environment operators detect faults in machinery by hearing an abnormal sound. Detecting faults is important because failure in some critical component might cause the entire plant to halt.

In this, the sound of electric motors is analyzed in order to obtain information for the detection of faults. Sound is an important parameter for the condition monitoring of machines and their elements. In a machine under operation, sound is always present. The levels of sound usually increase with deterioration in the condition of the machine. The analysis of sound spectrum is used for the detection of bearing faults. The faults detection will be done by comparing two values: the amplitudes of the harmonic components obtained from monitoring the sound spectrum at different frequencies and the amplitudes of the harmonic components at the same frequencies. Generally in bearings, the main type of high frequency oscillating forces are friction forces. When a defect develops in the bearing, shock pulses can also be found due to the breaks in the lubrication layer between the friction surfaces. This method of diagnosing bearings through analysis of high frequency noise has many advantages. It makes it possible to locate the defective bearing easier because the noise signal does not contain any components from other units of the machine

The defect in the bearing may arise due to improper mounting, improper operation, and overloading. The defects may be classified into distributed and localized defects. Surface roughness, waviness, and misaligned races are included into the class of distributed defects. For detecting the sound many devices are available, example microphone, sound meter and any electronic recording devices. Generally we prefer two method to detect bearing faults is music method and welch method. The experiment has target to single induction motor diagnosis, more precisely bearing fault using sound measurement. Initially the measurements were realized by using electric motor with healthy rotor. Then we made the measurement successive by the same motor with a bad bearing.

Music method an acronym for MUltiple SIgnal Classification. The MUSIC algorithm estimates the pseudo spectrum from a signal or a correlation matrix using Schmidt's Eigen space analysis method. The algorithm performs Eigen space analysis of the signal's correlation matrix in order to estimate the signal's frequency content. This algorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise.

In Welch method (also called the periodogram method) for estimating power spectra is carried out by dividing the time signal into successive blocks, forming the periodogram for each block, and averaging. It takes the original vibration signal (time-domain signal) as input, and Welch method transforms the data from time-domain signals to power spectrums and suppresses high strength noise.

The results over time were processed using WELCH, MUSIC analysis using the MATLAB functions for digital signal processing—Signal Processing Toolbox. The software in the Data

Acquisition toolbox allows MATLAB to acquire data from sensors and to send out electrical signals that can be used to control or drive external devices. We will be using this toolbox with two different pieces of hardware. One is the sound card built into our laptop, the microphone and speaker will serve as the data acquisition (and output) devices.

The technique of evaluating the motor condition by performing a WELCH/MUSIC of the induction motor sound. In this case electric motor sound motorizing is very useful to detect electric motor fault. The method of sound signature is efficient to make electrical motor diagnosis. In this way, the plant maintenance can successfully detect mechanical and electrical fault that lead to unexpected downtime. Purpose was to try find out if faulty sound could be recognized automatically using sound processing. There's scientific publications available from this topic. Most of them conclude that sound based fault detection method is feasible.

VIBRATIONAL ANALYSIS

Current spectrum at no load condition fails even to identify thepresence of the seeded faults i.e. healthy and faulty currentspectrums look alike even the motor is delta or star connected. On the other hand, Vibration spectrum (FFT) is very effective in detecting the bearing faults of induction motor under no load condition whether the motor is delta or star connected Also, we can observe minor decrease in thevibration amplitudes at fault frequencies when the motors are connected in star connection. Thus the effectiveness of vibrationspectrum over current spectrum in early detection of bearing faults in an induction motor at no load condition is much better.
Vibrational analysis detects bearing fault by observing the location and amplitude levels of side-bands present around supply frequency and its harmonics. In general, faults in rollingball bearings are classified as general roughness andlocalized defects. Generalized roughness in bearingsmay be present due to the gradual wear and it isdifficult to detect due to its non-stationery nature.

Localized defects may be single or multi point defectsand may be present either on any bearing part such as outer race, inner race, rolling element, cage assemblyand may be on combined parts. These defects can bedetected by monitoring the abrupt change in thecorresponding bearing frequencies asmentioned below in vibration spectrum.

$$f_{bpfo} = \left[\frac{n_b f}{2}\left(1 - \frac{d}{D} cos\theta\right)\right]$$

$$f_{bpfi} = \left[\frac{n_b f}{2}\left(1 + \frac{d}{D} cos\ \theta\right)\right]$$

$$f_{rf} = \left[\frac{Df}{d}\left(1 - \left(\frac{d^2}{D^2} cos^2\theta\right)\right)\right]$$

$$f_{cf} = \left[\frac{f}{2}\left(1 - \frac{d}{D} cos\ \theta\right)\right]$$

For experimental set-up we have to take 2- (3-ϕ) induction motors that are driven by direct online supply (DOL) with delta and star connections separately. Out of the two induction motors one is in healthy state (M1) and the other with outer race bearing fault (M2).ICP accelerometer or any other instrument to be used to acquire vibration data from the motor respectively. OROS data analyzer is used for raw signal acquisition. Experiments have to be carried out at no load condition for each motor driven under both delta and star connections at DOL supply. Samples of vibration are captured continuously for few seconds with high sampling rate of order of kS/s. After acquiring vibration signals of each motor FFT's can be plotted by post processing of time signals using 'MATLAB 2014a'
software. Increase in vibration amplitudes can be observed at the first four harmonics of bearing outer race frequency (BPFO) for the motor with bearing fault since the faulty motor has only outer race bearing fault.

Despite being a reliable, well studied robust technique, it requires that the motor under test has a vibration transducer installed. The measurements should be taken on the bearings, bearing support housing, or other structural parts that significantly respond to the dynamic forces and characterize the overall vibration of the machine. Therefore, the major disadvantage of vibration monitoring is that requires access to the machine, and specific accelerometer shousing over the machine is sometimes required. For accurate measurements, sensors should be mounted tightly on the machine, and expertise is required in the mounting,condition that makes its online application expensive.

MCSA AND STATOR CURRENT

ELECTRICAL machines are virtually in all industrial plants today. A commonly used propulsion system device is an induction motor. The simplicity of the construction of this engine makes its bearing the most damageable elements. Statistical studies clearly show, that almost half (40%) of engine failures is caused by damage to the bearings. Detection of bearing fault depends on the extraction of a deterministic signal and its analysis to localize the fault. In the case of a fault localized on the inner or outer race, whenever a rolling element passes through the fault
surface, a disturbance is generated. This disturbance is almost periodic series of impulses represent characteristics that vary with bearing geometry and fault localization; and also it produces resonance in the bearing and also in machine as a whole.

Since this series of generated impulse (disturbance) get amplitude modified when fault passes the load zone and these can be collected through sensors. Generation of this impulse varies with: the fault position (inner race, outer race, and cage), the bearing dimensions, and the machine shaft speed (fr). Therefore we can estimate the bearing characteristic frequencies, i.e., ball pass frequency of the outer race (BPFO), ball pass frequency of the inner race

(BPFI), fundamental train frequency (FTF), which is related to cage speed rotation, and ball spin frequency (BSF).

MCSA is one of the most commonly used techniques to fault detection in induction motors, since it allows identifying electrical and mechanical faults. It performs a spectral analysis of stator electrical current, which is usually monitored at one of three power supply phases. In case of bearing faults, we consider that machines inductances varies due to rotating eccentricities at bearing characteristic frequencies fC, i.e., BPFO, BPFI, etc., which produces a stator current modulation, described by

$f_E = f_s \pm k \cdot f_C$

where fE is the frequency related to a bearing fault; fs is the power supply frequency; and k = 1, 2, 3, … is the harmonic number. Thus, fC appears in the current spectrum as sidebands. In this context, it is import to observe that rotor inertia and winding inductances produce an electromechanical filtering effect in stator current, such that, this current is mainly affected by low frequency components.

Using another approach we can model the effect of localized bearing fault in stator current as air gap eccentricity.The current spectrum is not only corrupted by noise, but also by numerous harmonic components resulting from the regular magnetic behaviour of an induction machine. The biggest challenge for the practical implementation of MCSA is to measure and distinguish the fault frequencies from the other components and noise, located very close to and even faded with each other. However, by using an accurate frequency/magnitude resolution and the right signal processing methods, mechanical faults are detectable.

CONCLUSION

Bearings are mechanical assemblies that consist of rolling elements and usually inner and outer races which are used for rotating or linear shaft applications, and there are several different types of bearings, including ball and roller bearings, linear bearings, as well as mounted versions that may use either rolling element bearings or plain bearings. The bearing consists mainly of the outer and inner raceway, the balls and the cage which assures equidistance between the balls. The different faults occurring in a rolling-element bearing can be classified according to the affected element:

1. Outer raceway defect

2. Inner raceway defect

3. Ball defect or roller defect

4. Cage defect

Various fault techniques are available for fault detection in induction motor out of which the few techniques are as follows-

Thermal analysis

Sound analysis

Vibration analysis

Chemical analysis

In this major project infrared thermography was chosen as the fault Detection technique as it is a well-known technique in the electrical engineering area. Over decades, it has been a very useful tool for regular inspections of electrical installations and distribution lines. Two thermal images (one of healthy condition and other one for unhealthy conditions) were considered and a MATLAB code was developed for the detection of bearing fault.

Disadvantage of this technique is that it cannot tell exact bearing fault like outer race fault, inner race fault, ball defect etc. It just give us the information of possibility of fault in induction motor, but being an non invasive and cheap method as compared to other techniques we can definitely say that Thermal Imaging Technique is better and economical than other techniques to find bearing fault in Induction Motor.

The purpose of this project report is to diagnose the health condition of the induction motor by using an innovative technique where the whole motor will be monitored without having any physical contacts. Here no sensor is used to get any physical parameters. So, the system is very simple and chances of failure are almost nil. It is very much important for an engineer to monitor the induction motor while it is working in a system, because any fault generated in induction motor can be the reason of excessive heating. Excessive heat produced in the machine can burn the windings of the motor and the situation will be very harassing. In this method all the sensor which is normally used in conventional condition monitoring is replaced by an infrared digital camera alone. The system is almost maintenance free and analysis is very particular to the every part as if the whole motor condition is vivid in front of eyes. The analysis results showed that the proposed method is able to monitor the health condition of the induction motor. The method described provides a promising way to establish potential metrics for the description of the health of an induction motor. Therefore, it is desirable to develop an on line health monitoring system for the induction motor based on the above method and realize on-line health evaluation of each part of induction motor. With such a function, the critical failure of induction motor systems can be avoided, and the reliability and efficiency of motor can be increased.

REFERENCES

1) S. Bagavathiappan, B.B. Lahiri, T. Saravanan, John Philip, T.Jayakumar, “Infrared thermography for condition monitoring – A review,” Infrared Physics & Technology, vol. 60, pp. 35-55, Sep. 2013.
2) G. Duke, “Predictive maintenance a case study in infrared thermography,” Electrical Maintenance, pp. 11-12, 1998.
3) Bearing Fault Detection in Induction Motors using MCSA and Statistical Analysis- Carlos Morales-Perez∗, Jonas Grande-Barreto†, Jose Rangel-Magdaleno∗, and Hayde Peregrina-Barreto†∗Electronics Department †Computer Science Department
4) Comparing MCSA with Vibration Analysis in order to detect Bearing Faults - A Case Study Bram Corne, Bram Vervisch, Colin Debruyne, Jos Knockaert and Jan Desmet.
5) R.R. Schoen, T.G. Habetler, F.Kamran, and R.G. Bartheld, “Motor Bearing Damage Detection Using Stator Current Monitoring” IEEE 1994, hal. 110.
6) Pao, Y.-H., Gajewski, R. R., Ceranoglu, A. N. Acoustic emission and transient waves in an elastic plate J. Acoust. Soc. Am., 1979, 65 (1), 96–102.
7) Pollock, A. A. Acoustic emission inspection. Physical Acoustics Corporation technical report TR-103-96-12/89, 1989.
8) A. Bellini, F. Filippetti, C. Tassoni, and G. A. Capolino, “Advances in diagnostic techniques for induction machines,” IEEE Trans. Ind. Electron.vol. 55, no. 12, pp. 4109–4126, Dec. 2008.
9) S. Poyhonen, P. Jover, and H. Hyotyniemi, “Signal processing of vibrations for condition monitoring of an induction motor,” in Proc. 1st Int. Symp. Control, Commun. Signal Process., 2004, pp. 499–502.
10) S. Nandi, H. Toliyat, and X. Li, “Condition monitoring and fault diagnosis of electrical motors—A review,” IEEE Trans. Energy Convers., vol. 20,no. 4, pp. 719–729, Dec. 2005.
11) Arkan, M., H. Çaliş, and M. E. Tağluk. "Bearing and misalignment fault detection in induction motors by using the space vector angular fluctuation signal." Electrical Engineering 87, no. 4 (2005): 197-206.
12) Zhang, Pinjia, Yi Du, Thomas G. Habetler, and Bin Lu. "A survey of condition monitoring and protection methods for medium-voltage induction motors. "Industry Applications, IEEE Transactions on 47, no. 1 (2011): 34-46.
13) Effectiveness of Vibration and Current Monitoring in detecting Broken Rotor Bar and Bearing Faults in an Induction Motor- T. CH. Anil Kumar, Gurmeet Singh, V. N. A. Naika

14) Fabio Immovilli, Member, IEEE, Claudio Bianchini, Member, IEEE, Marco Cocconcelli, Alberto Bellini, ―Bearing Fault Model for Induction Motor withExternally Induced Vibration.
15) S.Nandi, H. A. Toliyat, and X. Li, ―Condition monitoring and fault diagnosis ofelectrical motors―A review, IEEE Trans. Energy Convers., vol. 20, no. 4, pp.719–729, Dec.2005.
16) M.Iorgulescu, University of Pitesti ―Study Relation between Fault Noise in Electric Motor.
17) A. Bellini, F. Filippetti, C. Tassoni, and G. A. Capolino, ―Advances in diagnostic echniques for induction machines,‖ IEEE Trans. Ind. Electron.,vol. 55, no. 12, pp. 41094126, Dec. 2008.
18) Randal R.B., Antoni J. Rolling element bearing diagnostics—a tutorial. Mechanical
19) Systems and Signal Processing. 2011;25(2):485–520DOI: 10.1016/j.ymssp.2010.07.017
20) Rai A., Upadhyay S. A review on signal processing techniques utilized in the fault diagnosis of rolling element bearings. Tribology International. 2016;96:289–306. DOI: 10.1016/j. triboint.2015.12.037
21) Bonaldi E.L., de Oliveira L.E.L., Lambert-Torres G., Borges da Silva L.E. Proposing a Procedure for the Application of Motor Current Signature Analysis on Predictive Maintenance of Induction Motors. In: 20th International Congress & Exhibition on Condition Monitoring and Diagnosis Engineering Management; June 13-15, 2007; Faro, Portugal. Faro, Portugal: COMADEM Press; 2007. DOI: 10.13140/RG.2.1.2836
22) Schoen R.R., Habetler T.G., Kamran F., Bartheld R.G. Motor bearing damage detection using stator current monitoring. IEEE Transactions on Industry Applications. 1995;31(6):1274–1279. DOI: 10.1109/28.475697
23) IEEE PROJECT REPORT-Comparing MCSA with Vibration Analysis in order to detect Bearing Faults - A Case Study Bram Corne, Bram Vervisch, Colin Debruyne, Jos Knockaert and Jan Desmet
24) D. López-Pérez and J. Antonino-Daviu 'Detection of mechanical faults in induction machines with infrared thermography: field cases', IEEE, 978-1-5090-3474-1/16, 2016, pp. 7107-7112.
25) https://www.electricalindia.in/contactless-health-monitoring-system-for-three-phase-induction/