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Diagnosis and monitoring of an induction motor with bearing fault

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General introduction

For economic reasons, the production line of oversized series should not be interrupted to ensure continuity of production and supply to the market. Fatal failures, such as broken tooth on a gear or damaged bearings, temporarily stop production until repaired. Such mistakes should be avoided as much as possible. The scientific community is working hard to develop methods for early diagnosis of such failures so that they can be prevented in time.

Industrial machines vibrate during operation, regardless of whether they are in new condition or not working properly. The level of degradation is indicated or quantified using a metric calculated by processing the signal. Our confidence in the ability of these indicators to detect the presence of an error or errors at an early stage is based on their sensitivity, robustness, reliability, etc.

The sensitivity of a monitoring indicator is its ability to visualize changes in how the equipment it is monitoring is performing.

There are many monitoring and diagnostic indicators, including statistical, spectral, energy, ...etc.

In this work, we are interested in the calculation of statistical kurtosis and spectral indicators such as envelope analysis.

in order to study the variance of the sensitivity of this indicator, the wavelet method is used as a pre-processing tool to see the improvement or not.

the present work is structured in four chapters.

We start our first chapter with a comprehensive exploration of the basics of maintenance and leasing. First, the concept of failure will be clarified, including its definition and an exploration of the various factors that lead to failure. Maintenance objectives will then be analyzed, including economic and operational considerations. The following sections provide a comprehensive overview of the different types of maintenance, providing a comprehensive understanding of each category. This is followed by a focused study of vibration analysis and its applications, including the characterization of vibration signals. Finally, a detailed overview of bearings will be provided, including their construction, different types of bearing damage, and a general understanding of their functions. This deep understanding will help you make informed maintenance decisions.

The second chapter explores advanced techniques in vibration analysis, essential for diagnosing and monitoring machinery such as turbines, motors, and pumps. It is divided into sections focusing on unique signal processing techniques including temporal analysis, frequency analysis, time-frequency and time-scale analysis, energy operator analysis, and de-convolution with minimum entropy.
And by the chapter's end, you will gain a thorough understanding of these techniques, including their formulas, definitions, applications, and utility.

The third chapter will talk about the overview of the bearing signals from the Western Reserve University Bearing Data Center and ending this part with the bearing signal in healthy case and defect cases.

For the last chapter we will talk about the wavelet including it definition ,the history , the wavelet family and how this method works when it comes to bearing fault, and we will finish this chapter with the signals using the wavelet method with the envelope method , and comparing the results that we got with the theoretical results , and finish all of this project with a general conclusion and references

Chapter I: general information on maintenance and bearings

I.1 Introduction

In this chapter, we are going to represent a comprehensive overview of key maintenance and bearing concepts. Starting with the concept of failure, we will define what it means and explore the various causes of failure. Next, we discuss maintenance goals, both financial and operational. then we will go over the various type of maintenance and give a thorough understanding of each type. then we are going to concentrate on vibration analysis and its practice including the characterization of vibration signal .finally we will provide a detailed overview of bearing including their construction and the various types of bearings failure and an understanding of how bearing works allowing us to make informed maintenance decisions

I.2 Failure:

I.2.1 Definition of Failure:

Failure can be defined as an occurrence that causes a system to fall short of its intended objectives. This often results from various factors, such as faulty design, inadequate materials or equipment, and human error. The consequences of failure can vary greatly depending on the severity and impact of the problem.[1]

I.2.2 Causes of Failure:

The causes of failure can be broadly categorized into three categories: material failure, design failure, and operational failure. These categories are used to understand the root cause of the failure, as well as to guide the development of prevention and mitigation strategies.[2]

I.2.2.1 Material failure:

Material failure is a common occurrence caused by several internal or external factors. It is a complex process that involves physical, chemical, and mechanical factors. The consequences of material failure can be severe, resulting in financial loss and environmental and human damage. Therefore, it is crucial to comprehend the causes of material failure and how this can be prevented to ensure safety and reliability in various applications. Some of the types of material failure include fatigue and corrosion[3]

.I.2.2.1.1Brittle fracture:
A brittle fracture is characterized by a sudden and complete fracture without significant plastic deformation

Fig I. 1Brittle fracture

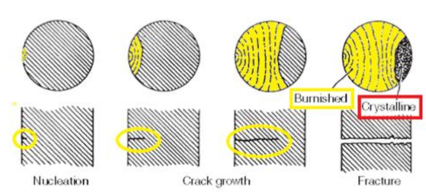


Fig I. 2 Fatigue fracture appearance

I.2.2.1.2 Corrosion:

Corrosion is the breakdown of a material as a result of chemical reactions with the surrounding environment.

Fig I. 3 Galvanized mild steel cable ladder with corrosion around stainless steel bolts

The causes of material damage can be roughly divided into two categories: internal and external. Important factors include the material's intrinsic properties, such as its micro-structure, chemical composition, and mechanical properties. External factors include environmental conditions such as temperature, stress, and corrosive substances that can interact with the material and cause damage. The prevention of material defects requires an interdisciplinary approach that takes into account both internal and external factors. Design engineers can select materials with appropriate mechanical and chemical properties to ensure that they can withstand the environmental conditions to which they will be exposed. Materials such as heat treatment, surface coating, and protection can also be treated to increase their resistance to damage.

I.2.2.2 Design failure:

As a college student, it's common to learn about design failures in engineering and product development. This kind of failure occurs when a product doesn't meet its expected performance or specifications, leading to issues like property damage or financial losses. There are many reasons why design failures happen, including:

- Undefined design specifications: When specs aren't clear, it can lead to misunderstandings and mistakes when designing a product or engineering a solution.

- Human error: Sometimes, design failures happen because engineers or designers make mistakes or miscalculations when working on a project.

- Poor materials choices: Using the wrong materials for a particular product or application can lead to failure.[4]

I.2.2.3 Operational failure

Operational failure is when a system, procedure, or piece of equipment is unable to carry out its intended purpose as expected. Several things, including bad design, poor maintenance, mistakes made by people, and natural disasters, might cause this failure. Operational failure can result in anything from little annoyances to major catastrophes that have disastrous effects on people, property, and the environment

There are several categories of operational failure, including:

- Equipment failure
- Process failure
- Human error
- Natural disasters

The most frequent reason for operational failure is equipment failure, which can be brought on by things like wear and tear, overloading, and inadequate maintenance. Equipment failure can be avoided through routine maintenance and inspection, but backup mechanisms must also be in place in case of failure.[5]

I.3 Notion of maintenance :

I.3.1 Definition of maintenance :

According to the International Organization for Standardization (ISO) definition, maintenance is the combination of all technical and associated administrative actions intended to retain an item or restore it to, a condition in which it can carry out the required function. [6]

I.3.2 objectives of maintenance :

Maintenance is a crucial aspect of any organization or facility. It involves preserving and repairing physical assets and systems to ensure their optimal performance, reliability, and safety. Over the years, the objectives of maintenance have evolved and expanded to meet the changing needs of industry and society. [7][8]

I.3.2.1 Financial objectives:

- The primary financial objectives of maintenance include
- reducing equipment downtime and repair costs.
- improving production output and equipment performance.
- maximizing equipment lifespan and reducing the need for replacements.
- Improving overall efficiency and reducing energy consumption.

I.3.2.2 Operational Objectives :

The primary operational objectives of maintenance include:

- Maintaining equipment reliability and reducing the likelihood of failure
- Improving equipment safety and eliminating the risk of injury or damage to people and property
- Ensure equipment availability and reduce downtime

- Ensure compliance with industry and safety regulations

I.4 Types of maintenance :

It becomes clear that two main types of maintenance can be carried out: corrective and preventive maintenance (Fig I.4). Nearly all industrial sectors utilize both types of maintenance.[9]

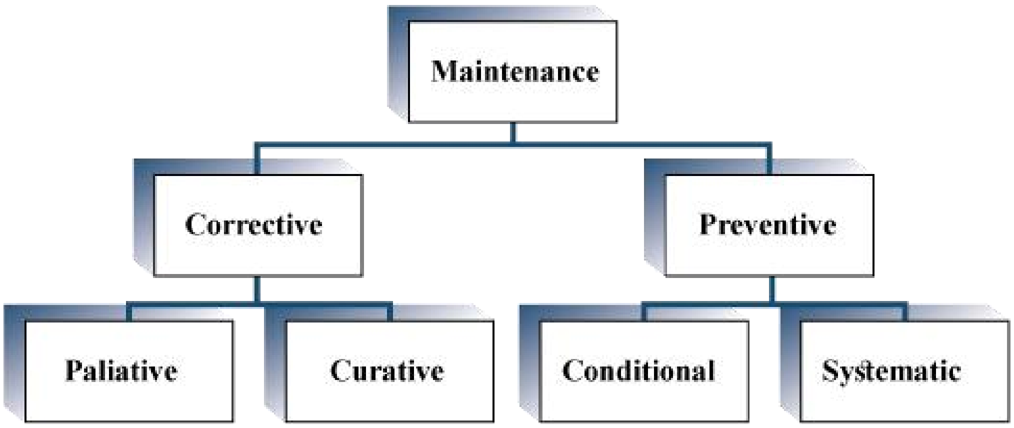


Fig I. 4 the different types of maintenance

I.4.1 Corrective maintenance :

Corrective maintenance is a type of maintenance that is performed after a breakdown or malfunction has occurred to restore the equipment or system to its original functioning state. It is also referred to as "reactive maintenance." The objective of corrective maintenance is to return the equipment to fully operational status as quickly as possible[10]. the corrective maintenance is categorized into two sections :

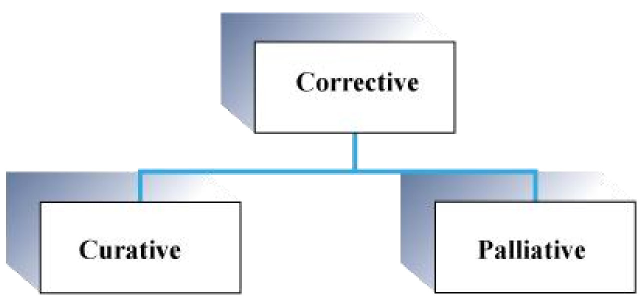


Fig I. 5 type of corrective maintenance

I.4.1.1 Palliative corrective maintenance :

Palliative corrective maintenance is a maintenance strategy that involves solving problems when they occur, rather than performing proactive maintenance to prevent them. The objective of palliative corrective maintenance is to return equipment to normal operating conditions as quickly as possible while minimizing production interruptions. [11]

So this some examples of where this type of maintenance could be used :

- power generation and distribution: it could be used to restore power quickly
- manufacturing: used to keep the production lines running
- Emergency services: used to keep vehicles and equipment operational

I.4.1.2 Curative corrective maintenance :

Curative corrective maintenance is a type of maintenance that involves fixing a problem or repairing equipment after it has failed or broken down. It is the process of fixing something that has already gone wrong and bringing it back to its original working condition. This type of maintenance is typically carried out in response to an unexpected event or equipment failure.[7]

These are some examples of situations where this kind of maintenance might be applied:

- -used in industries that require continuous operation of critical equipment
- -used to restore equipment to working condition as quickly as possible to minimize downtime

I.4.2 Preventive maintenance:

Preventive maintenance is planned and regular maintenance activities performed on equipment or systems to prevent or reduce the likelihood of equipment failure. The purpose of preventive maintenance is to keep the equipment in good condition, reduce downtime and extend its life of the equipment.[13]

Preventive maintenance is divided into two parts:

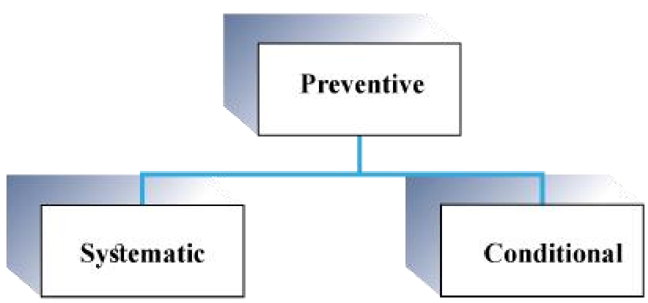


Fig I. 6 Type of preventive maintenance

I.4.2.1 systematic preventive maintenance :

Systematic preventive maintenance refers to the proactive maintenance of equipment and machinery to prevent breakdowns or failures. The goal of systematic preventive maintenance is to identify potential problems before they occur and schedule maintenance to keep the equipment in top condition. This type of maintenance helps reduce downtime and lower costs by avoiding costly repairs and replacements[10].

Systematic preventive maintenance is commonly used in :

- Crucial to keep production lines running smoothly

- To keep vehicles in good working order and avoid disruptions to service
- Essential for ensuring the safety and reliability of medical equipment

I.4.2.1 conditional preventive maintenance :

Conditional preventive maintenance is a maintenance strategy in which maintenance activities are performed based on the condition of the equipment rather than a fixed schedule. In other words, it's a proactive maintenance approach that uses real-time data and predictive analytics to identify potential equipment failures before they occur. This allows timely corrective action, reducing the likelihood of unplanned downtime and increasing equipment reliability.[12]

Conditional preventive maintenance is most commonly used in industries that rely heavily on machinery and equipment, such as manufacturing, power generation, and oil and gas. Some examples include

Conditional preventive maintenance is commonly used in :

- To monitor the performance of vehicles and identify the potential issue before they become a serious problem
- Used to monitor the performance of turbines and generators in real-time
- Used to monitor the performance of drilling equipment, pipelines, and other critical assets
-

I.5 maintenance level :

Maintenance level, in the context of standards, refers to the extent and frequency of maintenance activities required to keep equipment or systems in proper working condition. The definition of maintenance level can vary depending on the type of equipment or system and the industry or sector it is used in.[13]

I.5.1 First-level maintenance:

Maintenance that is performed to correct a failure or malfunction in an asset

- Easy adjustment provided by the manufacturer using available components without disassembling or opening the device.
- Replacement of wearing parts with easy access (fuses, indicators, etc.)

I.5.2 second-level maintenance:

Maintenance is performed regularly to prevent failures or malfunctions in an asset.

- Troubleshooting by standard replacement of the elements supplied for this purpose.
- Minor maintenance operations.
- Check if it works properly.

I.5.3 third-level maintenance:

Maintenance is performed based on a prediction of when an asset is likely to fail or malfunction.

- Incorrect identification.
- Component level repair or replacement of functional elements.
- Minor mechanical repairs.
- General adjustment and re-adjustment of equipment.

I.5.4 Fourth-level maintenance:

Maintenance is performed to improve the performance or extend the life of an asset.

- Inspection of technical maintenance at a specialized agency.
- Secondary standards belonging to professional organizations, verified.
- Get the repaired machinery on the fifth floor.
- Promote training of tertiary maintenance agents.

I.5.5 fifth-level maintenance:

Maintenance is performed based on the actual condition of an asset.

- Performing refurbishments.
- Execution of major repairs normally under the jurisdiction of the fourth degree
- but assigned for economic or opportunity reasons.
- Training of maintenance personnel (normally only fourth level)

I.6 Characterization of a vibration signal

Vibration analysis is an important tool for monitoring the condition of rotating equipment such as electric motors, generators, and other equipment. The operation of these machines can be understood by analyzing the vibration signals they produce. characterization of the vibration signal involves identifying the frequency components and their amplitudes and determining time domain parameters such as speed, displacement, and acceleration

I.6.1 Amplitude:

Amplitude is defined as the maximum deviation of a vibration or oscillation from its mean value. The amplitude of a vibration signal can be represented mathematically using various equations:

- Peak amplitude (A_p) is the maximum absolute value of a vibration signal.
- Peak-to-peak amplitude (A_{pp}) is the difference between the maximum and minimum values of a vibration signal
- Root Mean Square (RMS) is a measure of the average amplitude of a vibration signal It is defined as the square root of the mean squares of the signal's value

$$A_{RMS} = \frac{A_p}{\sqrt{2}} = \frac{A_{pp}}{2\sqrt{2}} \qquad (I.1)$$

The following figure shows the different amplitudes.

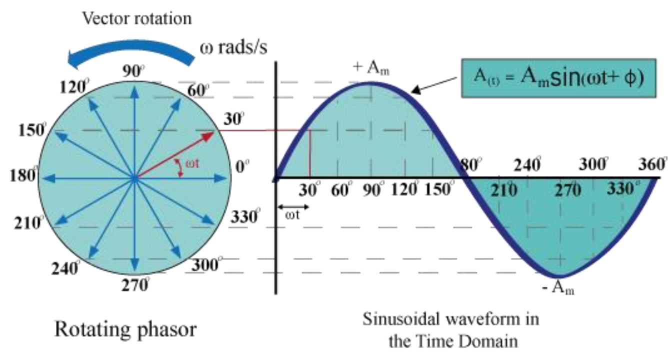


Fig I. 7 Different amplitudes (sinusoidal vibration)

I.6.2 Frequency :

Frequency is defined as the number of cycles of a periodic wave that occur in one second. It is typically expressed in units of Hertz (Hz).

1 HZ=1 cycle/second. the frequency is the inverse of the period T f=1/T

I.6.3 Nature of a vibration :

Vibration is a mechanical phenomenon where oscillations occur at an equilibrium point. The nature of a vibration can be described in terms of its frequency, amplitude, and phase.

The equations that describe the nature of vibration can vary depending on the type of vibration and the mathematical model used. However, a commonly used equation for simple harmonic motion

Displacement equation: this equation describes the displacement of a point on a structure or machine as a function of time

$$X(t) = A * \sin \quad (2\pi f t + \Phi)$$

(I.2)

x(t): is the displacement at time t, **A: is the amplitude,**

f: is the frequency, **t: is time,**

Φ: is the phase.

where X(t) is the displacement, A is the amplitude, f is the frequency, t is time, and φ is the phase angle.

Speed Equation: This equation describes the velocity of a point on a structure or machine as a function of time.

$$V(t)\frac{d[x(t)]}{dt} = V_{max} * \sin\left(2\pi f t + \frac{\pi}{2}\right) \qquad (I.3)$$

Acceleration Equation: This equation describes the acceleration of a point on a structure or machine as a function of time

$$A(t)\frac{d[v(t)]}{dt} = A_{max} * \sin(2\pi f t + \pi) \qquad \text{I.4}$$

I.6.4 Practice of vibration

Various methods for measuring and analyzing vibration include handheld instruments, data collectors, and online monitoring systems. The type of equipment used and the specific method of analysis will depend on the application, the machinery being monitored, and the objectives of the analysis.

I.6.4.1 Data collection

The first step in obtaining vibration readings is to convert the mechanical vibrations produced by the machine into an equivalent electrical signal. This operation is performed using vibration sensors, the most common of which are a Displacement Transducer (measuring displacement), Velocity Transducer (measuring speed) and accelerometers (measuring acceleration).

I.6.4.1.1 Displacement Transducer

A displacement sensor, also known as a position sensor, is a device used to measure the linear or angular motion of an object. It converts the physical movement of an object into an electrical signal that can be read and interpreted by a measuring instrument or controller. Displacement sensors can be used to measure the movement of mechanical parts such as gears, levers, and actuators, or to monitor the position of objects in a machine or process.

Fig I. 8 Displacement sensor

Advantage:

- Directly measures shaft motion.
- Same sensor for axial stops, radial vibrations and speed.
- Directly measures displacement.

Disadvantage:

- Sensitive to shaft material.
- The frequency range is limited.
- No bearing defects were found.
- temperature limit.

Problems and faults detected:

- Shaft.
- Plain bearing.
- Thrust.
- General: unbalance, misalignment, wear, etc.

I.6.4.1.2 Velocity transducer

A velocity transducer is a sensor that is widely used in vibration analysis to determine the speed of an object or surface. It's a handy tool for detecting and diagnosing flaws in rotating machinery's bearings, gears, and other components. The mechanism of this transducer is straightforward: it translates mechanical motion into an electrical signal that is subsequently evaluated and comprehended for proper analysis.

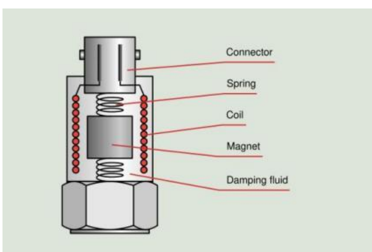


Fig I. 9 Principle diagram of velocity transducer

Fig I. 10 Velocity transducer

Advantages :

- Accurate and reliable measurement of velocity
- Wide frequency response range
- Can be used in various industrial applications
- High sensitivity and stability
- Compact size and easy to install

Disadvantages

- Expensive compared to other transducer types
- Vulnerable to noise and electromagnetic interference
- Requires calibration and maintenance
- Sensitive to temperature changes
- Can be affected by vibration and shock

Problems and Faults detected

- Misalignment or offset of the sensor
- Calibration drift or error

- Wiring or connection problems
- Damage to the sensing element
- Interference from other equipment
- High levels of noise or vibration

I.6.4.1.3 Accelerometer

The accelerometer is a device that measure acceleration , or the pace at which an item’s speed transformation .it notes and alters changes in motion and alignment in all three dimension into electric signal. Although it can be found in various setups, such as piezoelectric and capacitive accelerometer ,it is commonly used to measure vibration in rotating machinery or detect bearing faults

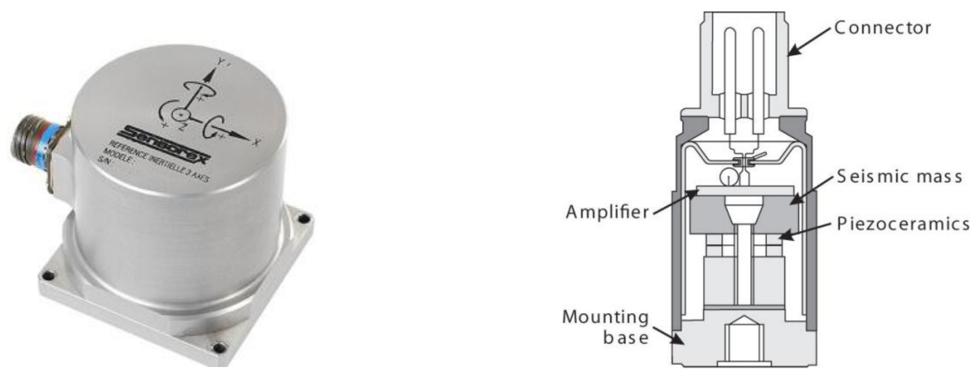


Fig I. 11 Principle diagram of an accelerometer.

Advantages:

- High sensitivity: Accelerometers are capable of detecting even small movements and vibrations.
- Wide range of applications: Accelerometers are used in various fields, including automotive, aerospace, industrial, and medical.
- Versatility: Accelerometers can measure acceleration in any direction, making them suitable for a wide range of applications.

Disadvantages:

- High cost: Some high-end accelerometers can be expensive, especially those with high accuracy and resolution.
- Power consumption: Accelerometers can consume a significant amount of power, especially when used for extended periods of time.
- Interference: Accelerometers can be sensitive to external sources of interference, such as electromagnetic noise, which can affect measurement accuracy.

Problems and faults detected:

- Mechanical wear: Mechanical wear can cause the accelerometer's sensitivity to deteriorate over time, affecting measurement accuracy.
- Thermal drift: Changes in temperature can cause the accelerometer's sensitivity to change, affecting measurement accuracy.
- Non-linear behavior: Some accelerometer may exhibit non-linear behavior, which can result in measurement errors.

- Sensor saturation: Some accelerometer may become saturated, or "clipped", at high acceleration levels, resulting in measurement errors.

I.7 General on bearing

Bearings are components that enable movement between two parts, typically rotating or oscillating shafts, while maintaining precise motion and low friction. They are essential for the effective operation of rotating devices in various settings, from household appliances to industrial machinery. Bearings may be categorized as ball bearings, roller bearings, plain bearings, or fluid bearings, based on their design and intended use.

The bearing is used in so many fields we note some :

- Automotive bearings are used in the wheel, engines, and transmissions of automobile
- Manufacturing: Bearings are used in various manufacturing processes, including assembly lines, conveyors, and robots.
- Agriculture: Bearings are used in the components of tractors and other agricultural equipment.

Types of bearings:

I.7.1 composition of bearings:

The main components of a bearing are:

Inner Ring: This is the inner component of the bearing that rotates with the shaft. It provides a smooth surface for the rolling elements to rotate against.

Outer Ring: This is the outer component of the bearing that is stationary. It provides a smooth surface for the rolling elements to rotate against.

Rolling Elements: These are the balls or rollers that move in the raceways. They provide the low-friction interface between the moving and stationary parts of the bearing.

Cage: This is the component that separates and guides the rolling elements. It is typically made of a lightweight material, such as plastic or metal.

Seals: These are the components that prevent contamination and lubricant loss from the bearing. They are typically made of rubber or metal and are located on the outer surface of the bearing.

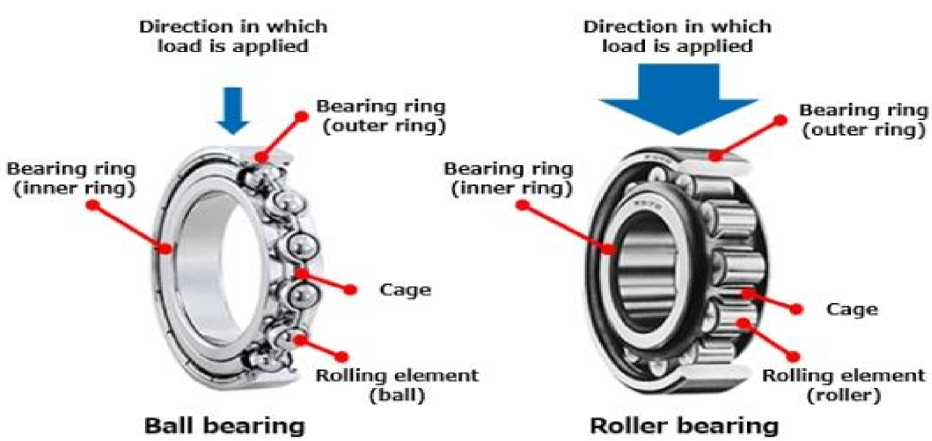


Fig I. 12Bearing composition

I.7.2 bearing main

Bearings are an essential component in many electrical applications, as they provide stability, and support, and reduce friction for rotating parts. Some of the main bearings used in electrical applications :

Ball Bearings: Ball bearings are commonly used in electrical motors, generators, and transformers. They are capable of handling both radial and axial loads and are ideal for high-speed applications.

Fig I. 13 Ball bearing

Spherical Roller Bearings: Spherical roller bearings are commonly used in high-load electrical applications, such as electric motors and gearboxes. They are capable of handling heavy radial loads and are ideal for high-speed applications.

Fig I. 14 spherical roller bearing

Tapered Roller Bearings: Tapered roller bearings are used in applications such as electric motors and gearboxes, where combined radial and thrust loads are present. They are designed to handle high loads and are ideal for applications with high axial loads.

Fig I. 15 Tapered Roller Bearings

Insert Bearings: Insert bearings are commonly used in electrical applications, such as electric motors and generators. They are designed to provide stability and support for rotating shafts and are easy to install.

Fig I. 16 Insert Bearings

I.7.3 different types of bearing faults and their origins

Bearings play a crucial role in many electrical applications, providing stability, support, and reducing friction for rotating parts. However, bearings can also fail due to a variety of reasons, leading to costly downtime and repairs. Some of the most common types of bearing faults in the electrical field include:

Wear : Wear and tear is the most common type of bearing fault, resulting from continuous operation, poor maintenance, and the use of incorrect lubrication. This can lead to surface damage, reduction in radial clearance, and loss of bearing performance.

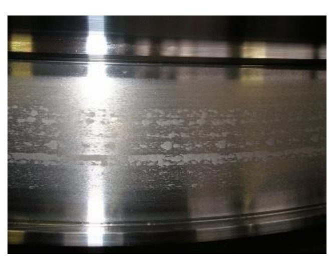


Fig I. 17 Wear and surface fatigue in rolling bearings

Fatigue:

Fatigue is another common type of bearing fault, caused by repeated loads and stress on the bearing components. This can lead to crack formation, surface degradation, and eventually, bearing failure

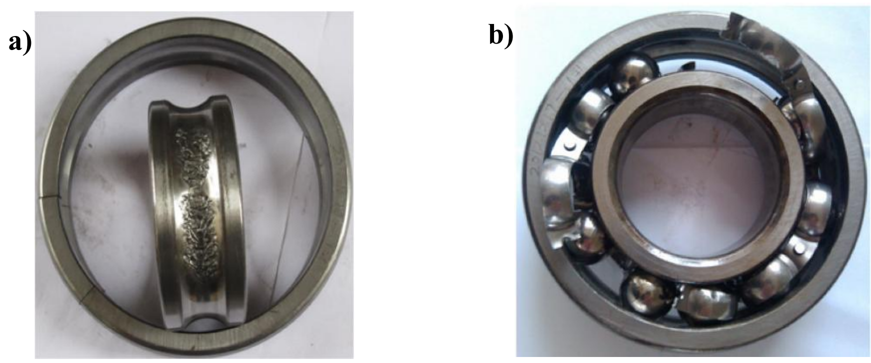


Fig I. 18 Illustration of: a) fatigue failed bearing, b) fatigue spalling observation

Corrosion:

Corrosion is a type of bearing fault that can occur in environments with high humidity, corrosive gases, or liquids. This can lead to surface corrosion and loss of bearing performance, causing decreased bearing life.

Fig I. 19 Fretting corrosion on the outer diameter of a bearing

Lubricant degradation:

due to local high temperatures , the additives in the lubrication oils burn on the base oils .thus ,the supplement is consumed faster .with grease lubrication ,the grease turns black and hardens .this rapid breakdown can drastically reduce grease and bearing life . if the lubrication is not replenished in time, it ca, cause secondary damage due to poor lubrication

Fig I. 20 Lubricant degradation Black discolored grease on the cage bars caused by passage of current

Overloading:

Overloading is a type of bearing fault that can occur when the bearing is subjected to loads that exceed its rated capacity. This can result in surface damage, reduced radial clearance, and decreased bearing performance.

Fig I. 21The dents, resulting from wrong mounting, are overrolled and quickly lead to spalls

I.7.3.1 Characteristic frequencies for the defects of a bearing :

Defects that can occur are: cracking, flaking, corrosion (causing a crack), etc. A damaged bearing produces vibrations whose frequency is equal to the rotational speed of each part of the bearing. They are particularly suitable for the rotation of balls, rollers or the cage and the movement of balls around the ring. We can consider each type of bearing and depending on its production size The natural frequencies given by Equations (I.5)(I.6)(I.7)(I.8)

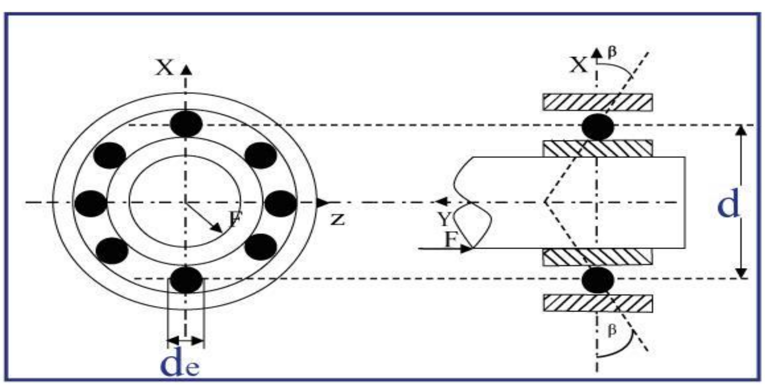


Fig I. 22: Characteristics of a bearing

- **n: the number of rolling elements (balls, rollers or needles).**
- **d: the pitch diameter.**
- **de: the diameter of the rolling elements.**
- **β: contact angle.**
- **ω: is the speed of rotation.**

I.7.3.1.1 Defect on the inner ring

The equation gives its characteristic frequency(I.5).This frequency varies with the rotation frequency of the shaft (sidebands around the fault line).

$$f_i = \frac{n\omega}{2}\left(1 + \frac{d}{d_e}\cos\beta\right) \qquad \text{I.5}$$

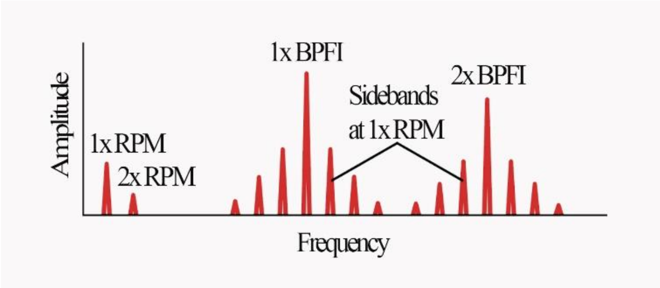


Fig I. 23Inner race defect

I.7.3.1.2 Defect on the outer ring

The equation gives its characteristic frequency (I.6). It is possible to detect an amplitude modulation at the shaft rotation frequency around the fault frequency even when the load supplied to the outer ring is constant.

$$f_o = \frac{n\omega}{2}\left(1 - \frac{d}{d_e}\cos\beta\right) \qquad \text{I.6}$$

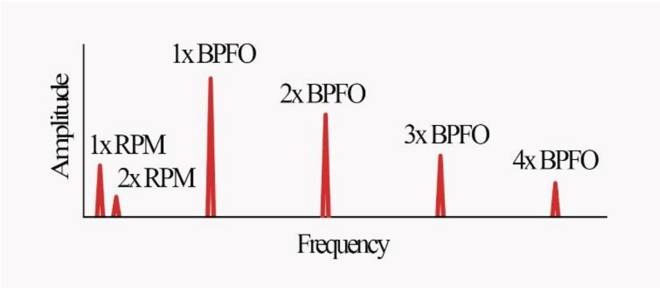
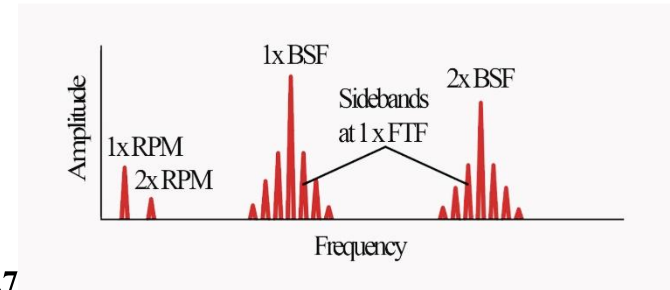


Fig I. 24 Outer race defect

I.7.3.1.3 Defect on the rolling element

The equation describes the frequency at which a bill (or roll) defect will appear on the inner or outer ring. The frequency of rotation of the rolling element on itself corresponds to the first characteristic defect frequency. This rolling element produces shocks at a double frequency because it only contacts the inner and outer rings once each throughout a rotation.

$$f_{ball} = \frac{d_e\omega}{d}\left(1-\left(\frac{d}{d_e}cos\beta\right)^2\right)$$



I.7

Fig I. 25 Ball or roller defect

I.7.3.1.4 Defect on the cage

Equation (I.3) gives the frequency of passage of a cage fault: The existence of lines at the frequency f_i and its harmonics is a symptom of this problem. As for the inner ring, lateral bands can be observed around f_i, (fault frequency of the rolling element) and 2f ball . These bands are separated by a frequency equal to the cage fault frequency.

$$f_{cage} = \frac{\omega}{2}\left(1-\frac{d}{d_e}cos\beta\right) \quad \text{I.8}$$

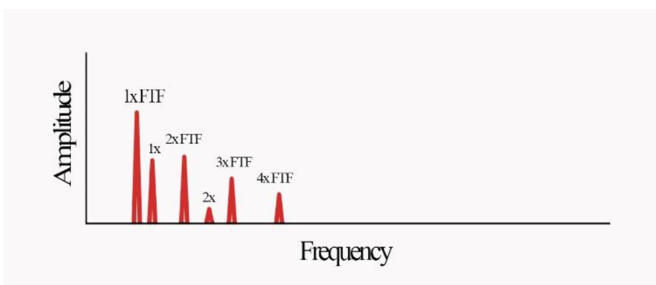


Fig I. 26 Bearing cage defect

Conclusion

In conclusion, this chapter we've discussed comprehensive overview of maintenance, monitoring, and bearings. It covers the different types of maintenance and their goals, as well as the causes of failure in bearings. Additionally, it delves into the practice of vibration analysis and its importance in maintenance and monitoring. Overall, this file serves as a valuable resource for those seeking to improve their understanding of maintenance practices and how to effectively monitor equipment performance.

And for the next chapter we are going to talk about the techniques that used in vibration analysis from the oldest methods to the most advanced ones

Chapter II:

State of the art on signal processing techniques applied to vibration

II.1 Introduction :

In this chapter where we'll explore the most advanced techniques used in vibration analysis. These techniques are vital for diagnosing and monitoring different machines like turbines, motors, and pumps. We'll break down the chapter into several sections, and each section focuses on a unique signal processing technique. We'll cover temporal analysis, frequency analysis, time-frequency and time-scale analysis, energy operator analysis, de-convolution with minimum entropy, and more. By the end of this chapter, you'll grasp the meaning of different signal processing techniques and their formulas, definitions, applications, and usefulness.

II.2 Temporal analysis:

Temporal analysis, also known as time series analysis, is a statistical technique for analyzing time-varying data and is an effective method for detecting faults in rotating machinery, such as bearing faults. Bearing failures are one of the most common causes of machinery failure, and detecting them early can save money on downtime and repairs.

Vibration data from sensors on the machinery is collected in temporal analysis for bearing fault detection. This information is then analyzed to identify patterns and trends that may indicate the presence of a bearing fault. Temporal analysis techniques for detecting bearing faults include[14]

Overall, temporal analysis techniques can aid in detecting bearing faults and preventing machinery failure. By detecting faults early, maintenance can be performed before the machinery fails, reducing downtime and repair costs.[15]

II.2.1 RMS value :

Root mean square (RMS) is a popular statistical measure in temporal analysis, particularly in signal and vibration analysis. The RMS value is a measure of a signal's or vibration's amplitude and is frequently used to characterize the intensity of noise or the magnitude of an electrical signal. [16]

The RMS value is calculated in temporal analysis whilst also taking the square root of the mean of the squared values of a signal over a given period. The RMS value can be mathematically in the time domain formulated as:

$$RMS = \sqrt{\frac{1}{N}\sum_{n}^{i=1} x_i^2} \quad \text{II.1}$$

Where :

- N represents the number of data points in the signal

- x represents the signal's value at each data point.

The RMS can be applied to many fields such as [17]:

- used to track vibration amplitude variations as time passes, permitting for predictive maintenance
- can be combined with other statistical measures to determine the presence of defects in rotating equipment, such as kurtosis or crest factor
- can be used to evaluate the performance of vibration isolation systems or to compare the vibration levels of various machines or components.

II.2.2 crest factor :

Crest factor is a parameter of a waveform that shows the ratio of peak values to the effective value .it indicates how extreme the peaks are in a waveform divided by its RMS value the minimum possible crest factor is 1 which indicates no peaks, such as direct current or a square wave. The crest factor is a useful metric for characterizing a signal's dynamic range, and it can provide useful information for system design and performance evaluation.

The crest factor is defined mathematically as [18]:

$$C = \frac{X_{peak}}{X_{RMS}} \qquad \text{II.3}$$

$$crest\ factor = \frac{peak\ value}{rms\ value} = \left| \frac{max|x(n)|}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n)]^2}} \right| \qquad \text{II.3}$$

Where:

- C: the crest factor
- X_{peak}: the maximum amplitude of the signal
- X_{RMS} : the root mean square root of the means squared values of the signal over time.

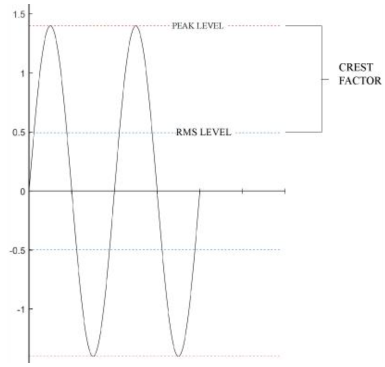


Fig II. 1 Crest factor of a sinusoidal signal

The crest factor can be used in so many fields such as [20]:

- the impact of the crest factor in audio signal processing because it indicates the dynamic range of a signal
- used to ensure that equipment is rated for peak currents that may occur during small disturbances
- useful parameter in vibration analysis for detecting faults in rotating machinery such as bearing faults. [19]

II.2.3 K factor :

The k factor is a vibration analysis parameter that is commonly used to determine the degree of bearing faults in rotating machinery. It is a unit of measure that describes the connection between an applied load and a bearing's dynamic response. The K factor is used to calculate the equivalent stiffness of the bearings, which can be used to determine the degree of bearing faults.[8]

$$\text{k factor} = \text{peak value} * \text{RMS value} \qquad \text{II.4}$$

The application and the usefulness of the K factor in identifying bearing faults:

- Detecting bearing faults in rotating machinery: In vibration analysis, the K factor is frequently employed to identify bearing faults in rotating machinery such as pumps, motors, and gearboxes.

- Can be used to track the evolution of bearing faults over time. by comparing current measurements to previous measurements
- The K factor is extremely sensitive to bearing faults and can detect them early on before they become severe enough to cause machine failure
- It provides a quantitative measurement of the severity of the bearing fault.
- Vibration analysis, including the use of the K factor, is a non-invasive diagnostic tool that does not necessitate disassembling the machine. [21] [22] [23]

II.2.4 Global level :

The global level analysis is a technique used in vibration analysis to detect and identify unbalanced faults in rotating machinery .unbalance is a common fault in rotating machinery that occurs when the center of mass of a rotating component is not aligned with its axis of rotation

The global level is a measure of the overall vibration level of a machine .it calculated by taking the square root of the sum of the squares of the vibration amplitude in the directions (X, Y, and Z)[21]

$$Global\ level = \sqrt{X^2 + Y^2 + Z^2} \quad \text{II.5}$$

The application and the usefulness of the global level:

- Is capable of detecting changes in vibration patterns that may indicate the presence of an unbalanced fault.
- Is a useful tool for ensuring the dependability and safety of rotating machinery [8]

II.2.5 Statistical Moments :

The statistical moment is a parameter used to characterize a vibration signal's frequency distribution. It's also useful for analyzing vibration signals in rotating machinery. They provided important insights into the signal's statistical properties and can be used to detect changes in the behavior of machinery components.[9]

The statistical moment is classified into four orders:

II.2.3.1 Moment of order 1:

The first-order moment or the mean is a crucial indicator for detecting faults, particularly those related to bearings. By analyzing a machine's vibration signal's mean value, one can gain insights into its overall operational state, which can be compared to past data to uncover any changes that may suggest a fault is present. [24]

$$M_1 = \left(\frac{1}{N}\right) * \sum_{i=1}^{N} x_i \quad \text{II.6}$$

- m1: the first-order moment
- N: the number of samples in the signal
- x_i: the number of samples of the signal

The application of the moment of order 1 can be :

- Measuring the magnitude of the vibrations.
- Identifying the source of the vibrations.
- Analyzing the frequency and amplitude of the vibrations.
- Calculating the power losses due to the vibrations.
- Predicting the effects of the vibrations on other structures.

II.2.3.1 Moment of order 2:

The second-order moment, also known as variance, is a measure of the spread of the distribution and is used to indicate its width. The greater the variance, the more distorted the distribution.[25]

$$M2 = \left(\frac{1}{N}\right) * \sum_{i=1}^{N} (x_i - M_1)^2 \qquad \text{II.7}$$

the application and usefulness of the second-order moment

- Detection of unbalanced faults in rotating machinery and can cause excessive vibration in the machine
- Identify Misalignment faults
- Identify the type of vibration and diagnose bearing faults
- Early fault detection
- Accurate fault diagnosis
- Reduction in maintenance costs

II.2.3.1 3rd order moment (skewness) :

In vibration analysis, the third-order moment, also known as skewness, is a statistical measure that describes the asymmetry of a probability distribution. Skewness is used to quantify the degree of asymmetry of the vibration signal. A high skewness value indicates that the vibration signal is skewed (distorted) to one side of the mean more than the other. This can be an indication of the presence of fault conditions in rotating machineries, such as misalignment and bearing defects.[21]

$$Skewness = \frac{1}{n} \sum \left[\frac{x_{i-\mu}}{\sigma}\right]^3 \qquad \text{II.7}$$

Where:

- E = expected value
- X = random variable

- μ = mean
- σ = standard deviation

this statistical moment is used mostly in detecting and diagnosing faults in rotating machinery

II.2.3.1 Moment of order 4 (Kurtosis) :

Kurtosis is a measure of a probability distribution's peakedness or flatness .it compares the amount of extreme value (tails) to the amount around the mean(center)

$$\boldsymbol{Kurtosis} = \frac{1}{N} * \sum \frac{(x_i - \bar{x})^4}{s^4} \qquad \text{II.8}$$

- where:
- n = sample size
- xi = data point
- x̄ = sample mean
- s = sample standard deviation

Kurtosis can be used to detect bearing faults in rotating machinery, with high values indicating the presence of impulsive events.

II.2.6 TALAF and THIKAT

Many descriptors have been employed in literature for fault identification, including Peak, RMS, Crest Factor, Kurtosis, and others. Two indicators that are especially well suited for flaw detection in the initial stages of degradation are the Ku and the CF. Nevertheless, some of these descriptors lose their usefulness for tracking fault evolution after a certain amount of degradation. To enhance the monitoring, new descriptors called Talaf and Thikat have been created. The classical terms Kurtosis and RMS are combined by Talaf[26]

$$TALAF = log\left[kurtosis + \frac{RMS}{RMS_0}\right] \qquad \text{II.9}$$

Where

$RMS_0$is the root mean square value defined under healthy conditions

$$THIKAT = log\left[(kurtosis)^{cf} + \left(\frac{RMS}{RMS_0}\right)^{peak}\right] \qquad \text{II.10}$$

II.2.7 Non-linear indicators:

Nonlinear indicators are mathematical methods that examine the nonlinear characteristics of a system's reaction to external excitation in order to find problems in mechanical systems, such as bearings. Nonlinear indicators are founded on the idea that, even when a system is subjected to minute changes in the input signal, variations in the system's reaction may reveal the presence of a malfunction.

II.2.7.1 Approximate entropy (ApEn):

Approximate entropy is a statistical measure sued to quantify the regularity and predictability of time series data. Since Pincus initially presented it as a signal complexity metric in 1991, it has been used for a variety of purposes, including detection and diagnosis to detect anomalies or irregularities in the data such as bearing fault which can used to analyze the vibration signal of the bearing [27]

The formula for ApEn is:

$$ApEn(m, r, N) = \emptyset^{m}(r) - \emptyset^{m+1}(r) \qquad \text{II.11}$$

where

- m: embedding dimension
- r: tolerance
- N: length of the time series
- Φm(r, N): natural logarithm
- ApEn(m, r, N): Approximate entropy,

II.2.7.2 Sample entropy:

A well-known non-linear strategy for detecting bearing issues is sample entropy, based on analyzing time series signals' regularity and intricacy. This technique gauges the probability that two sets of m data points (within a certain tolerance) will sustain their likeness across time.

The equation for sample entropy is as follows:

$$SampEn(m, r, N) = -\ln \frac{C_{m}^{(N)}}{C_{m+1}^{(N)}} \qquad \text{II.12}$$

Where :

m: is the length of the sequences to be compared

r: the tolerance

N: the length if the time series

C_m: the number of pairs of sequences of length

m: distance is less than the tolerance r

C_{m+1}: the number of pairs of sequences of length m+1 whose distance is less than the tolerance

II.2.7.3 Lempel–Ziv complexity:

Lempel complexity is a way to measure how complex a signal is, and it's often used to find mechanical problems in vibration data. To calculate Lempel complexity, you figure out how many different patterns you need to describe the whole signal. This method has been proven to work well for detecting issues with things like bearings in mechanical systems.

The formula of Lempel-Ziv complexity is written as follows:

$$C_N = \frac{C(n) log_{\alpha} n}{n} \qquad \text{II.13}$$

Where

- C_N: Lempel complexity of a signal of length N
- C(n): Lempel complexity of a segment of the signal of length n
- α: the base of the logarithm used in the calculation
- n: the length of the segment used to calculate C(n)

II.3. Frequency analysis:

Frequency analysis is a technique used in various fields such as cryptography, signal processing, and linguistics to analyze the frequency distribution of a signal or language. There are several methods of frequency analysis, each with its definition, field of use, and working mechanism.

II.3.1 Spectral Analysis:

Spectral analysis is a technique used to analyze the frequency content of a signal or system. It involves decomposing a complex signal into its individual frequency components to study its properties. Spectral analysis is widely used in various fields, including signal processing, communication systems, acoustics, and seismology, to name a few. The general mathematical relationship for spectral analysis is the Fourier transform, which represents a signal in terms of its frequency components. For a continuous-time signal x(t) The Fourier transform is given by[28] :

$$X(f) = x(t)e^{(-j2ft)dt} \qquad \text{II.14}$$

Where

- $X(f)$ is the frequency in Hertz (Hz)
- (j) is the imaginary unit,

and the integral is taken over the entire time period.

The mechanism of spectral analysis involves taking a time-domain signal and transforming it into its frequency-domain representation using the Fourier transform. This allows the identification and measurement of individual frequency components in the signal, which can provide valuable insights into the nature and behavior of the signal

II.3.2 Envelope analysis ：

A signal processing method called envelope analysis is used to extract a modulated signal's slowly varying amplitude envelope. It is frequently used in vibration analysis to assess the condition of rotating machinery and find faults like gear wear and bearing flaws.

The Hilbert transform is used to derive the general mathematical relationship for envelope analysis. In response to a real-valued signal. $\boldsymbol{X(t)}$, the Hilbert transform $\boldsymbol{H(X(t))}$ generates an imaginary signal $\boldsymbol{y(t)}$in the manner described below. [29]

$$\boldsymbol{X(t) + j * y(t) = H(X(t)) = 1/\pi * \int_{-\infty}^{+\infty} X(\tau)/(t-\tau) d\,\tau} \qquad \textbf{II.15}$$

The magnitude of the complex signal, $\boldsymbol{Z(t)}$= $\boldsymbol{X(t) + j * y(t)}$, can then be used to determine the envelope of $\boldsymbol{X(t)}$

$$\boldsymbol{E(t) = |Z(t)|} \qquad \textbf{II.16}$$

The Hilbert transform is used in envelope analysis to obtain a complex representation of a time-domain signal. The magnitude of the complex signal is then taken to obtain the signal's envelope. This enables the signal's slowly varying amplitude variations to be extracted, which may shed light on the underlying physical processes.

Envelope analysis has the advantage of early fault detection in rotating machinery, allowing for prompt maintenance and repair. Additionally, it can offer details about how the equipment is running, enabling optimization and raising efficiency.

II.3.3 Spectral Kurtosis :

A signal processing method called spectral kurtosis is used to examine the statistical distribution of a signal's frequency components. It is especially helpful in identifying impulsive noise or vibration signals that are frequently linked to mechanical issues in rotating machinery.

It is necessary to calculate the fourth-order moment of a signal's frequency spectrum in order to understand the general mathematical relationship for spectral kurtosis. The spectral kurtosis, denoted as $\boldsymbol{SK(F)}$, for a discrete-time signal, $\boldsymbol{X(n)}$, with N samples, is denoted as follows[30].

$$\boldsymbol{SK(f) = \left[\frac{\mu 4(f)}{\mu 2^2(f)}\right] - 2} \qquad \textbf{II.17}$$

where $\boldsymbol{\mu 2}(\boldsymbol{f})$ is the second-order moment of the frequency spectrum at frequency f and $\boldsymbol{\mu 4}(\boldsymbol{f})$ is the fourth-order moment of the frequency spectrum at frequency $\boldsymbol{f}$. The moments are calculated as follows.

$$\boldsymbol{\mu 2}(\boldsymbol{f}) = \frac{1}{N}\sum_{n=0}^{N-1} |X(n,f)|^2 \quad \text{II.18}$$

$$\boldsymbol{\mu 4}(\boldsymbol{f}) = \frac{1}{N}\sum_{n=0}^{N-1} |X(n,f)|^4 \quad \text{II.19}$$

Where $\boldsymbol{X}(\boldsymbol{n},\boldsymbol{f})$ represents the discrete Fourier transform of$\boldsymbol{X}(\boldsymbol{n})$ at frequency $\boldsymbol{f}$Calculating the fourth-order statistical moment of a signal's frequency spectrum is a key step in the mechanism of spectral kurtosis. Impulsive noise or vibration signals linked to mechanical problems frequently have high spectral kurtosis values. In order to understand the presence and severity of faults in rotating machinery, spectral kurtosis analysis is useful.

The advantages of spectral kurtosis include its capability to accurately differentiate impulsive noise from other noise types and to offer a numerical measure of the severity of faults in rotating machinery. It is widely used in the field of rotating machinery condition monitoring and fault diagnostic

II.3.4 kurtogram:

The kurtogram is a signal processing technique used for detecting faults or anomalies in mechanical systems such as bearings, pneumatic machines, gears, etc. It is based on the statistical measure known as kurtosis, which characterizes the degree of peakedness or flatness of a distribution.[31]

The general mathematical relationship for the kurtogram can be expressed as follows:

$$y = \frac{E[(x(t)-\mu)^4]}{\sigma^4} \quad \text{II.20}$$

where:

E[.] denotes the expected value

μ is the mean of the signal x(t)

σ is the standard deviation of the signal x(t)

The kurtogram works by decomposing the signal into multiple sub-bands using wavelet transforms and then calculating the kurtosis value for each sub-band at different time-frequency points. The maximum kurtosis value across all sub-bands is then plotted as a function of time and frequency to form the kurtogram.

The benefits of using the kurtogram include its ability to detect faults or anomalies in mechanical systems at an early stage, which can help prevent catastrophic failures and reduce maintenance costs.

Additionally, it is a non-invasive technique that can be used to monitor systems in real-time without the need for expensive equipment

II.3.5 Ceptral analysis :

A signal processing method used to examine the frequency content of a time-varying signal is central analysis, also referred to as spectral analysis or frequency analysis. It is frequently used to diagnose faults and monitor the condition of rotating machinery, including gears, bearings, and bearing assemblies.[31]

The Fourier transform, which depicts the signal as the sum of sinusoidal components at various frequencies, provides the general mathematical relationship for central analysis. $x(t)$ is a time-domain signal, and the Fourier transform of it is:

$$X(f) = \left[x(t) * e^{(-2if*t)}\right]dt \qquad \text{II.21}$$

where (f) is the frequency variable, the signal is represented by $\{X(f)\}$, and the integral is calculated over the entire time interval.

While the phase, arg$\{X(f)\}$, represents each component's phase shift, the magnitude of the Fourier transform, $|X(f)|$, represents the amplitude of each sinusoidal component at frequency(f).

In order to diagnose mechanical faults and keep track of equipment condition, central analysis is frequently used. It is possible to identify faults like imbalance, misalignment, bearing defects, gear damage, etc. by looking at the frequency content of a signal. This can aid in spotting potential issues before they cause serious harm to or the machine's failure.

II.4 Time-frequency and time-scale analysis:

Time-frequency and time-scale analysis are signal processing techniques used for analyzing non-stationary signals, which are signals that vary in time and frequency. These techniques are widely used in the field of machinery fault diagnosis and condition monitoring, particularly for the analysis of gear, bearing, and rotating machinery signals.[32]

The general mathematical relationship for time-frequency analysis is given by the short-time Fourier transform ($STFT$), which represents the signal as a series of overlapping Fourier transforms calculated over short time intervals. The STFT of a signal x(t) is defined as:

$$STFT(f,\tau) = \int \left[x(t) * w(t-\tau) * e^{(-2\pi if*t)}\right]dt \qquad \text{II.22}$$

$STFT(f,\tau)$ is the frequency-domain representation of the signal at frequency (f) and time (τ),
$w(t-\tau)$ is a window function that is typically chosen to be a Gaussian or a Hamming window, and the integral is taken over a short time interval centered at (τ).

The general mathematical relationship for time-scale analysis is given by the continuous wavelet transform **(CWT)**, which represents the signal as a series of wavelet transforms calculated over a range of scales. The **CWT** of a signal $x(t)$ is defined as:

$$\mathbf{CWT}(\mathbf{a},\mathbf{b}) = \int [x(t) * \psi[(t-b)/a]]dt \qquad \text{II.23}$$

where $\mathbf{CWT(a,b)}$ is the wavelet transform of the signal at scale a and translation **b**, **ψ(t)** is the mother wavelet function, and the integral is taken over all time.
Time-frequency and time-scale analysis are powerful tools for analyzing non-stationary signals because they allow the frequency and time properties of the signal to be examined simultaneously. By using these techniques, it is possible to identify and diagnose faults in rotating machinery, such as gear wear, bearing defects, and misalignment, at an early stage before they cause serious damage or failure

II.4.1 Short-term Fourier transform (STFT):

To analyze non-stationary signals, people frequently employ the short-term Fourier transform (STFT), a time-frequency analysis technique. It entails breaking a signal up into manageable segments and calculating the Fourier transform of each segment separately. In doing so, we can produce a time-frequency representation of the signal that illustrates how its spectral content varies over time.[33]
According to: the $\boldsymbol{STFT}$ mathematical relationship.

$$\boldsymbol{STFT(t,f) = \int x(\tau) * w(t-\tau) * e^{(-i2\pi f\tau)} d\tau} \quad \textbf{II.24}$$

Where $\boldsymbol{w(t)}$ is a window function that is used to weight each segment,$\boldsymbol{STFT(t,f)}$ is the$\boldsymbol{STFT}$ of the signal $\boldsymbol{x(t)}$ at time t and frequency f, is the time lag, and $\boldsymbol{STFT(t,f)}$ is the$\boldsymbol{STFT}$ of the signal.
$\boldsymbol{STFT}$ is frequently employed in the analysis of vibration signals in the field of bearings, gears, and rotating machines. The frequency content of the vibration signal can be examined over time to reveal specific faults in the rotating machinery. For instance, the vibration signal may contain particular frequency components that can be identified using $\boldsymbol{STFT}$ analysis when a bearing has a crack or other defect.

II.4.2 Distribution of Wigner-ville:

The Wigner-Ville distribution (WVD), also referred to as the Wigner-Ville distribution, is a time-frequency analysis technique used to examine non-stationary signals. Although it is comparable to the short-time Fourier transform (STFT), the WVD does not make use of a fixed window function. Instead, it calculates a signal's Fourier transform at every point in time and frequency to produce a high-resolution time-frequency representation.[34]

The Wigner-Ville distribution follows the following mathematical relationship.

$$\boldsymbol{WVD(t,f) = \int x(\tau) * x(\tau - t) * e^{(-i2\pi ft)} d\tau} \quad \mathrm{II.\,25}$$

WVD(t,f) is the Wigner-Ville distribution of the signal x(t) at time t and frequency f, x*(-t) is the complex conjugate of x(-t), and is the time delay.

The WVD is frequently used to analyze vibration signals to find particular flaws in the machinery in the field of rotating machines, bearings, and gears. The WVD can be used to identify specific frequency components in the vibration signal that are caused by, for instance, the presence of a crack or other defect in a bearing.

The WVD is superior to other time-frequency analysis techniques because it can separate closely spaced frequency components and offers high-resolution time-frequency representations. But because it is noise-sensitive and has the potential to produce negative values, interpretation can be challenging.

II.4.3 Wavelet transform:

An analytical and processing method for signals is known mathematically as the wavelet transform. It breaks down a signal into a collection of wavelets that can be used to examine the frequency content and time localization of the signal. Scaling and shifting operations are used to create the wavelets from a mother wavelet function.

The following gives the general mathematical relationship for the wavelet transform.

$$\boldsymbol{W}(\boldsymbol{a},\boldsymbol{b}) = \int \boldsymbol{f}(\boldsymbol{t}) * \boldsymbol{\psi} * [(\mathbf{t}-\mathbf{b})/\mathbf{a}]\mathbf{dt} \qquad \textbf{II.26}$$

where $\boldsymbol{W}(\boldsymbol{a},\boldsymbol{b})$ represents the wavelet coefficients at scale a and position $(\mathbf{b})$, $\boldsymbol{f}(\boldsymbol{t})$ is the input signal, (ψ) is the complex conjugate of the wavelet function ψ, and the integral is taken over all time.

The wavelet transform has been used to diagnose problems with bearings and gearboxes in the field of rotating machines and bearings. Its operation is based on the wavelet-based analysis of vibration signals produced by rotating machinery. The presence of particular fault frequencies can then be determined using the wavelet coefficients, which can also be used to determine the nature and severity of the fault.

II.4.4 Hilbert-Huang Transform

A signal processing method called the Hilbert-Huang Transform (HHT), also referred to as the Empirical Mode Decomposition (EMD), breaks down a non-stationary signal into its intrinsic mode functions (IMFs). The oscillatory signal components with various time scales are extracted during the sifting process, which yields the IMFs. The frequency content and time-varying properties of signals can be examined using the HHT.

The HHT can be used to analyze vibration signals in the context of rotating machines and bearings in order to find faults and assess their severity. The vibration signals' frequency and amplitude modulation can reveal the presence of faults like misalignment, unbalance, and bearing defects. The HHT can provide information about these vibration signal parameters.

The HHT's basic mathematical relationship can be stated as follows. [35]

$$\boldsymbol{X}(\boldsymbol{t}) = \sum \boldsymbol{i} = \boldsymbol{ln}\, \boldsymbol{Ci}(\boldsymbol{t}) + \boldsymbol{Rn}(\boldsymbol{t}) \qquad \text{II. 27}$$

where $\boldsymbol{x}(\boldsymbol{t})$ denotes the initial signal, $\boldsymbol{Ci}(\boldsymbol{t})$ denotes the i-th intrinsic mode function, $\boldsymbol{Rn}(\boldsymbol{t})$ denotes the residual signal, and n denotes the total number of IMFs.

The signal decomposition, sifting, and Hilbert transformation are just a few of the steps that make up the HHT's mechanism of action. First, using the sifting procedure, the signal is broken down into its IMFs. The analytical signal, which contains the signal's amplitude and phase information, is then produced by applying the Hilbert transformation to each IMF. By using the analytical signal's phase and envelope, it is possible to determine the instantaneous frequency and amplitude modulation, respectively.

II.5 Energy operator analysis

A technique for locating problems in rotating machinery, such as bearings, is called energy operator analysis. By applying a Hilbert transform to the vibration signal, it produces an envelope signal. The energy operator is then used to calculate the envelope signal's energy level. The envelope of a vibration signal is used in the Energy Operator Analysis technique to identify the fault frequencies and their harmonics. When a bearing develops a problem, impulses are produced that propagate throughout the bearing structure and cause vibrations in the machine. The rotating parts of the machine shape these vibrations, resulting in a cyclic waveform. The Energy Operator Analysis can be used to decipher the essential information included in this waveform on the fault frequencies and their harmonics.[36]

$$E(x) = x^2 - x(n-1)x(n+1) \qquad \text{II.28}$$

Where :

- x(n): the original signal
- x(n-1) , x(n+1): the past and next signal respectively

II.6 Deconvolution with minimum entropy

Deconvolution with minimum entropy (DEM) is a way of processing signals that can help isolate important information from interfering noise in diverse applications, such as analyzing vibrations. The aim of this technique is to produce a refined signal that has the smallest degree of randomness or disorder possible, in order to extract the most useful data.[37].

$$y(n) = h(n) + x(n) + e(n) \qquad \text{II.29}$$

where :

- e(n): the background noise,
- x(n): the impulse sequence
- h(n): the transfer function

Table: Comparative study (the advantages and disadvantages) between the method of analysis

Analysis	Advantages	Disadvantages

methods		
Short-term Fourier transform (STFT)	● Can capture both the time and frequency characteristics of non-stationary signals, such as those generated by rotating machinery, allowing for comprehensive analysis and diagnosis. ● Provides a high-resolution time-frequency representation of the signal, which can help identify specific frequency components and their temporal evolution. ● Can be computationally efficient, especially for short-duration signals or signals with a limited frequency range	● The time-frequency resolution is limited by the choice of window length and shape, which can impact the accuracy of the results. ● Interpretation of the results can be challenging, especially in the presence of noise or interference. ● May not be suitable for analyzing signals with highly non-stationary or non-linear behavior, as it assumes that the signal properties are stationary over the duration of the analysis window
Wigner-vile distribution	● Provides a high-resolution time-frequency representation of signals, which can be useful in identifying and characterizing frequency components that change over time. ● Can be effective in analyzing signals with non-stationary or non-linear characteristics, as it does not assume stationarity or linearity. ● Can be used for both signal analysis and signal synthesis.	● The method is computationally intensive and can be time-consuming, especially for long-duration signals. ● The distribution can be sensitive to noise and interference, which can impact the accuracy of the results. ● Interpretation of the results can be challenging, as the distribution can show interference and cross-terms that may be difficult to separate and interpret.
Wavelet Transform	● Provides a flexible time-frequency analysis tool that can capture both low-frequency and high-frequency content in a	● The choice of wavelet basis function can impact the accuracy of the results, and selecting the appropriate wavelet can be challenging. ● The method can be computationally intensive,

	signal. ● Can be used to identify localized features in signals, such as sharp edges and sudden changes in frequency content. ● The use of multi-resolution analysis enables efficient processing of signals with varying time-frequency characteristics	particularly for long-duration signals or high-resolution analyses. ● Interpretation of the results can be challenging, particularly when multiple scales and features are present, and the choice of thresholding and rebuilding methods can impact the accuracy of the results.

Analysis methods	Advantages	Disadvantages
Hilbert-Huang Transform	● Provides a time-frequency analysis tool that can capture both non-stationary and non-linear features in signals. ● The Empirical Mode Decomposition (EMD) method used in HHT allows for data-driven decomposition of signals without the need for prior assumptions about the signal characteristics.	● The EMD method used in HHT can be sensitive to noise and can produce mode mixing, leading to inaccurate decomposition of signals. ● The computation of HHT can be time-consuming, particularly for long-duration signals or high-resolution analyses. ● The interpretation of the results can be challenging, particularly when multiple modes and features are present, and the choice of thresholding and reconstruction methods can impact the accuracy of the results
Energy operator analysis	● It is a non-parametric method, which means it does not require any prior knowledge about the underlying statistical distribution of the data. ● It is effective in detecting and	● It can be computationally intensive, particularly for large datasets, which can limit its practical use in real-time applications. ● It is sensitive to noise and other forms of interference, which can affect the accuracy of

	localizing transient events in time-varying signals, such as bearing faults. ● It can provide high-resolution time-frequency representations, allowing for better visualization and interpretation of the signal	the results. ● It may require some level of expertise to properly interpret and analyze the results.
Minimum entropy deconvolution	● Provides a clear identification of the different frequency components in a signal, making it easier to isolate and analyze individual components. ● Can be used to detect faults and defects in rotating machinery, such as bearings and gears, at an early stage. ● Offers a high level of sensitivity, enabling the detection of very small changes in a signal.	● The technique requires a high level of expertise and may require specialized equipment for accurate results. ● The method can be computationally intensive, which can increase the time required for analysis and may require high-performance computing resources. ● The approach assumes that the frequency content of the signal is stationary, which may not be the case in certain situations

Conclusion:

In this chapter, various types and methods of analysis were examined. The mechanisms and procedures for each method were discussed, as well as the fields in which they are applied and their respective advantages and disadvantages. It was found that some methods excel in speed and accuracy across multiple fields while others are specialized for specific applications. The focus of our continued study will be on the wavelet method. This modern technique is distinguished by its speed and precision in all fields where it is employed.

Chapter III:

Description of a measuring rig

III.1 Introduction

In this chapter, we are going to represent the test rig using the bearing data center (**Western Reserve University Bearing Data Center**) and we will provide the signal of bearing in healthy case and in defected case

III.2Signals of bearings

The vibration signals that we propose to study were provided by the Case Western Reserve University- Bearing Data Center; a database of normal and faulty inner race, ball and outer race of bearing tests collected on a very simple test rig, consisting of a induction motor, a coupling, and a generator. Simple defects in the form of points "of different diameters and speed" were created on the various components of the test bearings.

III.3 Overview of Western Reserve University Bearing Data Center Website:

This website provides access to ball-bearing test data for normal and faulty bearings. Experiments were conducted using a 2 hp Reliance Electric motor, and acceleration data was measured at locations near and remote from the motor bearings. These web pages are unique in that the actual test conditions of the motor as well as the bearing fault status have been carefully documented for each experiment.

Motor bearings were seeded with faults using electro-discharge machining (EDM). Faults ranging from 0.007 inches in diameter to 0.040 inches in diameter were introduced separately at the inner raceway, rolling element (i.e. ball), and outer raceway. Faulted bearings were reinstalled into the test motor and vibration data was recorded for motor loads of 0 to 3 horsepower (motor speeds of 1797 to 1720 RPM).

III.3.1 Project History:

Experiments are often required to validate new technologies, theories, and techniques. These motor bearing experiments were initiated to characterize the performance of IQ PreAlert, a motor bearing condition assessment system developed at Rockwell. From the time of this original impetus, the experimental program has expanded to provide a motor performance database that can be used to validate and/or improve a host of motor condition assessment techniques. Some projects which have recently or are currently making use of this database include Winsnode condition assessment technology, model-based diagnostic techniques, and motor speed determination algorithms.

III.4 Presentation of test rig:

The next website: " https://engineering.case.edu/bearingdatacenter/apparatus-and-procedures” provides access to the database of ball-bearing tests, both healthy case and faulty case. As shown in Figure (**III.1**), the test rig consists mainly of induction motor (left) a transducer/encoder coupling (center), a dynamometer (right), and control circuits (not shown) [38][39]

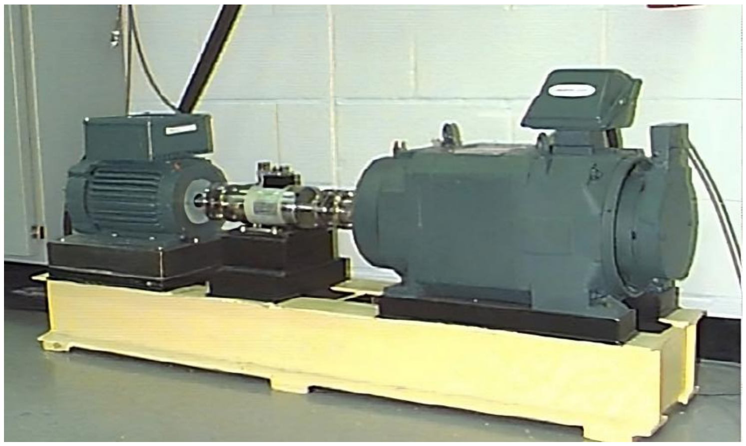


Fig III. 1 Bearing test rig

The tested bearings support the motor shaft on both sides (drive side and fan side).

The figure (**III.2**.) represents a cross-section of a motor

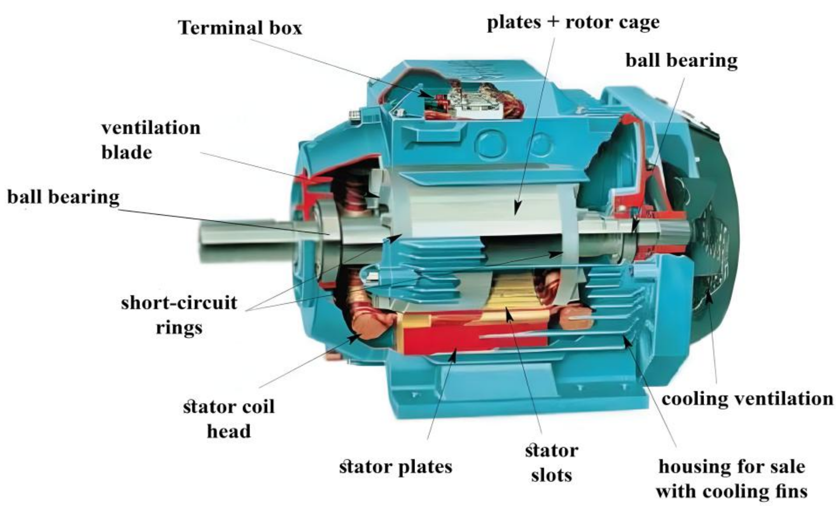


Fig III. 2 Section of an engine

The signals were recorded using accelerometers, which were attached to the motor cage by the motor cage. For different resistive torques (thus different rotational speeds).

The torques are respectively 0, 1, 2, and 3 Hp whose respective speeds are 1797, 1772, 1750, and 1730 rpm.

The sensors were placed at the $f_e = 12KHz$ o'clock position "vertical", on both sides coupling and fan of the motor cage.

The sampling frequency is 12 and the total number of points is N_p =243938 pts

Data were recorded for:

- Bearings without defects.
- Single faults on the coupling side (12,000 and 48,000 counts/second).
- Single faults on the fan side (12,000 counts/second)

The speed [rpm] and power [Hp] for each test were recorded manually using the transducer/encoder pair

III.5 Bearing Information:

Drive end bearing: 6205-2RS JEM SKF, deep groove ball bearing

Size: (inches)

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

Defect frequencies: (multiple of running speed **in Hz**)

Inner Ring	Outer Ring	Cage Train	Rolling Element
5.4152	3.5848	0.39828	4.7135

Fan end bearing: 6203-2RS JEM SKF, deep groove ball bearing

Size: (inches)

Inside Diameter	Outside Diameter	Thickness	Ball Diameter	Pitch Diameter
0.6693	1.5748	0.4724	0.2656	1.122

Defect frequencies: (multiple of running speed **in Hz**)

Inner Ring	Outer Ring	Cage Train	Rolling Element
4.9469	3.0530	0.3817	3.9874

Fault Specifications

Bearing	Fault Location	Diameter	Depth	Bearing Manufacturer
Drive End	Inner Race	.007	.011	SKF
Drive End	Inner Race	.014	.011	SKF
Drive End	Inner Race	.021	.011	SKF
Drive End	Inner Race	.028	.050	NTN
Drive End	Outer Race	.007	.011	SKF
Drive End	Outer Race	.014	.011	SKF
Drive End	Outer Race	.021	.011	SKF
Drive End	Outer Race	.040	.050	NTN
Drive End	Ball	.007	.011	SKF
Drive End	Ball	.014	.011	SKF
Drive End	Ball	.021	.011	SKF
Drive End	Ball	.028	.150	NTN

Fan End	Inner Race	.007	.011	SKF
Fan End	Inner Race	.014	.011	SKF
Fan End	Inner Race	.021	.011	SKF
Fan End	Outer Race	.007	.011	SKF
Fan End	Outer Race	.014	.011	SKF
Fan End	Outer Race	.021	.011	SKF
Fan End	Ball	.007	.011	SKF
Fan End	Ball	.014	.011	SKF
Fan End	Ball	.021	.011	SKF

We start with the Normal Baseline data

Motor Load (HP)	Approx. Motor Speed (rpm)	Normal Baseline Data
0	1797	Normal_0
1	1772	Normal_1
2	1750	Normal_2
3	1730	Normal_3

In this work, the signal analyzed is normal

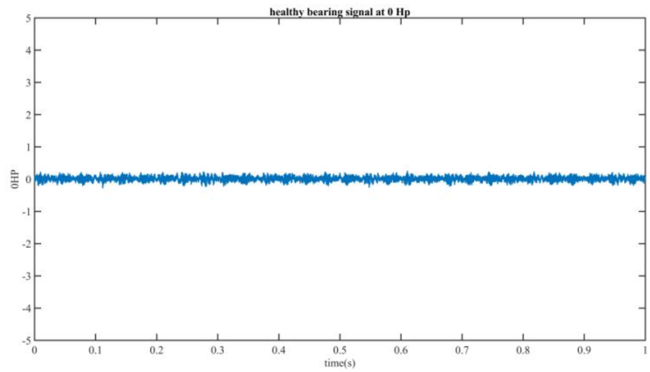


Fig III. 4 healthy signal with motor load of 0HP

The table below represent the 12K Drive End Bearing Fault Data

Fault Diameter	Motor Load (HP)	Approx. Motor Speed (rpm)	Inner Race	Ball	Outer Race Position Relative to Load Zone (Load Zone Centered at 6:00)		
					Centered @6:00	Orthogonal @3:00	Opposite @12:00
0.007"	0	1797	IR007_0	B007_0	OR007@6_0	OR007@3_0	OR007@12_0
	1	1772	IR007_1	B007_1	OR007@6_1	OR007@3_1	OR007@12_1
	2	1750	IR007_2	B007_2	OR007@6_2	OR007@3_2	OR007@12_2
	3	1730	IR007_3	B007_3	OR007@6_3	OR007@3_3	OR007@12_3
0.014"	0	1797	IR014_0	B014_0	OR014@6_0	*	*
	1	1772	IR014_1	B014_1	OR014@6_1	*	*

	2	1750	IR014_2	B014_2	OR014@6_2	*	*
	3	1730	IR014_3	B014_3	OR014@6_3	*	*
0.021"	0	1797	IR021_0	B021_0	OR021@6_0	OR021@3_0	OR021@12_0
	1	1772	IR021_1	B021_1	OR021@6_1	OR021@3_1	OR021@12_1
	2	1750	IR021_2	B021_2	OR021@6_2	OR021@3_2	OR021@12_2
	3	1730	IR021_3	B021_3	OR021@6_3	OR021@3_3	OR021@12_3

In our case we just choose the bearing with Diameter of 0.007 inches with motor load of 0 Hp .and we get the signals as it shown below :

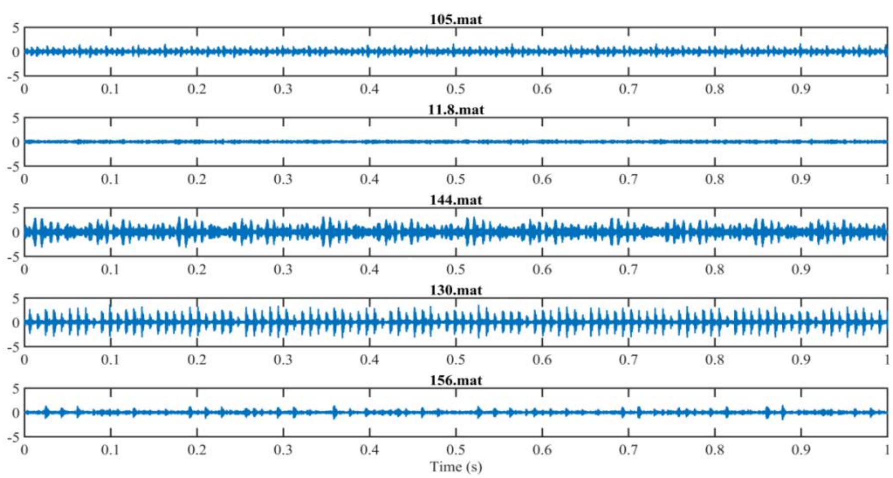


Fig III. 5 The test signals on the bearing for the inner ring, ball and outer ring with motor load of 0HP

Conclusion :

In conclusion, we have conducted experiments on a measuring bench to diagnose and monitor the motor with bearing faults. The signals were obtained from the Western Reserve University Bearing

Data Center website. We have presented the details of the test rig used in our study. Additionally, we have plotted the healthy signal (normal at 0 HP) and the defect signal at 0.007 with 0 HP to visualize the differences between them.

In the next and final chapter, we will use the wavelet method to analyze and detect the faults in the motor bearings. This technique is expected to provide a reliable and efficient way to diagnose and monitor the health of motors and prevent costly damages. Overall, the findings of this study contribute to the development of effective fault diagnosis and monitoring techniques for industrial applications.

Chapter IV : Simulation and results

Introduction

In this chapter, we will apply the discrete wavelet transform(DWT) to real signals understanding the capabilities of this technique.

Real-world signals were transformed(DWT) to see the ability of this technique to detect bearing faults at an early stage.

The aim is to conduct research in the test rig gain insights into how the machine behaves during operation and also find out new ways of monitoring and diagnostics .

IV.1 Definition of a wavelet

The wavelet method, also called the Wavelet method, is a mathematical method for analyzing signals and data in the time and frequency domains. It is based on the decomposition of a signal into a collection of wavelet functions, each of which captures various frequency components of the signal at various scales.

The wavelet method can be applied to bearings analyzes vibration signals and find bearing system flaws. The method can detect distinctive patterns linked to various types of bearing faults, such as flaws in the inner or outer race and bale , or lubrication issues, by breaking down the vibration signal into its component wavelet functions.

The wavelet method does, however, also have some drawbacks. The accuracy of fault detection can be affected by the choice of wavelet function and decomposition level, which is one of its limitations. The method also requires a certain level of signal processing knowledge, so it might not be appropriate for beginners.

IV.2 Wavelet Transform

IV.2.1 History of wavelets:

The development of wavelets emerged in response to the need for a more comprehensive analysis of signals in both the frequency and time domains. During the 19th century, Fourier analysis was the primary technique utilized for decomposing a signal, as well as its reconstruction, without any loss of information. However, Fourier analysis was limited in its ability to precisely localize abrupt changes in signals, such as the occurrence of a second shock following a first shock.

It was in 1909 that Alfréd Haar defined the first wavelet, which was comprised of a short negative pulse followed by a short positive pulse. Following this, in 1946, Dennis Gabor, a mathematician from Hungary, developed a function transformation similar to that of Joseph Fourier. This transformation was applied to a time window that was expressed by a Gaussian function.

The term wavelet was formally introduced into the mathematical lexicon by Jean Morlet and Alex Grossmann in 1984. Initially, it was a French term that was later translated into English as "wavelet", combining the words "wave" and "let".

In 1986, Yves Meyer, who is recognized as one of the pioneers of wavelet theory, consolidated all the previous discoveries, totaling 16, and defined the orthogonal wavelets. That same year, Stéphane Mallat established the connection between wavelets and multiresolution analysis. Finally, in 1987, Ingrid Daubechies developed orthogonal wavelets known as Daubechies wavelets, which were easy to implement and subsequently used in the JPEG 2000 standard.

IV.2.2 Definition of a wavelet

A wavelet is an elementary function, with real or complex values, very concentrated both in time and in frequency .[40]

It must meet two criteria: [41]

1- It must have a compact support, i.e. it must be localized on a small time interval.

2- It must have zero mean.

$$\int_{-\infty}^{+\infty} \psi(\mathrm{t})\mathrm{dt} = 0 \qquad \textbf{(IV.1)}$$

This is the admissibility condition because it is this condition that gave the name wavelet.

The wavelet transform of a signal s(t) is defined by the formula :

$$\mathrm{C}_{\mathrm{a,b}} = \int_{-\infty}^{+\infty} S(t).\psi_{a,b}(t)dt \qquad \textbf{(IV.2)}$$

The wavelet transform of a signal s(t) is the family $c_{a,b}$ of wavelet coefficients wavelet coefficients which depend on the two parameters a and b. According to the needs of the analysis of the signal s(t), the parameters (a,b) can be used in a continuous (CWT) or discrete (DWT) way. The wavelet coefficient $c_{a,b}$ of a signal s(t) depends on its shape in the vicinity of time b. near the time b.

When s(t) is approximately constant (1) figure (IV.1) around a time b (figure (IV.1)), the product of s(t) and the psi wavelet (of zero area) has a very small area, in other words in other words $c_{a,b}$ is very small. When on the contrary, the fragment of the signal around a time b' is irregular (2) and that its variations are of "frequency" comparable to that of the wavelet, the area of the signal-wavelet product (thus $c_{a,b}$) is generally much larger

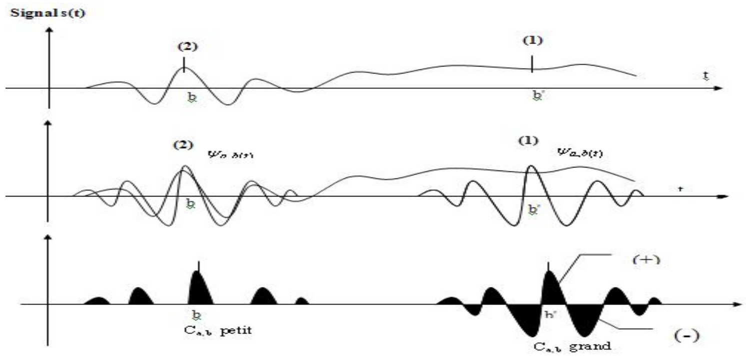


Fig IV. 1 : Projection of the wavelet onto the signal

IV.2.3 The wavelet family :

There are several mother wavelets used for the calculation of the wavelet transform of the analyzed signals. Each of them has a defined area of application of the studied signal shape. Table (IV.1) contains the most common families

Name of wavelet families	Short name in Matlab
Haar's wavelet	Haar
Daubechies wavelet	db
Symlets	sym
Coiflets	coif
Biorthogonal wavelets	bior
Meyer's wavelet	meyr
Discrete approximation of the Meyer wavelet	dmey
Battle and Lemarie wavelets	btlm
Gaussian wavelets	gaus
Mexican hat	mexh
Morlet's wavelet	morl
Complex Gaussian wavelets	cgau
Complex Shannon wavelets	shan
Complex frequency B-spline wavelets	fbsp
Complex Morlet waves	cmor

Table IV.1. Wavelet families

IV.2.3.1 Haar wavelet :

It was Alfred Harr who in 1909 constructed the foundations that are now considered to be the basis of wavelet theory. the foundation of wavelet theory. Haar defined a function h(t) which corresponds to the Haar wavelet.

$$h(t) = \begin{cases} 1 \; pour \; 0 \; \leq t \leq \frac{1}{2} \\ -1 \; pour \; 0 \; \leq t \leq \frac{1}{2} \\ 0 \; eleswehere \end{cases} \qquad \text{(IV.3)}$$

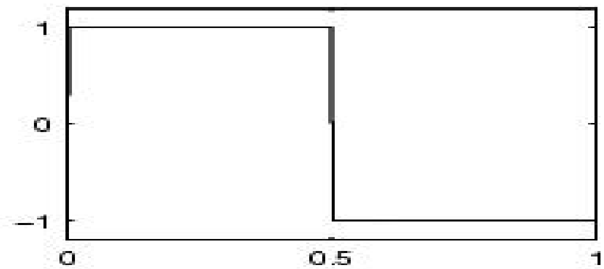


Fig IV. 2 Shape of the Haar wavelet

IV.2.3.2 Daubechies wavelets:

This family of wavelets has one parameter allowing to handle orthogonal wavelets with compact support of arbitrary regularity. For N, it is the order of the wavelet dbN.

For N=1, we have the db1 wavelet, it is only the Haar wavelet. The figure (IV.3)

shows the shapes of the Daubechies wavelets for different orders.

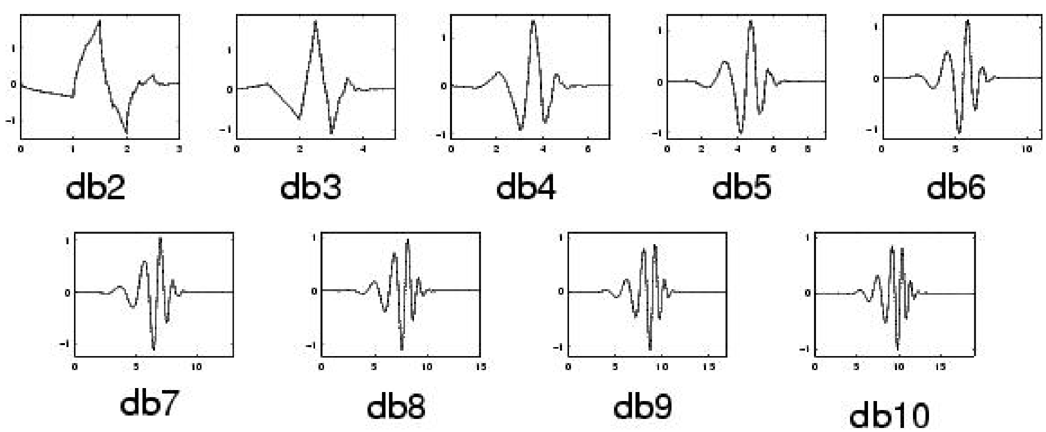


Fig IV. 3: Daubechies wavelet shapes

This family of wavelets has the following properties:

- The dbN wavelets are asymmetric, especially for small values of N, except the Haar wavelet.

- The regularity increases with the order N
- The analysis is orthogonal.

IV.2.3.3 Daubechies symlets:

Daubechies has constructed the most symmetrically supported wavelets possible called Symlets; indeed, there are no symmetrically supported wavelets in an orthogonal multiresolution analysis, except the Haar wavelet which is antisymmetric.

The symlets have the same number m of zero moments as the Daubechies wavelets for a given support: again we have d = 2m , and the number of non-zero elements of the filter is 2m. We will name them D6s, D8s, etc., always in reference to the support of the basic functions

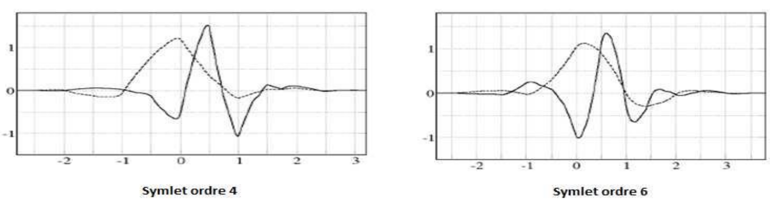


Fig IV. 4 Symlet wavelet shapes

IV.2.3.4 Morlet wavelet :

This function only approximately checks the admissibility condition, it is defined by **:**

$$\psi(\mathrm{t}) = \boldsymbol{C}\boldsymbol{e}^{-\frac{\boldsymbol{X}^2}{2}}\,\mathbf{cos}\,(\mathbf{5}\boldsymbol{X}) \qquad \textbf{IV.4}$$

Where "C" is a reconstruction normalisation constant. Figure (IV.4) shows the

shape of this wavelet.

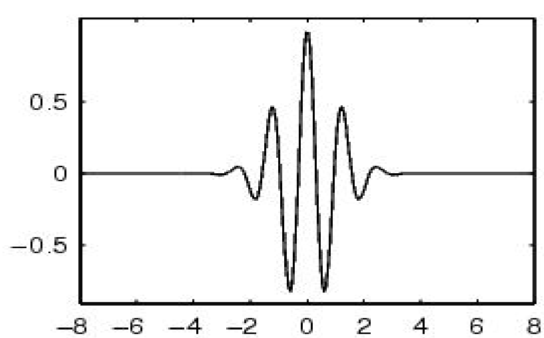


Fig IV. 5 Morlet wavelet

IV.2.3.5 Mexican hat wavelet:

It is a function that is proportional to the second derivative of the Gaussian probability density function probability density function:

$$\psi(\mathrm{t}) = (\frac{2}{\sqrt{3}}\pi^{-1/4})(1 - X^2)e^{-X^2/2} \qquad \text{IV.5}$$

It oscillates very little as Figure (II.4) shows.

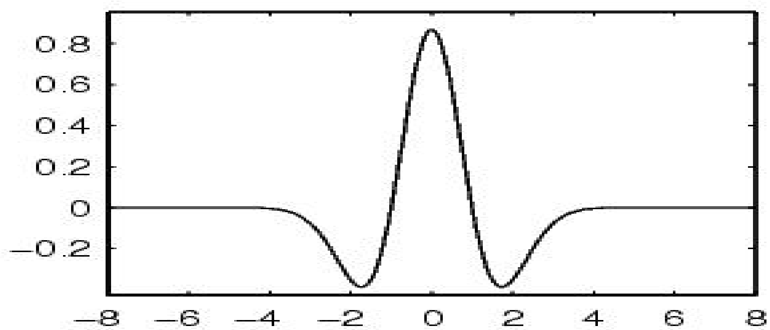


Fig IV. 6 Mexican hat wavelet

IV.2.3.6 Meyer wavelets:

The Meyer wavelet is one of the first wavelets. It was constructed by Y. Meyer in the mid-1980s. It is an orthogonal wavelet which does not have a support .The shape of this wavelet is given in figure (IV.6):

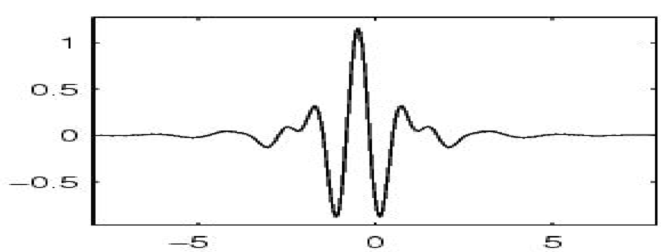


Fig IV. 7 Meyer wavelets

The function ψ is defined in the frequency domain, where :

$$\psi(\omega) = \begin{cases} (2\pi)^{1/2} e^{1\omega/2} \sin\left(\frac{\pi}{2} v\left(\frac{3}{2\pi}|\omega| - 1\right)\right) si\ \frac{2\pi}{3} \leq |\omega| \leq \frac{4\pi}{3} \\ (2\pi)^{1/2} e^{1\omega/2} \cos\left(\frac{\pi}{2} v\left(\frac{3}{2\pi}|\omega| - 1\right)\right) si\ \frac{4\pi}{3} \leq |\omega| \leq \frac{8\pi}{3} \\ 0 \qquad si\ |\omega| \notin \left[\frac{2\pi}{3}, \frac{8\pi}{3}\right] \end{cases} \qquad \text{(IV.6)}$$

Remarks

- Morlet wavelets do not allow the construction of an orthogonal basis.
- Daubechies wavelets are the most commonly used.
- Daubechies wavelets form an infinite family and are noted db1, db2, db3,... in the Matlab toolbox. A Daubechies wavelet dbk uses 2k coefficients and is therefore computed from 2k points

IV.2.4 Wavelets and time-scale resolution:

If one simply wishes to analyse a non-stationary signal, one can produce its time-scale representation time-scale representation using very long, small-step scaling factor vectors 'a' and offset vectors 'b'. "b" vectors that are very long and vary with a small step size. The resulting representation then contains a lot of redundant information. Apart from the problem of computation time, this redundancy often facilitates interpretation.

The higher the dilation factor "a", the more the wavelet is extended along the time axis, and the more concentrated it is. axis, and the more concentrated it is along the frequency axis. As a result, the accuracy in time and frequency Therefore, the accuracy in time and frequency is variable depending on the scaling factor.

Scale factor	frequency	Accuracy in time	Frequency accuracy
Low	High	Elevated	low
High	Low	Weak	Elevated

Table IV.2 time-scale resolution of wavelet

The tiling of the time scale plane is therefore not regular like that of the time frequency plane. time-frequency plane. In analysis with short term Fourier transform " STFT", the size of the window is always the same figure(IV.8), it does not depend on the frequency. always the same figure (IV.8), it does not depend on the frequency. In other words, the In other words, the accuracy in time and frequency is the same for high and low frequencies.

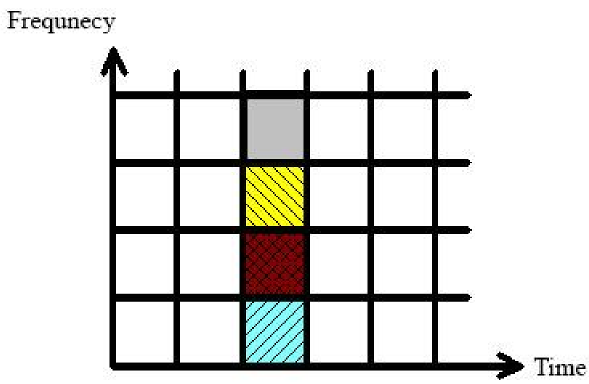


Fig IV. 8 Time-frequency resolution of the STFT

The advantage of varying these widths becomes obvious: the number of translations in time and number of translations in time and frequency of the window by optimising its width. window. Thus, in the low frequencies, a large width in frequency is not necessary.

Thus, at low frequencies, a large width in frequency is not necessary, so rectangles wider in time can be used. At high frequencies, we will use rectangles that are wider in frequency and more localized in time.

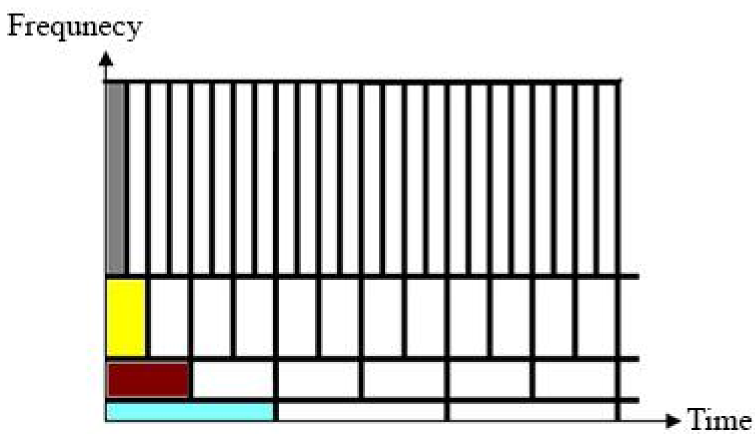


Fig IV. 9 Time-frequency resolution of WT

Each box corresponds to a WT value in the frequency time plane.

At low frequencies, the bin sizes are shorter (which corresponds to better frequency resolutions, since there is less ambiguity about better frequency resolutions, since there is less ambiguity about the exact frequency value), but their widths are the exact value of the frequency), but their widths are larger (which corresponds to low time

resolution, since there is more ambiguity about the exact value of the time), but their widths are larger (which corresponds to lower time resolution, since there is more ambiguity about the exact value of the time)

At higher frequencies the width of the bins decreases, the time resolution is better, and the bin sizes increase, the frequency resolution becomes lower. The time resolution is thus more important for high frequencies than for low frequencies. Conversely, the frequency resolution is more important for low frequencies important for low frequencies than for high frequencies.

The wavelets can therefore overcome the disadvantage of the STFT by adapting the accuracy according to the frequency. A simultaneous resolution is obtained by the wavelet transform in which the analysis window can have different durations.

IV.2.5 The wavelet transform:

The idea of the wavelet is to be able to vary the time and frequency widths of a function of a function while translating it along the signal as in the windowed Fourier transform.

From the mother wavelet$\boldsymbol{\psi(t)}$, we construct by translation and dilation a family of functions $\boldsymbol{\psi}$a,b(t) which are its basic atoms. These functions of $\boldsymbol{\psi}$a,b(t) are given by relation (IV.7) :[42] [43]

$$\boldsymbol{\psi_{(a,b)}} = \frac{\mathbf{1}}{\sqrt{\boldsymbol{a}}}\boldsymbol{\psi}\left(\frac{\boldsymbol{t-b}}{\boldsymbol{a}}\right) \quad \textbf{(IV.7)}$$

The parameter (b) of the wavelet represents its translation on the time axis, while the parameter (a) gives control over the frequency of the wavelet, knowing that a 1/f. where "f" is

the frequency.

If a<1, the wavelet 5a,b(t) becomes very concentrated compared to the parent wavelet 5(t) and its frequency content will lean towards the high frequencies of the analysis plane.

If a>1, the 5a,b(t) wavelet is very large, and the frequency content will lean towards the low frequencies of the analysis plane.

There are several types of the wavelet transform; the main ones are listed in the following

follows:

IV.2.5.1 The continuous wavelet transform (CWT):

It is similar to the Short Term Fourier Transform (STFT), only the sliding window used for the analysis is variable with time. window used for the analysis is variable with time.

Fig IV. 10 Wavelet scan on signal to calculate "CWT"

Fig IV. 10 Wavelet scan on signal to calculate "CWT"

The continuous wavelet transform is a function of two parameters "a" for the scale parameters, and "b" for the translation parameters.

for the scale parameters, and "b" for the translation parameters.

The continuous wavelet transform of a function x(t) HL2

(R) is defined in the time domain by the following scalar product X: [44]

$$X_{TO(a,b)} = < x, \psi_{a,b} > \quad \textbf{(IV.8)}$$

So :

$$X_{TO(a,b)} = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\, \psi * \left(\frac{t-b}{a}\right) dt \quad \textbf{(IV.9)}$$

By performing the change of variable $t_1 = \frac{t}{a}$ **we will have**

b: is the temporal location parameter.

a: is the frequency localisation parameter.

$\sqrt{a}$: ensures the same energy for the expanded wavelet.

IV.2.5.2 The discrete wavelet transform (DWT)

The discrete wavelet transform is derived from the continuous version.

The discrete wavelet transform is derived from the continuous version, but unlike the continuous version, the DWT uses a discretised scaling factor and translation.

In this case the parameters a and b become: [44]

$$a = a_0^m \quad \text{et} \quad b = n\, b_0\, a_0^m \quad n,m \in$$

With

a0: is an expansion parameter.

b0: is a translation parameter.

A discrete wavelet transform is any wavelet basis working with a scale factor a=2n . This type of transform is practical in implementation on any digital system.

digital system.

II.2.6 Multi-resolution:

This technique consists in decomposing the signal with the wavelet transform by

passing through two filters. One is a low pass to get the approximations that represent the general the general shape of the signal, and the other is a high-pass filter to get its details. The diagram in figure (IV.11) shows the operation.

The approximation coefficients $A_{j,k}$ of equation (IV.11) to the solution 2^{j-1} obtained from the approximation coefficients at the resolution 2^j by filtering using an impulse response filter h[n] followed by adS, Tsare obtained from the approximation coefficients of thecimator coefficients of order 2, $A_{j,k}$ from of equation (IV.12), by filtering using an impulse response filter g[n] followed by a decimator of order(2) figure (IV.11).

$$\boldsymbol{A_{j,k}} = \sum_{\boldsymbol{n}=-\infty}^{+\infty} \boldsymbol{h(n)}\, \boldsymbol{A_{j-1,2k+n}} \qquad \textbf{(IV.11)}$$

$$\boldsymbol{D_{j,k}} = \sqrt{2} \sum_{\boldsymbol{n}=-\infty}^{+\infty} \boldsymbol{g(n)}\, \boldsymbol{A_{j-1,2k+n}} \qquad \textbf{(IV.12)}$$

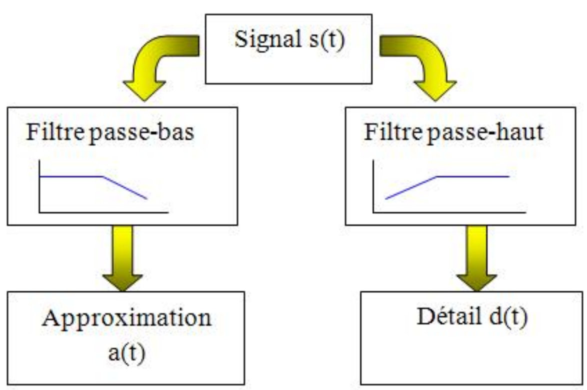


Fig IV. 11 Multi-resolution wavelet transform

The general shape of the signal during decomposition is shown in Figure (II.12)

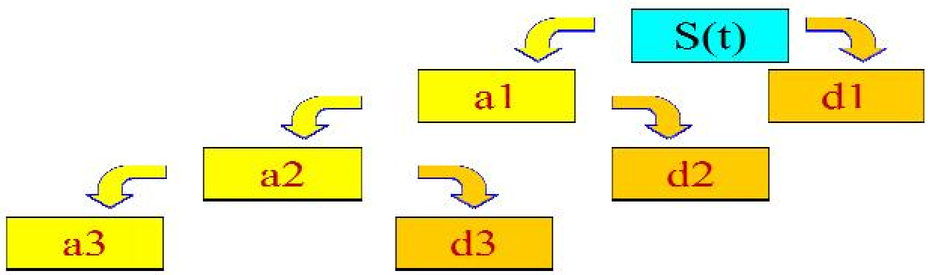


Fig IV. 12 Signal decomposition into approximations and details

Thus the decomposed signal is written as (IV.12):

$$S(t) = d1 + d2 + d3 + a3 \qquad \textbf{(IV.12)}$$

Here the level presented is of value 3 as an example

IV.2.7 The wavelet packet transform:

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. In wavelet analysis, a signal is decomposed into approximations and details.

The approximation is then itself split into second level approximation and detail, and the process is repeated. For a decomposition of "n" levels, there are (n+1) ways possible ways to decompose or code the signal.

In wavelet packet analysis, details as well as approximations can be decomposed. This yields more than 2n+1 different decompositions of the signal. The wavelet packet decomposition tree is shown in Figure (IV.12)

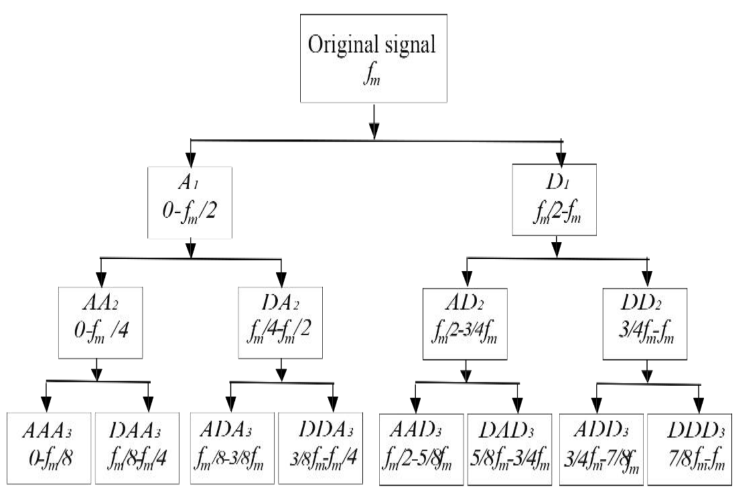


Fig IV. 13 Wavelet packet transform

IV.2.8 Choice of wavelet and number of calculation levels for the decomposition:

The choice of the wavelet (type and order) suitable for the analysis of signals such as those of gears and bearings is not an easy task to achieve the desired objective.

The choice of the wavelet (type and order) suitable for the analysis of signals such as gears and bearings is not an easy task to achieve the desired objective. In In order to address the

difficult choice of wavelet type and order, and to give more emphasis to the analysis of these

In order to address the delicate choice of wavelet type and order, and to further highlight the

analysis of these types of signals according to the importance of their superimposed blasts, we have applied a number of wavelets in the analysis of the signals studied in Chapter 4.

The appropriate number of levels of the decomposition (nLS) depends on the sampling frequency (fs) of the signal. (fs) of the signal to be analysed.

For each of the wavelet decomposition-based diagnostic approaches, the For each of the wavelet decomposition-based diagnostic approaches, the number of levels must be chosen wisely to allow high-level signals (approximation and detail) to cover the (approximation and detail) to cover the full range of frequencies along which the the fault component changes during all operating regimes.

IV.3 Application the wavelet method

The theoretical fault frequencies used the two equations (I.5) and (I.6) for the example of the motor with no-load under fault diameter of 0.1778 mm are summarized in Table IV.3.

Rotation frequency	Outer race frequency	Rolling element frequency	Inner race frequency
29.5 Hz	107.12 Hz	139.86 Hz	162.42 HZ

Table IV.3 Calculated theoretical frequencies

Fig. IV.13, shows the details in the healthy case and the case of internal ring defect.

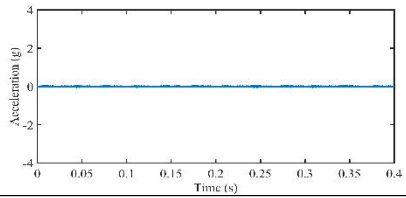
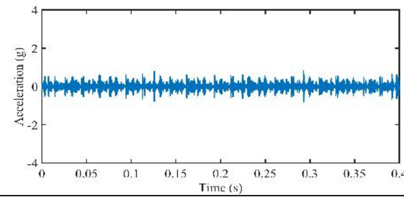
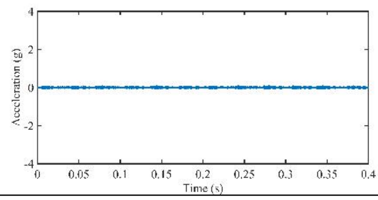
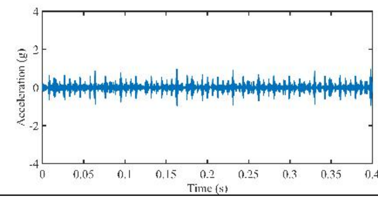
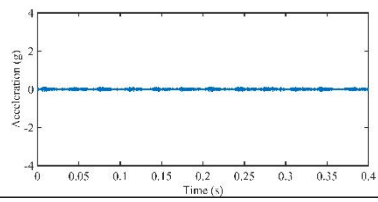
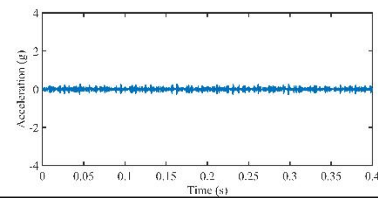
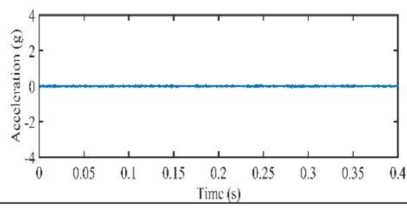
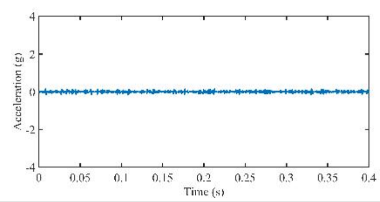
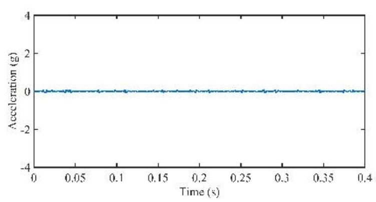
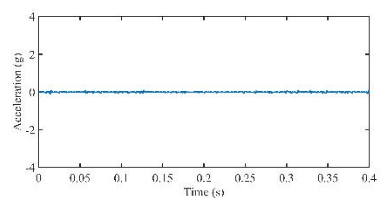
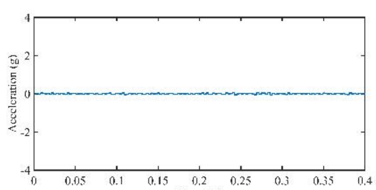
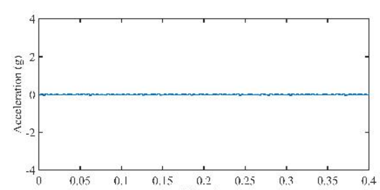
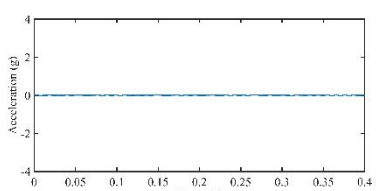
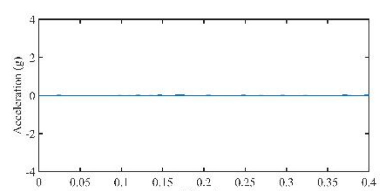
Healthy case	inner race defect case
	
	
	
	
	
	
	

Fig IV. 14 Details of inner ring defects

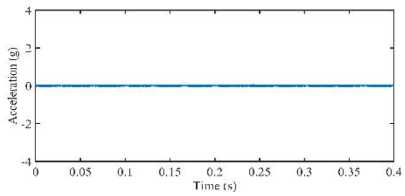
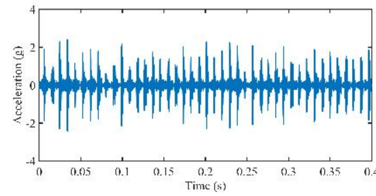
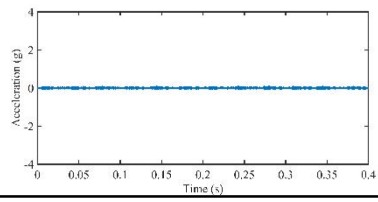
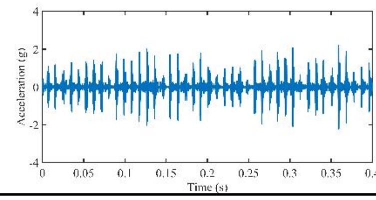
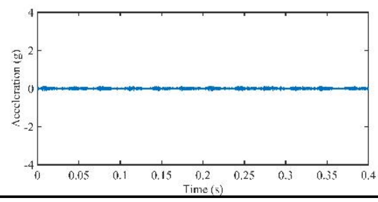
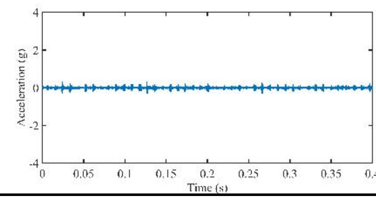
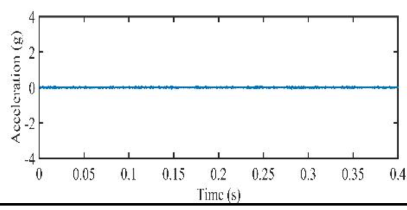
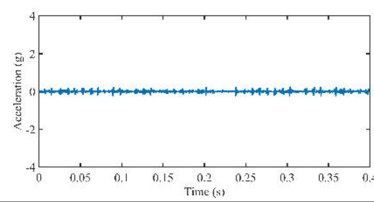
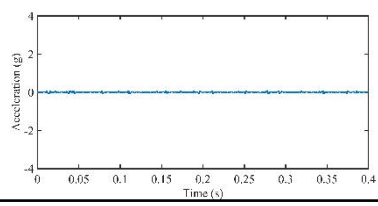
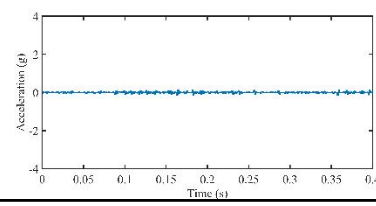
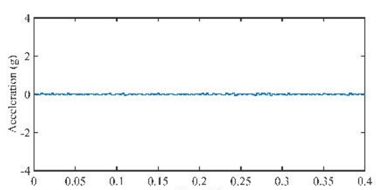
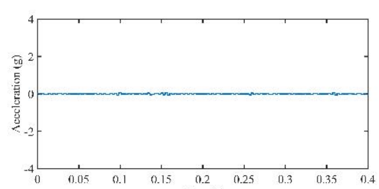
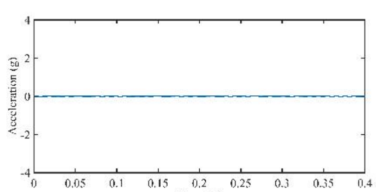
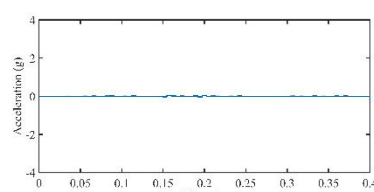
Healthy case	outer race fault case
	
	
	
	
	
	
	

Fig IV. 15 Details of inner ring defects

Kurtosis	D1	D2	D3	D4	D5	D6	D7
Healthy case	2.5777	2.5803	2.5761	2.8195	3.0778	3.0247	3.4556
Inner race	5.9830	5.0605	3.6383	2.7437	3.5541	2.9135	3.2930
Outer race	7.5929	7.7574	5.6043	5.1073	5.1039	3.8080	3.4255

The vibratory signatures and the spectral envelop analysis for the following case : healthy bearing , bearing with an outer race fault , bearing with a rolling element fault and for an inner race fault for example of a motor with no-load under fault diameter of 01778mm.

The ENV in fig IV.16 ,shows clearly the frequency of rotation fr = 30Hz and its harmonic 2f . one can see that there are on frequencies of faults this confirms that the bearing is in healthy condition .

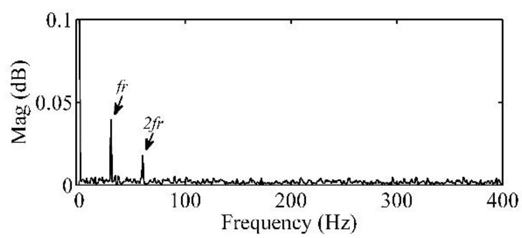


Fig IV. 16 Healthy bearing frequency

The envelope spectrum of vibratory signal of the bearing under outer race fault is shown in fig IV.17 .for the speed of 1797RPM ,the ENV shows the following frequency peak

F_{or}=108 HZ f_{or}-f_r=78 Hz f_{or}+f_r=138 Hz , 2f_{or}=216 Hz ,2f_{or}-f_r=185 Hz , 3f_{pr}=324 Hz and

3f_{or}-f_r=293 Hz , These frequencies are very close to those calculated theoretically for the fault of the outer race. Thus, a defect is definitely present in the outer race.

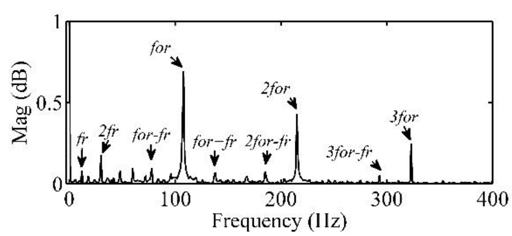


Fig IV. 17 Outer race frequency fault

Likewise ,Fig IV.18 represents the envelope spectrum of the vibratory signal when the bearing has an inner race fault. Also, for the speed of rotation of 1797 rpm, the following frequency peaks appear : f_{ir}=162Hz , f_{ir}-2 f_{ir}=102 Hz ,f_{ir}+2 f_r=222 Hz , 2 f_{ir}=324 Hz , and f_{ir}+2f_r=384 . These frequencies are very close to those calculated for the fault of the inner race. This clearly indicates the presence of a fault in the inner race.

Conclusion

In conclusion , this chapter examined the use of the discrete wavelet transform (DWT) on real-world data, showing the potential of this technique. We were able to evaluate the usefulness of DWT in detecting bearing problems early on by translating real-world information. The fundamental goal of our research was to get valuable insights into machine behavior during operation and to investigate novel techniques to monitoring and diagnostics. We have provided the groundwork for additional research and developments in the sector with this chapter, opening the way for improved maintenance procedures and improved industrial system performance.

General conclusion

The primary focus of this study revolves around the application of a highly effective bearing fault detection method in asynchronous machines. By harnessing the power of vibration signals, we have successfully developed an innovative approach that promises significant advancements in fault detection capabilities.

Our proposed method leverages the combined strength of Discrete Wavelet Transform (DWT) and Hilbert Transform (HT) to achieve remarkable accuracy in identifying bearing faults. Through meticulous analysis, we have determined that the computation of kurtosis at each level of DWT's decompositions plays a pivotal role in the identification process. By carefully maximizing the kurtosis, we are able to pinpoint the optimal decomposition level that holds the key to detecting and characterizing bearing faults with unparalleled precision.

In addition to the DWT, we have integrated the HT to extract valuable information from the vibration signals. By analyzing the spectral envelope using HT, we have successfully obtained highly satisfactory results that facilitate a more distinct and unambiguous identification of fault frequencies. This refined approach significantly enhances the fault detection capabilities, enabling engineers and technicians to swiftly and accurately identify the underlying causes of machine malfunctions.

To ensure the reliability and validity of our proposed technique, we have diligently conducted both theoretical analyses and experimental investigations. The theoretical results have been meticulously validated against the empirical findings, establishing a solid foundation for our method's efficacy. The experimental results, in particular, have unequivocally affirmed the exceptional performance and robustness of our proposed technique. These outcomes provide resounding evidence of the viability and applicability of our method for the detection of rolling defects in industries, thereby elevating the monitoring and diagnostics practices to unprecedented levels of accuracy and efficiency.

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