Université Mohamed Khider de Biskra
Faculté des Sciences et de la Technologie
Département de génie électrique

MÉMOIRE DE MASTER

Sciences et Technologies
Electrotechnique
Machine Electrique

Réf. : ……………………

Présenté et soutenu par :
AMROUS Mohamed Wafik

Le : lundi 8 juillet 2019

Detection des défauts de roulement du moteur asynchrone par la transformée en ondelette

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Resume

Abstract—Fault diagnosis is useful for ensuring the safe running of machines. Vibration analysis is one of the most important techniques for fault diagnosis of rotating machinery; as the vibration signal carries the dynamic information of the system. Many signal analysis methods are able to extract useful information from vibration data. In the present work, we are interested to the vibration signal analysis by the wavelet transform. The monitoring results indicate that the wavelet transform can diagnose the abnormal change in the measured data.

Keywords—fault diagnosis; vibration analysis; rolling element bearing; monitoring; wavelet transform; Fourier transform

الملخص

معالجة الاخطاء مهمة جدا للحفاظ على الالات في حالة عمل جيدة,التحليل الاهتزازي تقنية مهمة وفعالة في دراسة حالة الالات الكهرباءبة لان الاهتزازات تحمل في طياتها الكثير من المعلومات.

هناك الكثير من التقنيات و الطرق القادرة على استخراج المعلومات من الاهتزازات ,في هدا العمل اهتممنا باحد تلك التقنيان وهي "الوافلات " .

بعد معاينة النتائج وجدنا ان "الوافلات" قادرة على استحراج الكثير من المعلومات من الاهتزازات .

الكلمات المفتاحية : معالجة الاخطاء ; تحليل الاهتزازات; الملف الدوار; تحويل الوافلات; تحويل فوري.

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Symbols List

EPRI:	Electric Power Research Institute
DSP:	Digital signal processing
ASP:	Analogue signal processing
Δt:	Variation in time
$\Delta \omega$:	Variation in frequency
RMS:	Root Mean Square
FT:	Fourier transforms
STFT:	Short time Fourier transform
WVD:	Wigner-Ville distribution
WA:	Wavelet Analysis
CWT:	Continuous Wavelet Transform
DWT:	Discreet Wavelet Transform
$h_{a,b}(t)$:	Basis function of WT
h(t):	Mother wavelet
b:	Translation parameter
a:	Scaling parameter
$\Phi_{m_0,n}(t)$	Scaling function
$\phi_{0,0}$	Father wavelet
α:	Contact angle
nb:	The number of rolling elements
Db:	The rolling element diameter
Dp:	The pitch diameter
BPFO:	Ball pass frequency, outer race
BPFI:	Ball pass frequency, inner race
FTF:	Fundamental train frequency
BSF:	Ball spin frequency
M:	The load life exponent

Summary

Chapter I:

Induction Motor and Condition Monitoring

Chapter II:

Signal Analysis: Methods and Techniques

Summary

Chapter III:

Rolling Element Bearings: Construction and Faults

Chapter IV:

Faults Detection of Rolling Element Bearing Using Wavelets

General Introduction

Condition monitoring of machines is very important in maintenance of factories. By monitoring the condition of machines, maintenances can be planned better and unnecessary loss of production and break down’s can be avoided.

There are four kinds of maintenance strategies. predictive maintenance is one of them, where the condition of the machinery is monitored in real time or in specific time intervals. This way faults can be noticed at an early stage, which makes it possible to plan the plant run downs better and remove the need for big spare part amounts in storage. Hence predictive maintenance is an important part of manufacturing processes today.

The predictive maintenance philosophy of using vibration information to lower operating costs and increase machinery availability is gaining acceptance throughout industry. Since most of the machinery in a predictive maintenance program contains rolling element bearings, it is imperative to establish a suitable condition monitoring procedure to prevent malfunction and breakage during operation.

The vibration signal analysis is essential in improving condition monitoring and fault diagnosis of rotating machinery, because it always carries the dynamic information of the system. Effective utilization of the vibration signals depends upon the effectiveness of the applied signal processing techniques. A wide variety of techniques have been introduced such as: time domain and frequency domain. Unfortunately, they are not suitable for non-stationary signal analysis. In order to solve this problem, Wavelet Transform (WT) has been developed. The WT, also called time-frequency analysis, is a kind of variable window technology, which uses a time interval to analyze the frequency components of the signal.

The wavelet transform resolves all the deficiencies such as bearing faults, gear faults and provides good frequency resolution and low time resolution for low frequency components as well as low frequency resolution and good time resolution for high-frequency components. Therefore, the wavelet transform has been widely applied in the field of vibration signal analysis and feature extraction for bearing.

Chapter I:

Induction Motor and Condition Monitoring

I.1. Introduction

Electric motors can be found in almost every production process today. The popularity of induction motors is because of their simple, robust, rugged construction, low cost, good operating characteristics, absence of commutator and good speed regulation.

In this first chapter we will see:

- The parts that makes an induction motor.
- A look at the different faults that may happen to a squirrel cage induction motor.
- A look at the different faults detection and diagnosis methods for the induction motor.

I.2. Construction

Like any electric motor, an induction motor has two main parts a stator and a rotor.

- The stator: is the stationary part of the induction motor.
- The rotor: is the rotating part.

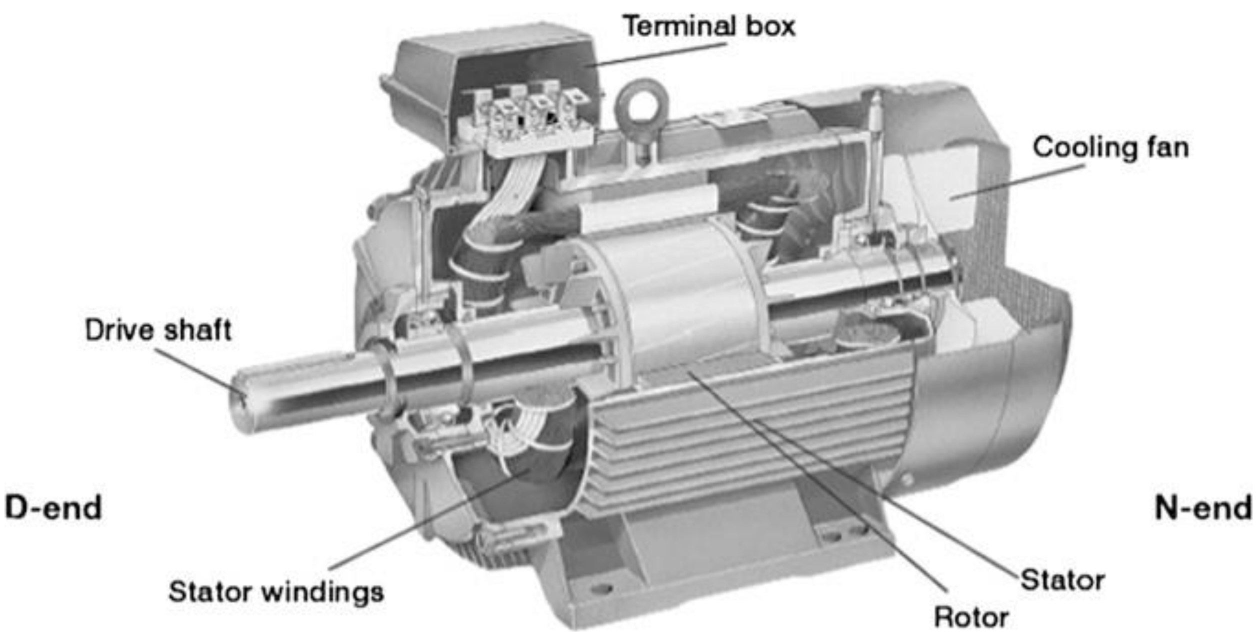

Figure I.1. AC Induction Motor(dissected) [1]

I.2.1. Stator

The stator, shown in Figure I.2 is the outer stationary part of the motor. It consists of:

i. **The outer cylindrical frame:** It is made either of cast iron or cast aluminum alloy or welded fabricated sheet steel [1].

ii. **The magnetic path:** It comprises a set of slotted high-grade alloy steel laminations supported into the outer cylindrical stator frame. The magnetic path is laminated to reduce eddy current losses and heating [1].

iii. **A set of insulated electrical windings:** For a 3-phase motor, the stator circuit has three sets of coils, one for each phase, which is separated by 120° and it's excited by a three-phase supply. These coils are placed inside the slots of the laminated magnetic path [1].

Figure I.2. Stator of three-phase induction motor [3].

I.2.2. Rotor

It is the rotating part of the motor. It is placed inside the stator bore and rotates coaxially with the stator. Like the stator, rotor is also made of a set of slotted thin sheets, called laminations, of electromagnetic substance (special core steel) pressed together in the form of a cylinder. Thin sheets are insulated from each other by means of paper and varnish [1].

Slots consist of the electrical circuit and the cylindrical electromagnetic substance acts as magnetic path. Rotor winding of an induction motor may be of two types: (a) squirrel-cage type and (b) wound type. Thus motors are classified into two groups [1]:

i. **Squirrel-cage type induction motor:** Here rotor comprises a set of bars made of either copper or aluminum or alloy as rotor conductors which are embedded in rotor slots. This gives a very rugged construction of the rotor. Rotor bars are connected on both ends to an end ring to make a close path. Figure I.3. shows a squirrel-cage type rotor.

ii. **Wound-rotor type induction motor:** In this case rotor conductors are insulated windings which are not shorted by end rings but the terminals of windings are brought out to connect them to three numbers of insulated slip rings which are mounted on the shaft, as shown in Figure I.4. External electrical connections to the rotor are made through brushes placed on the slip rings. For the presence of these slip rings this type of motor is also called slip ring induction motor.

Besides the above two main parts, an induction motor consists some other parts which are named as follows [1]:

i. **End flanges:** There are two end flanges which are used to support the two bearings on both the ends of the motor.

ii. **Bearings:** There are two set of bearings which are placed at both the ends of the rotor and are used to support the rotating shaft.

iii. **Shaft:** It is made of steel and is used to transmit generated torque to the load.

iv. **Cooling fan:** It is normally located at the opposite end of the load side, called non-driving end of the motor, for forced cooling of the both stator and rotor.

v. **Terminal box:** It is on top or either side of the outer cylindrical frame of stator to receive the external electrical connections.

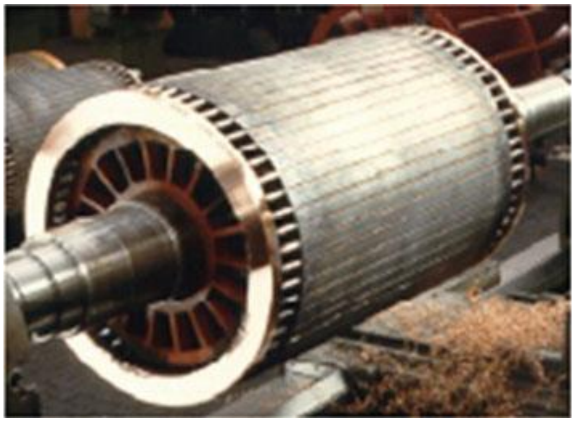

Figure I.3. Squirrel-cage rotor [1]

Figure I.4. Slip ring rotor [1]

I.3. Motor Faults

Induction motors are reliable in operations but they are subject to different types of undesirable faults.

From the study of construction and operation of an induction motor, it reveals that the most vulnerable parts for fault in the induction motor are bearing, stator winding, rotor bar, and shaft. Different studies have been performed so far to study reliability of motors, their performance, and faults occurred [1].

The statistical studies of IEEE and EPRI (Electric Power Research Institute) was carried out on various motors in industrial applications. Part of these studies was to specify the percentage of different faults with respect to the total number of faults. [1].

The study was conducted by General Electric Company on the basis of the report of the motor manufacturer. As per their report the main motor faults are presented in the Table I.1 [1].

Studied by	Bearing fault (%)	Stator fault (%)	Rotor fault (%)	Others (%)
IEEE	42	28	8	22
EPRI	41	36	9	14

Table I.1. Fault occurrence possibility on induction motor [1]

Faults shown in Table I.1 are in broad sense; stator fault may be of different kinds, and different types of faults may occur in rotor itself. For identification, faults in induction motors may be listed as follows—(i) broken bar fault, (ii) rotor mass unbalance fault, (iii) bowed rotor fault, (iv) bearing fault, (v) stator winding fault, (vi) single phasing fault, etc. Besides, the phenomenon called crawling (motor does not accelerate up to its rated speed but runs at nearly one-seventh of its synchronous speed) is also considered as a fault of an induction motor.

Faults listed (i)–(iii) are in general stated as rotor fault which contributes about 8–9 % of the total motor fault. In an induction motor multiple faults may occur simultaneously and in that case determination of the initial problem is quite difficult [1].

Effects of such faults in induction motor result in unbalanced stator currents and voltages, oscillations in torque, reduction in efficiency and torque, overheating, and excessive vibration [1].

Moreover, these motor faults can increase the magnitude of certain harmonic components of currents and voltages. Induction motor performance may be affected by any of the faults. Faults in induction motors can be categorized as follows:

a) **Electrical-related faults:** Faults under this classification are unbalance supply voltage or current, single phasing, under or over voltage of current, reverse phase sequence, earth fault, overload, inter-turn short-circuit fault, and crawling.

b) **Mechanical-related faults:** Faults under this classification are broken rotor bar, mass unbalance, air gap eccentricity, bearing damage, rotor winding failure, and stator winding failure.

c) **Environmental-related faults:** Ambient temperature as well as external moisture will affect the performance of induction motor. Vibrations of machine, due to any reason such as installation defect, foundation defect, etc.,

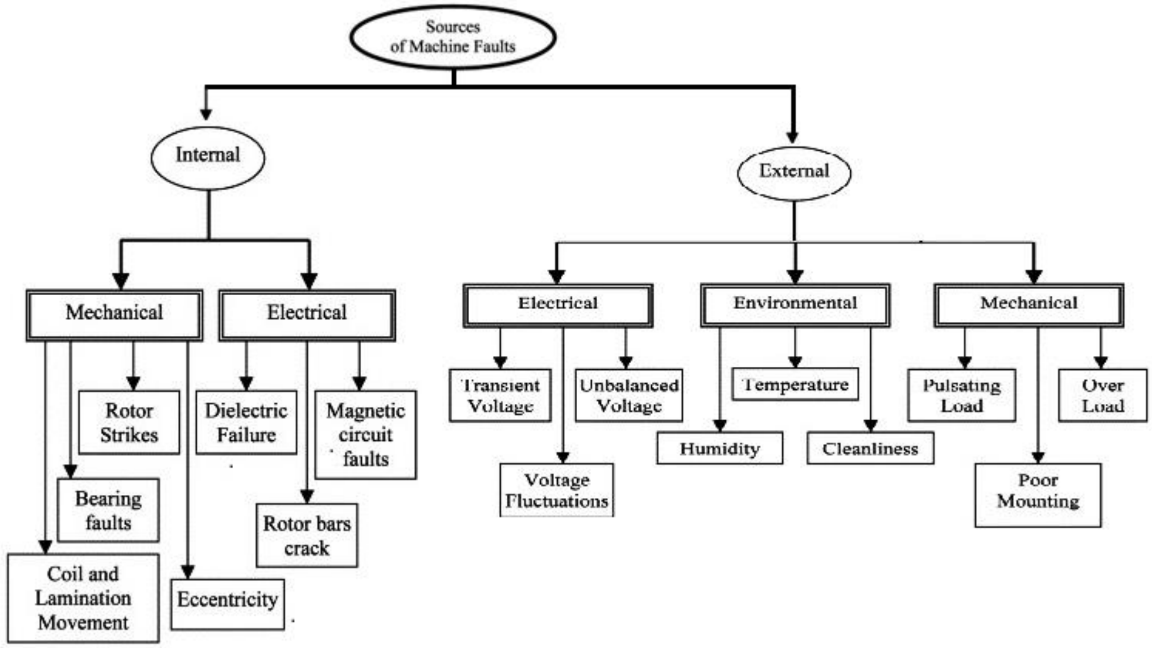

Figure I.5. Different failures modes [4].

I.3.1. Stator Faults

An induction motor is subjected to various stresses like thermal, electrical, mechanical, and environmental [4]. Most stator faults can be attributed to such stressful operating conditions. Faults in the stator winding such as turn-to-turn, coil-to-coil, open circuit, phase-to-phase and coil-to-ground [4], are some of the more prevalent and potentially destructive faults. If left undetected, these may eventually cause cataclysmic failure of the motor. The three main divisions of stator faults are the following:

a) Frame:
   - Vibration
   - Circulating currents
   - Earth faults
   - Loss of coolants

b) Lamination
   - Core slackening
   - Core hot spot

c) Stator windings faults:

- End winding portion (turn-to-turn faults, fretting of insulation, local damage to insulation, damage to connectors, discharge erosion of insulation, displacement of conductors, contamination of insulation by moisture, oil or dirt, cracking of insulation and so forth).
- Slot portion (insulation fretting, displacement of conductors).

I.3.2. Rotor Faults

From the investigations on different failure modes in electrical machines, the rotor-related faults are around 20% of failures may happen in the motor [1]. Rotor faults can be induced by electrical failures such as a bar defect or bar breakage or mechanical failures such as rotor eccentricity. The first fault occurs from thermal stresses, hot spots, or fatigue stresses during transient operations such as start-up, especially in large motors. A broken bar changes torque significantly and became dangerous to the safety and consistent operation of electric machines [4].

The second type of rotor fault is related to air gap eccentricity. This fault is a common effect related to a range of mechanical problems in induction motors such as load unbalance or shaft misalignment. Long-term load unbalance can damage the bearings and the bearing housing and influence air gap symmetry. Shaft misalignment means horizontal, vertical or radial misalignment between a shaft and its coupled load. With shaft misalignment, the rotor will be displaced from its normal position because of a constant radial force.

I.3.3. Bearing Faults

Generally, a rolling-element bearing is an arrangement of two concentric rings. A set of balls or rollers spin in raceways between the inner ring and outer ring. Bearing defects [4] may be categorized as “distributed” or “local”. Distributed defects include misaligned races, waviness, surface roughness and off-size rolling elements. Localized defects include spalls, pits and cracks on the rolling surfaces. These localized defects create a series of impact vibrations at the instant when a running roller passes over the surface of a defect whose period and amplitude are calculated by the anomaly’s position, speed and bearing dimension. Mechanical vibrations are produced by the flawed bearings. These vibrations are at the rotational speed of every component.

I.4. Condition Monitoring

Condition monitoring programme which can predict a failure in electrical machines has received considerable attention for many years [5]. Successful detection of any failure in electrical machines is achieved by using suitable condition monitoring. When a failure occurs, some machine parameters are exposed to changes that depend upon the fault degree. Any irregularity in the electrical machine presents with variation distributed in the currents. The feedback of these currents to the air-gap field produces specific signatures of fault in the spectrum of speed, torque, current, and power. Reliable condition monitoring techniques depend on the best understanding of the mechanical and electrical characteristics of the electrical machines in both fault-free and faulty situations. There are many different technologies that can be applied to the field of condition based maintenance, but the following are the most common ones:

- Oil analysis
- Thermal Analysis
- Motor current analysis
- Vibration analysis

I.4.1. Oil Debris Analysis

Lubrication of a system may be provided in liquid, grease, or solid form and the type of lubrication is generally chosen depending on the operating conditions. Debris analysis does have a rare application on grease or solid form but generally used with oil lubricants. Mechanical failures in some machines generate significant debris in their oil systems [9].

Oil analysis program on a bearing consists of oil sampling, analytical tests and data interpretation. There are number of oil debris analysis techniques tests and data interpretation. There are number of oil debris analysis techniques such as elementary spectroscopy, wear particle analysis, fine particulates analysis, molecular analysis, and electrochemical chemistry used to diagnose a failure on a bearing. These oil debris analyses provide information on quantity, form, and size distribution of the debris, which can lead to damage type detection.

I.4.2. Thermal Analysis

Thermal analysis is defined as a tool used to generate warnings about the overheating of the system [12].

The thermocouples or other temperature monitoring devices usually employed at the inlet and outlet of the test chamber indicate two points of interest to study any temperature gradient. However, thermal analysis cannot be used to identify the type and size of the defects in a system.

I.4.3. Vibration analysis

From the different technologies applicable to predictive maintenance, vibration analysis is the most popular. The reason for that is versatility determining a large number of defects, in a wide range of machines at a reasonable initial economic investment [9].

Vibration is one of the clearest indicators of the health condition of a machine. Low levels of vibration indicate equipment in good condition, and when these levels rise it is clear that something is starting to go wrong. The equipment used for vibration data acquisition in industrial machinery ranges from portable data collectors to on line or permanent monitoring systems. Production and maintenance are the two areas of activity most closely linked to the productivity of an industrial installation [9].

The management of process parameters (pressure, temperature, flow, etc.) has been subject of automation for more than a decade. On the other hand, the management of maintenance parameters (vibration, temperature, etc.) for the same asset still has a long way to go before achieving widespread implementation and integration within the plant process network [9].

Vibration spectral analysis simply performs a transformation of a time based signal into the frequency domain, where we can identify the characteristic vibration related to each of the components or defects that can suffer our asset. Some of the problems that can be easily detected with vibration analysis: unbalance, misalignment, rotating or structural looseness, sleeve bearing lubrication problems, rolling element bearing damage, gear damage, electric motor issues, hydraulic problems, etc. [9].

I.4.4. Motor current analysis

MCA is simply the process by which motor current readings are recorded and analyzed in the frequency domain. It has been around since 1985 and proven itself well over the years in locating rotor faults and air gap problems in motors [9].

On a practical level this technology can be performed in parallel with vibration analysis, using the same data collectors.

Mechanical faults related to belts, couplers, alignment and more are easily found through the use of a demodulated current spectrum, where is possible to identify and trend frequencies such as shaft speed, pole pass, belt pass, vane pass, gear mesh and bearing fault related.

There are many reasons why using MCA to look for mechanical faults can benefit a condition monitoring program. For example, when it comes to belt and coupler problems, current will give an earlier and often more accurate fault indication than vibration analysis. The amount of energy created by the early stages of this type of fault is relatively low. When belts or couplers begin to wear, it is often not noticed in a vibration spectrum until the fault is nearing catastrophic failure. A demodulated current spectrum has the ability to detect the fault early enough to provide plenty of time to plan and schedule the repairs. However, demodulated MCA is not intended to take the place of a vibration program. It is best used as a complimentary technology to a good vibration program [9].

An added benefit of this technology would be in remote equipment locations or areas where equipment is not accessible during normal operations. On this type of equipment, visual inspections can be difficult, and the ability to perform vibration analysis is limited. Depending on the risk assessment, remote wiring transducers for vibration may be too costly. In this case, MCA would work well due to the ability of the equipment to be tested from the motor control cabinet.

I.5.Conclusion

In this chapter we have seen the elements that the induction motor consists of and the different faults that may happen to an AC induction motor, particularly squirrel cage motor. We've also mentioned multiple diagnosis methods.

In the next chapter we will go in depth with the different Signal analysis techniques especially wavelets and Fourier transforms.

Chapter II:

Signal Analysis Methods and Techniques

II.1. Introduction

Signal processing is transforming a time-domain signal into another domain, with the purpose of extracting the characteristic information embedded within the time series that is otherwise not readily observable in its original form.

II.2. Basic Concepts of Signals

A signal can be defined as a function that describes a physical variable as it evolves over time. Analogue signals, such as sound, noise, light and heat, represent the majority of signals in nature. Variations in these signals are continuous over time and the processing of analogue signals is called analogue signal processing (ASP). By sampling such continuous signals at repeated time intervals using data acquisition equipment, they can be converted into discrete format, and the processing of the digital (discrete) signal is named digital signal processing (DSP) [17].

A discrete signal, on the other hand, has values only at specific time periods. The benefits of converting signals from analogue to discrete (digital) form are that it can avoid the degradation and corruption of the signals. Knowing the type of signal to be analyzed has a significant influence on the type of analytic technique chosen. Subsequently, it is necessary to carefully inspect the various types of signal that are encountered in practice [17]. Thus, signals can be classified as shown in Figure II.1.

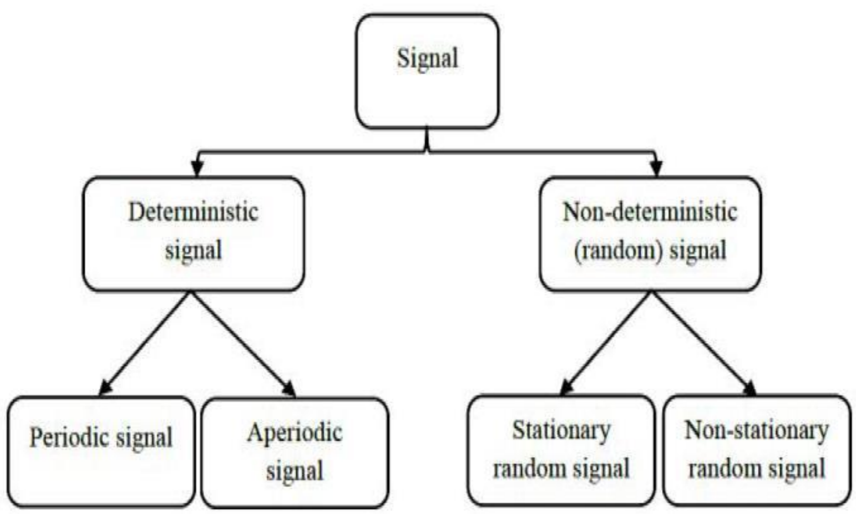

Figure.II.1. Schematic diagram of signal classification [17].

II.2.a. Deterministic signal

If after a suitable number of measurements, the signal can be described by an analytical expression and its values can be predicted at any time in the past and future, then it is called a deterministic signal, such as a sinusoid signal [17].

A deterministic signal may be classified as a periodic signal if the change in the magnitude of the signal repeated at regular time intervals, and if not it is termed an aperiodic signal [17].

II.2.b. Non-deterministic signal (random signal)

Non-deterministic or random signals cannot be described by a deterministic mathematical expression and they are more complex than deterministic signals. By determining their statistical properties, random signals can be broken down into stationary and non-stationary parts. Therefore, the statistical properties of the random signal which do not change with time can be called stationary, otherwise, they are named non-stationary [17].

However, the majority of the signals emitted from industrial machines are non-deterministic. And when a fault starts to appear in a machine the signals monitored tend to non-stationary in nature [17].

II.2.c. Stationary and non-stationary signals

The first natural division of all signals is into either stationary or non-stationary categories. Stationary signals (Figure.II.2.) are constant in their statistical parameters over time. If you look at a stationary signal for a few moments and then wait an hour and look at it again, it would look essentially the same, i.e. its overall level would be about the same and its amplitude distribution and standard deviation would be about the same. Rotating machinery generally produces stationary vibration signals **[17]**.

Stationary signals are further divided into deterministic and random signals. Random signals are unpredictable in their frequency content and their amplitude level, but they still have relatively uniform statistical characteristics over time. Examples of random signals are rain falling on a roof, jet engine noise, turbulence in pump flow patterns and cavitation **[17]**.

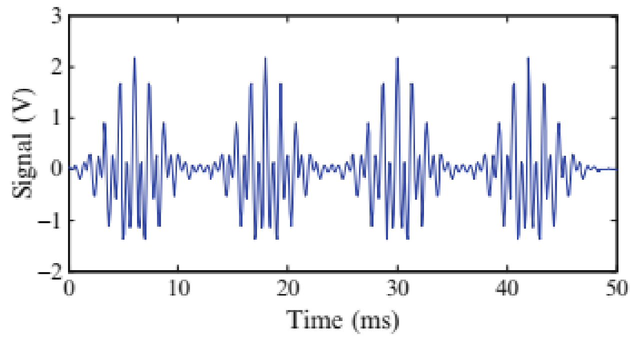

Figure.II.2. A nonstationary signal x(t) [18].

II.2.d. The Heisenberg uncertainty principle

The Heisenberg uncertainty principle states that certain pairs of physical properties, like position and momentum, cannot both be known to arbitrary precision. The same principle holds in signal processing. We cannot locate both time and frequency very precisely.

The product of variation in time (Δt) and variation in frequency ($\Delta\omega$) is greater than $\frac{1}{2}$. Look at (equation II.1).

$$\Delta t * \Delta\omega \geq \frac{1}{2} \qquad \text{II.1.}$$

It can be viewed as a rectangle with constant area and different transform adjusts the width and height of the rectangle [17].

II.3. Signal analysis techniques

After a signal is being captured, a large number of signal processing techniques can be utilized to extract the most sensitive and interesting features concerning defects.

Signal processing techniques are classified as using time domain, frequency domain, and time-frequency domain methods. These methods are not totally independent, and in many situations they complement each other. As a matter of fact, choosing the most suitable method for each specific task represents a major challenge in condition monitoring [17].

II.3.1. Time domain analysis

The technique used in processing the signal can be classified as a time domain method if it processes a raw signal directly in the time domain without being transformed into another domain,

The purpose of time domain analysis is to determine the statistical features of the original signal by manipulating the series of discrete numbers. In this technique statistical parameters such as standard deviation and root mean square can be used to give useful information about the hidden defects [17] and as trend parameters for detecting the presence of incipient bearing faults [6].

II.3.1.a. Peak Value

The peak level of the signal is defined simply as half the difference between the maximum and minimum vibration level:

$$Peak\ Value = \frac{1}{2}\Big(max\big(x(t)\big) - min\big(x(t)\big)\Big) \qquad \text{II. 2.}$$

Because the peak level is not a statistical value, it is often not a reliable indicator of damage; false data caused by noise may have effects on the peak value.

II.3.1.b. Root Mean Square

The RMS (Root Mean Square) value of the signal is the normalized second statistical moment of the signal. In other words, it is the standard deviation of the signal.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\big(x(i)\big)^2} \qquad \text{II. 3.}$$

II.3.1.c. Crest factor

The crest factor is defined as the ratio of the peak value to the RMS of the signal:

$$Crest\ factor = \frac{peak}{RMS} \qquad \text{II. 4.}$$

The crest factor is often used as a measure of the impulsive nature of a signal. It will increase in the presence of discrete impulses, which are larger in amplitude than the background signal but do not occur frequently enough to significantly increase the RMS level of the signal. It is important to note that the value of the crest factor varies in the presence of random noise [6].

II.3.1.d. Kurtosis

Kurtosis is the normalized fourth statistical moment of the signal.
For continuous time signals this is defined as:

$$Kurtosis = \frac{\frac{1}{T}\int_0^T (x(t) - \bar{x})^4}{\sigma^4} \; ; (\sigma = RMS) \qquad \text{II.5.}$$

For discrete signals the kurtosis is:

$$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N} (x(i) - \bar{x})^4}{\sigma^4} \; ; (\sigma = RMS) \qquad \text{II.6.}$$

Kurtosis provides a measure of the impulsive nature of the signal. Increasing signal to the fourth power effectively amplifies isolated peaks in the signal.

II.3.1.e. Standard deviation

$$Standard\ Deviation\ (\sigma) = \sqrt{\frac{1}{N}\sum_{i=0}^{N} (x(i) - \bar{x})^2} \qquad \text{II.7.}$$

II.3.2. Frequency domain analysis

In most applications, signal representation in the time domain is not the best method, since much of the relevant information is hidden in the frequency content of the signal. Frequency or spectral analysis provides additional information about time series data, and can be used to explain the spectra of frequencies which exist in the signal. The parameters of frequency domain analysis are more reliable in damage detection than time domain parameters.

However, time-amplitude signals can be represented by a family of complex exponents with infinite time duration using Fourier transforms (FTs). Additionally, any given time domain signal can be written as a function of all of the frequencies present in it using Fourier transforms [17].

II.3.2.a. Fourier Transform

The Fourier transform is probably the most widely applied signal processing tool in science and engineering. It reveals the frequency composition of a time series x(t) by transforming it from the time domain into the frequency domain. Using the notation of inner product, the Fourier transform of a signal x(t) can be expressed as

$$X(f) = \langle x, e^{i2\pi ft} \rangle = \int_{-\infty}^{\infty} x(t) e^{i2\pi ft} dt \qquad \text{II.8}$$

II.3.3. Time-frequency analysis

The signals from faulty parts have a non-stationary nature. However, if the frequency component of non-stationary signals is calculated using for example the Fourier transform, the results will represent the frequency composition averaged over the duration of the signal.

Consequently, the characteristics of the transient signal cannot be described adequately by the Fourier transform. Therefore, time frequency analysis has been investigated and applied for the fault diagnosis of machinery because of its capability of signal representation in both the frequency and time domains. This unique feature of time-frequency analysis techniques means that it is suitable for non-stationary signals. Moreover, time frequency methods can give interesting information in regards to energy distribution over frequency bands [17].

There are three popular types of analysis when analysing signals in both time and frequency domain (time–frequency analysis), which are:

- Short time Fourier transform (STFT).
- Wigner-Ville distribution (WVD).
- Wavelet Analysis (WA).

II.3.3.a. Short time Fourier transform (STFT)

A straightforward solution to overcoming the limitations of the Fourier transform is to introduce an analysis window of certain length that glides through the signal along the time axis to perform a “time-localized” Fourier transform. Such a concept led to the short-time Fourier transform [17]. As shown in Figure.II.3.

The STFT employs a sliding window function g(t) that is centered at time t. For each specific time (t), a time-localized Fourier transform is performed on the signal x(t) within the window.

Subsequently, the window is moved by t along the time line, and another Fourier transform is performed. Through such consecutive operations, Fourier transform of the entire signal can be performed. The signal segment within the window function is assumed to be approximately stationary [17].

As a result, the STFT decomposes a time domain signal into a 2D time frequency representation, and variations of the frequency content of that signal within the window function are revealed [17].

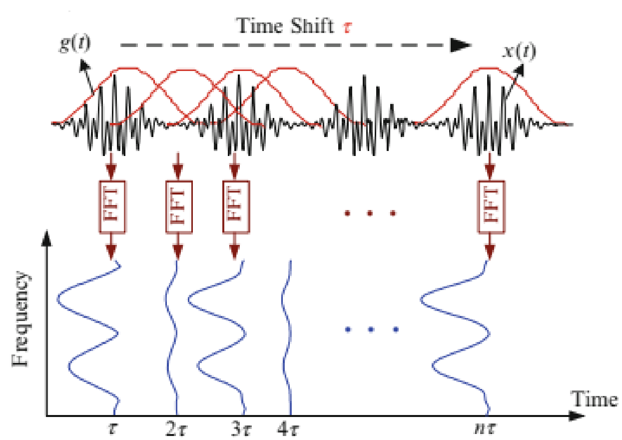

Figure II.3. Illustration of short-time Fourier transform on signal x(t) [18].

II.3.3.b. Wavelets Analysis

A wavelet is a waveform of effectively limited duration that has an average value of zero. Wavelet analysis is a time frequency method and applied to non-stationary signals. It is breaking up the signal into shifted and scaled versions of the original (or mother) wavelet. Wavelets are a recently developed signal processing tool enabling the analysis on several timescales of the local properties of complex signals that can present non-stationary zones [18].

Wavelet transform (WT) is similar to Fourier Transform (FT), but unlike FT, which uses sine and cosine functions as its basis, WT uses special functions with finite support, called wavelets. The most basic wavelet is Haar wavelet Ψ H which is demonstrated in Figure II.4.

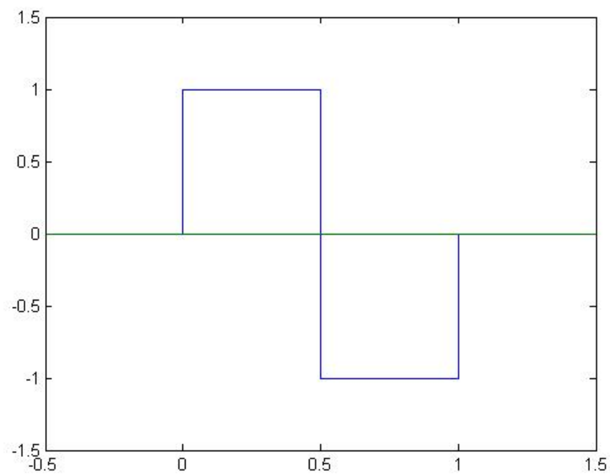

Figure II.4. Haar wavelet [18].

By using wavelet base functions, WT can capture frequencies in transient states. Figure II.5. shows some wavelet base functions.

The advantages of WT over FT is its scalability and shifting operations which allow inspections of local properties of even nonperiodic signals with discontinuities instead of just global inspection of periodic signals because scalability generates series of wavelet functions with different window sizes. The different window sizes enable multi-resolution analysis which makes the analysis of non-stationary signals easier. Like FT, WT can be either discrete or continuous.

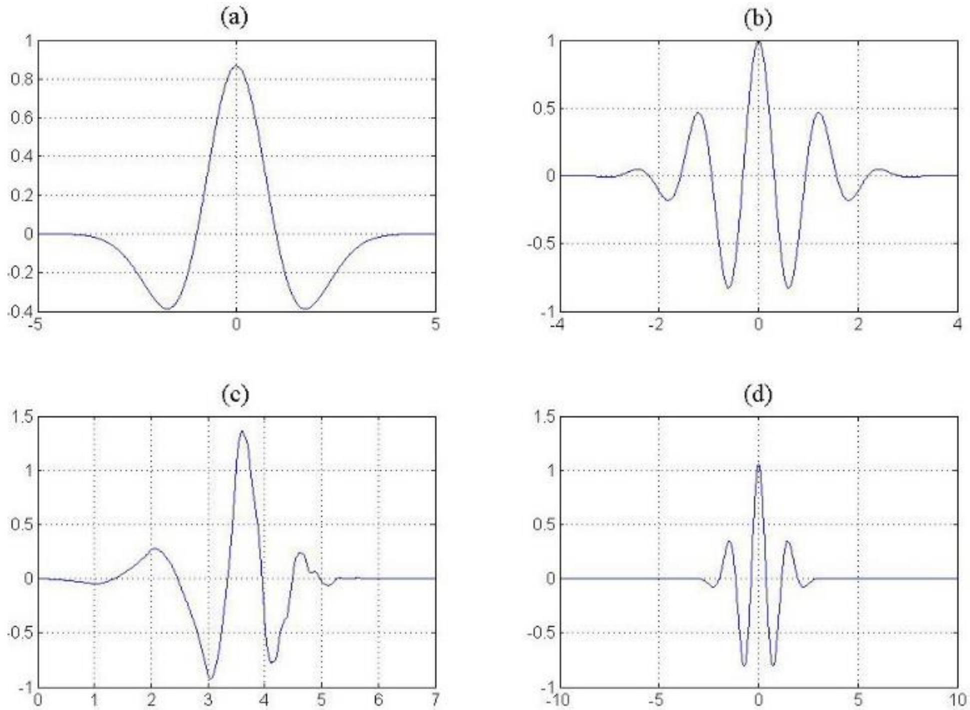

Figure II.5. (**a**) Mexican Hat Wavelet (**b**) Morlet Wavelet (**c**) Daubechies Wavelet db4 (**d**) Gaussian Wavelet [18].

II.3.3.b.1. Continuous Wavelet Transform

The CWT of a continuous signal f(t) is defined as:

$$X_w(a,b) = \int_{-\infty}^{\infty} f(t) h_{a,b}(t)\, dt \qquad \text{II.9}$$

where $h_{a,b}(t)$ is the basis function of WT. Basis functions are obtained from a mother wavelet h(t) by translation and scaling by using equation II.10.

$$h_{a,b}(t) = \frac{1}{\sqrt{a}} h\left(\frac{t-b}{a}\right) \qquad \text{II.10}$$

For the Continuous Wavelet Transform (CWT) parameters b and a are continuous.

Scale is proportional to the duration of the wavelet functions. Large scaling parameter makes the basis function a low frequency stretched version of the mother wavelet with long duration. Large scaling parameters are used to capture the long-term behaviors. If scaling parameter is small, the basis function is a contracted version of the mother wavelet with short duration and high frequency. Small scaling parameters are used to capture short term behavior of the signal. Because of the scaling of wavelet functions, WT captures both long and short term trends in a signal unlike FT, which captures only long term behavior because all the basic functions have infinite duration. The factor $1/\sqrt{a}$ guarantees that all the wavelets have the same energy.

Figure.II.6. shows the scaling effect of scaling parameter a and translation parameter b on Morlet (blue line) wavelet together with a sinusoidal wave (red line).

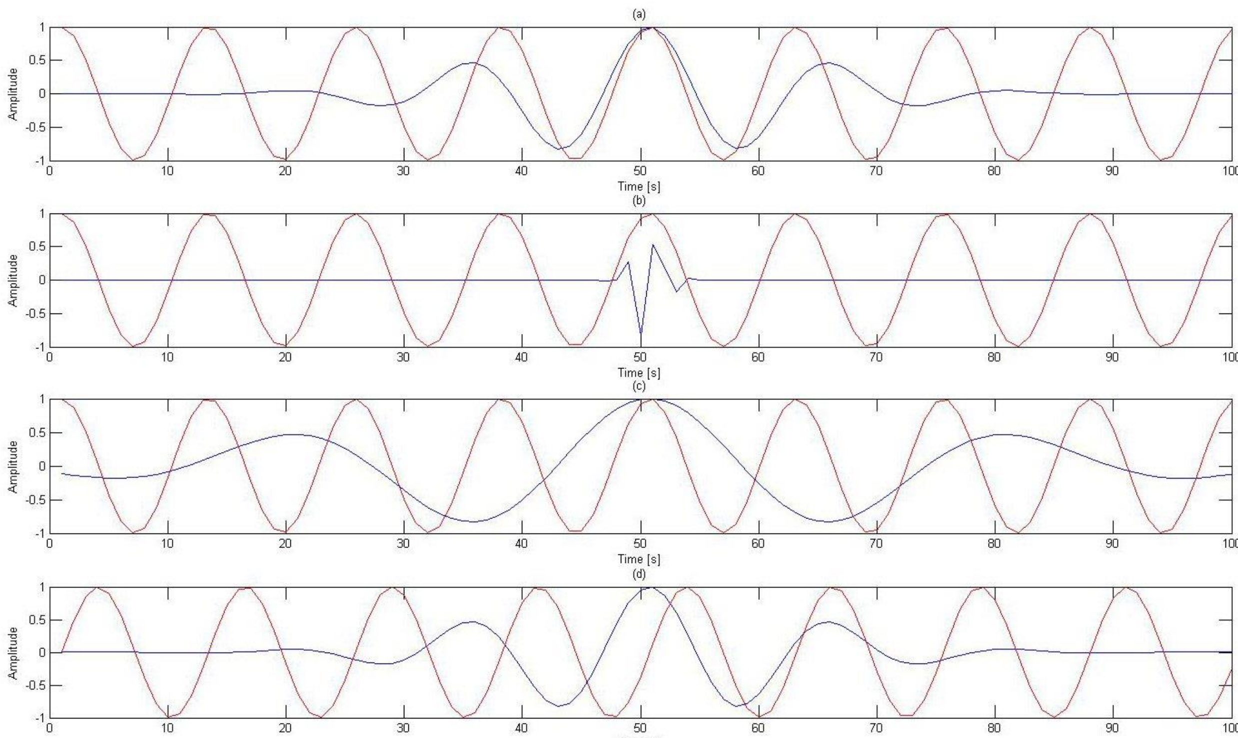

Figure.II.6. (**a**) Mother wavelet a = 1 (**b**) Basis function a = 0.1 (**c**) Basis function a = 2 (**d**) Basis function b = 1.25 [18].

II.3.3.b.2. Discrete Wavelet Transform

Using discrete scale and translation parameters in (equation II.10.) the signal f(t) can be expanded into wavelet series which uses summation rather than integral. This makes the WT computationally faster [6]. The wavelet series of f(t) is

$$f(t) = \sum_{n} a\left(m_{0,}n\right)\phi_{m_0,n}(t) + \sum_{m=m_0}^{\infty}\sum_{n=-\infty}^{\infty} d(m,n)\psi_{m,n}(t) \qquad \text{II. 11}$$

f(t) does not need to be periodic. In (II.11) $\Phi_{m_0,n}(\mathrm{t})$ is a basis function with a fixed scale j0 and the first summation is over all possible translation values k.

Functions $\Phi_{m_0,n}(\mathrm{t})$ are called scaling function and they are obtained by scaling and translating a prototype function

$$\phi_{m,n}(t) = 2^{\frac{m}{2}}\phi(2^m t - n) \qquad \text{II. 12}$$

which has the property $\int_{-\infty}^{\infty}\phi_{0,0}(t)dt = 1$. $\phi_{0,0}$ is sometimes called the father wavelet. $\psi_{m,n}(t)$ are called the dyadic wavelets, which are expressed as:

$$\psi_{m,n}(t) = 2^{\frac{m}{2}}\psi(2^m t - n) \qquad \text{II. 13}$$

The wavelet series parameters in (II.11) can be defined as

$$a(m_0, n) = \langle f, \phi_{m_0,n}\rangle = 2^{\frac{m}{2}}\int_{-\infty}^{\infty} f(t)\,\phi_{m_0,n}(t)dt \qquad \text{II. 14}$$

$$d(m,n) = \langle f, \Psi_{m_0,n} \rangle = 2^{\frac{m}{2}} \int_{-\infty}^{\infty} f(t)\, \Psi_{m_0,n}(t) dt \qquad \text{II. 15}$$

Similar to scaling and wavelet functions, the coefficients a are called the scaling parameters and the d parameters are called the detail parameters. If the signal's scaling functions and the wavelets are discrete in time, then (II.11) is called the discrete wavelet transform.

DWT consists of two series expansions, one for approximation and the other for details of the sequence. The formal definition of DWT of a sequence $X[k], 0 \leq k \leq N-1$ is

$$\text{DWT } f(t) = S_\phi(m_0, n) + T_\psi(m,n) \qquad \text{II. 16}$$

Where

$$S_\phi(m_0, n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} x[k] \phi_{m_0,n}[k] \qquad \text{II. 17}$$

$$T_\psi(m,n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} x[k] \psi_{m,n}[k]; m \geq m_0 \qquad \text{II. 18}$$

II.3.2. Multiresolution Analysis

We have shown that the CWT has a unique advantage because its window width can be controlled by the scale parameter a. However, we also see that the computation load of the CWT is quite heavy in order to capture all the characteristics of the signal. To alleviate this computational burden, mathematicians have developed the Discrete Wavelet Transform (DWT) to minimize the redundancies existing in CWT.

Although the algorithm of DWT is identical to that of the two-channel filter bank analysis, the underlying meanings of these algorithms are different. The most important feature of multiresolution analysis (MRA) is the ability to separate a signal into many components at different scales (or resolutions). For a specific choice of the scaling parameter (such as $\mathbf{a} = 2^J$, $\mathbf{j} \in Z$), the decomposition algorithm is equivalent to putting signal components into successive frequency octaves. Similar to multiband signal decomposition, the goal here is to apply the "divide and conquer" strategy on the signal so that individual components may be processed by different algorithms. We present here the essence of the MRA by considering the properties of the approximation subspaces and the wavelet subspaces. Multiresolution Analysis (MRA) is at the heart of wavelet theory. It shows how orthonormal wavelet bases can be used as a tool to describe mathematically the “increment of information” needed to go from a coarse approximation to a higher resolution of approximation.

Figure.II.7 shows a typical wavelet multiresolution analysis for an electrical power system transient signal. The signal is decomposed with different resolutions corresponding to different scale factors of the wavelets. The signal components in multiple frequency bands and the times of occurrence of those components are well presented in the figure. This figure is a time-scale joint representation, with the vertical axis in each discrete scale representing the amplitude of wavelet components.

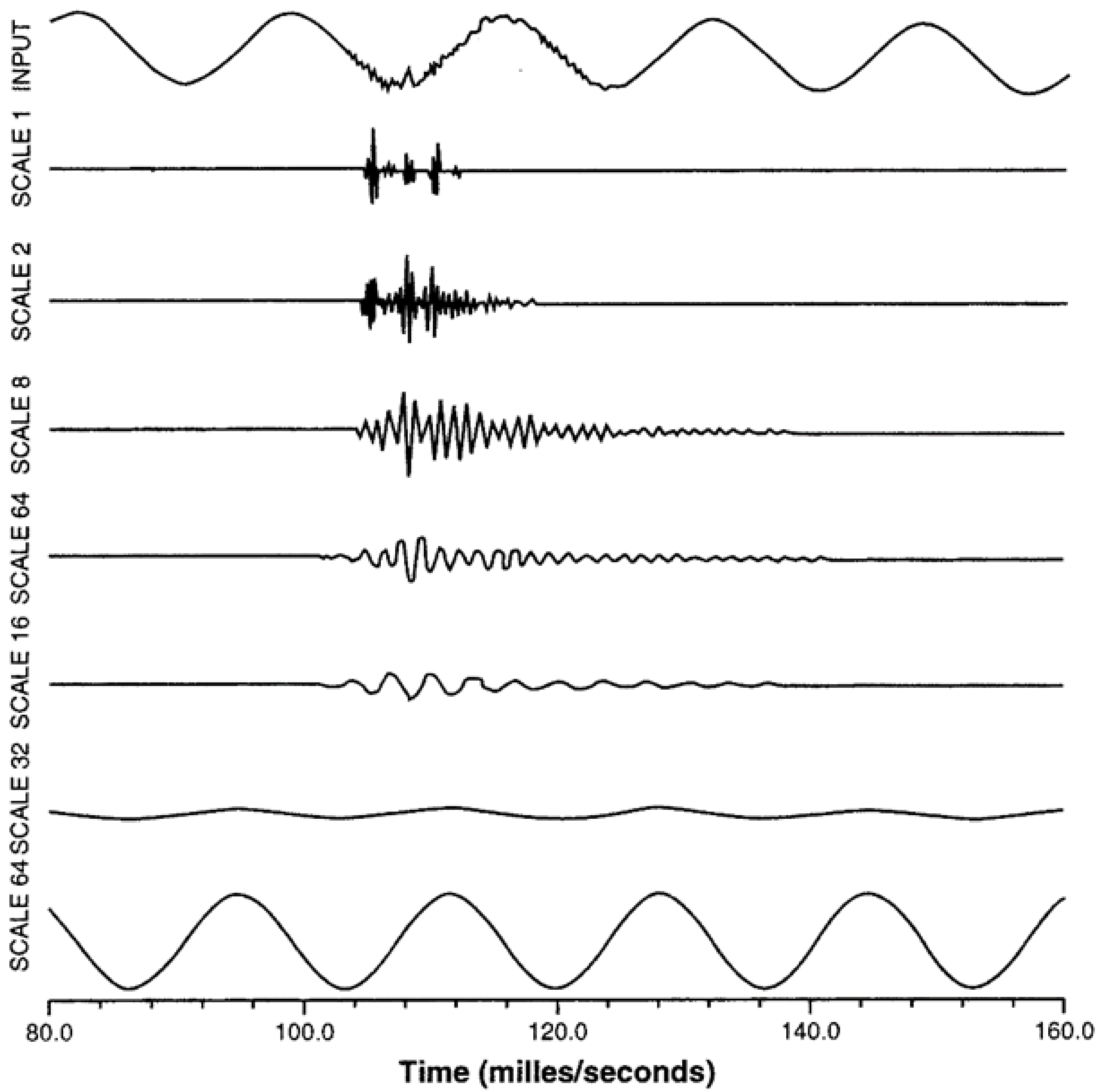

Figure.II.7. Multiresolution wavelet analysis of a transient signal [6].

II.4. Conclusion

In this chapter we have had a small introduction of signals and the different analysis techniques, we've discussed wavelets (continues and discrete).

In the next chapter we will talk about the Rolling Elements Bearings.

Chapter III:

Rolling Element Bearings Construction and Faults

III.1. Introduction

Rolling element bearings exist in a broad range of applications across almost all industries. There are many types of rolling element bearings, each designed and used for a specific application and load and with specific advantages and disadvantages.

This chapter introduces the reader to the basic knowledge of rolling element bearings and its failure modes.

III.2. Rolling element bearings

Bearings permit a smooth low friction motion between two surfaces (usually a shaft and housing) loaded against each other. The terms rolling-contact bearing, antifriction bearing, and rolling bearing are all used to describe that class of bearing in which the main load is transferred through elements in rolling contact rather than in sliding contact (sliding bearings) [10].

The basic concept of the rolling element bearing is simple. If loads are to be transmitted between surfaces in relative motion in a machine, the action can be achieved in the most effective way if the rolling elements are interposed between the sliding members. The frictional resistance encountered in sliding is then largely replaced by much smaller resistance associated with rolling, although this arrangement is accompanied with high stresses in the contact regions of effective load transmission [10].

The standard configuration of a rolling element bearing is an assembly of the outer and inner rings which enclose the rolling elements such as balls (ball bearings), Figure III.2.a., and cylindrical rollers (roller bearings), Figure III.2.b., and the cage or separator which assures annular equidistance between the rolling elements and prevents undesired contacts and rubbing friction among them. Some bearings also have seals as integrated components [10].

The main fundamental components of rolling element bearings are the outer race, the inner race, the cage and the rolling elements. The important geometrical quantities are the number of rolling elements nb, the element diameter Db, the pitch diameter Dp and the contact angle α [10].

The value for the contact angle α depends on the type of bearing; it is 0° for ball or cylindrical roller bearings, which only carry radial load whereas for thrust bearings that only carry axial load, the value is 90°. Figure III.3. shows these parameters and components along with the load zone associated with a unidirectional vertical load (outer race is fixed). [6].

Figure III.1. Ball bearing [1]

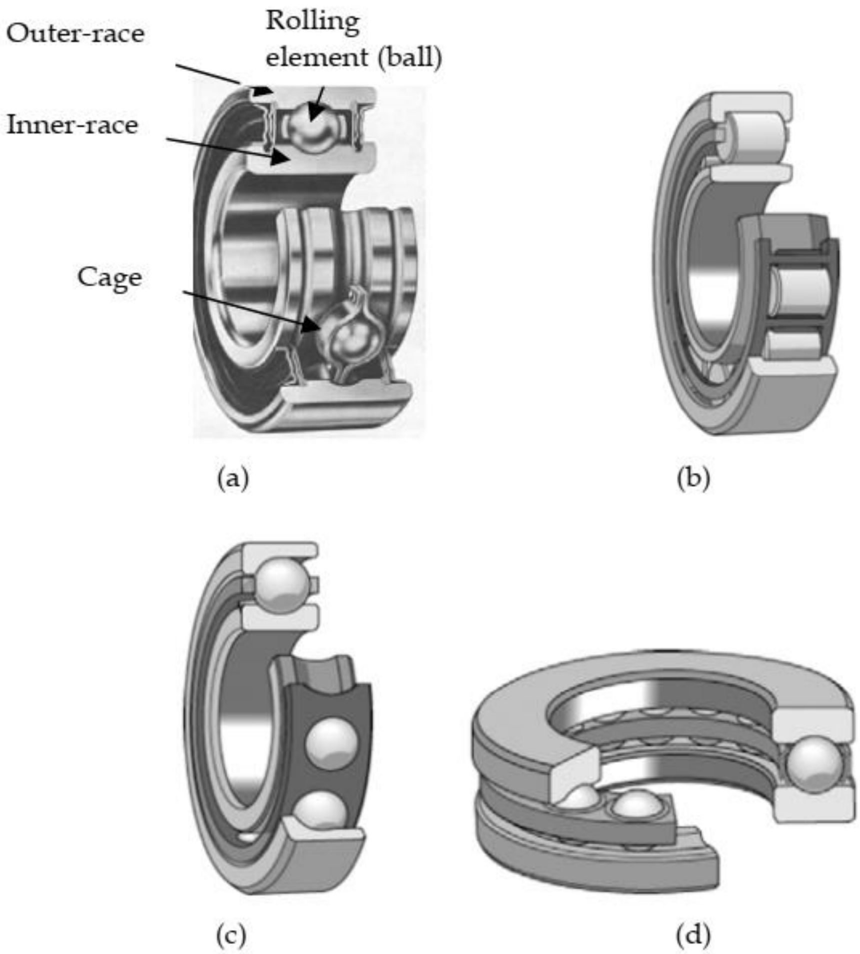

Figure III.2.(a) deep groove ball bearing, (**b**) roller bearing (**c**) angular contact ball bearing, and (**d**) thrust bearing [10]

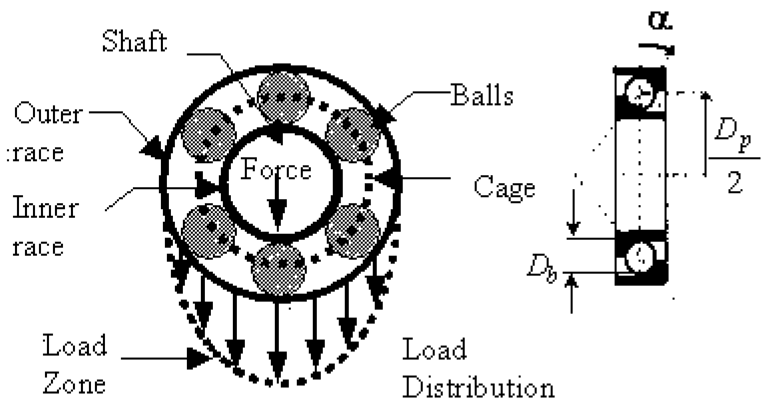

Figure III.3. Rolling bearing components and load distribution for a fixed outer race [6]

III.3. Failure modes

Rolling element bearings may fail in different ways and at different stages through the service life of the bearing (Figure III.4.).

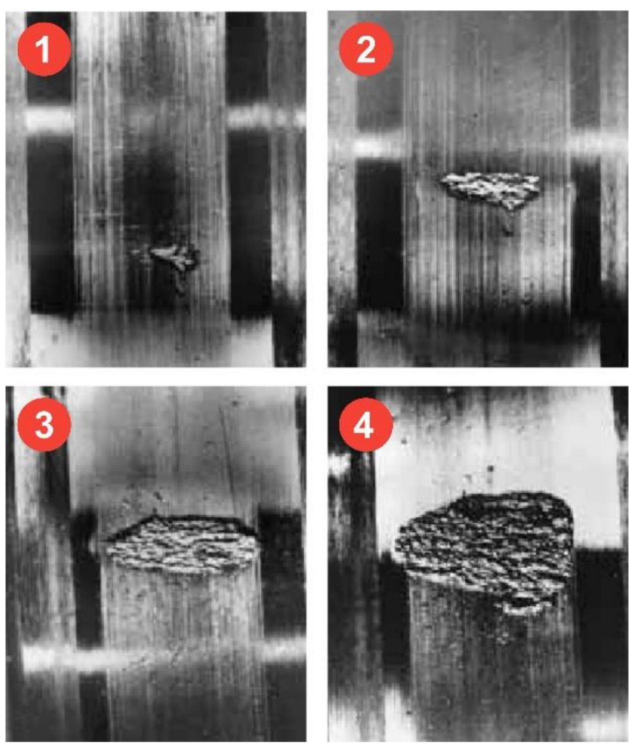

Figure III.4. Evolution of a bearing defect [9].

Under normal operating conditions of balanced load and good alignment, fatigue failure begins with a small fissure, located between the surface of the raceway and the rolling elements, which gradually propagate to the surface, generating detectable vibrations and increasing noise levels [11].

Continued stress causes fragments of the material to break loose producing a localized fatigue phenomena known as flaking or spalling [11]. Once started, the affected area expands rapidly contaminating the lubrication and causing localized overloading over the entire circumference of the raceway [11]. Eventually, the failure results in rough running of the bearing.

While this is the normal mode of failure in rolling element bearings, there are many other conditions which reduce time of bearing failure. These external sources include:

- Wear Damage.
- Fatigue Damage.
- corrosion Damage.
- Brinelling.
- Improper lubrication.
- Installation problems.

III.3.a. Wear Damage

Wear is a frequent cause of bearing damage. Wear occurs mainly due to dirt and foreign particles entering the bearing through inadequate sealing or contaminated lubrication, which result in an increase in friction between metal contacts, and changes of the raceway profile. The exposed bearing to the wear damage would gradually deteriorate leading to a loss of dimensions and associated problems [12].

III.3.b. Fatigue Damage

After a certain running time, a bearing that is subjected to loading fails due to fatigue of the material. If a bearing is also destructively preloaded or overstressed, after a shorter operating time, it will also stop working due to fatigue damage. A fatigue crack begins below the surface and propagates towards the surface as loading continues, until a piece of metal breaks away leaving a pit in the contact area.

Fatigue grows faster if the bearing is overloaded, over speeding, or oil starving. These conditions severely reduce the service life of bearings and they are normal occurrences in all bearings [12]. If a bearing fails due to fatigue sooner than its predicted time, the failure can generally be traced to either overloading (Figure III.5.) or bad installation or maintenance [12].

Figure III.5. Bearing failure as a result of excessive load [6]

III.3.c. Corrosion Damage

Contamination and corrosion frequently accelerate bearing failures because of the harsh environments present in most industrial settings. Dirt and other foreign matter that is commonly present often contaminate bearing lubricant. The abrasive nature of these minute particles, whose hardness can vary from relatively-soft to diamond-like, cause pitting and sanding actions that give way to measurable wear of the balls and raceways [11].

The rust pits caused by corrosion on a bearing element results in excessive noise during operation. The rust generates when the bearing is exposed to water, acid, acidic lubrication, or exposure to elements due to incorrect storage. Condensation is another cause of corrosion on a bearing. Condensation is caused by sudden cooling of the bearing from operating temperature in humid air. Condensation may even damage bearings prior to installation [12].

III.3.d. Brinelling

Permanent indention created by rolling element overload is called brinelling (Figure III.6.). The indentions may result from static loading, which leads to observable plastic deformation of the raceways. Similar damage may occur while a stationary rolling bearing is exposed to vibration and shock loads. When the lubricant is derived out of a loaded or vibrated region, the indentions and wear appear to mimics brinelling. Brinelling is evident in the raceways through the indents or wear and can increase bearing noise and vibration, leading to premature bearing failure [12].

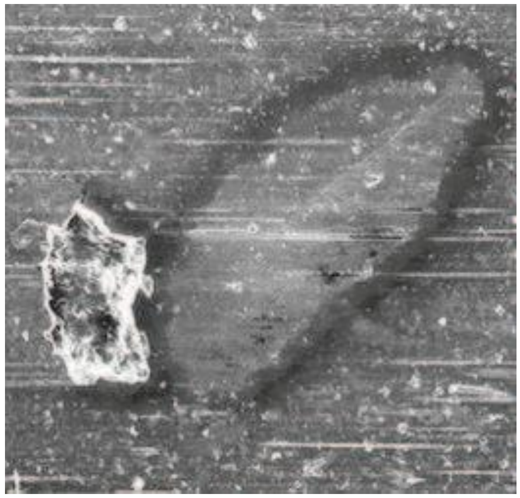

Figure III.6. Inner raceway spall originating on the surface from previous damage in the form of an indentation [14].

III.3.e. Improper lubrication

Improper lubrication includes both under- and over-lubrication. In either case, the rolling elements are not allowed to rotate on the designed oil film, causing increased levels of heating. Excessive heating causes the grease to break down which reduces its ability to lubricate the bearing elements and thus accelerates the failure process [11].

III.3.f. Installation problems

Installation problems are often caused by improperly forcing the bearing onto the shaft or in to the housing. This produces physical damage in the form of brinelling or false brinelling of the raceways which leads to premature failure. Misalignment of the bearing, which occurs in the four ways depicted in Figure III.7. It is also a common result of defective bearing installation. The most common of these is caused by tilted races [11].

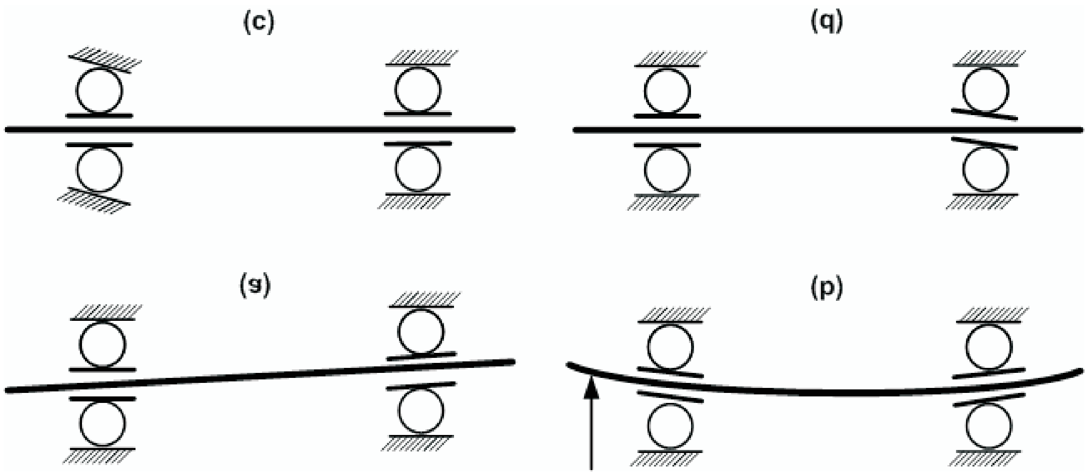

Figure III.7. (a) Misalignment (out-of-line), (b) shaft deflection, (c) crooked or tilted outer race, (d) crooked or tilted inner race [11].

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

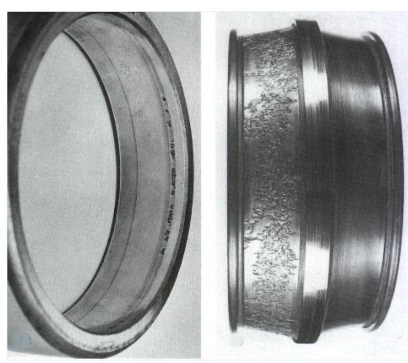

Figure III.8. Bearing in advanced state of deterioration [9].

III.4. Defect frequencies

Faults in rolling element bearings give rise to impulses as the elements contact the fault and the typical vibration produced from that (in the case of a stationary outer race with unidirectional vertical load) is illustrated in Figure III.9.

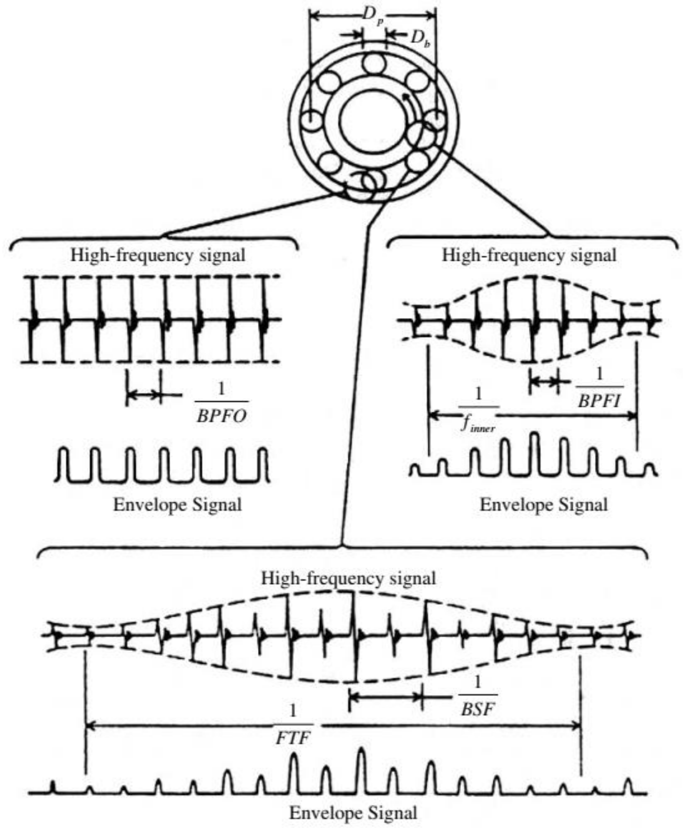

Figure III.9 Typical vibration signals generated by local faults in rolling element bearings (stationary outer race) BPFO, BPFI [6].

For unidirectional vertical load and a stationary outer race (the load direction is fixed with respect to the outer race), as indicated in Figure III.3., an outer race fault would be located in the load zone, and have uniform conditions for the passage of each rolling element, giving a series of uniform impulse responses from excitation of all resonances in the signal transmission path.

The rate of generation of the pulses is called “ball pass frequency, outer race” (BPFO as in equation (III.1)).

The rolling element and inner race faults experience a variation of the load while passing through the load zone. This has the effect of modulating the impulse train by either the cage speed (rolling element fault) or the shaft speed (inner race fault) [6]. An inner race fault passes through the load zone at shaft speed, and the series of impulse responses at the “ball pass frequency, inner race” (BPFI, equation (III.2)) (fixed outer race only) is modulated by this frequency.

A fault on a rolling element passes through the load zone at cage speed (“fundamental train frequency” or FTF (equation (III.3)), (fixed outer race only) and the series of impulse responses are modulated at this rate. In that case, the so-called “ball spin frequency” (BSF) is the rate at which the fault strikes the same race, but in between it would strike the other race, so there are normally two pulses per rotation of the ball (roller), but not necessarily identical, so the fundamental frequency is still BSF (equation (III.4)).

Equations (III.1 – III.4) [6] are used to calculate the defect frequencies for the case of a stationary outer race as follows:

Inner race defect frequency (BPFI):

$$f_{BPFI} = \frac{n_b f_{inner}\left(1 + \frac{D_b}{D_p}\cos(\alpha)\right)}{2} \qquad \text{III. 1}$$

Outer race defect frequency (BPFO):

$$f_{BPFO} = \frac{n_b f_{inner}\left(1 - \frac{D_b}{D_p}\cos(\alpha)\right)}{2} \qquad \text{III. 2}$$

Cage rotational frequency relative to outer race
(Fundamental train frequency) (FTF)

$$f_{FTF} = \frac{f_{inner}\left(1 - \frac{D_b}{D_p}\cos(\alpha)\right)}{2} \qquad \text{III. 3}$$

Ball/Roller rotational speed around its axis
(Ball/roller spin frequency) (BSF)

$$f_{BSF} = \frac{f_{inner}}{2}\frac{D_p}{D_b}\left(1 - \left(\frac{D_b}{D_p}\cos(\alpha)\right)^2\right) \qquad \text{III. 4}$$

When both races are rotating (as in the case of a planetary bearing), the defect frequencies could be calculated using the general equations (equations III.5- III.8).

Note that this will modify the modulation frequencies, as the load is no longer fixed with respect to the outer race [6].

Outer race defect frequency (BPFO):

$$f_{BPFO} = \frac{n_b(f_{inner} - f_{out})\left(1 - \frac{D_b}{D_p}\cos(\alpha)\right)}{2} \qquad \text{III.5}$$

Inner race defect frequency (BPFI):

$$f_{BPFI} = \frac{n_b(f_{inner} - f_{out})\left(1 + \frac{D_b}{D_p}\cos(\alpha)\right)}{2} \qquad \text{III.6}$$

Cage rotational frequency (absolute)

$$f_{cage} = \frac{f_{inner}\left(1 - \frac{D_b}{D_p}\cos(\alpha)\right)}{2} + \frac{f_{out}\left(1 + \frac{D_b}{D_p}\cos(\alpha)\right)}{2} \qquad \text{III.7}$$

Ball/Roller rotational speed relative to both races
(Ball/roller spin frequency) (BSF)

$$f_{BSF} = \frac{f_{inner} - f_{out}}{2}\frac{D_p}{D_b}\left(1 - \left(\frac{D_b}{D_p}\cos(\alpha)\right)^2\right) \qquad \text{III.8}$$

The load angle α is taken for the dominant load path, but actually varies for each rolling element, which is the reason for the random slip that always occurs (which happens in practice as a result of fluctuations in the load angle, and the tolerances of the cage.). Thus, actual mean bearing frequencies typically differ from the theoretical ones by 1-2%, and the corresponding pulse period also varies randomly by about the same amount [6].

III.5. Bearing Fault Progression

The fault patterns exhibited by progressive stages of bearing damage are well established in industrial applications (Figure III.10.) [15]

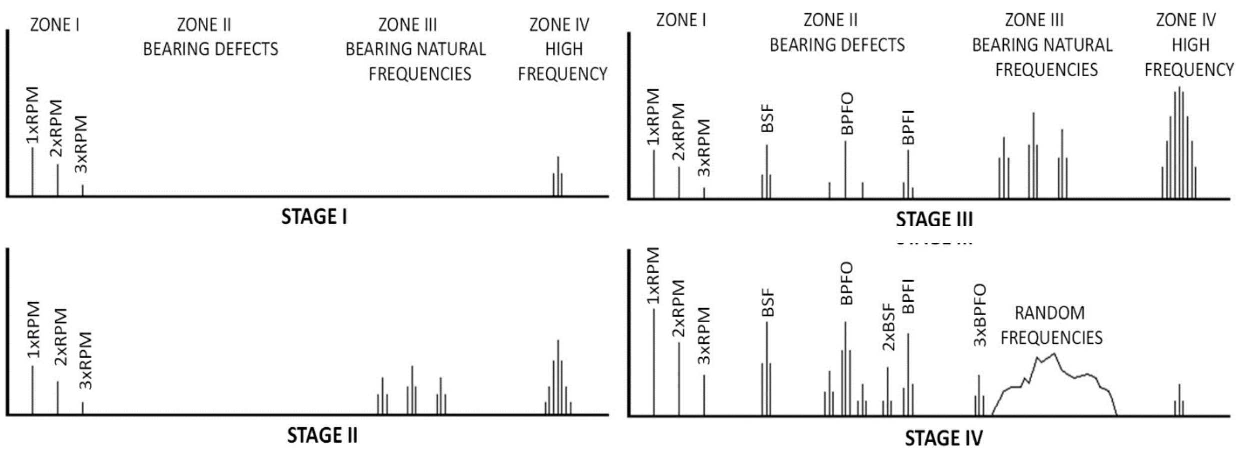

Figure III.10. Bearing damage stages [15].

In Stage I, micro-defects and crack initiation causes ultra-high frequency activities. These activities are typically monitored using Acoustic Emission rather than accelerometers [15].

In Stage II, the micro faults develop into pits which begins to excite bearing elements and causes signals associated with their natural frequencies to be appear. Enveloping analysis is commonly used to demodulate a selected high frequency bandwidth of the FFT spectra and extract the bearing defect frequencies in this stage. As the pits become larger, fundamental bearing defect frequencies and their harmonics can be observed from the FFT spectra. Depending on the extent of the damage, these frequencies can be modulated by the shaft frequency and be observed as sidebands [15].

Stage IV is the final condition before bearing catastrophic failure. As the defect becomes widespread, the bearing elements vibrate more randomly with the higher clearances.

The localized defects may also have ‘smoothen’ out which reduces the signature of the periodic vibration. As such, the distinct bearing defect frequencies diminishes as an increase in noise floor or ‘haystack’ rises in the higher frequencies ranges [15].

III.6. Rolling element bearing fatigue life

If a bearing is clean, properly lubricated, sealed from the entrance of dust and dirt, not undersized and operates at reasonable temperature, then metal fatigue will be the main cause of its failure.

Fatigue in rolling element bearings is caused by the application of repeated stresses on a finite volume of material [6]. Fatigue failure includes names such as peeling, flaking (Figure III.11.), pitting and spalling and results in the removal of the material from the inner race, the outer race or the rollers.

Figure III.11. Ripple pattern flaking of a tapered roller bearing [14].

Generally, there are three types of fatigue: Surface distress appears as a smooth surface resulting from plastic deformation in the asperity region (typically less than 10 μ m) [7].

Pitting appears as shallow craters at contact surfaces with a depth of, at most, the thickness of the work-hardened layer (approximately 10 μ m) as shown in figure III.12. [7]. Spalling leaves deeper cavities at contact surfaces with a depth of 20 μ m to 100 μ m (figure III.12.).

In most of the literature, spalling and pitting are used indiscriminately, and in some they are used to distinguish the severities of the surface contact fatigue [7].

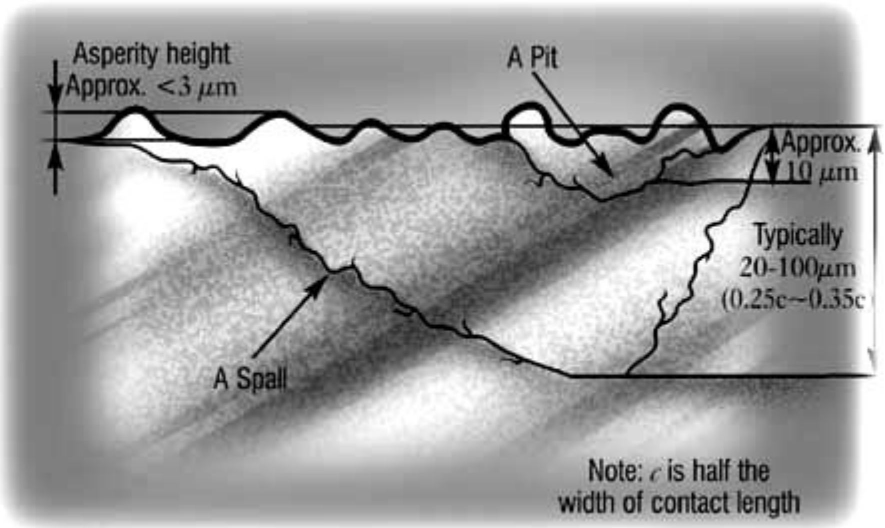

Figure III.12 Pitting and spalling [7].

In rolling element bearings, the common life measure (bearing life) is either the number of revolutions (usually in millions of cycles) of the inner race (outer race stationary) until the first spall occurs, or the number of hours of use at a standard angular speed until the first evidence of spalling is noticed [6].

Fatigue life prediction theories give an important means of estimating the survival of the rolling element bearing using equation (III.9)

$$\ln \ln\left(\frac{1}{S}\right) = e \ln\left(\frac{L}{A}\right) \qquad \text{III. 9}$$

The rolling bearing life equation (III.10), which was standardized by ISO [ISO 281:1990], and is the most widely used equation to estimate the bearing life.

$$L = \left(\frac{C}{f_e}\right)^m \qquad \text{III. 10}$$

m is the load life exponent, which is dependent upon the bearing type (3 for ball bearings and 10/3 for angular contact bearings).

Of most interest is the L10 life (S = 0.9) and the L50 life (S = 0.5); L10 is the life in millions of revolutions that 90 percent of the identical bearings will complete or exceed.

L10 is described by

$$L10 = \frac{10^6}{60n}\left(\frac{C}{f_e}\right)^m \qquad \text{III.11}$$

III.7.Conclusion

In this chapter, the failure modes of rolling bearing elements, the causes, and the commonly used techniques to diagnose the defect on the bearings were reviewed. The role of the characteristic frequency in vibration analysis has been examined.

In the next chapter, we dive into the action by analyzing a vibration signal from a rolling element bearing to identify its defects frequencies.

Chapter IV:

Faults Detection of Rolling Element Bearing Using Wavelets

IV.1. Introduction

Bearings are key machinery elements, whose failure without forewarning can damage the system to uncorrectable levels. In most cases, the cost of the bearing is not significant in comparison to the production losses caused due to unscheduled maintenance resulting from the bearing failure.

This necessitates a robust diagnostic system for the bearings. This chapter addresses diagnostics of bearings with outer race and inner race. A vibration-based method to detect and identify bearing damage is more common due to the ease in measurement, and the measured data can then be further processed in the time domain, frequency domain and time frequency domain to extract useful information that can be related to the severity and type of bearing damage.

IV.2. Experimental test-rig

this study uses experimental data from the bearing data center of Case Western Reserve University (CWRU) [19].

Experiments were conducted using induction motor (left), a torque sensor (middle) and a dynamometer (right) connected by a self-aligning coupling (middle), as shown in Figure.IV.1. The dynamometer is controlled so that desired torque load levels can be achieved.

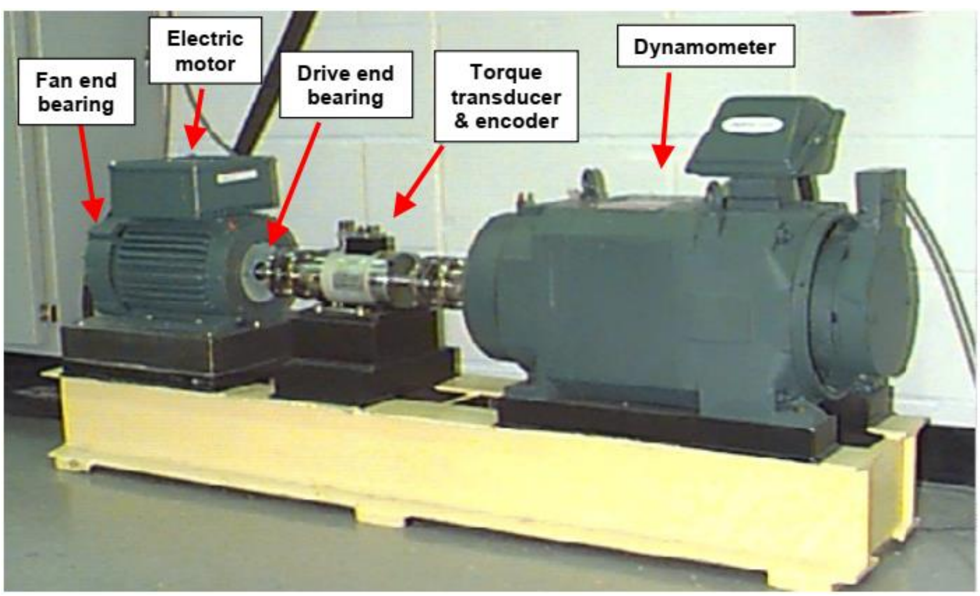

Figure.IV.1. Bearing test stand used by Case Western Reserve University (CWRU) [19].

The test bearing (SKF 6205-2RS JEM) supports the motor shaft at the drive end. Single point faults were introduced into the test bearing using electro-discharge machining.

Bearing faults under consideration cover outer race fault and inner race fault. The fault size is 0.007 and 0.021 inch in diameter and 0.011 inch in depth for both the outer race (noted D1) and inner race (noted D2). The fault position relative to the load zone is: ‘centered’ (fault in the 6.00o’clock position).

The geometric characteristics of the bearing are listed in Table.IV.1. and the frequency characteristics of the bearing are listed in Table.IV.2.

Acceleration was measured in the vertical direction on the housing of the drive-end bearing. Besides, the sampling frequency is 12,000 Hz (1s acquisition), The shaft rotating speed of the motor was 1796 rpm without motor load.

Inside Diameter	Outside Diameter	Thickness	Ball Diameter	Pitch Diameter
0.9843 inch (25 mm)	2.0472 inch (52 mm)	0.5906 inch (15 mm)	0.3126 inch (7.94 mm)	1.537 inch (39 mm)

Table.IV.1. Geometric characteristic of the bearing [19].

Rotation frequency	Inner ring	Outer ring
Order 1	Order 5.4152	Order 3.5848

Table.IV.2. Frequency characteristics of the bearing (SKF 6205-2RS JEM) (multiple of running speed in Hz) [19].

IV.3. Data Base Guidelines

The objective of this work is to detect different faults of a rolling element bearing, and to do so there’s some guidelines that we shall follow which are:

- Two load situation are considered; 0HP and 3HP
- The sampling frequency is 12 KHz;
- Two Fault Diameters considered are:
    1. 0.007 inch (0.1778 mm)

2. 0.014 inch (0.3556 mm)

- Three conditions of a rolling element bearing are considered:
  1. Healthy
  2. Inner Race Fault
  3. Outer Race Fault

IV.3.a. Motor speeds

The table below represent the different motor speeds in relation of fault diameter and load

Fault Diameter (in)	**Load (HP)**	**Motor Speed (RPM) (Inner Race Fault)**	**Motor Speed (RPM) (Outer Race Fault)**
0.007”	0	1797	1796
	3	1721	1725
0.014”	0	1796	1796
	3	1728	1723

Table.IV.3 Motor speeds (Faulty bearing)

The table below represent the healthy bearing motor speeds in relation of load

Signals (Normal Baseline Data)	**Load (HP)**	**Motor Speed (RPM)**
Normal_0	0	1796
Normal_3	3	1725

Table.IV.4. Motor speeds (Healthy bearing)

IV.3.b. Rotation frequencies

according to the equation IV.1. the values of the rotation frequencies shown in the table below

$$f_r = \frac{N}{60} \qquad \text{IV. 1.}$$

The table below represent the different rotation frequencies in relation of fault diameter and load

Faults	Load (HP)	Rotation Frequency (Hz) (Inner Race Fault))	Rotation Frequency (Hz) (Outer Race Fault)
0.007”	0 HP	29.95	29.93
	3 HP	28.68	28.75
0.014”	0 HP	29.93	29.93
	3 HP	28.8	28.71

Table.IV.5. Rotation frequency (Hz) in relation of fault diameter and load.

The table below represent the healthy bearing rotation frequencies in relation of load

Signals (Normal Baseline Data)	Load (HP)	Rotation Frequency (Hz)
Normal_0	0	29.93
Normal_3	3	28.75

Table.IV.6. Rotation frequency of healthy bearing in relation of load.

IV.3.c Defect frequencies

According to equation III.1 and III.2 from chapter III the faults frequencies (BPFI and BPFO) are shown in the table below

Faults	Load (HP)	BPFI (Hz)	BPFO (Hz)
0.007”	0 HP	161.73	107.75
	3 HP	154.87	103.5
0.014”	0 HP	161.62	107.75
	3 HP	155.52	103.36

Table.IV.7. Faults frequencies

IV.4 Work Methodology

The chart below represents the steps that we have followed in order to get a comprehensive result.

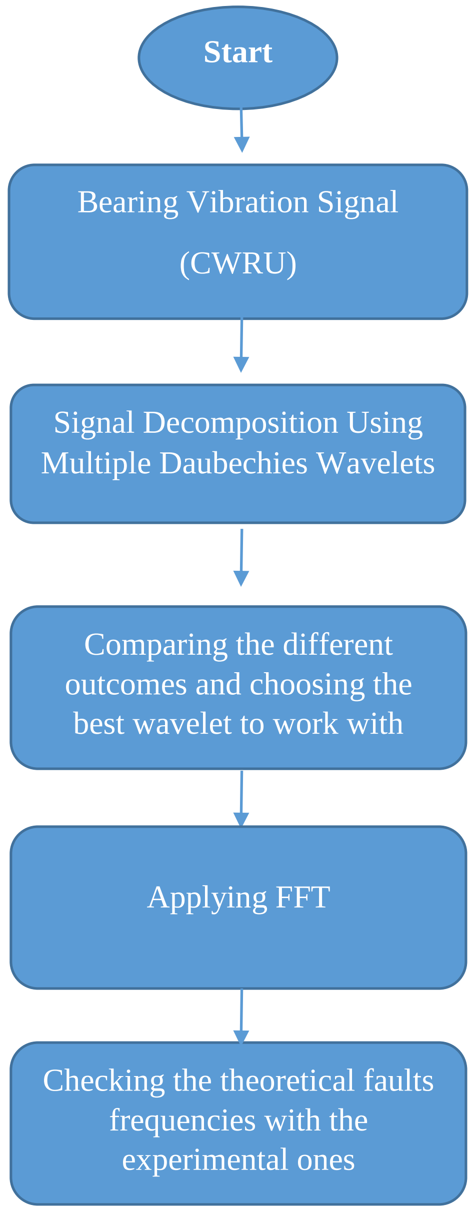

Figure IV.2. Flowchart of the proposed work methodology

IV.5. Working with wavelets

The first step is typing “waveletAnalyzer” in the command editor which will give us the interface (GUI) of the wavelet analyzer application

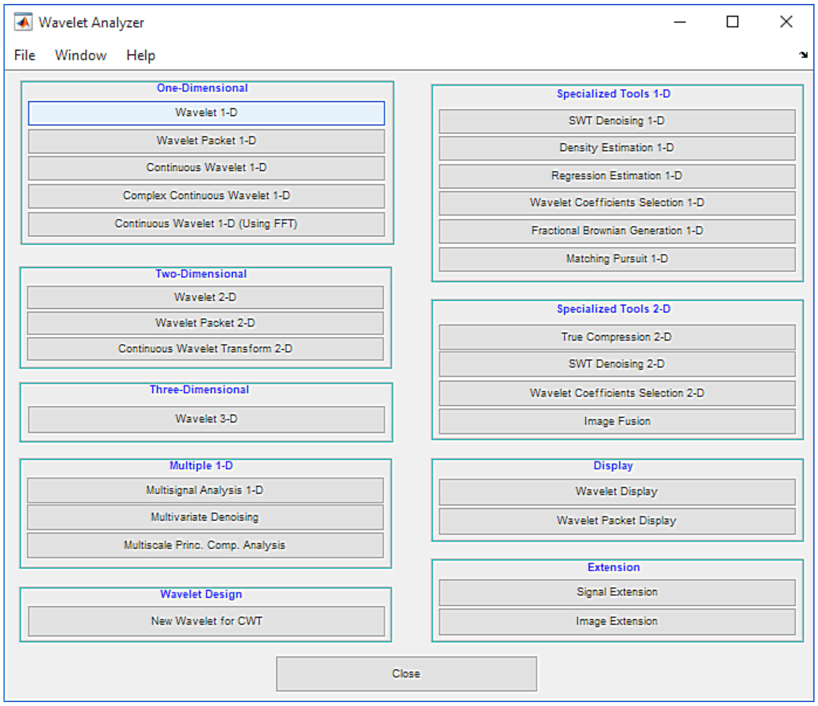

Figure.IV.3. Wavelet Analyzer application interface (GUI)

The second step is to choose “Wavelet 1-D” option, then choose from the right menu which wavelet to use (Daubechies, Morlet, Haar …) and what variation of it (1, 2, 3, …) and what level of decomposition

The level of decomposition is based on the sampling frequency and the rotation frequency, look at the equation IV.2.

$$l_{decom} = \frac{\log\left(\frac{F_s}{f_r}\right)}{\log(2)} = \frac{\log\left(\frac{12000}{28.75}\right)}{\log(2)} = 8.73 \approx 9 \qquad \text{IV. 2.}$$

IV.5.a. Frequency range

The next step is choosing the right frequency range to work with, the table IV.8. shows all the possible frequency ranges for different decomposition levels of CWRU data

Decomposition level	Approximation	Frequency range (Hz)	Detail	Frequency range (Hz)
1	a1	(0 - 6000)	d1	(6000 - 12000)
2	a2	(0 - 3000)	d2	(3000 - 6000)
3	a3	(0 - 1500)	d3	(1500 - 3000)
4	a4	(0 - 750)	d4	(750 - 1500)
5	a5	(0 - 375)	d5	(375 - 750)
6	a6	(0 – 187.5)	d6	(187.5 - 375)
7	a7	(0 – 93.75)	d7	(93.75 – 187.5)
8	a8	(0 – 46.87)	d8	(46.87 – 93.75)
9	a9	(0 – 23.43)	d9	(23.43 – 46.87)

Table.IV.8. The frequency intervals corresponding to the decomposition of a signal at the ninth level (Fs = 12,000 Hz).

Our main focus is on the approximations, so according to table IV.7. the right frequency range to find the faults frequencies is from 0 to 375 which corresponds to approximation a5.

Decomposition level	Approximation	Frequency range (Hz)
5	a5	(0 - 375)

Table IV.9. The chosen frequency range.

IV.5.b. Wavelet variation

Daubechies are well known, and heavily used wavelets in vibration analysis, we’ve put to the test 6 variation of the Daubechies family, after applying the FFT we have got figure IV.4.

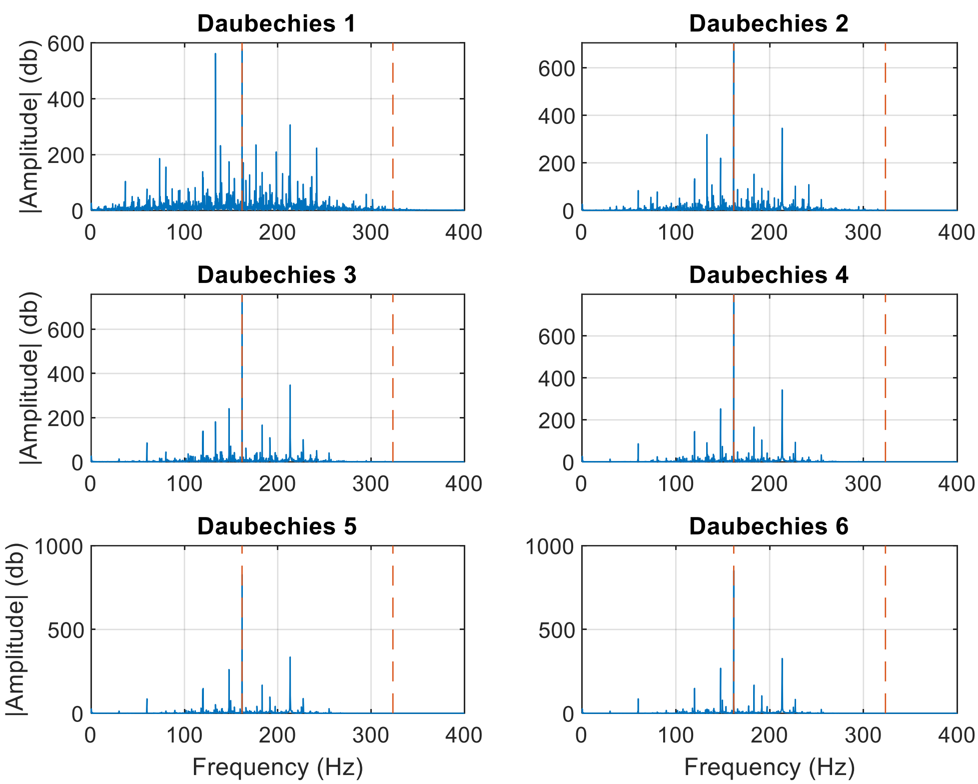

Figure.IV.4. Inner race fault sample.

By analyzing each of the 6 frequency spectrums produced by a 9th level decomposition, the best can be selected by searching for the signal with the clearest fault harmonics and minimal noise. The optimum spectrum of a 9th level decomposition by far the one corresponding to the Daubechies 6 spectrum

IV.6. Results and analysis

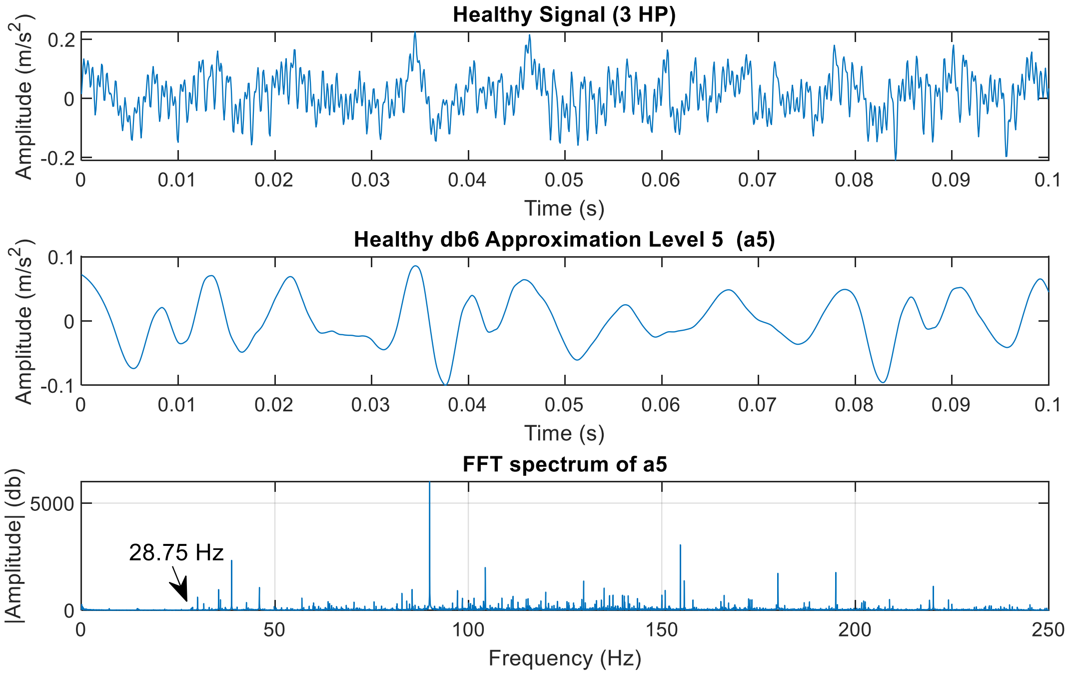

Figure.IV.5. Healthy signal (3 HP)

The upper graph in Figure.IV.5 is the signal of a healthy bearing under 3 HP load represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above and the lower graph is the FFT spectrum of it.

The Rotation frequency is 28.75 Hz

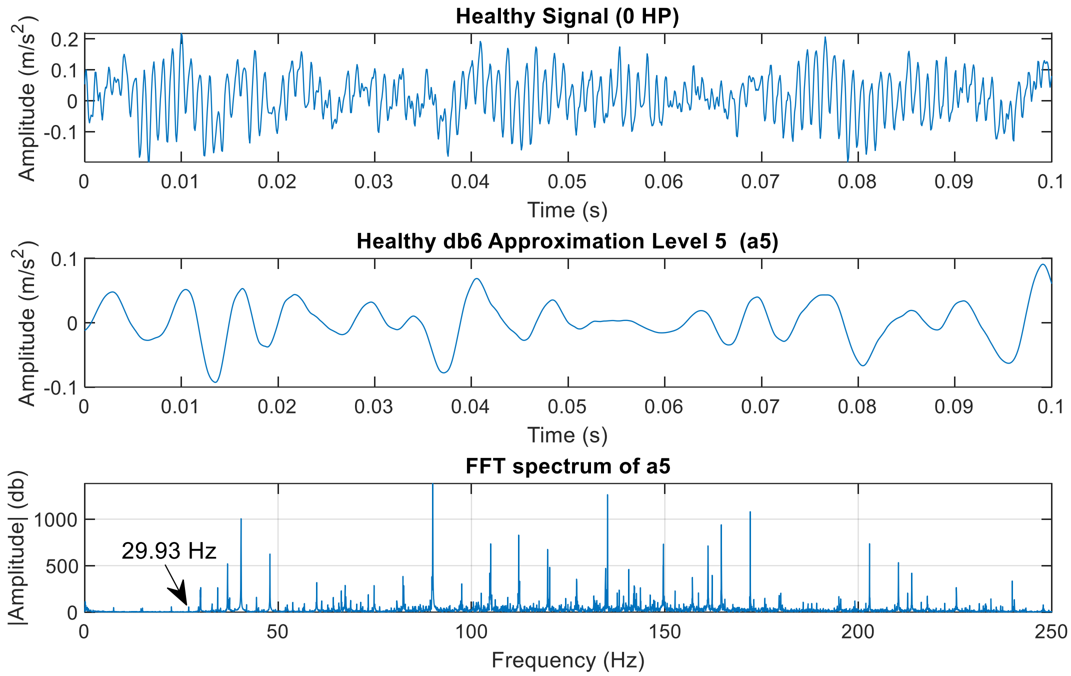

Figure.IV.6. Healthy signal (0 HP)

The upper graph in Figure.IV.6 is the signal of a healthy bearing under no load (0 HP) represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above and the lower graph is the FFT spectrum of it.

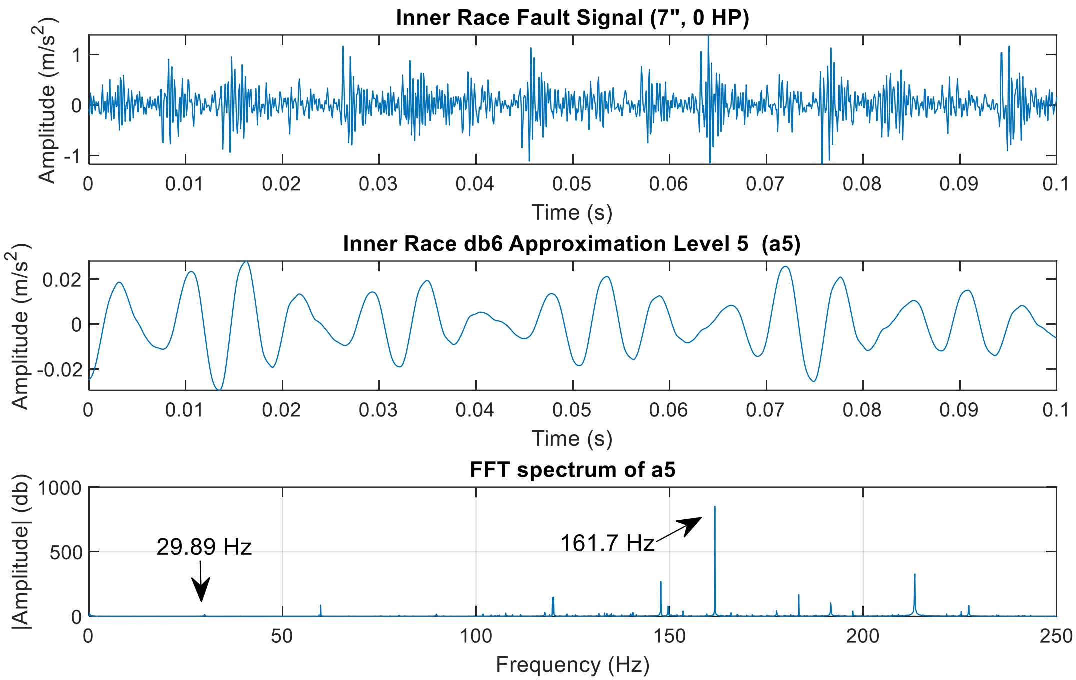

Figure.IV.7. The 3 levels of the applied method for inner race fault signal (0HP, 0.007")

The upper graph in Figure.IV.7 is the Inner Race fault signal with 0HP load and 0.007inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above and the lower graph is the FFT spectrum of it.

Analysis of this frequency spectrum clearly identifies a dominant frequency at 161.1 Hz and a rotation frequency at 29.89 Hz.

Computation of theoretical fault frequencies shows that the Inner Race frequency (BPFI) is predicted to be 161.73 Hz and the Rotation frequency (fr) to be 29.95 Hz according to table IV.9.

Given that the two values are within 1 Hz of each other, which is acceptable when allowing for shaft and rolling element slip, it can be concluded from this spectrum that a rolling element fault exists.

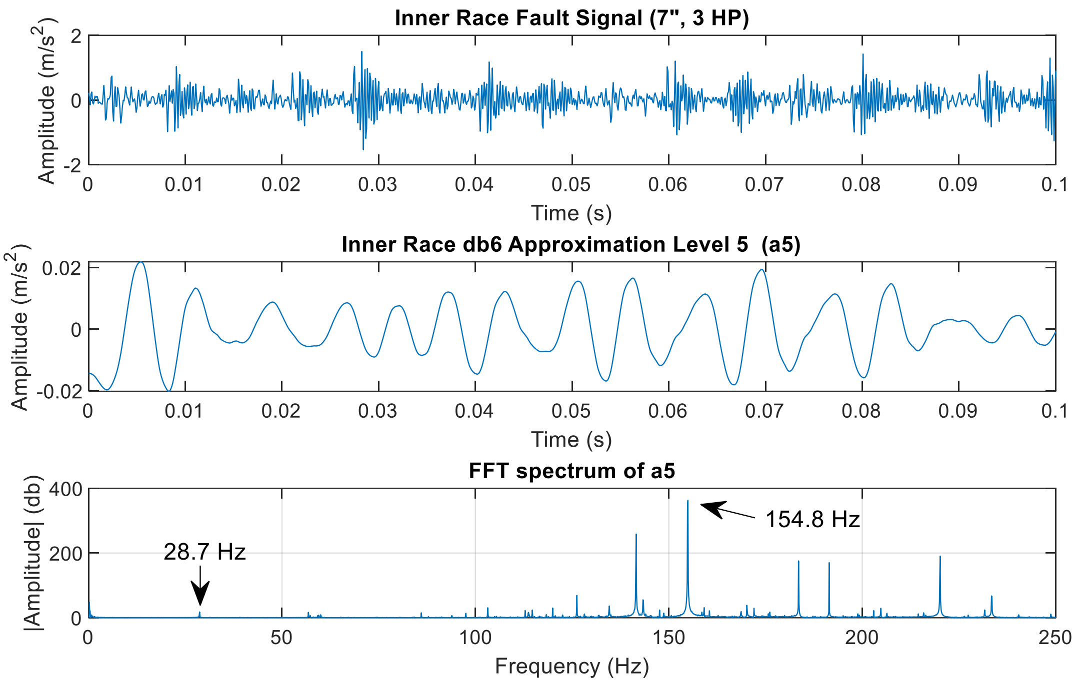

Figure.IV.8. The 3 levels of the applied method for inner race fault signal (3HP, 0.007”)

The upper graph in Figure.IV.8 is the Inner Race fault signal with 3HP load and 0.007inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above it and the lower graph is the FFT spectrum of it.

This spectrum again clearly identifies a dominant frequency component at 154.8 Hz and a frequency component which corresponds to the rotation frequency at 28.7 Hz, exactly matching the theoretical frequencies that were previously calculated in table IV.9 and table IV.7.

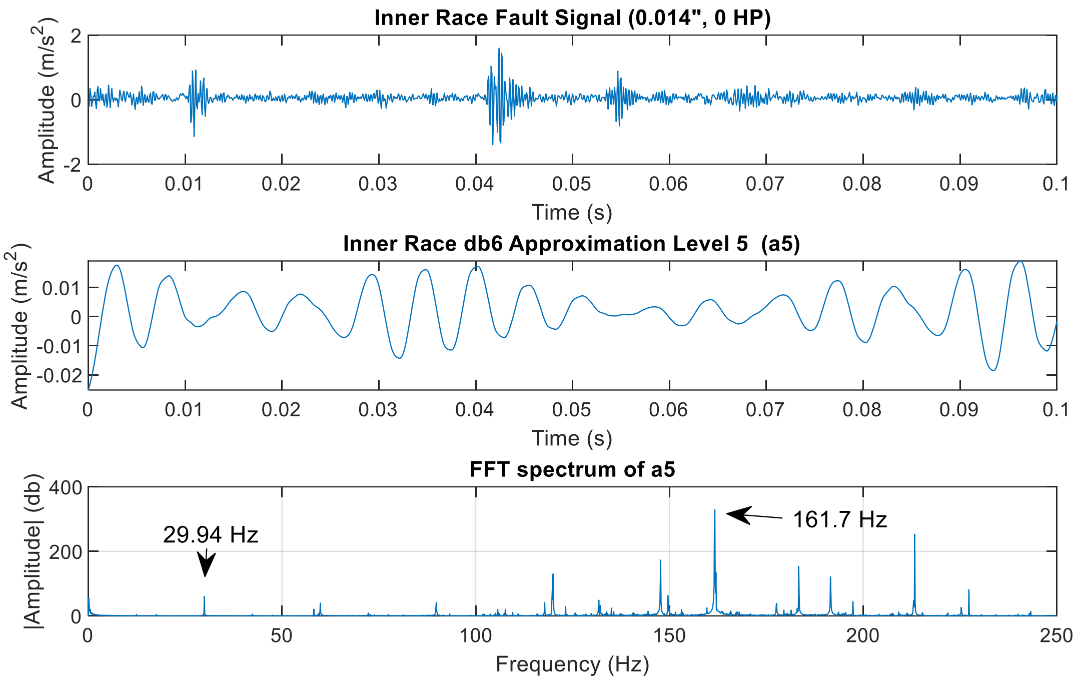

Figure.IV.9. The 3 levels of the applied method for inner race fault signal (0HP, 0.014”)

The upper graph in Figure.IV.9 is the Inner Race fault signal with 0HP load and 0.014inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above it and the lower graph is the FFT spectrum of it.

The same remark as the previous Figures goes for the Figure.IV.9; A dominant frequency component at 161.7 Hz and a 29.94 Hz frequency which corresponds to the rotation frequency. It should be noted that the dominant frequency in Figure.IV.9 is the same in Figure.IV.7.

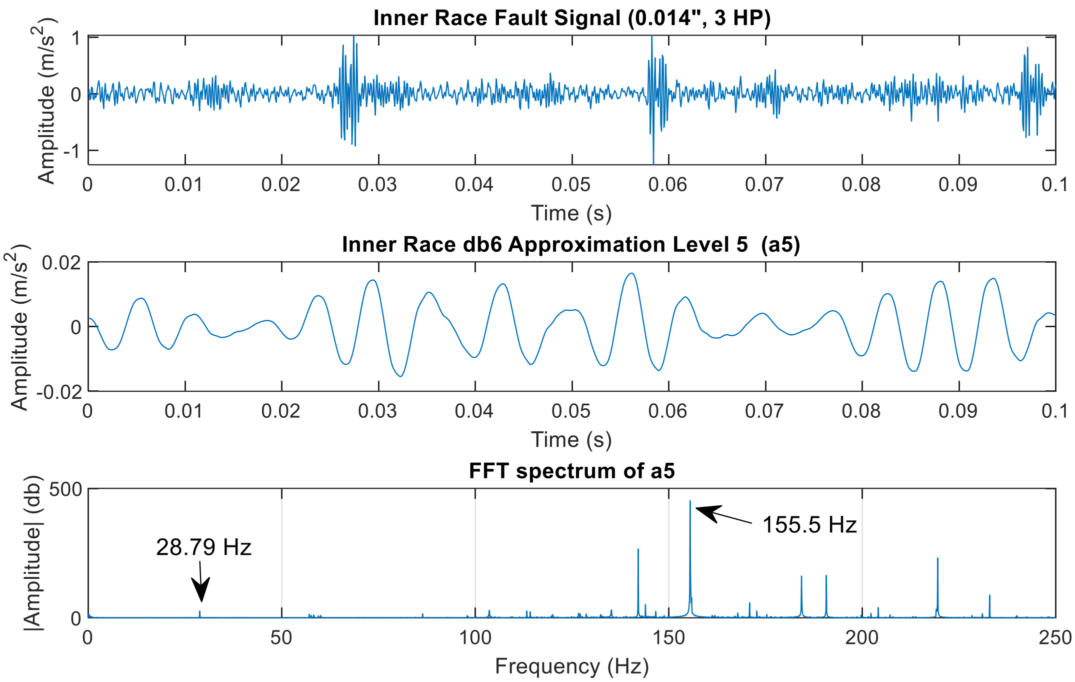

Figure.IV.10. The 3 levels of the applied method for inner race fault signal (3HP, 0.014")

The upper graph in Figure.IV.10 is the Inner Race fault signal with 3HP load and 0.014inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above it and the lower graph is the FFT spectrum of it.

A dominant frequency component at 155.5 Hz and a 28.79 Hz frequency which corresponds to the rotation frequency.

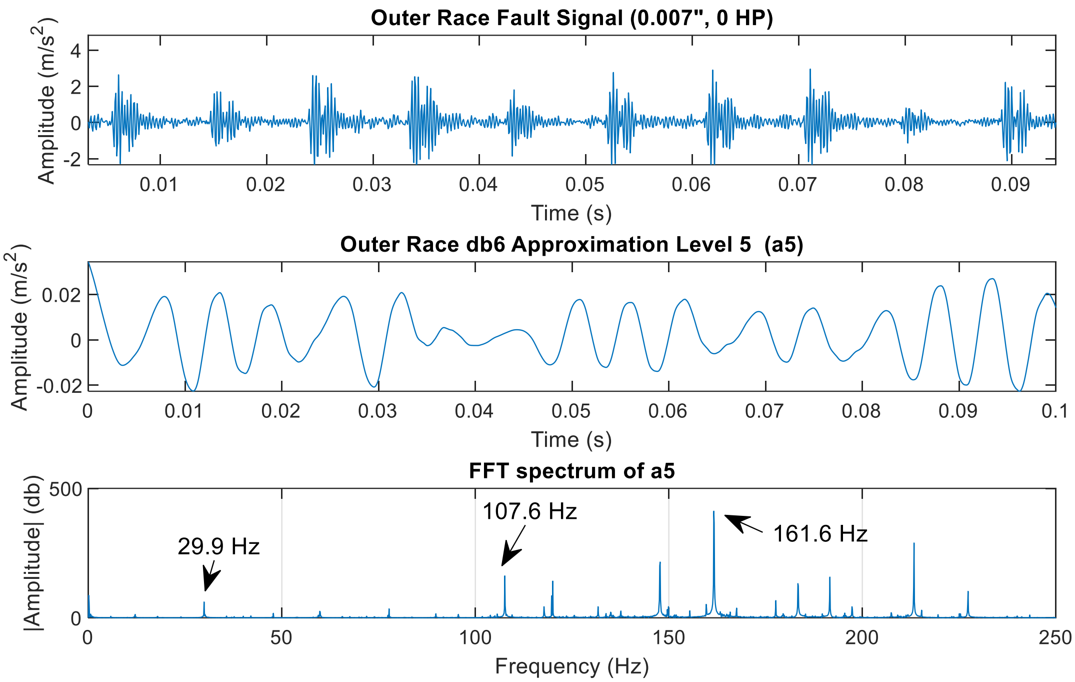

Figure.IV.11. The 3 levels of the applied method for outer race fault signal (0HP, 0.007")

The upper graph in Figure.IV.11 is the Outer Race fault signal with 0HP load and 0.007inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above and the lower graph is the FFT spectrum of it

The dominant frequency in the spectrum is at 161.6 Hz, and BPFO frequency is at 107.6 Hz and the rotation frequency is 29.9 Hz.

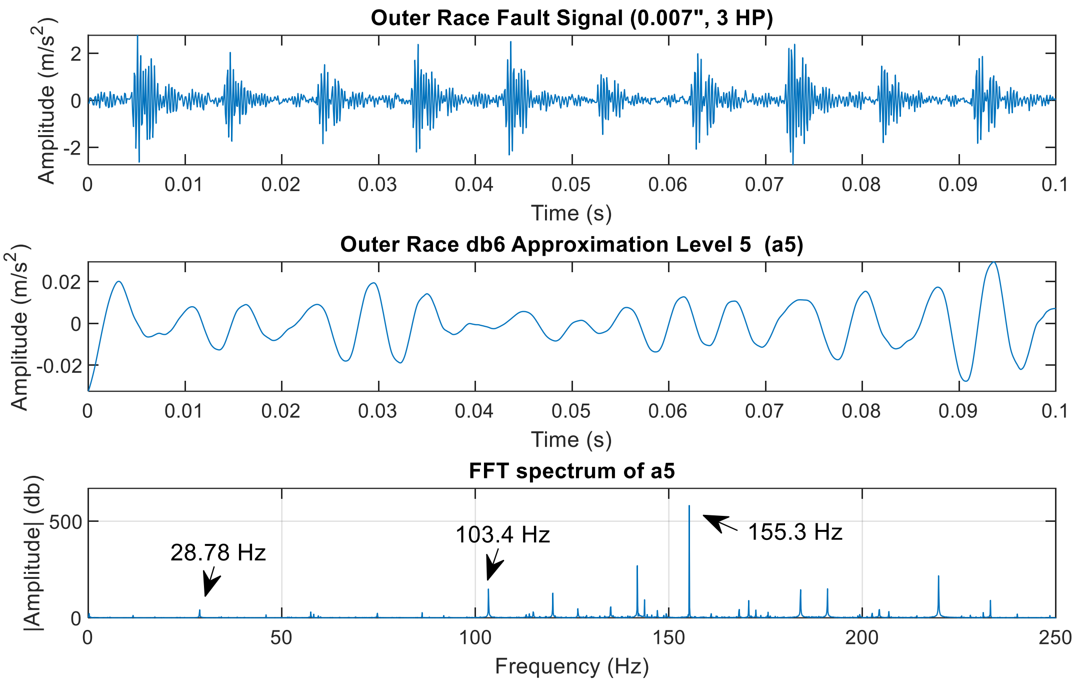

Figure.IV.12. The 3 levels of the applied method for outer race fault signal (3HP, 0.007")

The upper graph in Figure.IV.12 is the Outer Race fault signal with 3HP load and 0.007inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above and the lower graph is the FFT spectrum of it

The dominant frequency in the spectrum is at 155.3 Hz, and BPFO frequency is at 103.4 Hz and the rotation frequency is 28.78 Hz.

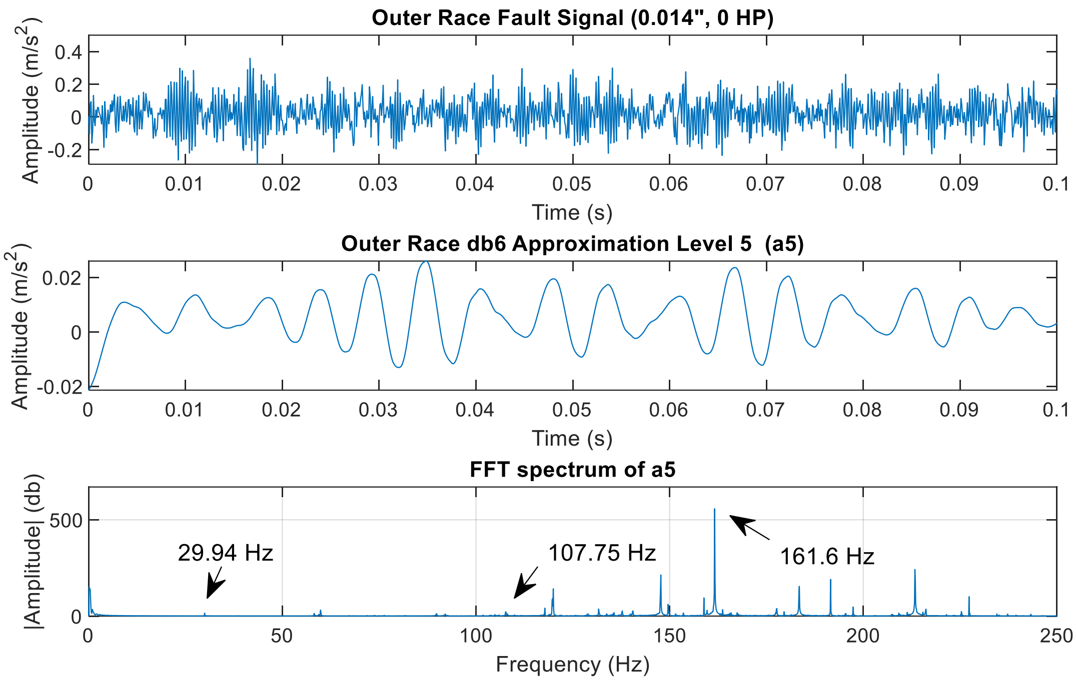

Figure.IV.13. The 3 levels of the applied method for outer race fault signal (0HP, 0.014")

The upper graph in Figure.IV.13 is the Outer Race fault signal with 0HP load and 0.014inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above and the lower graph is the FFT spectrum of it

The dominant frequency in the spectrum is at 161.1 Hz, and BPFO frequency is at 107.75 Hz and the rotation frequency is 29.94 Hz.

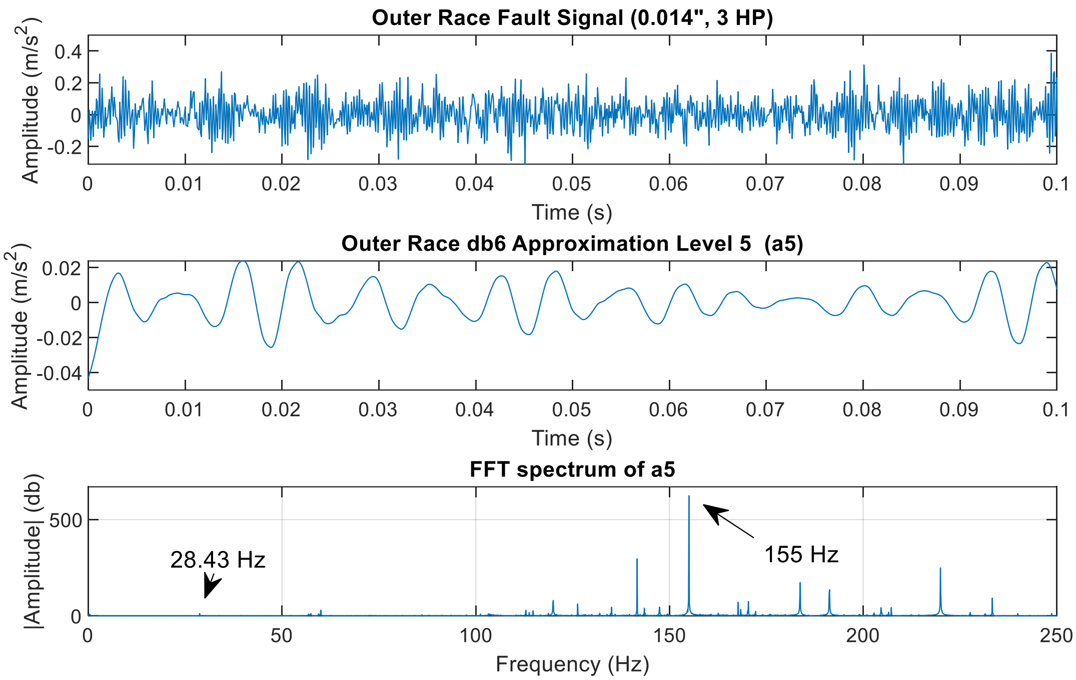

Figure.IV.14. The 3 levels of the applied method for outer race fault signal (3HP, 0.014")

The upper graph in Figure.IV.14 is the Outer Race fault signal with 3HP load and 0.014inch fault diameter represented in the time domain, the middle graph is the level 5 approximation (db6) of the signal above and the lower graph is the FFT spectrum of it.

The dominant frequency in the spectrum is at 155 Hz and the rotation frequency is 28.43 Hz and The magnitude of BPFO frequency is so small.

The dominant frequency in Figure.IV.11 to 14 is not the BPFO frequency, which is a common theme in all the graphs of outer race's fault that we've been throw until now.

IV.6.a. Discussion

Each figure presented above represent the 3 stages that we've gone throw with fault signals to get to the results with the wavelet transform.

The first stage (the upper graph) is the time domain signal (raw data) (time (s) on the x axis and amplitude (m/s^2) on y axis).

The second stage (the middle graph) is a level 5 approximation of a raw signal (the first stage signal) treated with the Daubechies 6 wavelet transform (time (s) in x axis and amplitude (m/s^2) in y axis).

The third stage is the application of the FFT over the level 5 approximation then comparing the theoretical faults frequencies with the experimental ones (frequency (Hz) in x axis and |amplitude| (db) in y axis).

By comparing the results that we had from the graphs and the result we got in table IV.9.
It's clear that theirs a match between the theoretical and the experimental frequencies.

The figure IV.13. and figure IV.14. are a signals with a BPFO faults but there is no sign of any match between the theoretical fault frequency and the experimental which gives us our first challenge with method we've followed.

It's clear that our method is great for small faults like 0.007 inch but when the faults gets bigger especially in the outer race it is hard to detect it.

Outer race faults were more difficult to isolate and did not appear as the maximum value in the frequency spectrum, rather appearing at a lower magnitude. This is likely due to the movement of the distributed fault in and out of the bearing load zone, resulting in amplitude modulation by the shaft speed. This shows that the fault induced resonance frequencies are not being as well isolated from the non – diagnostic noise as is the case with localized faults.

We've used the Daubechies 6 (db6) because it's the clearest one, when we look at figure IV.4. it's obvious the supremacy of db6 over the other db's

.

IV.7. Conclusion

In this chapter, we have applied the wavelet transform (Daubechies 6) over raw signal data from the Case Western Reserve University then treated it with FFT which gave us the peaks that corresponds to the faults frequencies that were looking for which proves the effectiveness of the wavelet method.

General Conclusion

This work presented a method of Rolling Element Bearings (REB) fault diagnosis based on Wavelet Transform (WT) and Fast Fourier Transform (FFT). A case study on SKF bearing diagnosis with defective inner race and outer race has shown that The use of the combination of WT and FFT provides more information related to the bearing fault detection compared with the FFT frequency spectrum alone which can be used only for a stationary signal.

This method can greatly improve the accuracy of diagnosis. Hence, the proposed method is a successful approach for vibration monitoring. It remains to test its application on a signal containing other types of faults.

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