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Fault Diagnosis of Rotating Machinery Components

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Fault Diagnosis of Rotating Machinery Components

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DEDICATION

To my parents, for their unwavering love, encouragement, and sacrifices, which have made me who I am today. Your faith in my abilities has been my guiding light.

To my siblings Maroua, Ines and Hadil, for being my source of strength and always cheering me on.

To my best friends Maroua and Ibtissem , who provided endless support and understanding, especially during the toughest times.

And lastly, to myself, for the perseverance and dedication that brought me to this milestone.

Thank you for standing by me. This accomplishment is shared with everyone who helped along the way.

ALLAOUI Nedjoud

DEDICATION

Nestled within this MATLAB script lies my heartfelt dedication message

```
% Dedication
% This project is dedicated to my family, friends, and mentors,
% whose unwavering support and guidance have been the foundation
% of my success. Your love and encouragement have made this journey
% possible.

% Create a blank figure
figure;
axis off;

% Define the text to display
dedicationText = {
    'To my family, the unwavering foundation of my strength and
inspiration.'
    'To the silent champions whose belief turned doubts into dreams
achieved.'
    'And to those who wanted to know what I would do if I didn’t
win….I guess we’ll never know.'
};

% Display the text in the plot
text(0.5, 0.5, dedicationText, 'FontSize', 14, 'HorizontalAlignment',
'center', 'VerticalAlignment', 'middle', 'Color', 'black',
'FontWeight', 'bold');
title('Dedication');
```

BENAISSA Maroua

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LIST OF ABBREVIATIONS

CBM Condition Based Maintenance

RCM Reliability Centered Maintenance

PdM Predictive Maintenance

AE Acoustic emission

IRT Infrared Thermography

RMS Root Mean Square

PF Peak Factor

FFT Fast Fourier Transform

DFT Discrete Fourier Transform

PSD Power Spectral Density

HFRT High Frequency Resonance Technique

STFT Short-Time Fourier Transform

EMD Empirical Mode Decomposition

IMF Intrinsic Mode Function

WVD Wigner-Ville Distribution

CWT Continuous Wavelet Transform IA Intelligence Artificielle

SVM Support Vector Machine

QSVM Quadratic Support Vector Machine

KNN K-Nearseat Neighbors

NN Neural Network

LR Logistic Regression

SBS Sequential Backward Selection

DA Discriminant Analysis

DT Decision Tree

STD Standard Deviation

AMAV Absolute Mean Amplitude Value

CLI Clearance Indicator

CEEMDAN Complete Ensemble Empirical Mode Decomposition with Adaptive Noise

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GENERAL INTRODUCTION

In various fields and sectors such as industry, transportation, and energy production, rotating machinery plays a significant role in achieving the goals of current technology. Consequently, research and studies are currently underway on this type of machinery, aiming to increase its lifespan through maintenance technology, enhance its rotation speed, and improve its efficiency.

The monitoring of rotating machinery relies mainly on extracting information revealing encountered degradation conditions. In this case, many sources of information have been explored and tested in the past, with varying degrees of effectiveness. These include oil analysis, temperature analysis, acoustic emissions, and vibration analysis.

Diagnosis is a technique of non-destructive testing used for the operational condition monitoring of rotating machinery. As we know, all machines are subject to vibrational phenomena that generally increase as the machine's lifespan increases. If these vibrations become undesirable, it is necessary to intervene to discover the cause and attempt to reduce them.

Bearings are critical components in mechanical systems that support rotating shafts and reduce friction between moving parts. They play a vital role in ensuring the smooth operation of various machines by facilitating rotation and minimizing wear and tear. Bearings are used in a wide range of equipment and devices, and they have a broad spectrum of applications. These components can sustain significant loads and speeds, making them indispensable in machinery ranging from household appliances to industrial equipment.

As is well known, many machines and pieces of equipment rely on bearings. Therefore, a bearing failure can severely impair the operation of a machine or an entire system. For this reason, it has been proposed to design an intelligent diagnostic system capable of identifying a failure before the machines and equipment break down.

With the development of microelectronics and information systems, a new technological race related to the monitoring of rotating machinery through diagnostics or prognostics began among several companies interested in the maintenance of machines and components. All competitors in this field rely on artificial intelligence, which has so far demonstrated its effectiveness. In our project, we will use machine learning for the purpose of classification. But before that, we will go through various signal processing techniques.

This report for our final year project is divided into four chapters. In the first chapter, we will present concepts on maintenance and monitoring, specifically the different types of maintenance and monitoring techniques. In the second chapter, we will introduce the main faults of rotating machinery and conduct a study on the kinematic frequencies of faults that appear in each component. In the third chapter, we will detail diagnostic techniques. This will involve studying various signal processing techniques and examining the development of artificial intelligence and its contribution to the field of rotating machinery diagnostics. In the final chapter, we will conduct a study on the diagnosis of different faults in rotating machinery, including their detection and localization, and we will explain the various approaches followed for machine learning, also discussing the results obtained. This report concludes with a general conclusion, in which we summarize the work carried out and highlight some perspectives that should enable its further development

CHAPTER I

MAINTENANCE AND MONITORING STRATEGIES

I.1 Introduction

Industrial equipment serves as the cornerstone of various sectors, influencing dependability, safety, environmental sustainability, and economic efficiency. Ensuring optimal performance and longevity of these assets while managing costs throughout their lifecycle poses a significant challenge.

The maintenance landscape is evolving rapidly, driven by the need for more efficient strategies. This chapter delves into the intricacies of maintenance techniques, focusing on diagnosing and prognosticating challenges associated with rotating machinery.

As industries embrace advanced sensor technologies and real-time monitoring systems, the traditional reactive maintenance approach is being supplanted by proactive strategies. These modern monitoring techniques continuously collect and analyze data, facilitating early anomaly detection and predictive maintenance. Consequently, industries can minimize downtime, optimize performance, and prolong the lifespan of their machinery.

I.2 Generalities on maintenance

I.2.1 Definition of maintenance

Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function [1]"excerpt from standard NF-EN 13306."

I.2.2 Different types of maintenance

I.2.2.1 Reactive maintenance

Reactive maintenance, also known as unplanned maintenance, is a conventional approach characterized by addressing maintenance issues only after they've become apparent, such as defects, breakdowns, or stoppages. This method is typically suitable for facilities with minimal machinery and where the plant's operations aren't heavily reliant on the reliability of any single machine. Additionally, it might be justified when the failure rate is low and the consequences of failure don't entail significant cost or safety implications. This category encompasses breakdown or corrective maintenance as well as emergency repairs [2].

a. Corrective Maintenance

Corrective maintenance, as per the standard [NF EN 13306], involves executing maintenance operations subsequent to fault recognition, with the objective of restoring an item to a functional state capable of performing its intended function [1]. In this type of maintenance, the intervention occurs after the occurrence of the failure.

b. Emergency Maintenance

Emergency maintenance, also referred to as breakdown maintenance, is performed when machinery requires immediate attention to maintain its operation. This type of maintenance is highly disruptive as it interrupts the production process, diverts technicians from their regular tasks, and hampers adherence to schedules. In severe instances, emergency maintenance can even prevent organizations from meeting their schedules, depending on factors such as the extent of damage, repair time, availability of spare parts, and the importance of the affected machinery [3].

I.2.2.2 Proactive Maintenance

In broad terms, proactive maintenance, also known as planned maintenance, encompasses a range of activities involving meticulous planning, documentation, and monitoring to uphold a plant's maintenance standards at acceptable levels. This approach enhances the efficiency of day-to-day maintenance operations and ensures that maintenance tasks are anticipated and prepared for in advance. Planned maintenance leverages data from past maintenance activities to formulate precise time and cost projections, thereby enhancing maintenance efficiency and cost-effectiveness [3]. This strategy can be categorized into two main types: preventive and predictive maintenance. Preventive maintenance includes strategies such as constant interval, age-based, and conditional maintenance. Predictive maintenance, on the other hand, involves methodologies like Condition Based Maintenance (CBM) and Reliability Centered Maintenance (RCM), which anticipate maintenance needs based on equipment conditions and reliability analysis.

a. Preventive maintenance

As an alternative to corrective maintenance, Preventive maintenance has been adopted for emerging technologies since such systems are generally more complex than those based on the use of hand tools. The basic principle of a preventive maintenance system is that it involves predetermined maintenance tasks that are derived from machine or equipment functionalities and component lifetimes. Accordingly, tasks are planned to change components before they fail and are scheduled during machine stoppages or shutdowns [4]. This approach encompasses various methodologies such as these [2]:

- **Constant Interval Maintenance:** Maintenance tasks are carried out at fixed time intervals, with additional maintenance conducted in response to any system failures. The timing of these intervals is carefully chosen to balance the risk of potential failures with the costs associated with maintenance.

- **Age-Based Maintenance:** This strategy involves performing preventive maintenance only after a system has reached a specific age threshold, known as "t." If a system fails before reaching this threshold, maintenance is undertaken, and subsequent maintenance is scheduled for "t" units of time later. This strategy aims to reduce the frequency of maintenance intervals compared to constant interval maintenance by postponing maintenance until a predetermined age is reached.
- **Imperfect Maintenance:** This approach recognizes that after preventive maintenance, a system may not always return to its original condition but may instead remain between optimal and failure states. These maintenance strategies take into account the uncertainty surrounding the current state of the equipment when planning future maintenance activities, ensuring a flexible approach to scheduling.

b. Predictive maintenance

Predictive Maintenance (PdM) is a sophisticated maintenance approach that harnesses data analytics, machine learning, and predictive modeling to anticipate potential equipment or machinery failures. Unlike traditional fixed schedules or reactive responses to deterioration signs, predictive maintenance utilizes real-time sensor data, historical performance records, and external factors to forecast and avert equipment failures proactively [5]. This strategy can be classified into condition-based maintenance and reliability-centered maintenance:

- **Condition-based maintenance (CBM):** is a decision-making strategy where maintenance actions are determined by assessing the condition of the system and/or its components. This evaluation relies on continuously monitored parameters specific to the system or application. For example, vibration characteristics or indices are suitable for rotary systems. The advantage of this approach is evident as maintenance decisions are based on predictive and corroborative data that accurately reflect the system's state.

Reliability-centered maintenance (RCM): This method involves leveraging system reliability estimates to create a maintenance schedule that optimizes costs. Originally developed within the aircraft industry, Reliability-Centered Maintenance (RCM) prioritizes safety and availability alongside cost-effectiveness, particularly in safety-critical applications like aircraft maintenance. The primary objective is to minimize costs and downtime while ensuring failure prevention. RCM combines two main tasks: analyzing and categorizing failure modes based on their impact on the system, and evaluating how maintenance

Schedules affect reliability. The failure analysis begins with identifying all possible failure modes and then categorizing them according to their consequences [2].

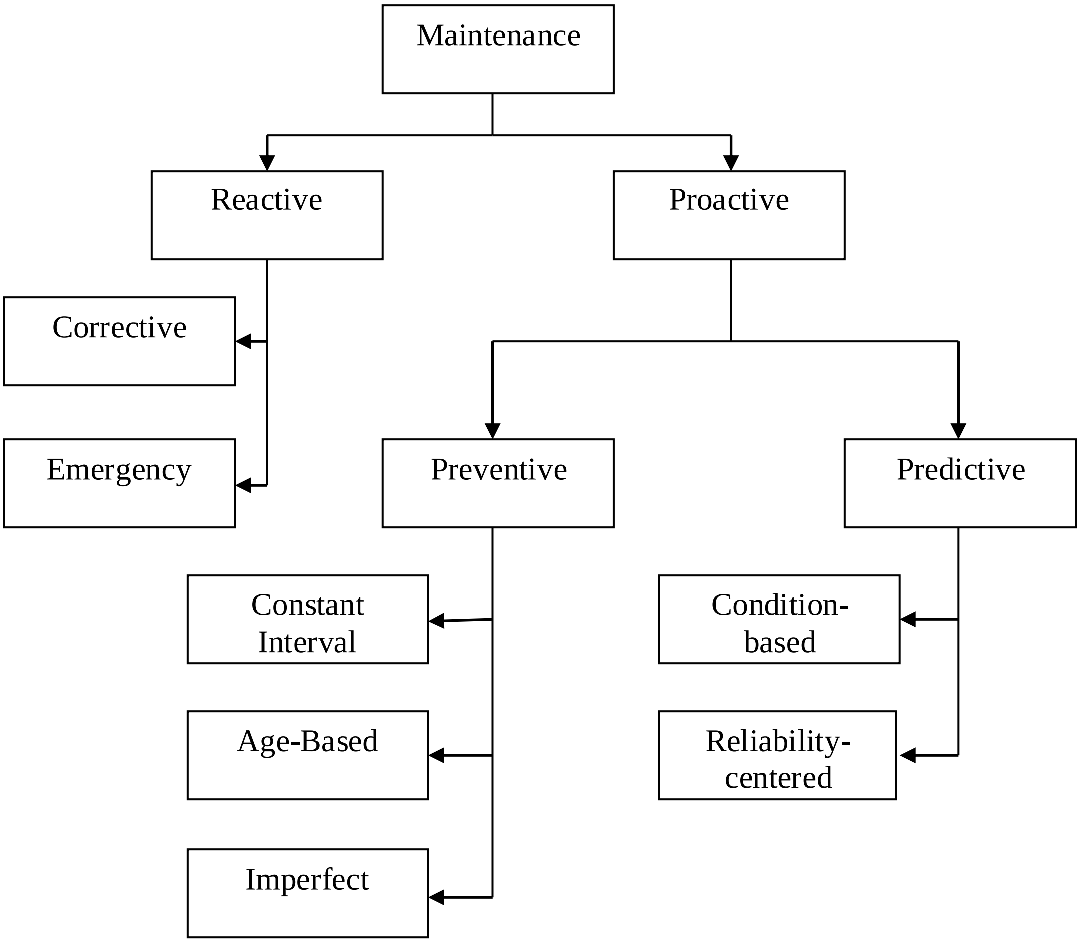

FIGURE I.1—Taxonomy of maintenance philosophies [2].

I.3 Dependability

I.3.1 Definition

Dependability is the ability to deliver service that can justifiably be trusted. This definition highlights the importance of trust validation [6]. The alternate, quantitative definition that establishes the service's dependability is dependability of a system, which is the ability to avoid service failures that are more frequent and more severe than is acceptable to the user(s).

I.3.2 Attributes

Over the last three decades, dependability has evolved into an integrated concept that includes the following attributes:

- **Availability:** readiness for correct service;
- **Reliability:** continuity of correct service;
- **Safety:** absence of catastrophic consequences on the user(s) and the environment;
- **Confidentiality:** absence of unauthorized disclosure of information;
- **Integrity**: absence of improper system alterations;

- **Maintainability:** ability to undergo, modifications, and repairs.

Security is the concurrent existence of availability for authorized users only, confidentiality, and integrity with 'improper' meaning 'unauthorized' [6]

The comprehensive taxonomy of dependable computing, detailing various attributes, is visually depicted in Figure I.2**,** illustrating the outlined schema.

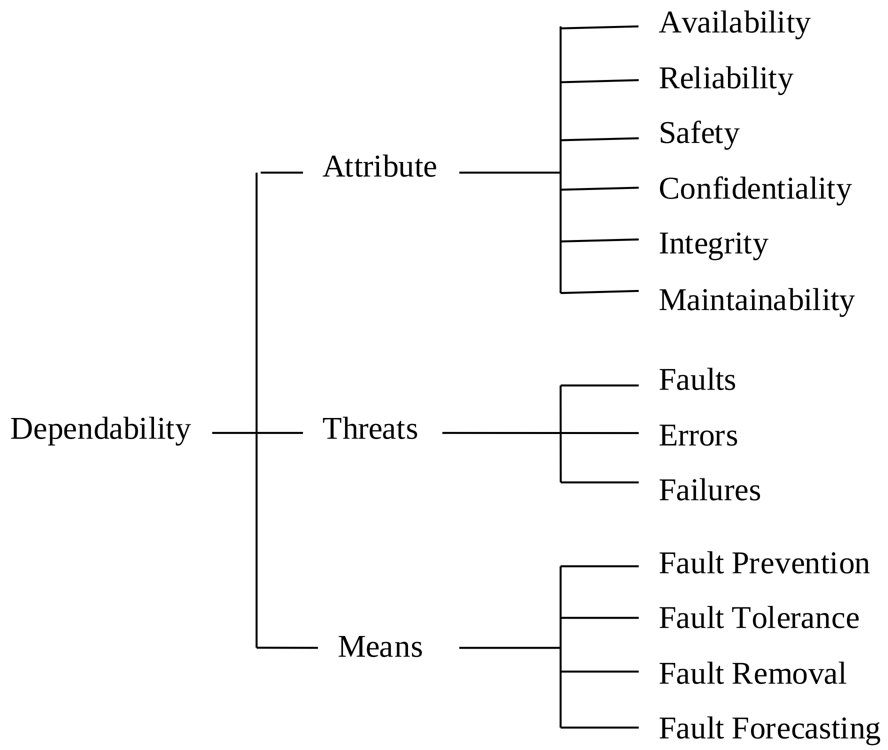

FIGURE I.2—Dependability tree [6]

I.4 Monitoring Techniques

Surveillance is a necessary operation that allows for monitoring the real-time condition of the asset. It can be conducted continuously, at predetermined or non-predetermined time intervals, measuring either time or the number of units used. This function is ensured through the regular recording of degradation or performance indicators to ensure the monitoring of machinery and equipment. Various analysis techniques exist (Figure I.3), such as:

- Vibration analysis.
- Acoustic emission.
- Ultrasonic testing.
- Thermography.
- Oil and lubricant analysis.
- Resistance variation in an electrical circuit.
- etc.

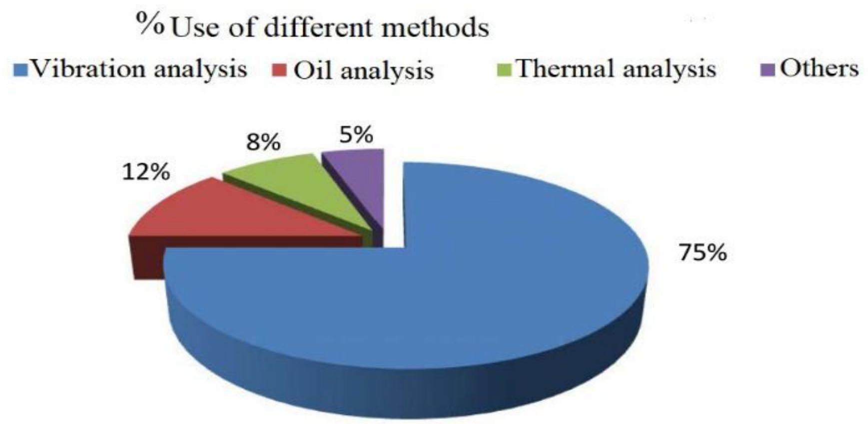

FIGURE I.3 — Partition of the different maintenance techniques [7].

I.4.1 Vibration analysis

Even in good condition, machines generate vibrations. Many such vibrations are directly linked to periodic events in the machine's operation, such as rotating shafts, meshing gear teeth, rotating electric fields, and so on [8].Vibration analysis of industrial equipment has been widely used in preventive maintenance activities and effectively detects most anomalies in rotating machines. Defects caused by bearings, worn clearances, or misalignment will manifest as a change in the internal forces of the machine, resulting in the appearance of vibrations. According to the ISO 2041 standard "Vibrations and shocks - Vocabulary (August 1990)," the concept of vibration is defined as follows: "Variation over time of the intensity of a characteristic quantity of the motion or position of a mechanical system, when the intensity alternates between greater and smaller than a certain average or reference value." [9]

I.4.2 Infrared Thermography

Infrared Thermography (IRT) is a science dedicated to the acquisition and processing of thermal information from non-contact measurement devices. It is based on infrared radiation (below red), a form of electromagnetic radiation with longer wavelengths than those of visible light. Any object at a temperature above absolute zero (i.e., T > 0 K) emits infrared radiation. The human eye cannot see this type of radiation. Thus, infrared measuring devices are required to acquire and process this information [10]. Thermal cameras are commonly used to monitor live electrical equipment, heating systems, or certain industrial processes (such as welding and rolling). Its application program for monitoring the operating condition of rotating machines is not significant. One of the main reasons is that it does not require any obstacles between the camera and the object being observed.

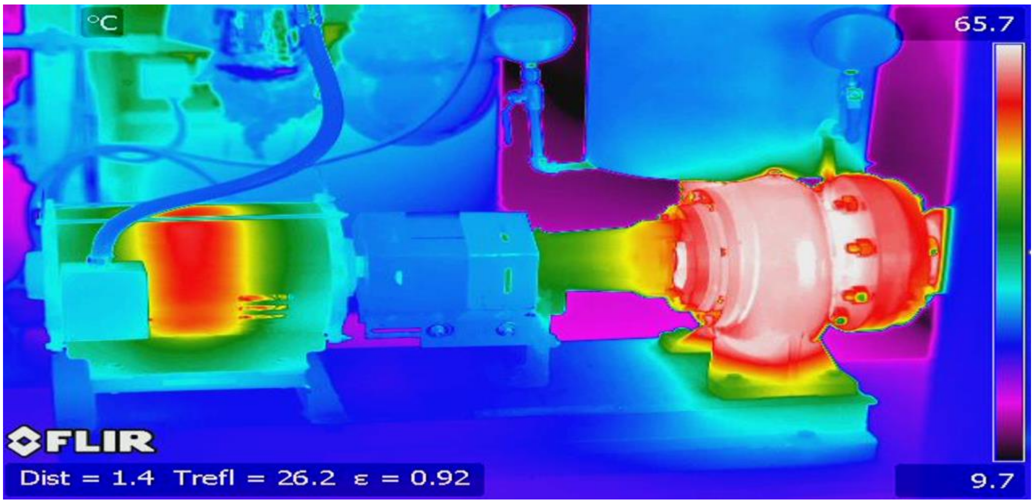

FIGURE I.4 —Thermal image of a rotating machine [11].

I.4.3 Acoustic emission

Acoustic emission (AE) is the phenomenon of energy release, in the form of transient elastic waves, resulting from micro-local displacements within a material subjected to static or dynamic stress (standard AFNOR NFA 09350) [12]. When stress is applied, a portion of the energy is converted into elastic waves that propagate in various directions within the material, reaching its boundaries. By analyzing the vibrations of these elastic waves detected on the material's surface, valuable insights can be gathered regarding the underlying events causing these vibrations. This technique finds significant application in monitoring rotating machinery, where detecting and analyzing AE signals can provide crucial information about the condition and potential faults of such equipment.

I.4.4 Analysis oils and lubricants

The main function of lubricants is to ensure smooth contact between different components of the machine, thereby reducing the risk of wear. They can also perform other tasks, such as cooling, rust and corrosion prevention, and non-destructive monitoring of machine operating conditions. The lubricant also carries information from the inside to the outside of operating machines in the form of wear particles, chemical contaminants, and so on [8]. When a machine part fails, examining the physical and chemical characteristics of the lubricant becomes crucial, especially in the context of rotating machinery. This analysis offers insights into the extent and nature of lubricant degradation, whether originating from the lubricant itself or contamination caused by wear debris. Such insights are gathered through routine inspections and assessments, encompassing straightforward evaluations like visual checks, odor assessments, and monitoring changes in lubricant color. Additionally, more sophisticated laboratory methods such as chromatography, photometry, or spectroscopy contribute to a comprehensive understanding of lubricant health. While primarily applicable to circulating oil lubrication systems commonly utilized in rotating machinery, some analyses can also be adapted for grease lubricants.

Table I.1— Main Diagnostic Techniques and Their Uses [13]:

	Main advantages	**Main limitations**	**Field of application preferred**
Vibration analysis	-Early detection of early stage - Possibility of in-depth diagnosis - Enables continuous monitoring. - Allows remote monitoring of equipment (remote maintenance).	- Spectra are sometimes difficult to interpret. - In the case of continuous monitoring, relatively expensive installations.	- Detection of faults in all kinematic machine components (unbalance, misalignment, play, etc.) and in the machine structure.
Oil analysis	- Detection of abnormal lubricant pollution before it leads to wear or overheating. ıly can be identified by	- Cannot pinpoint fault location - Requires careful sampling.	- Control of lubricant physico-chemical properties, detection of lack of lubrication, analysis of wear elements, analysis of process contamination (sealing), etc
IR Thermography	- Enables quick system system. - Results are often results.	- Fault detection at earlier stage than vibration analysis - Control limited to what the camera can "see" (surface surface heating). - Does not diagnosis. in-depth	- Detection of all faults causing overheating (lack of lubrication in particular).

Acoustics analysis	- Allows detection of audible faults - Allows continuous monitoring.	- Sensitivity to ambient noise. - Diagnosis often difficult to perform. - Measurement repeatability problems.	- Detection of unusual noise that can then be analyzed by vibration analysis.

I.5 Sensors and Monitoring Devices

In the realm of rotating machinery surveillance and maintenance, sensors and monitoring devices serve as indispensable tools, continuously collecting critical data to ensure optimal performance and longevity. To further understand the landscape of rotating machinery surveillance and maintenance, it's essential to examine the primary types of sensors employed in this context. These include:

- Vibration Sensors.
- Microphones.
- Infrared (IR) Cameras.

I.5.1 Vibration Sensors

Vibration is characterized by three fundamental kinematics: displacement, velocity, and acceleration, expressed respectively in µm, [mm/s], and [m/s²]. The process of capturing vibration data begins with the conversion of mechanical oscillations generated by machinery into electrical signals, a task entrusted to vibration sensors. Among the widely adopted sensors for this purpose are proximity probes, velocimeters, and accelerometers, each
specializing in measuring a specific aspect of vibration dynamics—displacement, velocity, and acceleration, respectively. Manufacturers implement various physical principles to design these sensors, resulting in different types such as eddy current sensors, displacement sensors with capacitive or inductive probes, Doppler effect velocimeters, and piezoelectric accelerometers. Notably, piezoelectric technology stands out across these sensors for its exceptional metrological qualities, compatibility, and ease of use.

I.5.1.1 Proximity sensors

A proximity sensor is a device capable of detecting nearby objects without the need for physical contact. There are various types of proximity sensors, including:

- Inductive: These sensors detect nearby metallic objects by creating an electromagnetic field around themselves or on a sensing surface.

- Capacitive: Utilized for detecting both metallic and non-metallic objects.
- Photoelectric: These sensors detect objects using a light source and receiver as their main components.
- Magnetic: Operating based on the presence of permanent magnets in a sensing area, these sensors use an electrical switch to detect objects [14].

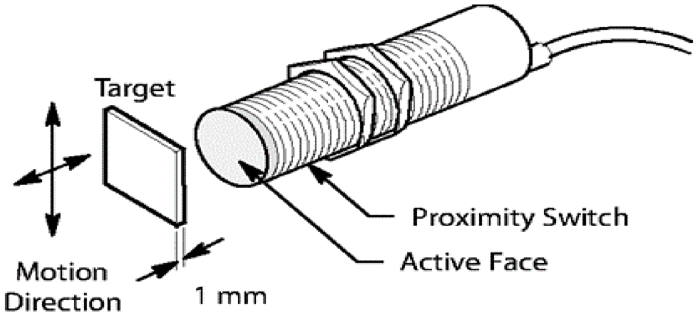

Figure 1.5—Proximity Sensors [15].

I.5.1.2 Velocimetery

Velocimeters, also known as speed sensors, play a critical role in vibration monitoring systems. They consist of a seismic probe that establishes contact with the machine component under observation to measure its absolute movement. The key points regarding velocimeters are:

1. **Design**: Velocimeters typically feature a design comprising a seismic mass connected to housing via a spring. This mass is attached to a coil, which moves within a permanent magnetic field generated by a magnetized rod.
2. **Functionality**: As the machine component vibrates, inducing motion in the sensor, the coil's movement within the magnetic field produces an electrical voltage. This voltage is directly proportional to the speed of the coil's movement and, consequently, to the velocity of the machine's vibration.
3. **Resonance Frequency**: The resonance frequency of velocimeters generally falls within the range of 8 to 15 Hz.
4. **Dynamic Range**: Velocimeters have a dynamic range that extends from 10 to 2000 Hz, making them suitable for monitoring a wide range of machinery and detecting variations in vibration speed across different operational frequencies.

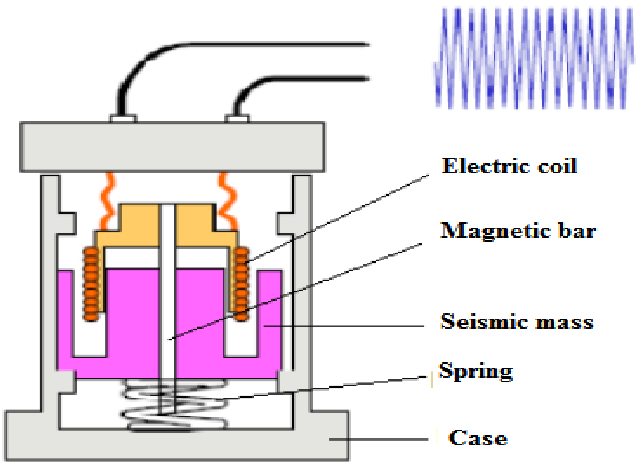

Figure I.6—Longitudinal section of a velocimeter [9]

I.5.1.3 Accelerometers

Accelerometers come in various types, including analog and digital variants. Analog accelerometers require the signal to be digitized by the microcontroller's ADC, with the developer responsible for enforcing measurement laws. On the other hand, digital accelerometers feature built-in ADCs, managing measurement laws independently. Communication with digital accelerometers often follows a specific protocol [9].

- **Analog accelerometers:** Analog accelerometers, like the piezoelectric accelerometer (Figure), consist of a disc made of piezoelectric material (such as Quartz). This disc acts as a spring upon which a preloaded seismic mass rests.

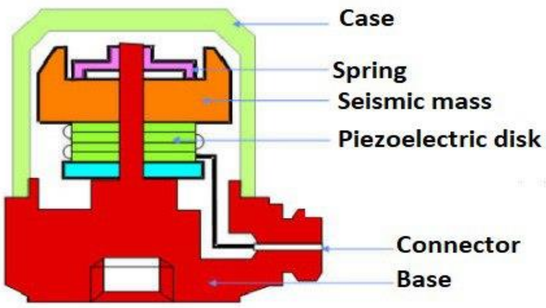

Figure I.7—Piezoelectric accelerometer [9].

- **Digital accelerometers: Digital** accelerometers are accelerometers with integrated electronics. They possess built-in or integrated charge conditioning to deliver a voltage proportional to the acceleration.

I.5.2 The infrared thermographic camera

The thermal imaging camera features a sensor in its structure that records radiation within the 3-5 μm and 8-12 μm thresholds. Ideal conditions for measuring thermal radiation are achieved when all radiation emitted by the object is captured and recorded by the camera, without considering possible disruptive factors such as the atmosphere or material emissivity. In the case of measurements at short distances from the object (a few meters), atmospheric absorption is not taken into account [16].

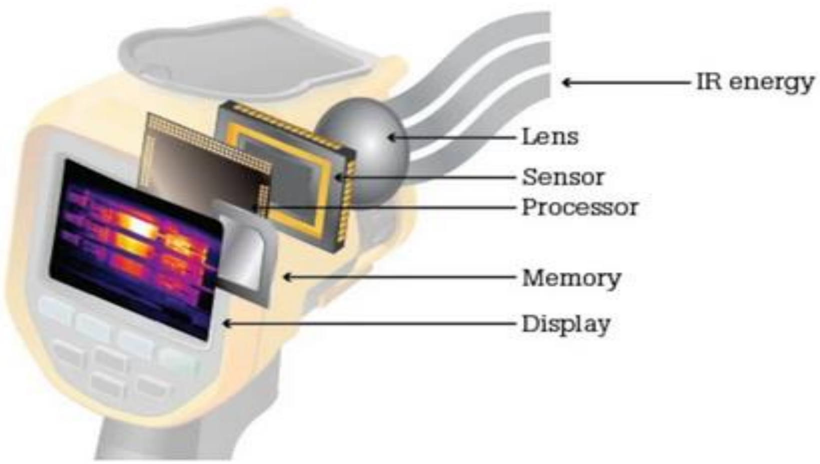

Figure I.8— Components of an Infrared Thermographic Camera [17]**.**

I.5.3 Microphones

The primary function of a microphone is to capture sound waves and transform them into an electrical signal called an audio signal. In other words, a microphone is an energy transducer that converts acoustic energy into electrical energy. There are several types of microphones (electret, condenser, ribbon, moving coil, dynamic, etc.), and the system used for energy conversion is generally specified by the microphone's name. The choice of microphone depends on various factors, such as the sound source (instrument, solo voice, etc.), the recording location (studio, multipurpose hall, outdoor, etc.), and the microphone's placement relative to the source, among others. In summary, microphones are fundamental tools in monitoring devices, enabling the effective capture of sound for surveillance, recording, and analysis across diverse applications and environments.

I.6 Vibration Diagnosis

Vibration diagnosis is a maintenance tool that has gained significant recognition due to advancements in computer science and signal processing. This technique involves utilizing a system that integrates vibration measurement, typically through accelerometers, to analyze the dynamic behavior of rotating machinery. By doing so, it facilitates the establishment of a diagnosis regarding the operating condition of the machinery.

I.6.1 Principle of diagnosis and vocabulary

The diagnosis of rotating machines follows a logical sequence for fault localization, evaluation of its severity, and decision-making at the end, as shown in Figure 1.8, the steps for implementing a diagnostic system

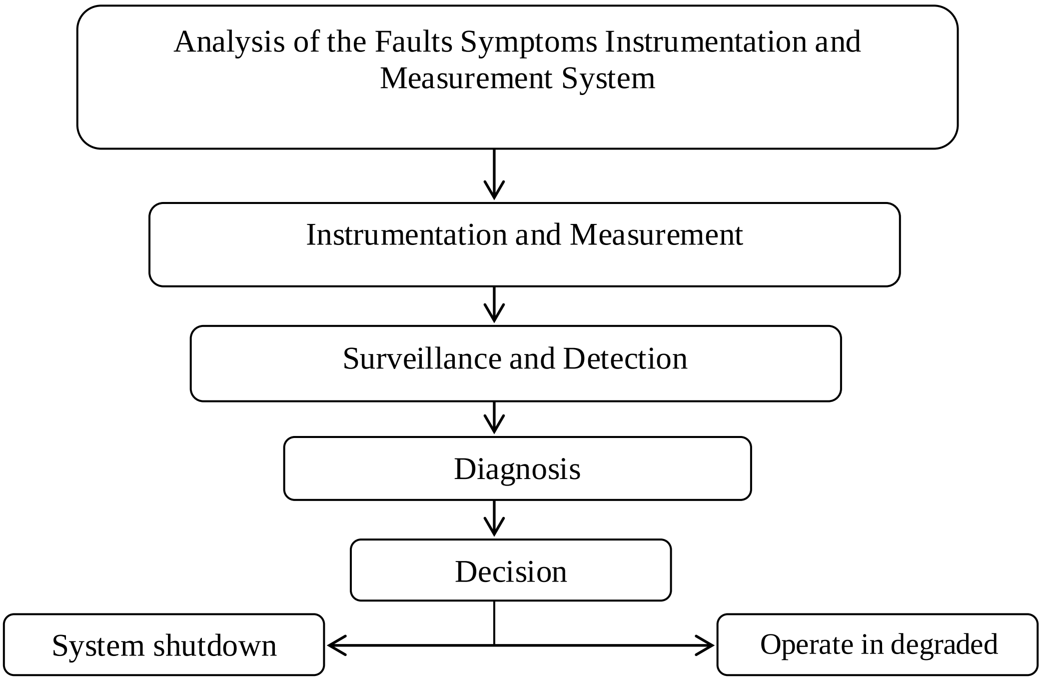

FIGURE I.9 — Steps for implementing a diagnostic system [18].

- **System Analysis:** This is a crucial step that involves defining an objective for the system to be implemented. In order to do so, it is necessary to investigate the system's characteristics (such as the number of gear teeth to monitor), the defect and the symptoms of the defect to identify, etc. It is this step that led to the selection of the method to be implemented, specifically the signal processing method to be used.
- **Instrumentation and measurement:** This step involves choosing the type of sensor to use (accelerometer, current sensor, microphone, etc.) based on the measurement conditions (contact surface, machine type, etc.), as well as the technical characteristics of the sensor (permissible frequency range, sensitivity, etc.). The second point is the choice of the acquisition card, which depends on the types of faults to be monitored. This allows for the definition of the acquisition frequency, the type of recording (continuous, periodic, etc.).

- **Monitoring and detection:** Once the sensor is installed and the acquisition begins, the monitoring operation consists of extracting statistical indicators from the acquired signals that reflect the state of the machine. The indicators used are generally "simple" and are usually only used for detection purposes, for example, to indicate when the indicator exceeds a certain threshold, which indicates an abnormal state of the machine. These thresholds are usually determined by empirical or statistical signal processing methods. Many signal processing methods are better suited for "detection"
- **Diagnostic:** The diagnostic process involves determining the faulty part of a complex system. The term "must be isolated" is often used by Anglo-Saxons. This is where signal processing can play its biggest role. It involves extracting from the signal, with knowledge of the system and the symptoms of the faults, the parameter(s) related to these symptoms. In addition to signal processing methods, this step can use "decision" methods, such as pattern recognition.
- **Decision:**This is the final step in the diagnostic procedure. In an industrial environment, it involves determining the actions to be taken, initiating maintenance operations, stopping the machine, etc.

I.7 Prognostics

Compared to diagnostics, prognostics literature is significantly less extensive. In machine prognostics, two primary prediction methodologies are employed. The prevalent approach involves forecasting the remaining operational time before a failure, considering the current machine state and historical operational patterns. This remaining operational time is commonly termed as the remaining useful life. Conversely, in critical scenarios where a fault or failure could lead to substantial consequences, predicting the likelihood of uninterrupted machine operation without faults or failures until a future point, such as the next inspection interval, becomes more favorable. Evaluating the probability of fault-free operation until the subsequent inspection or condition monitoring interval can serve as a valuable guide for maintenance personnel in assessing the adequacy of the inspection schedule [19]. Furthermore, machine prognostics offer the advantage of proactive maintenance planning, which can lead to significant cost savings and operational efficiencies, particularly in the realm of rotating machinery components. This proactive approach allows organizations to:

- Accurately predict the remaining useful life or the likelihood of fault-free operation for components such as bearings, gears, and shafts.
- Schedule maintenance activities in advance, minimizing unplanned downtime and reducing the risk of unexpected failures.
- Allocate resources more effectively and optimize equipment performance.

- Extend the lifespan of critical rotating machinery.

Additionally, machine prognostics facilitates condition-based maintenance strategies specific to rotating components. This includes:

- Triggering maintenance interventions based on the actual condition of rotating components rather than predetermined schedules.
- Reducing unnecessary maintenance tasks and improving operational efficiency.
- Lowering maintenance costs over time while ensuring the reliability and longevity of rotating machinery systems.

I.8 Conclusion

In conclusion, this chapter has provided a thorough examination of maintenance practices and challenges pertaining to rotating machinery. From the introductory discussion highlighting the significance of industrial equipment in various sectors to the detailed exploration of maintenance philosophies like preventive and predictive maintenance, we've underscored the importance of adopting proactive strategies to ensure optimal performance and longevity of machinery.

Furthermore, we delved into the realm of monitoring techniques, including vibration analysis, infrared thermography, acoustic emission, and analysis of oils and lubricants. These techniques serve as invaluable tools for early fault detection and informed decision-making in maintenance activities.

The role of sensors and monitoring devices was also emphasized, showcasing their indispensable nature in continuously collecting critical data to uphold machinery performance and reliability. From vibration sensors to infrared thermographic cameras, these devices play a crucial role in ensuring the efficient operation of rotating machinery.

Lastly, we discussed prognostics and its significance in assessing the remaining operational time before a failure and predicting fault-free operation. By evaluating the probability of uninterrupted machine operation, maintenance personnel can optimize inspection schedules and plan maintenance activities effectively.

In essence, this chapter highlights the necessity of proactive maintenance strategies and advanced monitoring techniques in ensuring the reliability, efficiency, and longevity of rotating machinery across industrial sectors.

As we transition to the subsequent chapter, which delves deeper into technical diagnosis and the identification of primary faults afflicting rotating machinery, the foundational understanding established here serves as a springboard for dissecting specific fault scenarios and implementing targeted diagnostic methodologies.

CHAPTER II

MAIN FAULTS IN ROTATING MACHINERY

II.1 Introduction

"A machine is an assembly of mechanical, hydraulic, or electrical parts contributing to exert one or more specific functions, and in particular, the application of a modulated or unmodulated force, intended to overcome resistance or to ensure movement with or without force transmission" [20].

Rotating machines absorb energy and convert the absorbed energy into another form of energy through rotation, which may or may not have the same properties. For example, an electric motor absorbs electrical energy, which is converted into mechanical energy. In another example, when translation and rotation change, this can result in elevators, saws, belts, etc. An alternator is a rotating electrical machine that converts mechanical energy, thermal energy, wind energy, nuclear energy, or hydraulic energy into electrical energy. Experience gained from rotating machines has led to numerous faults, including static or dynamic rotor imbalance, misalignment, bearing failure such as deterioration of the cage, tightening failure, coupling failure, not to mention faults that appear in gears, etc. In this chapter, we first present the main mechanical faults of rotating machines by discussing how to calculate the kinematic frequencies of some failure modes.

II.2 Main mechanical failures of a rotating machine

In general, mechanical faults are the most common faults among all faults of rotating machines.

II.2.1 Imbalance faults

This is the most common cause of vibration. This phenomenon occurs at the rotation speed and can be caused by the poor spatial distribution of mass in the structure, causing the center of gravity to move off the geometric axis of the rotor of the rotating machine. Imbalance is generally caused by material defects, design errors, manufacturing errors, or defects occurring during use.

Among the faults that occur during use, we mention

- Erosion or corrosion of the rotor,
- Accumulation of material on the propellers,
- Thermal deformation of fans of hot gas exhaust ducts,
- Blade fracturing on turbine rotors,
- Wear of grinding wheels,
- Displacement of rotor parts caused by centrifugal force,

• General wear.

• Etc.

II.2.1.1 Static Imbalance

This type of imbalance occurs when the principal axis of inertia and the axis of rotation are parallel but not coincident (Figure II.1).

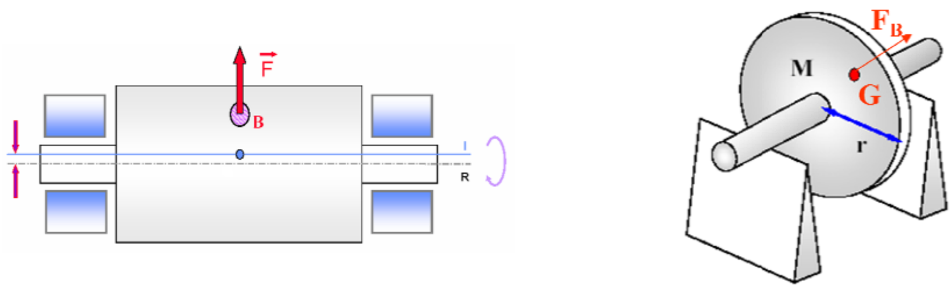

Figure II.1 — Static imbalance [21].

II.2.1.2 Imbalance Couple

This couple is generated when the principal axis of inertia forms a non-zero angle with respect to the axis of rotation, and their intersection coincides with the center of mass. (Figure II.2)

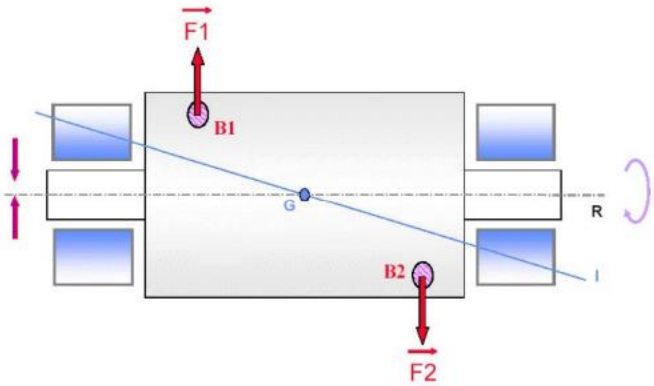

Figure II.2 — Imbalance couple [21].

II.2.1.3 Dynamic Imbalance

This represents the combination of static imbalance and imbalance couple. This type of imbalance occurs when the principal axis of inertia forms a non-zero angle with the axis of rotation, and their intersection does not coincide with the center of mass. (Figure II.3)

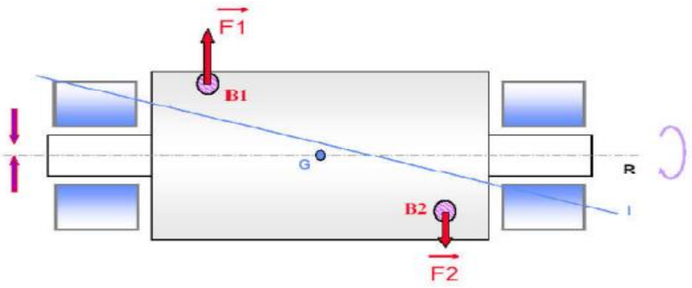

Figure II.3 — Dynamic imbalance [21].

II.2.2 Misalignment

Misalignment is a well-known issue in rotating machinery. Despite the use of self-aligning bearings and flexible couplings, aligning the two shafts and their bearings to ensure there are no forces that could cause vibrations can be challenging. This misalignment can lead to vibrations at the rotation frequency and shaft harmonics 2, 3 (and sometimes even4) of the rotation frequency. There are three types of misalignment (parallel, angular, and mixed), which are well illustrated in figures II.4, II.5, and II.6.

II.2.2.1 Parallel Misalignment

This occurs when the shaft axes have the same orientation angle but are separated vertically, horizontally, or both from each other.

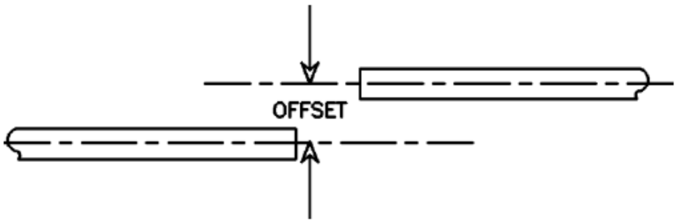

Figure II.4 — Parallel misalignment [22].

II.2.2.2 Angular Misalignment

In this type of misalignment, the two shaft axes form an angle, which can be in the vertical plane, horizontal plane, or in two planes.

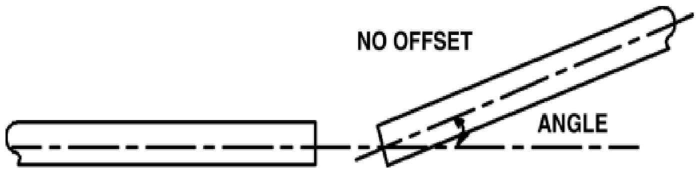

Figure II.5 — Angular misalignment [22].

II.2.2.3 Mixed Misalignment

This is the most common type of misalignment problem. It occurs when the shafts are not parallel (i.e., angular) and offset at the same time.

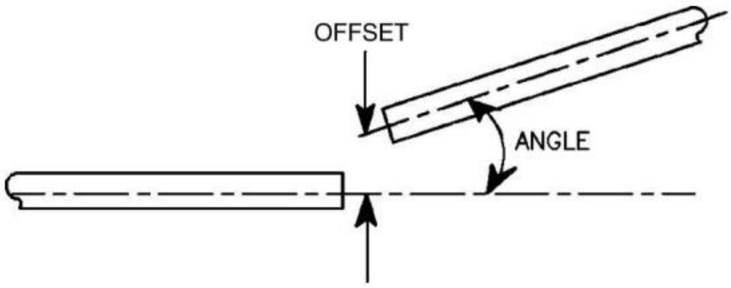

Figure II.6 — Mixed misalignment [22].

II.2.3 Gear Faults

Gear transmission is a widely used elementary mechanism for transmitting motion. It consists of two toothed wheels mobile around axes of rotation, with one driving the other through the action of teeth successively in contact. Depending on the arrangement of the shafts, there are three different types of gears, namely (Figure II.7):

Figure II.7 — Different types of gears [23].

Apart from manufacturing and assembly faults, two main categories of faults that can affect gear mesh are distinguished, generalized and localized faults [24].

II.2.3.1 Generalized Faults

• **Abrasive Wear:** This type of wear is caused by the presence of abrasive particles in the lubricant. When there is significant sliding between the two friction surfaces, the abrasive removes material. Additionally, when the lubricant contains corrosive substances, this phenomenon becomes more pronounced.

• Pitting: These are more or less deep holes that affect all teeth. They mainly occur on relatively hard construction steel gears. These damages can occur due to slight misalignment of the shaft (for example, due to local overpressure). Generalized defects are illustrated in Figure II.8.

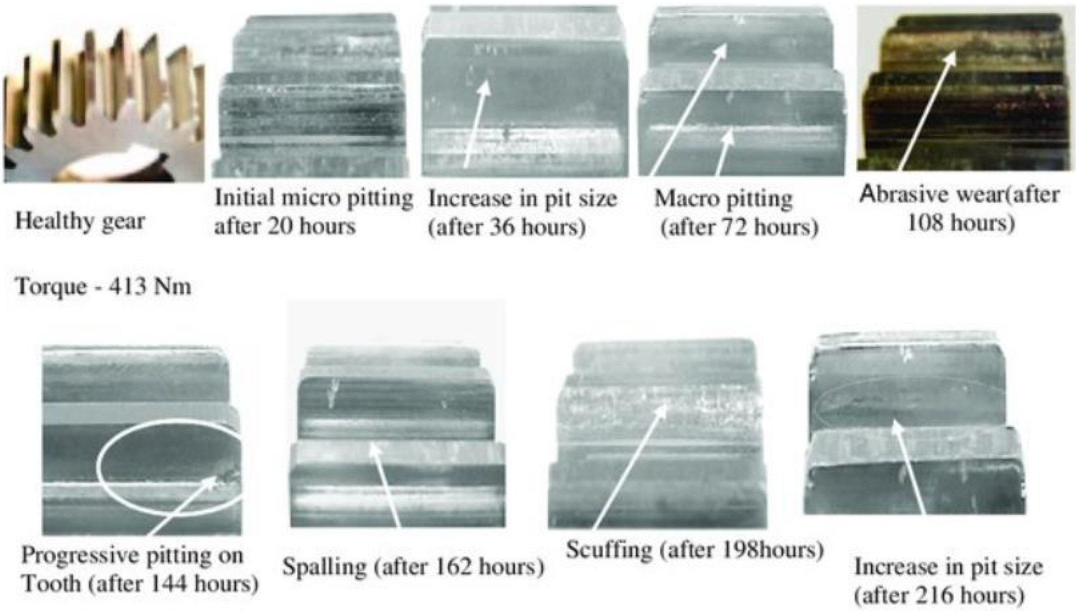

Figure II.8 — Generalized Gear Faults [23].

II.2.3.2 Localized Faults

• **Flaking**: The number of holes here is lower than that of pits, but deeper and more extensive, with more damage due to fatigue of the sublayer at the point of maximum shear. This phenomenon generally evolves rapidly towards failure without going through the wear phase.

• **Cracking:** Will progress with each load, starting from the almost always at the base of the tooth. It appears notably on fine steels hardened by heat treatment, very sensitive to stress concentration. These cracks occur because the stress at the base of the tooth exceeds the material's fatigue limit, and the stress is generally located on the side of the tooth subjected to traction.

• **Seizure:** The sudden destruction of the oil film or friction under load is a direct consequence of the temperature rise. Seizure is mainly favored by high speed, large modules, and few teeth in contact.

Flaking, seizure, and cracking of gears are illustrated in Figure II.9.

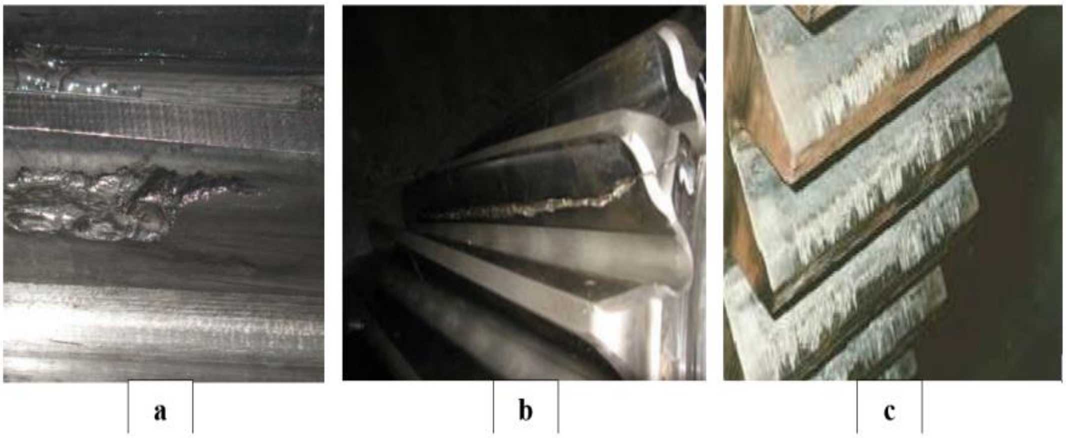

Figure II.9 — Localized faults in gears (a.Spalling b.Cracking c.Seizure) [24]

II.2.4 Bearing Faults

Generally, many machines are equipped with bearing housings for rotational guidance, as they provide a better solution to withstand the friction of rotating machine parts. Bearings consist of four essential elements (Figure II.10):

• The outer ring.

• The inner ring.

• The cage.

• The rolling elements (balls, cones, etc.).

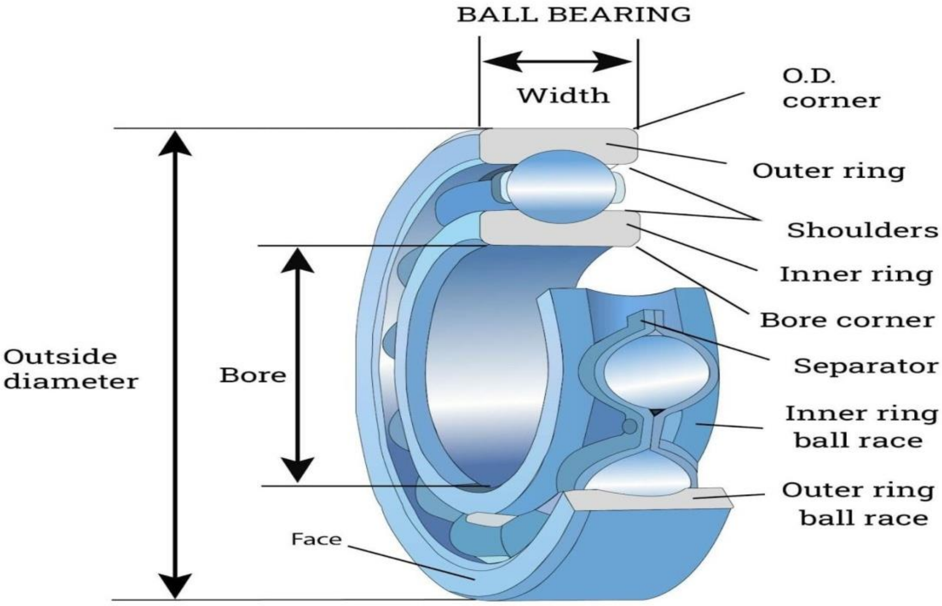

Figure II.10 — Ball Bearing Parts [25].

Depending on their applications and the criticality of the machines on which they are mounted, bearings require monitoring and preventive maintenance to avoid deterioration, which often manifests as more or less significant material removal [26]. These deteriorations are described as follows (Figure II.11):

• **Flaking:** Characterized by traces of cracking and material removal,

• **Contact corrosion:** Red or black discoloration on the bearing contact surfaces, in the bore, and on the outer diameter.

• **Rolling element imprints due to abrasion:** Impressions corresponding to the rolling element spacing or not. Material removal due to wear from vibrations experienced by the stationary bearing.

• **Cage deterioration:** Manifested in various forms: deformation, wear, or breakage of the cages,

• **Pits and grooves:** Sharp-edged pits or a series of narrow parallel bands, related to the passage of electrical current.

• **Impacts, cracks, fractures:** Violent impacts, surface material removal, cracks, ring fractures,

• **Seizure**: Removal of the material's dull area, brown heat marks, rolling element deformation, micro-fusion, and metal rolling.

• **Generalized wear:** Appearing on rolling elements, tracks, and cages (gray tint), due to the intrusion of an abrasive particle.

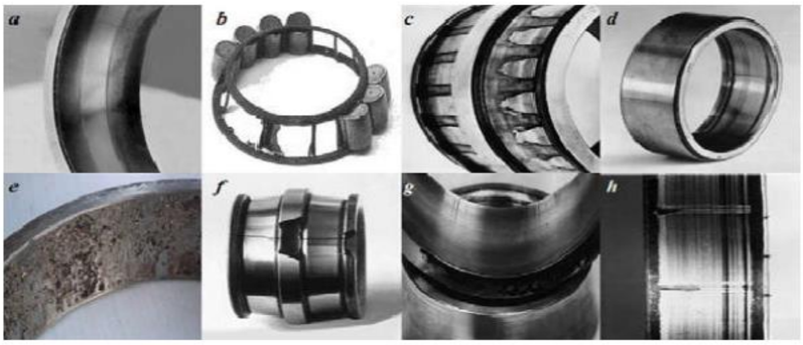

Figure II.11 — Some failures affecting the bearings: a- Generalized wear b- Deteriorated cage c- Corrosion d- Presence of craters e- Flaking f- Cracking and breakage g- Seizure h- Trace marks [27].

II.2.5 Belt Fault

The belt is indeed the heart of the system and is considered an essential component. Belts drive many different components, and even if one of them fails, it can lead to a dangerous situation. Once the engine is running, the belt is always functional. The high temperature under the hood and constant bending has taken their toll. Over time, even the best belts will wear out and need to be replaced.
Belt drive can be prone to many failures, such as: misalignment of pulleys or an eccentric pulley, localized deterioration (part torn off see Figure II.12, separation of ribs and joint defect), and belts that are too loose.

Figure II.12 — Belt Fault (Pull-Out) [26].

II.2.6 Loosening Faults

Mechanical loosening (Figure II.13) is one of the main causes of fault in rotating machinery. The sources of these causes are numerous, including:

- Shocks and vibrations.
- Compression.
- Temperature variations.
- Corrosion.

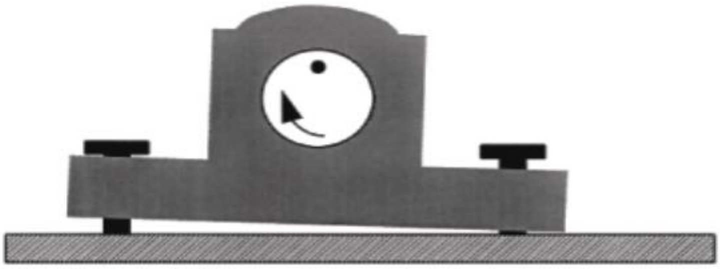

Figure II.13 — Improper mechanical tightening [21].

II.3 Electrical Faults

In some cases, electrical faults can lead to machine shutdown. Generally, electrical faults can be localized in the rotor, stator, transformer, etc. However, most electrical faults occur in the rotor and stator circuits [28] (Figure II.14).

II.3.1 Rotor Faults

The most common faults localized in the rotor can be defined as follows:

- Breakage or rupture of the rotor bar.
- Rupture of a portion of the ring.
- Opening of the electrical circuit.
- Static or dynamic rotor eccentricity.

II.3.2 Stator Faults

The most common faults found in the stator can be defined as follows:

- Insulation fault in a winding.
- Short circuit between turns.
- Short circuit between phase-frame.
- Short circuit phase-frame.

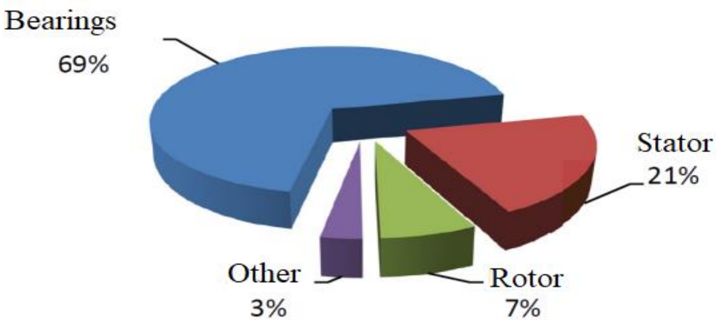

Figure II.14 — Percentage of occurrence of electrical faults in machinery [28].

II.4 Kinematic frequencies (characteristics) of rotating machines

Table II.1 shows the different characteristic frequencies of some failure modes in a rotating machine.

Table II.1—Characteristic frequencies of the main failures affecting rotating machines [29]

Faults	**Characteristic Frequencies and Formulas**
Imbalance	*Rotation frequency* f_r
Fixing fault	*Harmonics of rotational speed:* $\frac{1}{2} f_r$, f_r *and several of their harmonics*
Misalignment	f_r, $2 f_r$ *Generally,* $2 f_r$ *is higher than* f_r *, and axial vibrations are higher than radial vibrations.*
Bearing Defects	*Frequencies corresponding to the passages of rolling elements given by the following equations:* *Outer Race:* $f\,outer = \frac{fr}{2} \times N\,(1 - \frac{d}{D} \cos\alpha)$ *Inner Race:* $f\,inner = \frac{fr}{2} \times N\,(1 + \frac{d}{D} \cos\alpha)$ *Cage:* $fc = \frac{fr}{2} \times (1 - \frac{d}{D} \cos\alpha)$ *Ball:* $f ball = \frac{fr}{2} \times \frac{d}{D}\,(1 - (\frac{d}{D} \cos\alpha)^{2})$ *Where:* N *: Number of rolling elements;* d *: Diameter of rolling elements;* *D : Pitch diameter of the bearing;* α *: Contact angle.*
Gears	*Given by:* $f\,gear = Z \times f_r \pm k \times f_r$ *Where:* Z = *Number of teeth,* k*: 0, 1, 2, 3, ...*
Belts	*The rotation frequency of the belt is given by:* $fcr = \frac{\pi D1}{L} \times f1 = \frac{\pi D2}{L} \times f1$ *For the case of wear in toothed belts:* $fcrc = N \times f_r \pm k \times f_r$ *Where:* $D1$ *: Diameter of pulley 1* $D2$ *: Diameter of pulley 2,* L *: Belt length* *: Number of teeth on the pulley,* k *= 0, 1, 2, 3, ...*
Oil Whirl	*40-50 % of* f_r
Cavitation	$N \times f_r$ *extended spectrum to frequencies above 2000 Hz*

Electrical Faults	f_r *and higher-order harmonics: magnetic imbalance* fel *Fixed field fault:* $2\times fel$ $f_r \pm 2g \times fel,\ fel \times \{k(\frac{1-p}{g}) \pm g\}$ G *:Slip,* fel*: Electrical supply frequency* K/p*=1.5, 7, ... depending on motor winding*

II.5 Conclusion

In this chapter, we have presented the different faults encountered in rotating machines. These faults can lead to disastrous consequences in most cases. Furthermore, we have explained how to calculate the kinematic frequencies of the different faults in rotating machines.

In the next chapter, we will summarize the signal processing methods and also study the role of artificial intelligence in the field of rotating machine diagnostics.

CHAPTER III

DIAGNOSTIC TECHNIQUES

III.1 Introduction

In order to prevent machinery malfunctions, a monitoring and diagnostic system must be established and defined to detect faults before further issues arise, as the accumulation of faults can reduce the machine's lifespan. There are numerous techniques used in machinery diagnostics, most of which involve signal processing analyses. The three types of signal analyses include time domain analysis, frequency domain analysis, and time-frequency analysis. However, with the advancement of computing, specifically the development of calculation software, diagnostics have defined a new and effective strategy primarily based on artificial intelligence, which has currently proven its effective role in the field of rotating machinery diagnostics.

III.2 Different analysis methods

There are numerous and diverse analysis methods in the field of detection and diagnosis of faults in rotating machines, but they can be broadly divided into three main categories. Figure III.1 illustrates the different families of analysis methods.

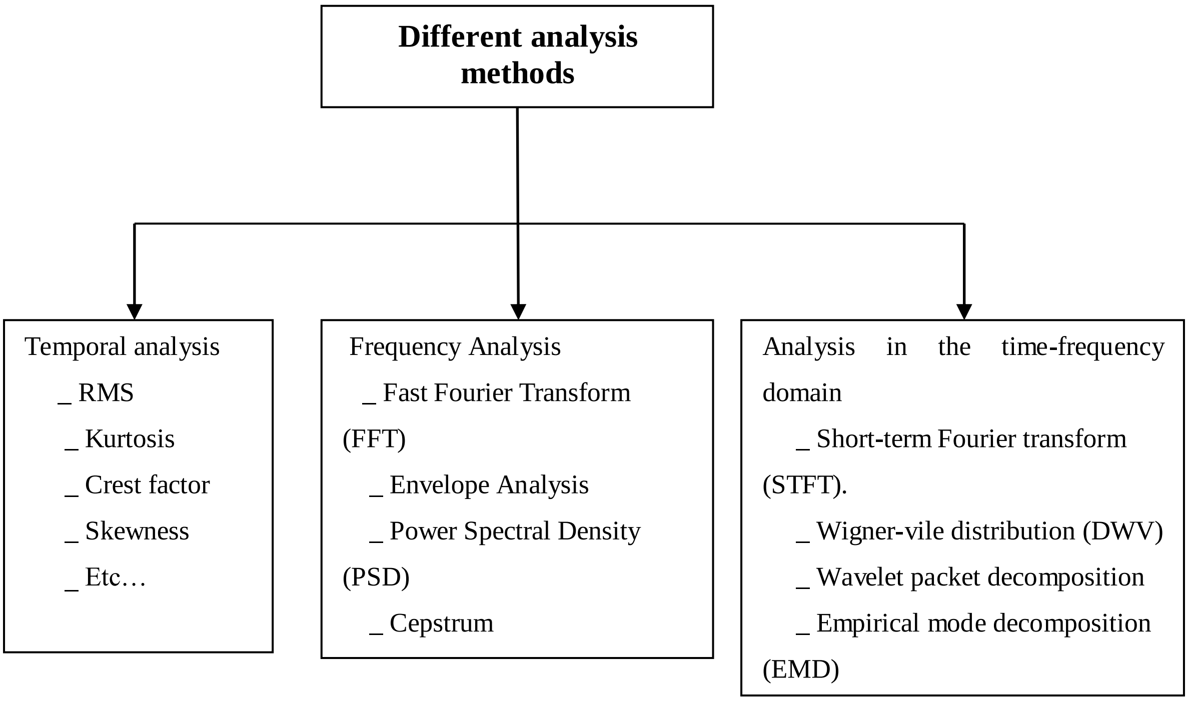

Figure III.1 —Different Analysis Methods.

III.2.1 Temporal Analysis

Temporal methods are the oldest ones. They involve analyzing the temporal characteristics of the recorded signal. Typically, they include finding the peak-to-peak value of the maximum amplitude between the extremes of the measured signal, the RMS (Root Mean Square) value of the average energy of the measured signal, the skewness factor, and kurtosis, which measures the impulsive nature of the signal, among others. These scalar indicators are used for monitoring and diagnostics, meaning that when the values of these indicators change, it directly implies the onset of a machine failure.

These statistical temporal indicators (see Figure III.2) are very simple and easy to interpret, with a high potential to increase the threshold when a fault begins to appear. Therefore, these indicators are particularly suitable for online monitoring and control, even in real-time. However, these descriptors yield good results only in the case of Gaussian signals.

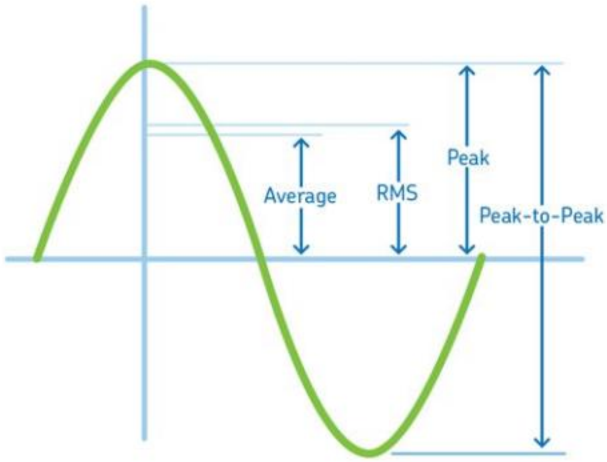

Figure III.2 — Statistical indicators of a signal [29].

III.2.1.1 Effective value or RMS value

The RMS, also known as the root mean square value of a signal, corresponds to the square root of the second-order moment and is calculated as follows:

$$\text{RMS} = \sqrt{\frac{1}{Ne}\sum_{i=1}^{Ne}[S(t)]^2} \quad \text{(III.1)}$$

Although S(t) is the measured time signal and N represents the number of samples taken from the signal.

The RMS is an indicator used in industry; when it varies excessively, it generally implies a malfunction and therefore a failure. Among the major disadvantages of using RMS is that it generally provides a rather late alarm, and it does not detect all defects globally, such as bearing faults.

III.2.1.2 Peak Factor PF

The peak factor Fc is defined as the ratio between the peak value and the root mean square value.

The formula for Fc is as follows:

$$\text{Fc} = \frac{Vpeak}{RMS} \quad \text{(III.2)}$$

For proper operation (without defects), the value of (Fc) typically ranges between 3 and 6 as the peak factor follows a Gaussian (normal) distribution. When its value exceeds 6, it is said that the failure has begun to appear.[30]

III.2.1.3 Kurtosis

Kurtosis is a statistical indicator used to detect the occurrence of shocks and monitor the development of a defect that causes periodic impulse forces. It can quickly detect bearing failures. Kurtosis corresponds to the normalized fourth-order moment of the statistical distribution of the signal. It is defined as follows:

$$\textbf{Kurtosis} = \frac{\boldsymbol{M4}}{\textbf{M2}} = \frac{\frac{1}{Ne}\sum_{1}^{Ne}(S(t)-\bar{S})4}{[\frac{1}{Ne}\sum_{1}^{Ne}(S(t)-\bar{S})2\,]2} \quad \text{(III.3)}$$

Where M2, M4 are the statistical moments of order 2 and order 4, respectively. With S being the signal mean formulated as follows:

$$\bar{\mathbf{S}} = \frac{1}{Ne}\sum_{1}^{Ne} Si \quad \text{(III.4)}$$

Kurtosis also follows a normal distribution in the case of proper functioning, so its value is close to 3. For example, in the case of a healthy bearing, its value belongs to the interval [2.8; 3.2]. When its value exceeds 3.2, it directly implies the appearance of a defect such as bearing spalling [31].

III.2.1.4 Skewness Factor

The skewness factor measures the degree of asymmetry of a distribution around its sample mean. It is calculated using the following formula:

$$\textbf{Skewness} = \frac{1}{Ne}\sum_{1}^{Ne}\left[\frac{S(t)-\bar{S}}{RMS}\right]^{3} \quad \text{(III.5)}$$

III.2.2 Frequency Analysis

Frequency analysis is based on the Fourier transform. It is even used for diagnosing electrical machines. After calculating the kinematic frequencies of each fault and performing spectrum analysis, the fault can be identified and localized through identification.

III.2.2.1 FFT Spectral Analysis

The signal provided by a sensor is represented in the time domain (Amplitude versus time). Spectral analysis is used to show the vibration amplitude at each frequency. This analysis is based on the Fourier transform, which converts the signal from the time domain to the frequency domain. The Fourier transform is formulated as follows:

$$\mathrm{X(f)} = \int_{-\infty}^{+\infty} x(t).e^{-j2\pi ft}\,\mathrm{dt}^2 \quad \text{(III.6)}$$

The inverse Fourier transform is formulated as follows:

$$\boldsymbol{x(t)} = \int_{-\infty}^{+\infty} \boldsymbol{x(f).e^{j2\pi ft}df}^2 \quad \text{(III.7)}$$

Where x(t), t, f, X(f) are respectively the analog signal, time, frequency, and the Fourier transform.

To discretize the analog signal, we use the Discrete Fourier Transform (DFT), formulated as follows:

$$\mathbf{X(k \cdot \Delta f)} = \boldsymbol{\frac{1}{n}\sum_{i=0}^{n-1}} \mathbf{x(i.te)}.\boldsymbol{e^{-j2\pi ft}df} \quad \text{(III.8)}$$

The Fast Fourier Transform (FFT) requires the discretization of the signal. FFT is the recipe that reduces the number of iterations needed to establish the Fourier transform of a discrete signal DFT. The FFT algorithm is performed by calculating the power spectrum or the power spectral density PSD, which is the ratio between the square of the Fourier transform module and the observation time (equation III.9) [32] .This power spectrum is another frequency representation of the signal that is widely used in the diagnosis of rotating machinery.

$$PSD(f) = \frac{\|X(f)\|^2}{d} \quad \text{(III.9)}$$

Where X(f), d, and P_SD(f) are the Fourier transform of the signal, the observation duration, and the power spectral density, respectively.

III.2.2.2 Cepstrum Analysis

The cepstrum is a diagnostic tool used to distinguish defects that produce complex images due to multiple associated amplitude modulations. It allows for the identification and quantification of impacts (comb lines) and sideband modulations. Therefore, gear fault detection often requires cepstrum analysis. This analysis is crucial for diagnosing repetitive impacts in complex kinematic machines such as gearboxes and screw compressors, etc. The complex cepstrum of a signal x (t) represents the Inverse Fourier Transform of the decimal logarithm of its direct Fourier transform [33].

$$C[x(t)] = C(\tau) = TF^{-1}[LogTF(x(t))] \quad \text{(III.10)}$$

Where τ represents the frequency.

III.2.2.3 Envelope Analysis

Envelope analysis or HFRF "High Frequency Resonance Technique" is notably used to analyze resonance phenomena caused by early defects in bearings and gears, even in machines running at very low speeds [34]. These defects, which cause periodic shocks, periodically excite the high frequency (resonance) of the structure. Consequently, the high frequency is modulated in amplitude at the characteristic frequency (low frequency) of the defect. By demodulating one of these resonances, the characteristics of the defect signal can be found[35]. This technique follows the following steps in order:

- Determine the resonance frequency and select the area to demodulate, then filter around the selected resonance.
- Calculate the envelope of the filtered signal using the Hilbert transform.
- Calculate the spectrum of the envelope of the signal using the Fourier transform.

The signal envelope is defined as follows:

$$E(t) = \|Z(t)\| = \sqrt{S^2(t) + \breve{S^2}(t)^2} \quad \text{(III.11)}$$

Where Z (t), E(t), S(t) and $\breve{\boldsymbol{S^2}}(\boldsymbol{t})$ are the analytic signal, the signal envelope, the temporal signal, and the Hilbert transform of the signal respectively. Knowing that:

$$\breve{\boldsymbol{S}}(\boldsymbol{t}) = \frac{\boldsymbol{S(t)}_2}{\boldsymbol{\pi.t}} \quad \text{(III.12)}$$

$$Z(t) = S(t) + i.\breve{S}(t)^2 \quad \text{(III.13)}$$

III.2.3 Time-Frequency Analysis

Although recent frequency techniques prove to be effective in detecting defects, they do have some limitations. The main drawback of these techniques is that they cannot handle non-stationary signals. It is for this reason that time-frequency domain analysis has come to provide an optimal mathematical framework for analyzing non-stationary signals. This type of analysis is based on real functions that define an energy distribution in the time-frequency plane. Among the techniques used in this analysis, we find the Short-time Fourier Transform STFT, Empirical Mode Decomposition EMD, the Wigner-Ville Distribution WVD, or wavelet-based techniques.

III.2.3.1 Empirical Mode Decomposition EMD

The Empirical Mode Decomposition (EMD) technique is a signal analysis method introduced by Norden Huang. EMD is a process called sifting that allows the signal to be decomposed into basic contributions called empirical modes or Intrinsic Mode Functions (IMF). EMD is particularly interesting because it is well-suited for the study of non-stationary signals and is also generated by nonlinear systems [36]. This decomposition has gained significant recognition in various fields such as oceanography, climatological studies, biology [37], non-destructive testing, underwater acoustics, and seismology [38].

Decomposition process by EMD (Figure III.3):

- Find local extrema (maximum and minimum) of the signal.
- Estimate upper and lower envelopes by respectively interpolating the local maxima and minima.
- Estimate the local mean envelope from the upper and lower envelopes.
- Subtract the mean envelope from the input signal. This corresponds to the first sifting iteration. Then calculate the stopping criterion.
- Check if the residue has a sufficient number of extreme values (more than two), and repeat the IMF extraction process for the resulting signal; otherwise, the residue is considered as the final residue r(t). Ideally, when the residue no longer contains extreme values, the IMF extraction process is completed. This means that the residue is a monotonic function, corresponding to the drift or trend of the initial signal x(t).

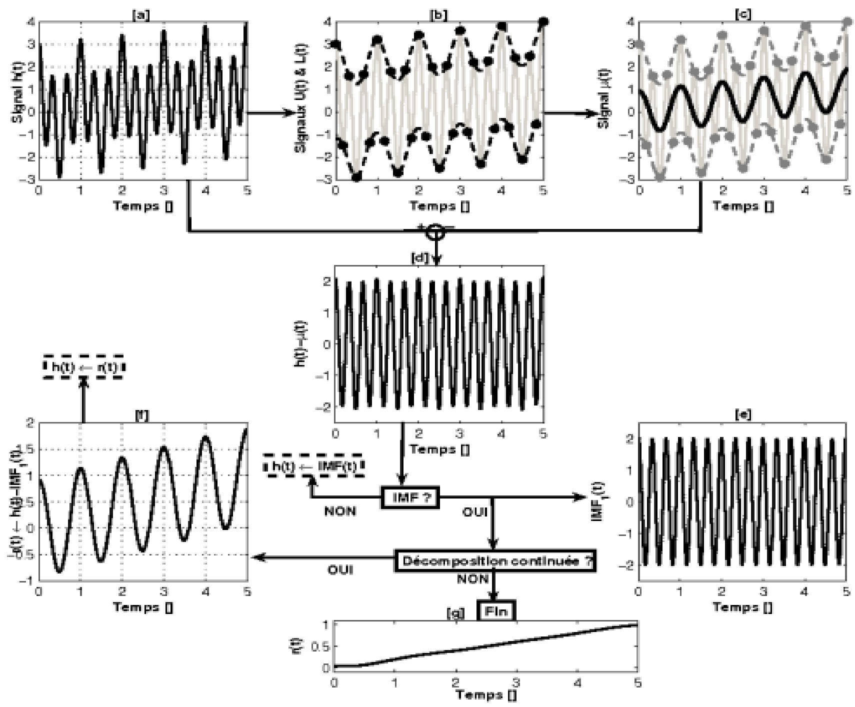

Figure III.3 — Sieving process to estimate the first IMF [39].

III.2.3.2 Short-Term Fourier Transform STFT

The Short-Term Fourier Transform (STFT) was developed by Gabor in 1946. The STFT is a modified version of the standard Fourier transform. The principle of this technique is to decompose the signal under study into segments assumed to be stationary. Therefore, the STFT can be considered as a method that decomposes the non-stationary signal into many small segments that can be locally assumed to be stationary, and conventional FFT is applied to these segments [40]. This is done using a window function of a chosen width, which is shifted and multiplied with the signal to obtain small stationary signals [41]. It is described by the following formula:

$$\mathbf{STFT}\{\mathbf{x(t)}\}(\boldsymbol{\tau},\boldsymbol{\omega}) \equiv \mathbf{X}(\boldsymbol{\tau},\boldsymbol{\omega}) = \int_{-\infty}^{+\infty} \mathbf{x(t)w(t-\boldsymbol{\tau})}\, e^{-iwt}\mathbf{dt} \quad \text{(III.14)}$$

The Short-Term Fourier Transform is an efficient method for time-frequency analysis and a powerful tool for monitoring the condition of rotating machinery. The short-term spectrum provides a clear representation of the time-frequency plane and a simple interpretation of energy variation and a clear representation of the time-frequency plane due to damage. Unfortunately, this approach poses a fundamental problem: high resolution cannot be achieved without the assistance of a monitoring system simultaneously in the time domain and in the frequency domain. To address this issue and achieve high accuracy, other methods have been developed, such as the Adaptive Short-Term Fourier

Transform. This method produces reasonable and useful window lengths for the form of the Short-Term Fourier Transform.

III.2.3.3 Continuous Wavelet Transform CWT

Continuous Wavelet Transform (CWT) is a very interesting tool for mapping the changing properties of non-stationary signals. The CWT is also an ideal tool for determining whether a signal is stationary or not in a global sense. When a signal is deemed non-stationary, the CWT can be used to identify the stationary sections of the data stream. The Continuous Wavelet Transform is defined as the sum over all time of the signal multiplied by scales [42]:

$$C(\mathrm{ScalePosition}) = \int_{-\infty}^{+\infty} f(t).\Psi(\mathrm{ScalePosition}, t)dt \quad \text{(III.15)}$$

such that

$$\Psi u, s(t) = \frac{1}{\sqrt{s}}\Psi(\frac{t-u}{s}) \quad \text{(III.16)}$$

Ψ: mother wavelet.

u: time translation coefficient.

s: scale coefficient.

There is a correspondence between wavelet scales and frequency as indicated by wavelet analysis, as shown in the following figure:

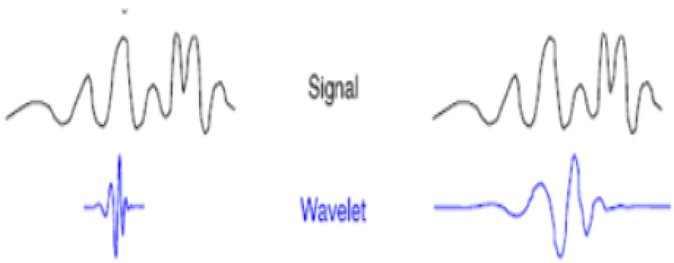

Figure III.4 — Signal scaling [34].

- Low scale a → compressed wavelet → rapidly changing detail → high frequency.
- High scale a → stretched wavelet → slowly changing detail → low frequency.

To perform the continuous wavelet transformation, five steps must be followed:

1. Choose a wavelet and compare it to a section at the beginning of the original signal.
2. Calculate a number C, which represents how closely correlated the wavelet is with the section chosen in the first step. The highest number C is the most similar. Specifically, if the signal energy and wavelet energy are both equal to 1, the latter can be interpreted as a correlation coefficient. Note that the results depend on the wavelet shape chosen.
3. Shift the wavelet to the right and repeat steps 1 and 2 for all signals.

4. Stretch the wavelet and repeat step 1 to 3.
5. Repeat steps 1 to 4 for all scales. When all the above steps are completed, coefficients will be produced at different scales by different sections of the signal.

III.3 Artificial Intelligence

Artificial intelligence (AI) techniques have demonstrated their effectiveness in diagnosing rotating machinery compared to conventional methods. AI enables machines to mimic a form of real intelligence and is used in various fields such as health, industry, and transportation. Historically, four AI methods have been developed: acting humanly (Turing test), thinking humanly (cognitive modeling), thinking rationally (laws of thought), and acting rationally (rational agents)[43], [44], [45]. These approaches combine empirical observations of human behavior with mathematical and engineering principles, thereby creating machines capable of intelligent perception, reasoning, and action.

III.3.1 Machine learning algorithm for faults classifications

Machine learning algorithms dedicated to fault classification are instrumental in automatically assigning input samples to predefined classes. The classification process involves two essential stages: initial training on a labeled set of samples, where each sample is associated with a specific class within the output class vector, and subsequent utilization of the trained model to classify new, unlabeled samples. Several classification algorithms, including decision trees (DT), logistic regression (LR), support vector machines (SVM), k-nearest neighbors (KNN), and neural networks (NN). In this study, DT, SVM and a novel method for enhancing fault diagnosis of bearing systems is developed, are employed in this investigation to showcase the effectiveness of the proposed methodology.

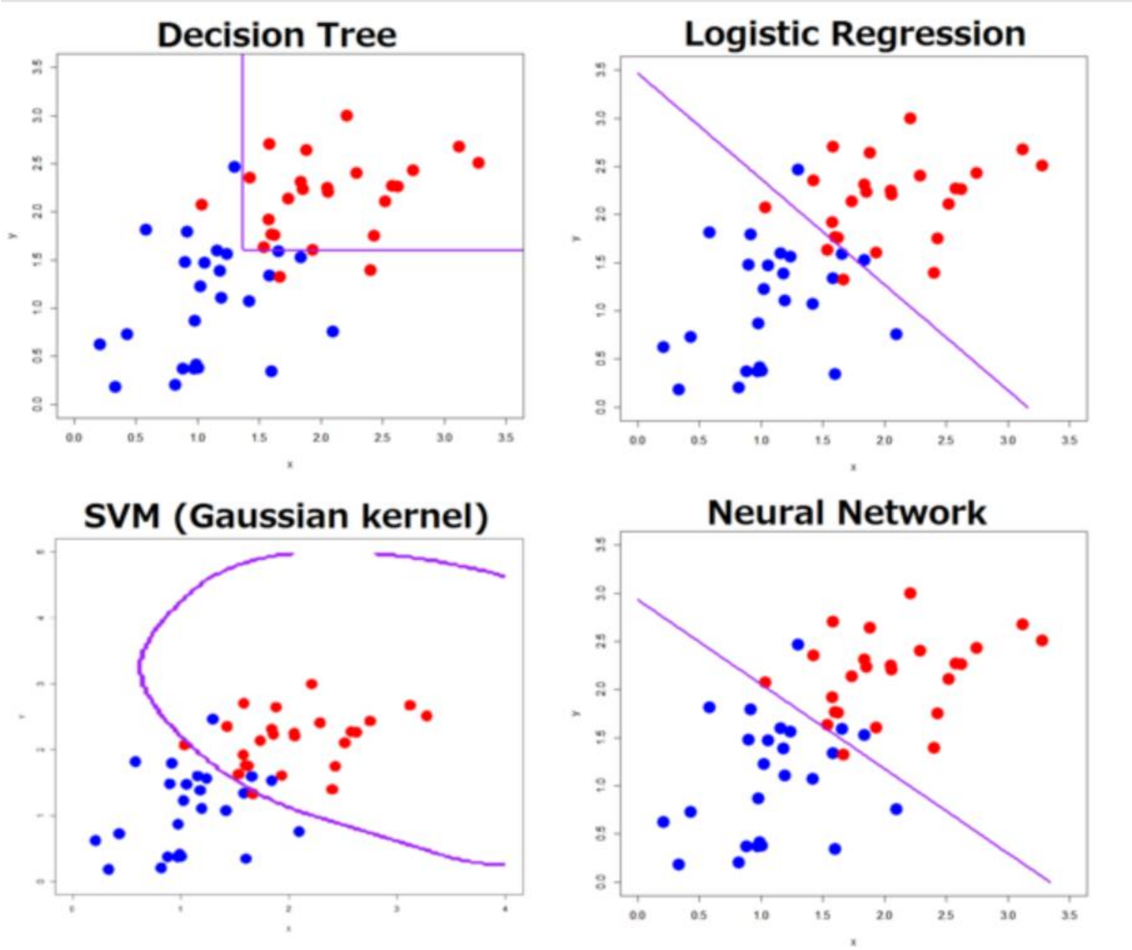

Figure III.5 — Fault Classification Boundaries [46].

III.4 Conclusion

In this chapter, we have discussed the various signal processing techniques used in diagnostics. We have also studied artificial intelligence of different kinds and know its effectiveness in diagnosing rotating machinery. Although signal processing techniques are still used today, it can be said that they have limitations in many cases. We have provided a general overview of one area of artificial intelligence.

CHAPTER IV

ADVANCING BEARING FAULT DIAGNOSIS

IV.1 Introduction

Bearings play a vital role in diverse industrial applications. Due to the rigorous demands placed on them, bearings are susceptible to high levels of stress and wear, with potential failures leading to costly repairs, unforeseen down-time, and safety risks. Consequently, monitoring the health of bearings is imperative to preempt unexpected break-downs, enhance equipment efficiency, and prolong machine lifespans [47].

In this chapter, a novel method for enhancing fault diagnosis of bearing systems is developed. First, we will present an experimental investigation into the diagnosis of bearing under varying operational speeds, utilizing acoustic signals obtained from experiments conducted at the Mechanical Structures Laboratory MSL of Polytechnic Military School, Bordj Elbahri, Algiers. Subsequently, we have integrated advanced signal processing techniques into our diagnostic approach by merging several health indicators and a powerful statistical technique is employed for fault classification. The results demonstrate the effectiveness of the proposed method in accurately identifying and classifying bearing faults across various working conditions. This approach holds promise for real-world industrial applications, offering a reliable method for condition monitoring and diagnostics in bearing systems.

IV.2 Methodology and diagnostic approach

The proposed diagnostic methodology comprises five essential steps, presented in FigureIV.1.

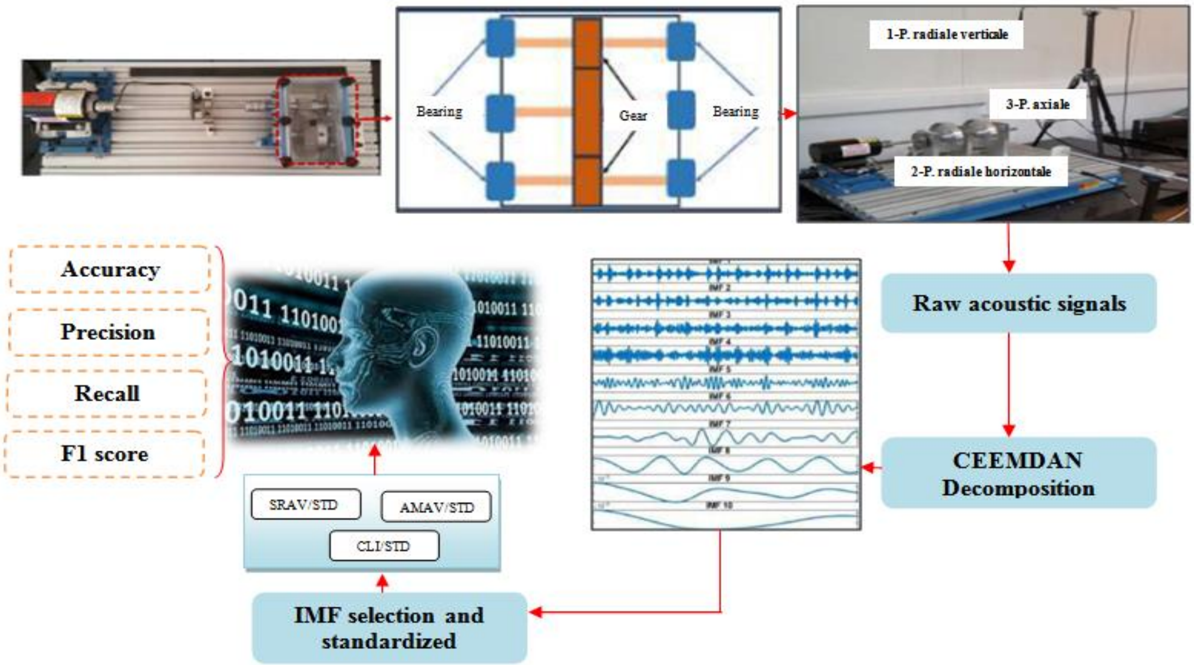

Figure IV.1 — Proposed bearing fault diagnostic methodology.

Initially, acoustic signals are acquired from the microphones, which are positioned on the target machine for monitoring purposes. These signals are then transmitted to a data acquisition system, adhering to predefined sample rates and acquisition times. The system records and analyzes the signals to detect any abnormal acoustic patterns bearing faults within the system.

The second step involves signal segmentation using a defined time window. This segmentation process aims to derive sub-signals that encapsulate samples representing distinct operational modes of the bearing.

The third step, the methodology incorporates the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) technique. This step decomposes vibration and current sub-signals into their frequency components by extracting intrinsic mode functions (IMFs). Notably, CEEMDAN includes an adaptive noise reduction step to diminish noise, thereby improving the accuracy of the decomposition. This step addresses the sensitivity to noise exhibited by Empirical Mode Decomposition (EMD) by ensuring the decomposition is not biased toward a specific frequency range [48].

In the fourth step, the obtained IMFs (energetic IMF) signals by calculating the Hilbert Envelope Spectrum (HES) are meticulously processed to extract health indicators, totaling three in our specific case. These indicators are computed from the most energetic IMF, accurately reflecting the condition of each bearing fault state. To minimize sample dispersion, a division by the standard deviation (STD) of the signal is performed in this step.

The refined indicators (three indicators calculated, divided by the STD of the original signal) undergo selection through the application of the Sequential Backward Selection (SBS) algorithm, aiming to retain the most relevant ones.

In the fifth and final step, the selected indicators (three in this case) serve as inputs for machine learning models to classify different modes (load levels) and identify bearing failures. The Discriminant Analysis algorithm (DA) in machine learning is employed to achieve this classification and fault detection.

This comprehensive methodology is designed to enhance the accuracy and efficiency of bearing fault diagnosis, ensuring robust performance across diverse operating conditions.

IV.2.1 Signal acquisition

In this experiment, our primary focus was on accurately localizing acoustic noise sources utilizing a setup comprising three microphones and acquisition channels equipped with acoustic transducers from Bruel & Kjaer. Specifically, we utilized Bruel & Kjaer’s high-precision microphones known for their exceptional performance in free field measurements with a sensitivity of 50mV/Pa and a frequency range up to 100 kHz. For data collection, we employed input modules along with the Pulse LabShop software, enabling seamless transfer of acquired signals for subsequent post-processing. Prior to the experiment, the equipment underwent amplitude calibration to ensure accurate measurements. The measured signals captured through these high-quality microphones formed a crucial dataset for our analysis[48].

IV.2.2 Signal segmentation

Once vibro-electric signals have been acquired, the next step involves dividing these signals into sub-signals, each representing a sample. The objective of this operation is to generate multiple samples to form classes that represent the distinct operating modes of the bearing. The segmentation process entails breaking down the acquired signal denoted as $x(t)$ into smaller segments denoted as $x_i(t)$, where $1 \leq i \leq N$.

Here, i represents the index of the sub-signal and N signifies the number of sub-signals. This segmentation process is pivotal as it establishes a database for training and testing, laying the groundwork for the development and evaluation of machine learning models in our study.

Mathematically, the segmentation process is summarized by the following equation [47]:

$$x(t) = [\underbrace{x_1(1), x_1(2), \dots, x_1(T)}_{x_1(t)}, \underbrace{x_2(1), x_2(2), \dots, x_2(T)}_{x_2(t)}, \dots, \underbrace{x_N(1) x_N(2), \dots, x_N(T)}_{x_N(t)}] \quad \text{(eq. IV.1)}$$

Where, t signifies the time within the segment and T represents the fixed window time length.

In this case, we employ CEEMDAN technique to decompose sub-signals $x_i(t)$ into an ensemble of IMFs, the detail of the method is illustrated in the reference [47].

IV.2.3 Health indicator calculation

The acoustic signals most energetic IMF, extracted through CEEMDAN decomposition are chosen for its superior representation of the bearing. This IMF epitomizing distinct states of the machinery components serves as the basis for calculating three pivotal indicators widely utilized in diagnosing bearings.

The indicators are described as follows [49]:

a - Square Root Amplitude Value (SRAV)

$$SRAV = \left(\frac{1}{T}\sum_{i=1}^{T} \sqrt{|u(t)|}\right)^2 \quad \text{(eq. IV.2)}$$

b - Absolute Mean Amplitude Value (AMAV)

$$AMAV = \frac{1}{T}\sum_{i=1}^{T} |u(t)| \quad \text{(eq. IV.3)}$$

c - Clearance Indicator (CLI)

$$CLI = \frac{max|u(t)|}{\left(\frac{1}{T}\sum_{i=1}^{T} \sqrt{|u(t)|}\right)^2} \quad \text{(eq. IV.4)}$$

A set of three (03) indicators will be calculated for the selected IMF, IMF selected (t) = u_1, u_2, u3,…u_T where T represents the length of the window size, which is also the number of vibration or current vector components. This vector will be used for the mathematical description of these indicators. These indicators play a vital role in diagnosing the condition of bearings providing valuable insights into their health and performance.

The next step is standardization, a crucial process where each calculated indicator signal is divided by the standard deviation of the signal for which the respective indicator was calculated. Standardization is vital for several reasons [48]:

- Standardization ensures that the scale of the indicators is uniform, allowing for meaningful comparisons and analyses across different signals and data points.
- It helps in reducing the influence of outliers or unusually large or small values, promoting more accurate and robust analysis results.
- By standardizing the indicators, we bring them to a common scale, aiding in a fair comparison of the health states of bearings.

Mathematically, the standardization process involves dividing each calculated indicator signal, by its respective standard deviation (STD).

IV.2.4 Discriminant Analysis for fault classification

Discriminant Analysis is a powerful statistical technique employed for fault classification in diverse applications, including machinery health monitoring [49]. In our study, we utilize Discriminant Analysis as a crucial tool to classify different fault modes in the bearing systems.

The fundamental principle of Discriminant Analysis involves determining a discriminant function that maximizes the separation between multiple classes as shown in Figure IV.2, enabling effective classification. We aim to develop a discriminant function that optimally distinguishes between various fault states, such as different types of bearing faults, and normal or healthy states. Mathematically, given a set of features or indicators, Discriminant Analysis seeks to find a linear combination of these features that maximizes the ratio of between-class variance to within-class variance. This discriminant function is then used to classify new instances into their respective fault categories.

In our specific application, the Discriminant Analysis algorithm analyzes the standardized indicators calculated from the segmented signals. These indicators serve as features for classification. The discriminant function developed through this analysis accurately categorizes the acoustic patterns into the distinct fault modes, aiding in the precise identification of bearing faults.

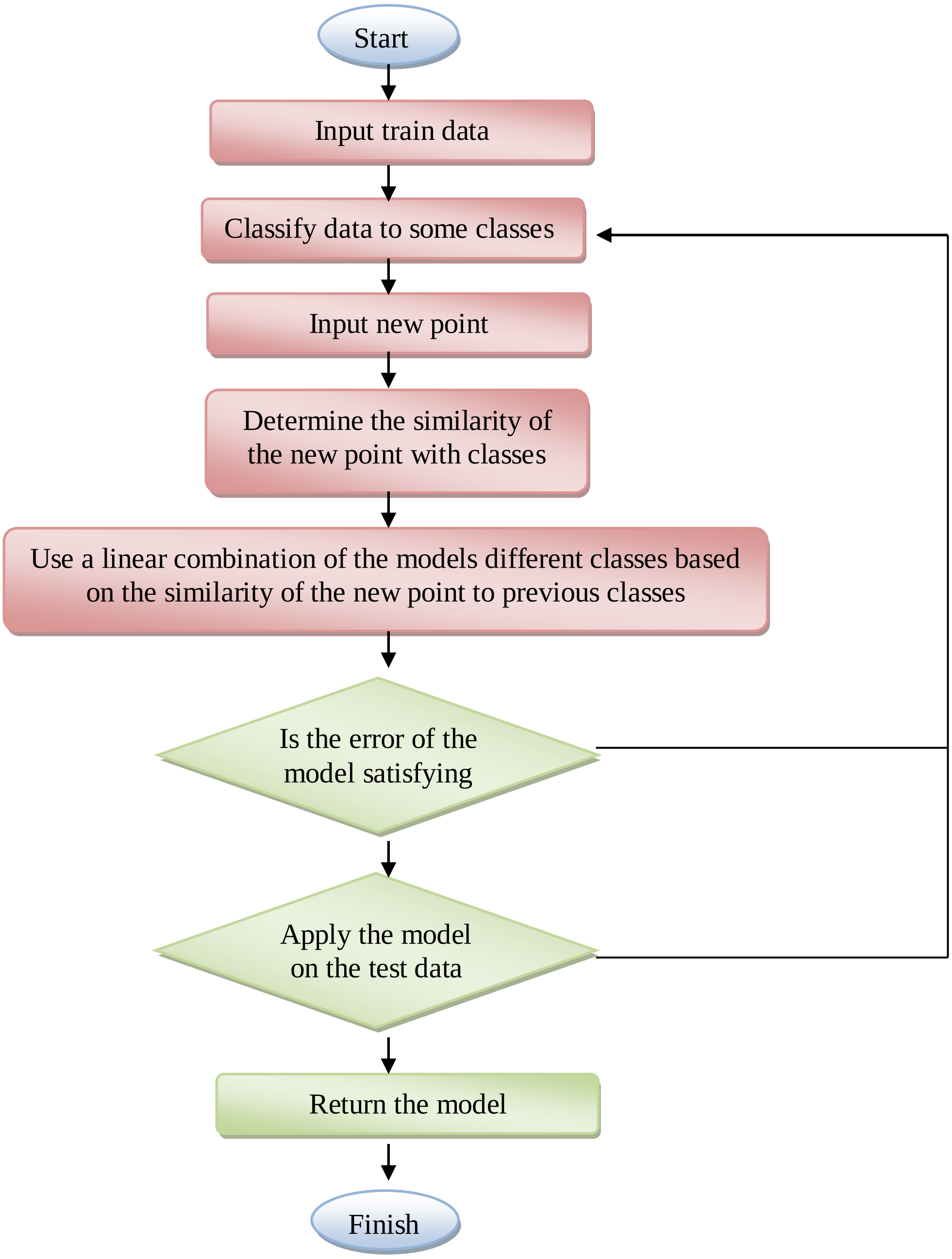

Figure IV.2 — Discriminant Analysis algorithm [48].

For evaluating the model's performance, metrics such as accuracy, precision, recall, and F1 score will be utilized. Precision is determined by considering correct positive predictions over all positive labels, while recall assesses the classifier's ability to identify positive cases. The F1 score offers a balanced measure of the model's performance, considering both precision and recall. These metrics are computed based on the indicators selected as input for this model. The detail of the calculation of these metrics is illustrated in the reference.

IV.3 Results and discussion

IV.3.1 Test bench and test description

The Figure IV.3, illustrate the experimental configuration utilized for our investigation and data acquisition. The shaft was set into motion by means of an electric motor, allowing for a varied rotational speed ranging from 0 to 6000 rpm. The MB Manufacturing ER-10K ball bearings are used, characterized by the presence of 8 ball rollers aligned in a singular row. The experiment was meticulously focused on localizing acoustic noise sources, employing three microphones and dedicated acquisition channels equipped with acoustic transducers from Brüel & Kjær.

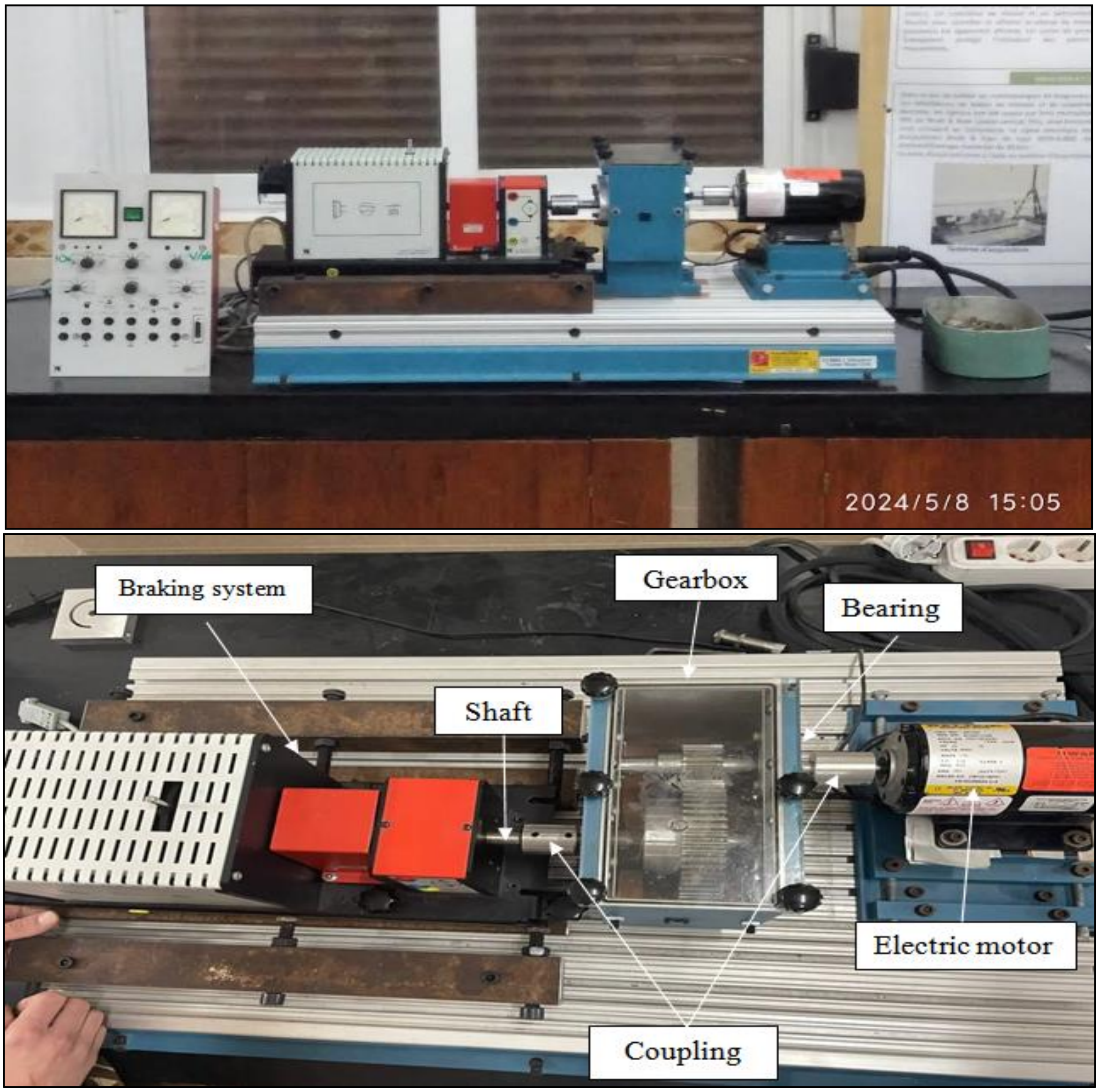

Figure IV.3 — Experimental setup.

a. Sensor used

The accelerometer integrated into our experimental setup is a piezoelectric sensor of type 4507 B 001 manufactured by Brüel & Kjær (see Figure IV.4**)**. This choice is motivated by its high sensitivity and its ability to accurately measure low frequencies, making it an ideal tool for vibration detection and analysis in our application.

Figure IV.4 — Accelerometer of type 4507-B-001.

The following table presents some characteristics of the accelerometer used:

Table IV.1 — Characteristics of accelerometer 4507-B-001.

Designation	Values
Frequency Range	[0. 3 ; 6000 Hz]
Temperature Range	[229 ; 394 K]
Sensitivity	10 mV/ms²
Resonance Frequency	18 kHz

b. Acquisition Card

The acquisition card used (Figure IV.5) is the Brüel & Kjær 3050-A-060 type, equipped with six LEMO channels and 7 pins, with each channel having a maximum sampling frequency of 50 kHz.

Figure IV.5 — Brüel & Kjær 3050-A-060 Acquisition Card.

c. Operating Software: PULSE Labshop

Brüel & Kjær's PULSE Labshop operating software is a platform for measuring vibrational accelerations and acoustic pressures. It can analyze and record various measured values (see Figure IV.6). It consists of several integrated modules and utilizes basic functions such as (FFT).

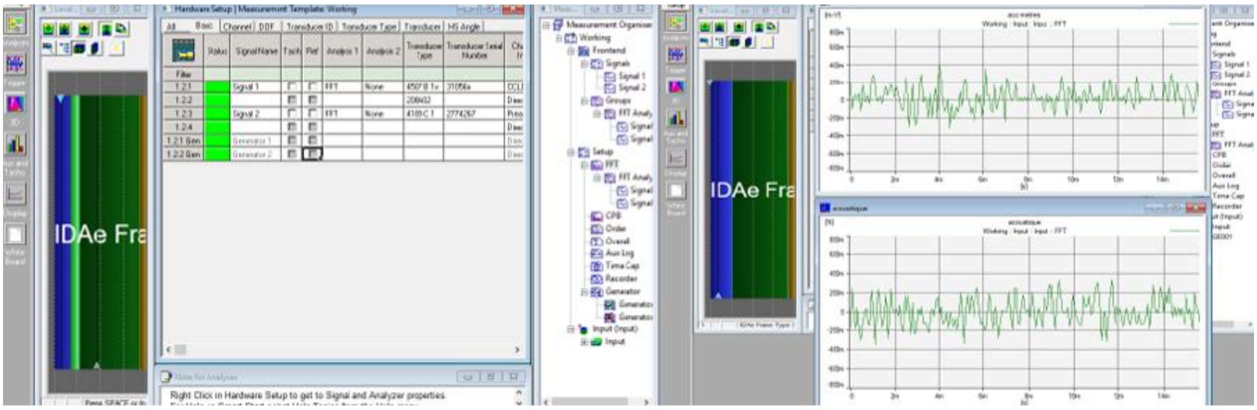

Figure IV.6 — PULSE LabShop Software Interface.

The measurement chain used to ensure signal acquisition consists of:

a. The test specimen to be monitored, which in our case is the bearings and their constituent components,
b. The sensor used,
c. The acquisition card, and finally
d. The computer for signal processing, as illustrated in the Figure IV.7,

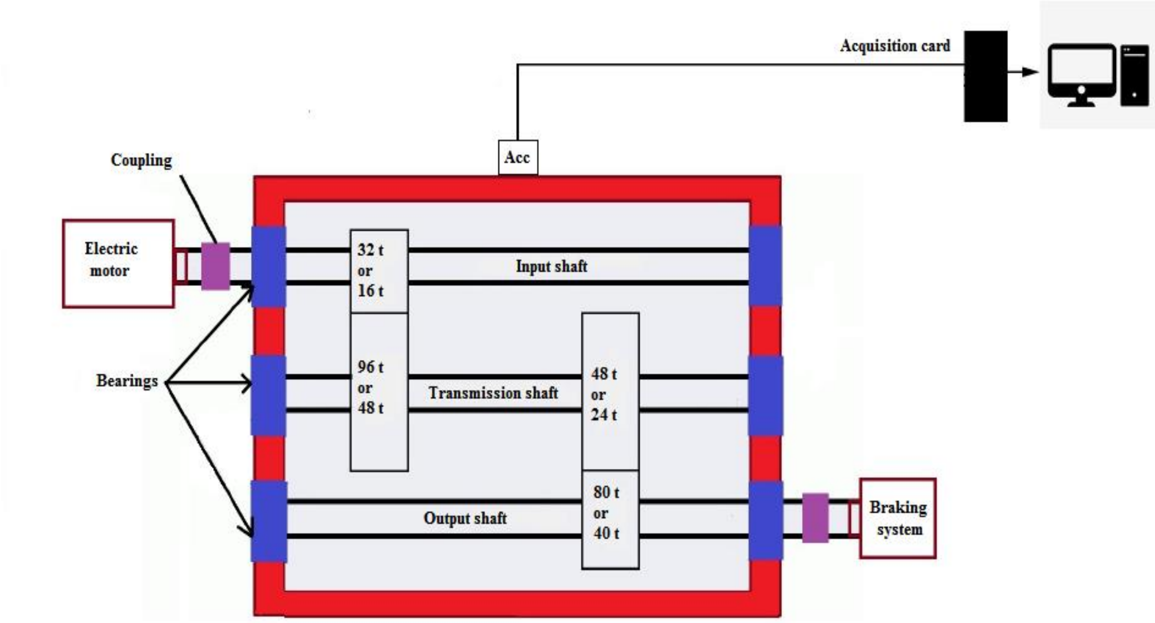

Figure IV.7 — Measurement Chain..

e. Creation of Defects

For simulating faults in rotating machinery, we used an MB Manufacturing ER-10K type bearing. Additional characteristics are presented in the following table.

Table IV.2 — Bearing Characteristics (MB Manufacturing ER-10K)

Bearing Dimension	Values
Number of Balls	8
Ball Diameter	7.9375 mm
Mean Diameter (Pitch)	33.5026 mm
Contact Angle	0 rad

We created several bearing faults (Table IV.3) during the tests, such as deterioration of the outer race, the inner race, and ball defects (Figures IV.8).

Figure IV.8 — Various Bearing Faults Created.

Table IV.3 — Various Bearing Faults Created

Case	**Bearings**									
	Inner race			**Outer race**			**Ball**			**Damage position**
	0.007	**0.014**	**0.021**	**0.007**	**0.014**	**0.021**	**0.007**	**0.014**	**0.021**	**Damage degree (inch)**
C1	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	
C2	**F**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	
C3	**GD**	**F**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	
C4	**GD**	**GD**	**F**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	
C5	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**F**	**GD**	**GD**	
C6	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**F**	**GD**	
C7	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**GD**	**F**	
C8	**GD**	**GD**	**GD**	**F**	**GD**	**GD**	**GD**	**GD**	**GD**	
C9	**GD**	**GD**	**GD**	**GD**	**F**	**GD**	**GD**	**GD**	**GD**	
C10	**GD**	**GD**	**GD**	**GD**	**GD**	**F**	**GD**	**GD**	**GD**	

GD is Good and F is Fault; with:

Table IV.4 — Bearing Condition Classification

Class	
C1	Normal condition (Healthy bearing)
C2	Inner race fault of the bearing
C3	Inner race fault of the bearing
C4	Inner race fault of the bearing
C5	Ball fault of the bearing
C6	Ball fault of the bearing
C7	Ball fault of the bearing
C8	Outer race fault of the bearing
C9	Outer race fault of the bearing
C10	Outer race fault of the bearing

In this work, vibrations are meticulously acquired from experiments conducted at the Mechanical Structures Laboratory MSL of Polytechnic Military School, Bordj Elbahri, Algiers, with the Laboratory's doctoral students.

IV.3.2 Results of the experiment

IV.3.2.1 Fault detection through time-domain analysis

In order to detect bearing faults, such as inner race faults, outer race faults, and ball faults, we perform a time-domain analysis of the acquired signals

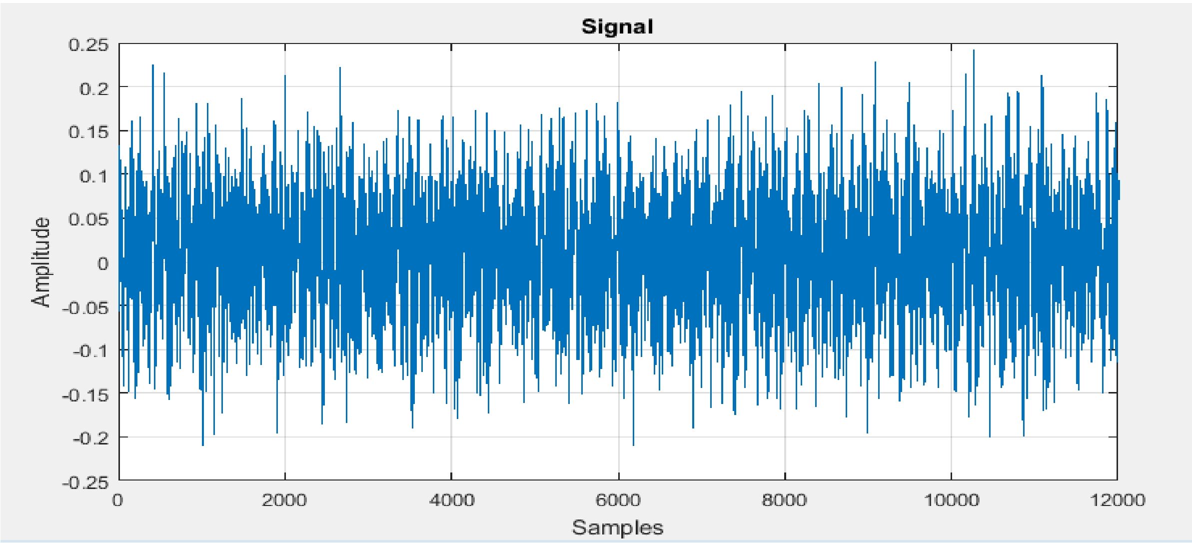

Figure IV.9 — Vibrational signal of normal condition (Healthy bearing).

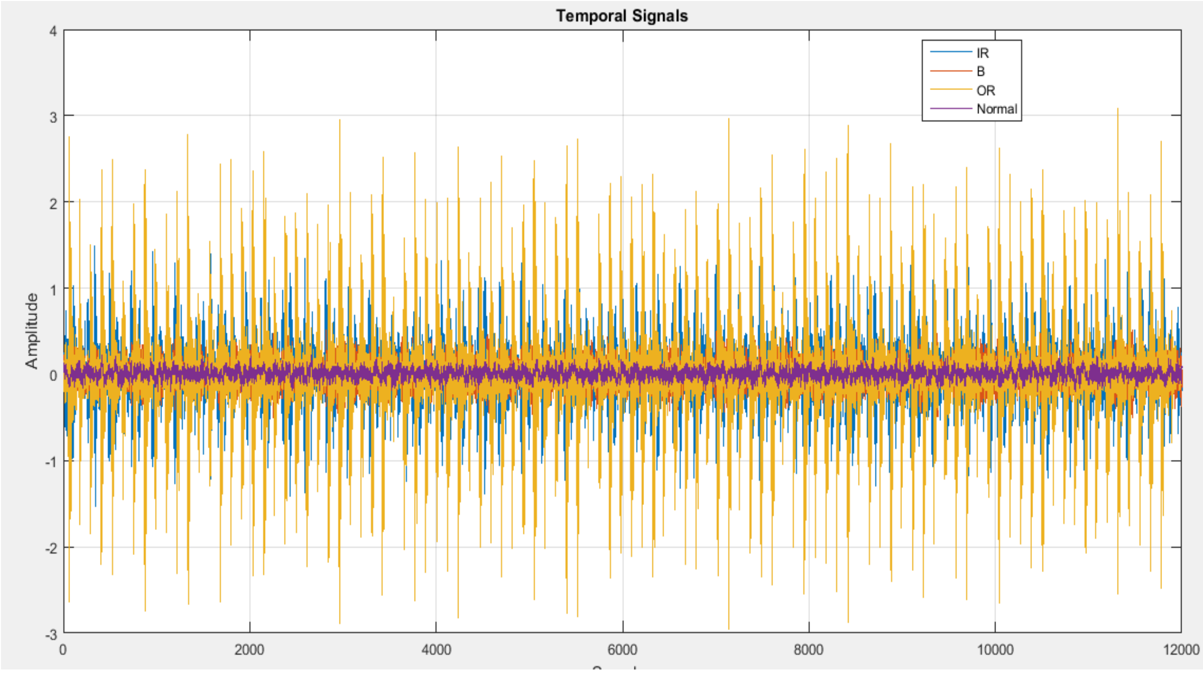

Figure IV.10 — Comparison of Temporal Signals: Healthy and. Faulty Bearings.

The analysis of the plotted temporal signals provides valuable insights into the condition of the bearings under investigation. The healthy bearing signal demonstrated a consistent pattern with relatively low amplitudes and minimal high-frequency peaks, indicative of smooth and normal operation. In contrast, the faulty bearing signals exhibited higher amplitudes, often accompanied by distinct high-frequency peaks or impulsive spikes. These deviations from the healthy signal suggest the presence of anomalies or defects within.

IV.3.2.2 Vibrational signal analysis

In Figure IV.11 (a-b-c-d), we present the vibrational signals decomposition using the CEEMDAN. Each signal is segmented into 118 non-overlapping sub-signals and each with a length of 1024 samples.

So, the CEEMDAN process is then applied to each sub-signal, yielding a distinct set of IMF components. The subsequent phase involves computing the Hilbert Envelope Spectrum (HSE) for each IMF and identifying the characteristic frequency associated with each fault. The underlying principle of these operations is the automated identification of the IMF with the maximum energy value around the frequency of the fault. For each sub-signal, we compute the CEEMDAN algorithm and then calculate the HES to determine the most energetic IMF to use it next for diagnosis purpose. After determination of the most energetic IMF, we compute the three indicators.

All simulations are obtained by scripts designed with MATLAB software of Laboratory.

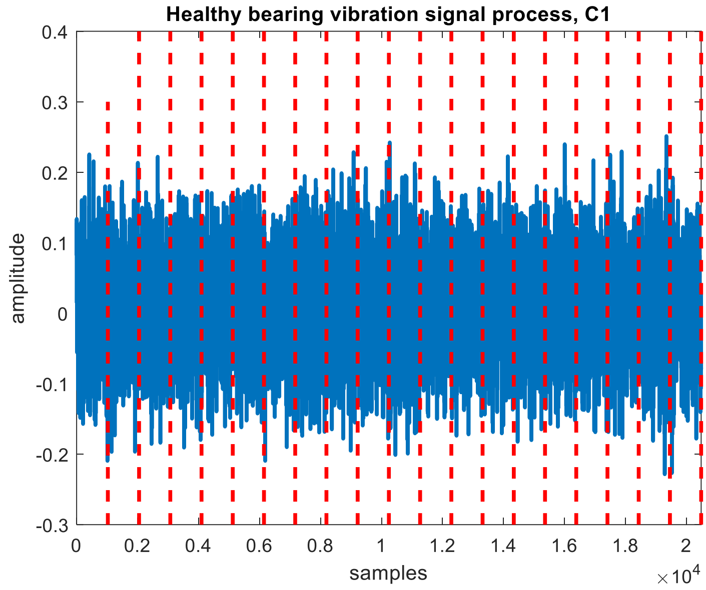

Figure IV.11-a — Healthy bearing vibration signal segmentation process.

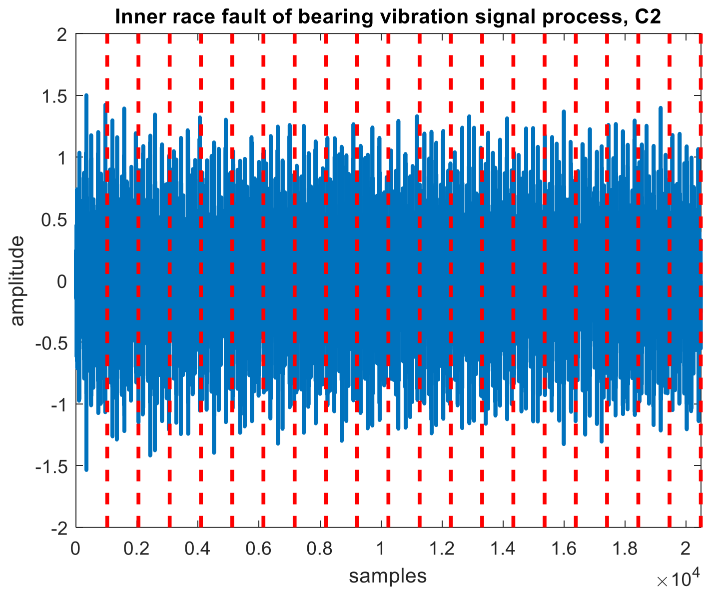

Figure IV.11-b — Inner race fault vibration signal segmentation process.

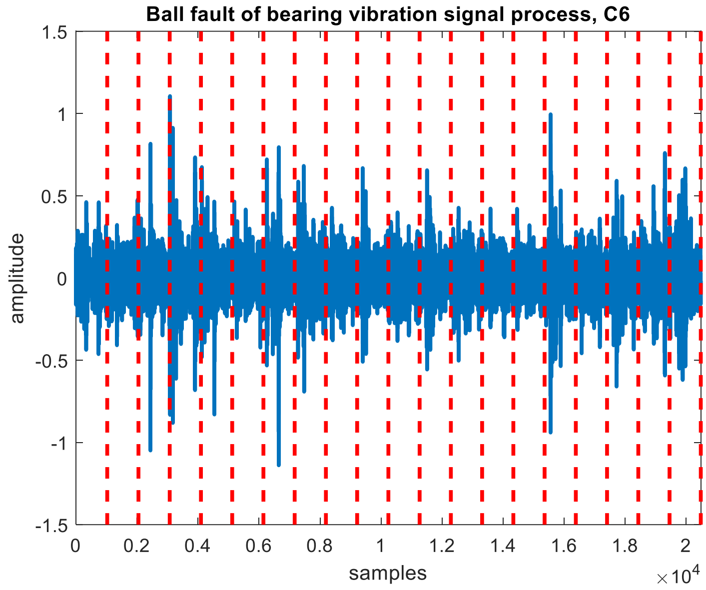

Figure IV.11-c — Ball fault vibration signal segmentation process.

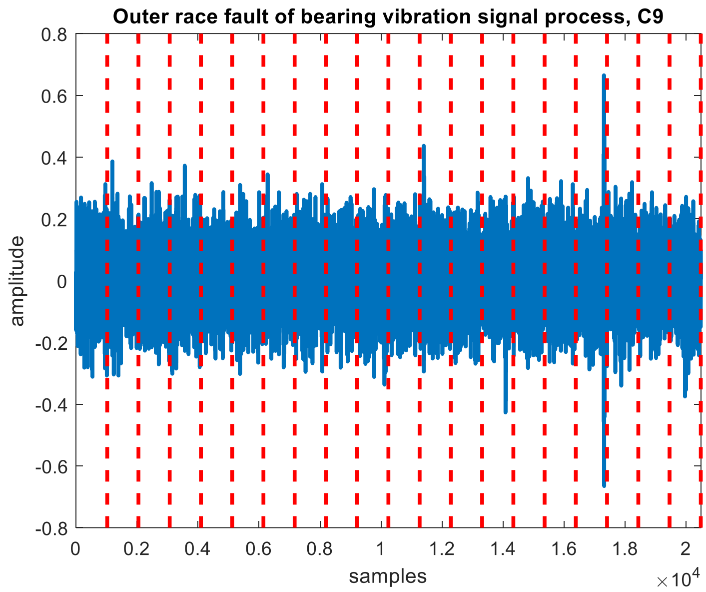

Figure IV.11-d — Outer race fault vibration signal segmentation process.

```
for i = 1:20
    x = i * 1024;
    yl = ylim;
    plot([x x], yl, 'r--','LineWidth', 2);
end
hold off;

% Ajouter des étiquettes et un titre
xlim([0, 20480]);
```

Figure IV.12 — Script block of vibration signal segmentation process.

The CEEMDAN process is subsequently applied to each sub-signal, generating a distinctive set of IMF components, as illustrated in Figure IV.13.

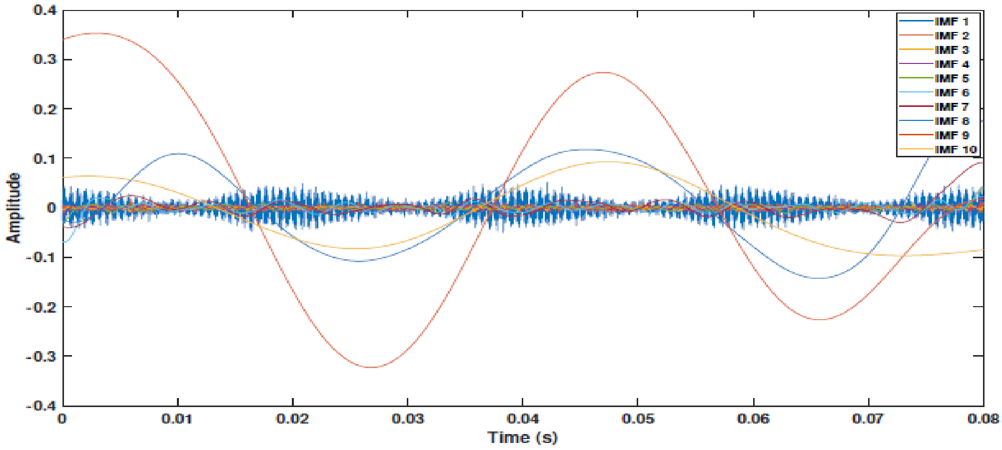

Figure IV.13 — CEEMDAN for IMFs extraction.

In this phase, for model classification and evaluation and a further refinement has been introduced to enhance the accuracy of the methodology. The key indicators identified through the SBS algorithm, namely SRAV, AMAV and CLI demonstrated proficiency in distinguishing between various types of faults. To augment precision, each indicator is now normalized by the signal standard deviation (STD), effectively mitigating class dispersion.

In order to consolidate our new model, we carried out simulations with models too used in fault diagnostics; firstly, the Figure IV.14 visually represents the dispersion parameter for the selected three indicators with Decision Tree (DT) analysis firstly. The result in accuracy with 84.3%.

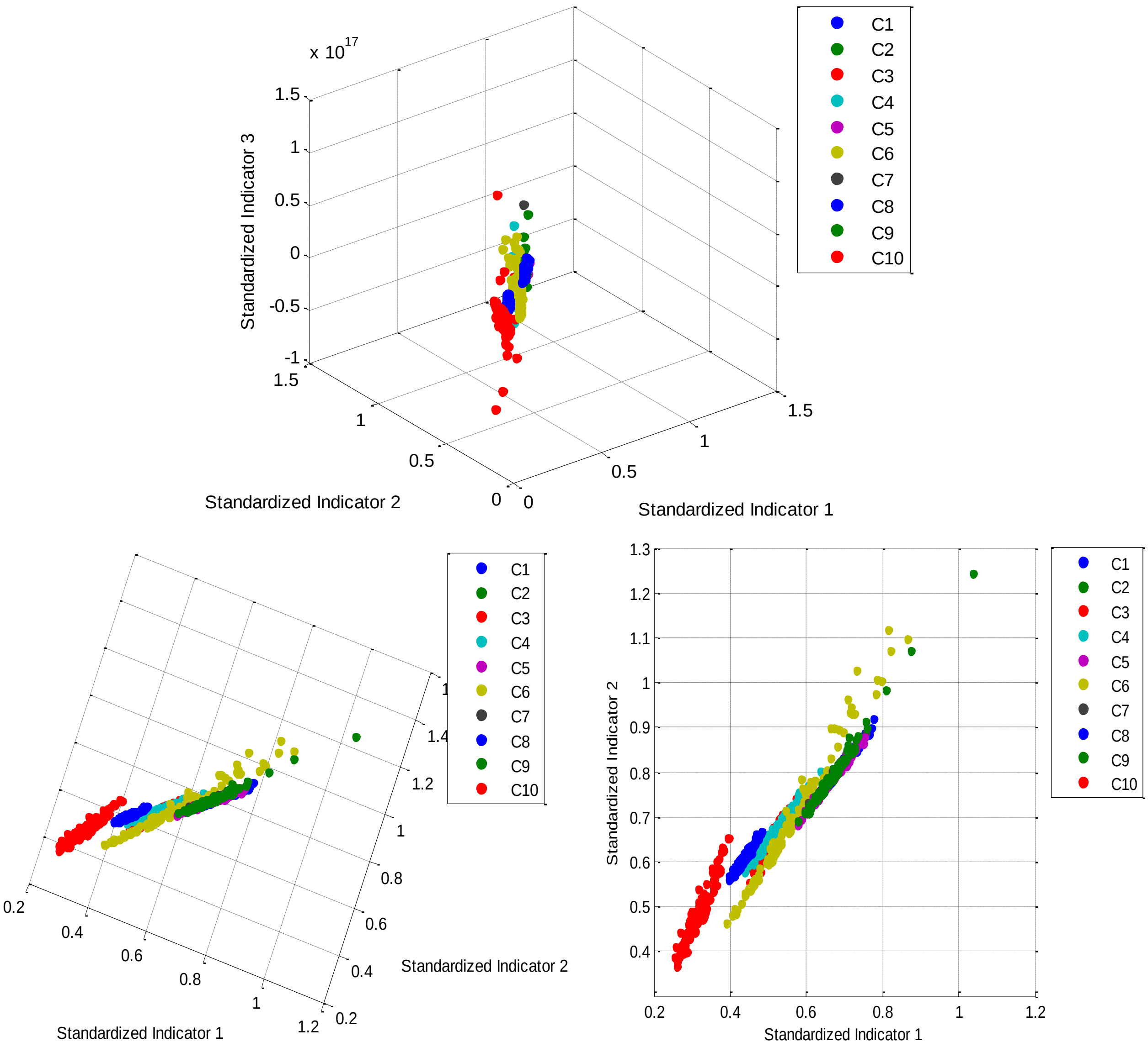

Figure IV.14 — Class distribution with Decision Tree analysis.

As well, we used the confusion matrix plot to understand how the currently selected classifier performed in each class. The confusion matrix help identify the areas where the classifier performed poorly. The diagonal cells show where the true class and predicted class match. If these diagonal cells are blue, the classifier has classified observations of this true class correctly. To see how the classifier performed per class, the TPR is the proportion of correctly classified observations per true class. The FNR is the proportion of incorrectly classified observations per true class.

In this figure analysis (Figure IV.15), the columns show the predicted classes, so the true positive rate for correctly classified points in this class, shown in the blue cell in the TPR column.

The false negative rate for incorrectly classified points in this class is shown in the orange cell in the FNR column.

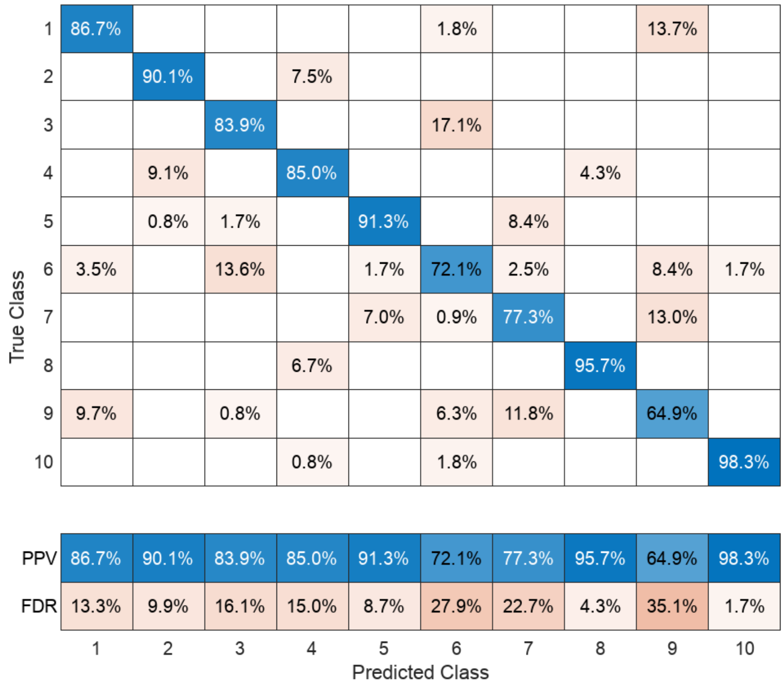

Figure IV.15 — Confusion matrix of Decision Tree analysis.

The following figure represents the prediction graph with Decision Tree analysis for class distribution, where the circle patterns (●) are correct prediction and the cross patterns (x) are incorrect prediction.

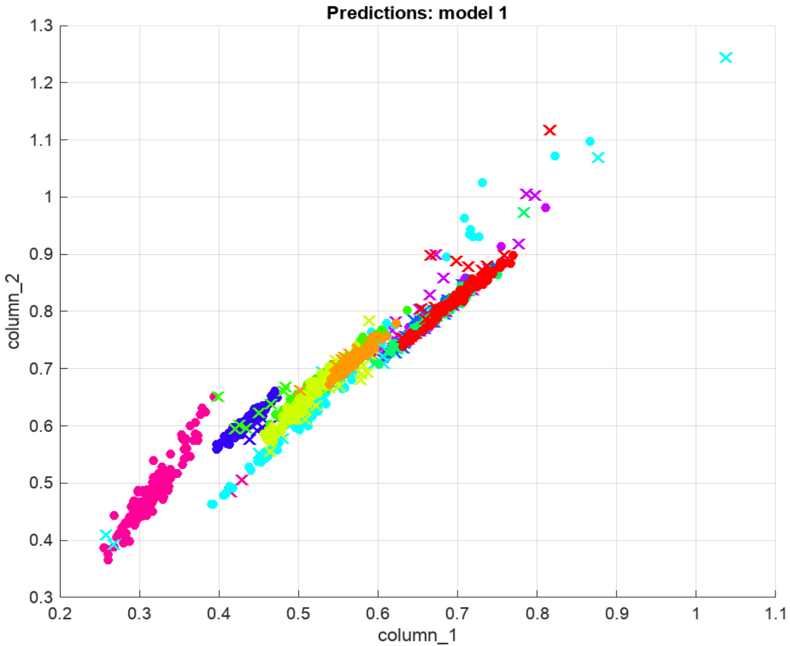

Figure IV.16—Prediction graph of Decision Tree analysis.

Also, we have used Quadratic Support Vector Machine analysis by using classification learner Toolbox in MATLAB in order to approve our new model, the result in accuracy with 92.5%. The following figures represent Confusion matrix and prediction graph of Quadratic SVM analysis

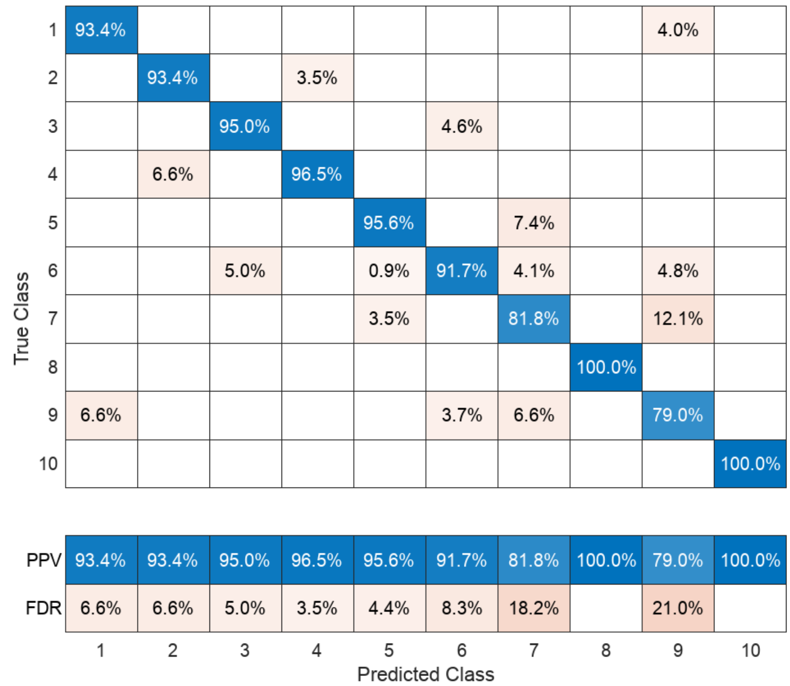

Figure IV.17—Confusion matrix of Quadratic SVM analysis.

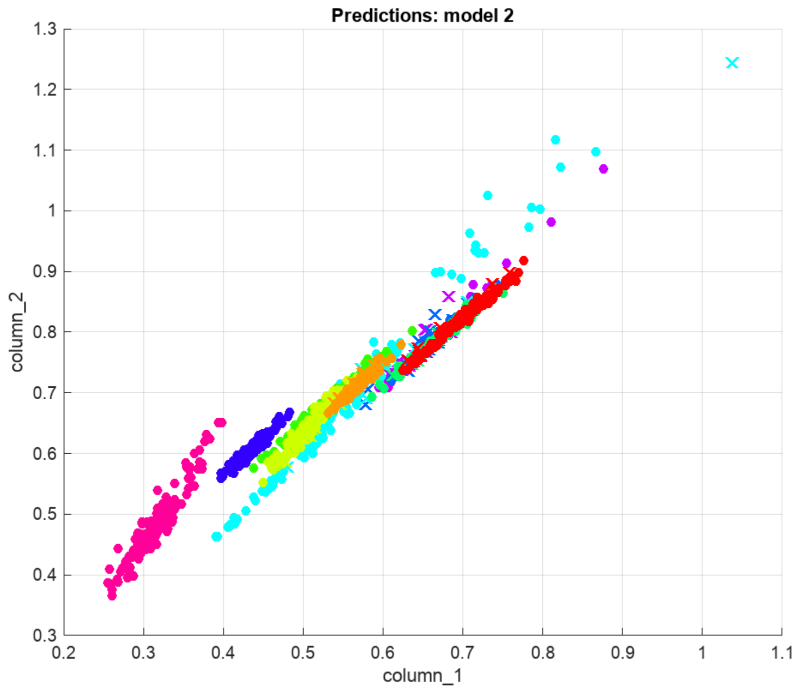

Figure IV.18—Prediction graph of Quadratic SVM analysis.

Following, among the machine learning techniques, Discriminant Analysis stands out as a widely embraced method for various reasons. It is a robust statistical technique designed to identify linear combinations of features that optimally discriminate between classes [48].

In this section the simulation results obtained by scripts designed with MATLAB software of the Discriminant Analysis algorithm in machine learning is employed to achieve this classification and fault detection.

For robust model performance assessment, a 5-fold cross-validation methodology was employed. Within this framework, key metrics including Accuracy, Precision, Recall, and F1 score were scrutinized meticulously to gauge the model's efficacy and proficiency.

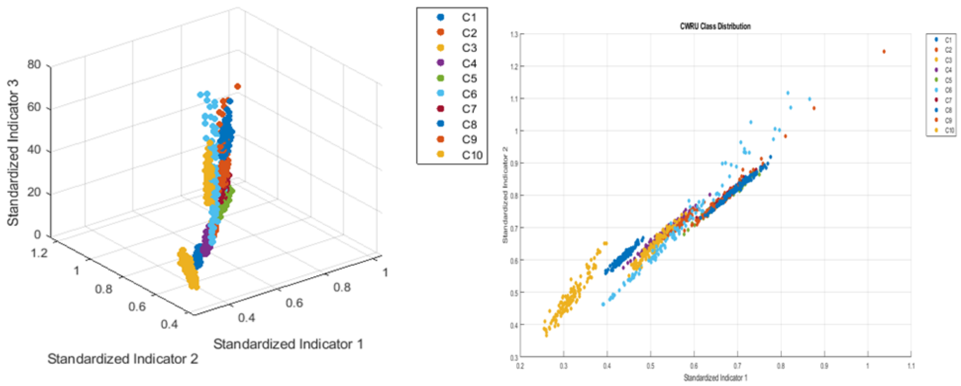

Figure IV.19—Classification results with Discriminant Analysis algorithm.

The Figure IV.19 illustrates the dispersion of classes with standardization, respectively. Standardizing the indicators significantly enhances class dispersion, resulting in a remarkable accuracy increase to 92.94%.

Classification results in Table IV.5 underscore the methodology's efficiency in distinguishing bearing failures under variable load levels, achieving an impressive accuracy of 92.94%. The trained model exhibits a high capacity to differentiate between various fault types, showcasing notable precision, recall, and F1 score. This proficiency is particularly significant for identifying faults in rotating machines under varying loads.

Table IV.5—Performance of the proposed model

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Store (%)
DA	92.94	93.02	93.39	93.11

```
information, click here.
Accuracy: 92.94%
Precision: 93.02%
Recall: 93.39%
F1 Score: 93.11%
fx >>
```

Figure IV.20 illustrates the outcomes of the classification using the Discriminant Analysis algorithm. It is crucial to emphasize that the classes exhibit clear separability, underscoring the efficacy of the selected indicators.

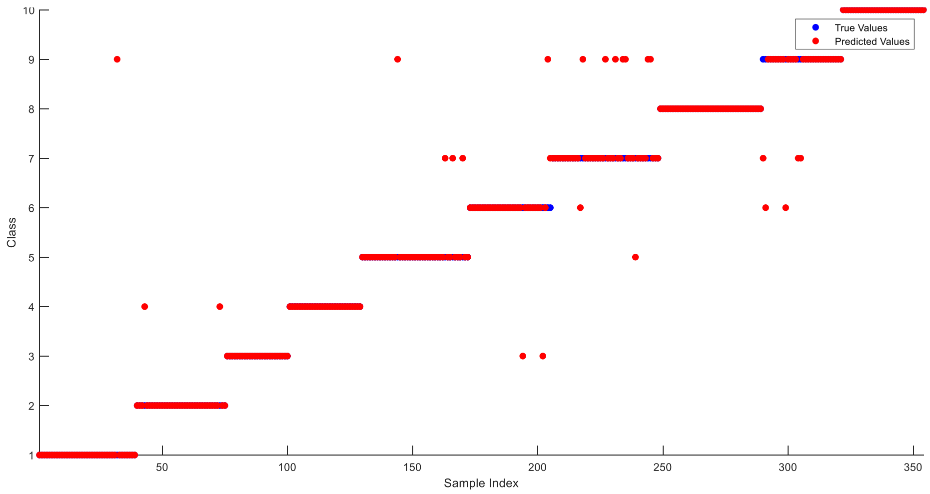

Figure IV.20— Classification results using Discriminant Analysis algorithm.

The Figure IV.21 visually represents the represents the results of simulations on MATLAB software

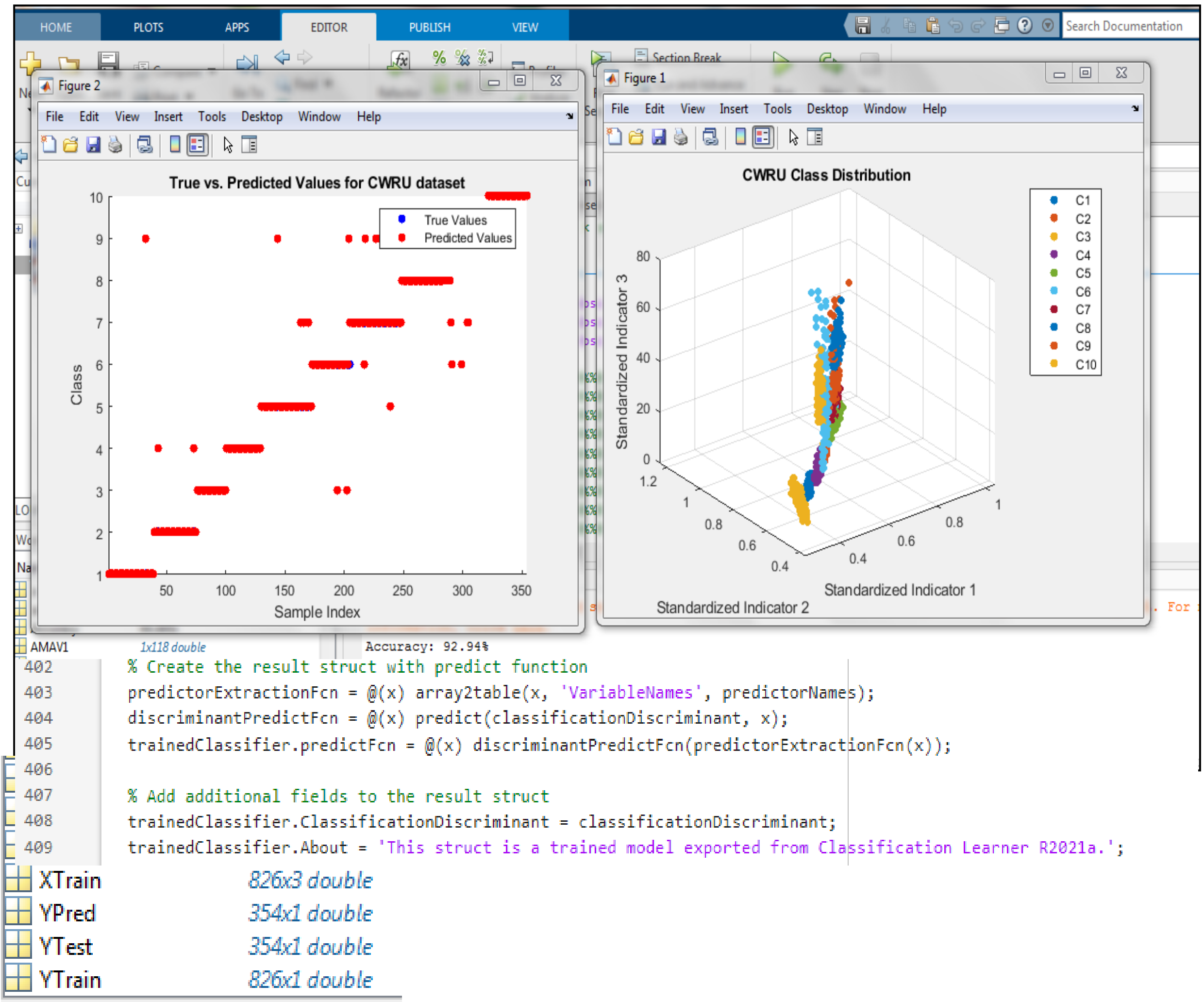

Figure IV.21—Results of simulations on MATLAB software.

IV.4 Conclusion

In conclusion, a novel method for enhancing fault diagnosis of bearing systems is developed in collaboration with the Mechanical Structures Laboratory MSL team of Polytechnic Military School, Bordj Elbahri, Algiers.

We used acoustic signals obtained from experiments and applied the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to derive the Intrinsic Mode Functions (IMF). Calculating the Hilbert envelope spectrum of these IMFs allowed us to identify the most energetic IMF, which was then chosen for the subsequent diagnostic analysis.

Three indicators are computed from the most energetic IMF, accurately reflecting the condition of each bearing fault state. To minimize sample dispersion, a division by the standard deviation (STD) of the signal is performed in this step.

Machine learning algorithms dedicated to fault classification are used, such as, Decision Tree analysis and Quadratic SVM analysis. The Discriminant Analysis algorithm provided the best result with accuracy of 92.94%.

The success of this approach holds significant promise for the field of machinery health assessment and fault detection.

GENERAL CONCLUSION

In this project, we have explored the multifaceted domain of fault diagnosis in rotating machinery, emphasizing the integration of advanced diagnostic techniques and machine learning algorithms to enhance maintenance practices. Our investigation commenced with a comprehensive review of various maintenance philosophies, highlighting the critical importance of predictive and preventive maintenance strategies in ensuring the operational efficiency and longevity of industrial equipment.

We delved into the primary faults that afflict rotating machinery, identifying common issues such as imbalance, misalignment, and bearing failures. By understanding the kinematic frequencies associated with these faults, we laid the groundwork for accurate fault detection and diagnosis. Our research progressed into the realm of signal processing techniques, essential for analyzing the complex, non-stationary signals generated by rotating machinery. Techniques such as the Short-Time Fourier Transform (STFT), Empirical Mode Decomposition (EMD), and Continuous Wavelet Transform (CWT) were examined for their efficacy in providing detailed insights into the condition of machinery.

A pivotal aspect of our study involved the application of machine learning algorithms to classify and predict machinery faults. This approach demonstrated significant promise in enhancing the precision and reliability of diagnostic systems, thus paving the way for more effective maintenance interventions. Specifically, in the experimental phase, we utilized acoustic signals obtained from experiments and applied the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to derive the Intrinsic Mode Functions (IMFs). By calculating the Hilbert envelope spectrum of these IMFs, we identified the most energetic IMF, which was then used for diagnostic analysis.

Three indicators were computed from the most energetic IMF, accurately reflecting the condition of each bearing fault state. To minimize sample dispersion, a division by the standard deviation (STD) of the signal was performed. Various machine learning algorithms were employed for fault classification, including Decision Tree analysis and Quadratic SVM analysis. The Discriminant Analysis algorithm provided the best result, with an accuracy of 92.94%.

In conclusion, this project underscores the necessity of integrating advanced diagnostic techniques with machine learning to create intelligent maintenance systems. These systems are capable of preemptively identifying potential failures, thereby minimizing downtime and maintenance costs while maximizing the operational lifespan of critical machinery. The success of this approach holds significant promise for the field of machinery health assessment and fault detection. Future research should continue to refine these techniques and explore their applications across a broader range of industrial contexts, ensuring that the advancements in this field translate into tangible benefits for various sectors reliant on rotating machinery.

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الملخص

في هذه الدراسة، تم تطوير طريقة متقدمة لتحسين تشخيص أعطال أنظمة المحامل. كما تم إجراء تحقيق تجريبي لتشخيص المحامل تحت سرعات تشغيلية مختلفة باستخدام الإشارات الصوتية من التجارب في مختبر الهياكل الميكانيكية بالمدرسة العسكرية المتعددة التقنيات، برج البحري، الجزائر. تمت معالجة الإشارات الصوتية باستخدام تحليل تجميع النمط الذاتي التجريبي الكامل مع الضوضاء التكيفية (CEEMDAN) لتحديد الدوال النمطية الذاتية (IMF) ذات أعلى قيم طاقة، والتي استخدمت لأغراض التشخيص. تم تحليل هذه الدوال باستخدام مؤشرات حرجة: قيمة الجذر التربيعي للسعة(SRAV) ، قيمة متوسط السعة المطلقة (AMAV) ومؤشر الخلوص .(CLI) استخدمت خوارزميات تصنيف مثل شجرة القرار(DT) ، وآلات دعم المتجهات التربيعية (SVM) وتحليل تمييزي بالتزامن مع معيار المؤشر والتحقق المتبادل، لعرض فعالية المنهجية المقترحة. هذا النهج المتكامل يعزز أداء ودقة المنهجية لتصنيف أوضاع الأعطال المختلفة في أنظمة المحامل .الكلمات المفتاحية: نظام المحامل، الإشارة الصوتية، تحليل تجميع النمط الذاتي التجريبي الكامل مع الضوضاء التكيفية(CEEMDAN) ، الدوال النمطية الذاتية(IMF) ، التحليل التمييزي، معيار المؤشر، التشخيص. **الكلمات المفتاحية:** نظام المحامل، الإشارة الصوتية، تحليل تجميع النمط الذاتي التجريبي الكامل مع الضوضاء التكيفية(CEEMDAN) ، الدوال النمطية الذاتية(IMF) ، التحليل التمييزي، معيار المؤشر، التشخيص.

ABSTRACT

In this study, an advancing method for enhancing fault diagnosis of bearing systems is developed. Equally an experimental investigation into the diagnosis of bearing under varying operational speeds, utilizing acoustic signals obtained from experiments conducted at the Mechanical Structures Laboratory MSL of Polytechnic Military School, Bordj Elbahri, Algiers is presented. The raw acoustic signals are preprocessed using the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for the determination of the Intrinsic Mode Functions (IMF) containing the highest energy values, which are then employed for diagnostic purposes. The IMFs with the most significant energy content are carefully analyzed using critical indicators: Square Root Amplitude Value (SRAV), Absolute Mean Amplitude Value (AMAV) and Clearance Indicator (CLI). Several classification algorithms, including Decision Tree (DT), Quadratic Support Vector Machines (SVM) and a novel the diagnostic approach involves the application of Discriminant Analysis (DA) in conjunction with indicator standardization and cross-validation are employed in this investigation to showcase the effectiveness of the proposed methodology. This integrated approach significantly enhances the methodology’s performance and accuracy to classify different fault modes in the bearing systems.

Keywords: Bearing System, Acoustic Signal, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Intrinsic Mode Functions (IMF), Discriminant Analysis, Indicator Standardization, Diagnosis.