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Predictive Maintenance of Electrical Machines

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Dedications

We dedicate this dissertation to our families, particularly our parents, for their unconditional love and unfailing support.

To those who believed in us, even when we doubted ourselves.

To our friends, who made us laugh in times of fatigue and stress.

To the teachers who passed on their knowledge to us with passion and high standards.

To all those who have inspired, encouraged or simply listened to us. This work reflects a journey that has at times been difficult, but has always been enriching.

It is the result of a collective effort, fuelled by trust, patience and determination.

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Finally, to everyone who has crossed our path throughout this journey, a huge thank you.

List of abbreviations

I2C : Inter-Integrated Circuit

SPI : Serial Peripheral Interface

UART : Universal Asynchronous Receiver-Transmitter

GPIO : General Purpose Input/Output

LCD : Liquid Crystal Display

CSV : Comma-Separated Values

RMS : Root Mean Square

VCC : Voltage Common Collector

GND : Ground

VDD : Voltage Drain Drain

VIN : Voltage In VOUT Voltage Out

VREF : Reference Voltage PC Personal Computer

IDE : Integrated Development Environment

HVAC : Heating, Ventilation, and Air Conditioning

CAD : Computer-Aided Design

MQTT : Message Queuing Telemetry Transport

PCB : Printed Circuit Board

SD : Secure Digital

UV : Ultraviolet

SCL : Serial Clock Line

SDA : Serial Data Line

RF : Radio Frequency

IC : Integrated Circuit

DC: Direct Current

AC : Alternating Current

EMF: Electromotive Force

ADC: Analog-to-Digital Conversion/Converter

FFT : Fast Fourier Transform

MCSA: Motor Current Signature Analysis

AI : Artificial Intelligence

IIoT: Industrial Internet of Things

PD : Partial Discharge

IEC : International Electrotechnical Commission

RTD : Resistance Temperature Detector

MCC : Motor Control Center

FEM: Finite Element Methods

SoC : System-on-Chip

IMU : Inertial Measurement Unit

MEMS: Micro Electro-Mechanical Systems

PdM : Predictive Maintenance

RUL : Remaining Useful Life DT Digital Twin

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Abstract

This project presents an innovative, low-cost predictive maintenance system for the continuous, real-time monitoring of faults in rotating electrical machinery. The system addresses two principal objectives: minimising unplanned industrial downtime and eliminating unnecessary preventive part replacements, thereby conserving resources.

The prototype is built around an ESP32 microcontroller operating as an edge node, processing data locally without reliance on external servers. Three sensors capture the operational parameters: an MPU6050 accelerometer to monitor vibration; a DS18B20 sensor to monitor temperature; and an ACS712 module to monitor electrical current.

Rather than offloading raw data to an external party for analysis, the data is processed directly within the microcontroller, which calculates rolling statistical metrics such as moving-window standard deviations and root-mean-square (RMS) values. These metrics serve as inputs to a prioritised, rule-based engine calibrated using experimental data.

System performance was evaluated across several operating conditions, including normal operation, overload, structural imbalance, and bearing faults. The results demonstrate high detection accuracy and reliable diagnostic classification, confirming that accessible, fully automated fault-diagnosis systems can be reliably deployed within Industry 4.0 frameworks.

Résumé

Notre projet a mis au point un système innovant de maintenance prédictive, caractérisé par son faible coût, qui vise à surveiller en continu et en temps réel les défaillances des machines électriques tournantes. Le système poursuit deux objectifs principaux : réduire les temps d'arrêt industriels imprévus et limiter les remplacements préventifs de pièces qui ne sont pas réellement nécessaires, ce qui permet d'économiser des ressources.

Le prototype du système repose sur un module de traitement de type ESP32 fonctionnant comme un « nœud périphérique », c'est-à-dire qu'il traite les données localement sans avoir recours à des serveurs externes. Ce module collecte ses données à partir de trois capteurs principaux : l'accéléromètre MPU6050 pour la surveillance des vibrations ; un capteur de température DS18B20 pour surveiller la température ; un capteur de courant ACS712 pour surveiller le courant électrique.

Au lieu d'envoyer les données brutes à un tiers pour analyse, celles-ci sont traitées directement au sein même du microcontrôleur, où le système calcule des indicateurs statistiques actualisés, tels que l'écart-type dans des fenêtres temporelles glissantes et la valeur efficace (RMS). Ces indicateurs sont ensuite utilisés comme entrées pour un moteur de règles logiques conçu, hiérarchisé et calibré à partir de données expérimentales réelles.

Afin d'évaluer les performances du système, celui-ci a été testé dans plusieurs conditions de fonctionnement différentes, notamment : fonctionnement normal, surcharge, déséquilibre structurel et pannes de roulements. Les résultats ont démontré une grande capacité à détecter et à classer les défaillances avec précision.

Sur la base de ces résultats, le projet conclut que les systèmes de diagnostic des défaillances peuvent être efficaces, faciles à mettre en œuvre et fonctionner de manière entièrement automatisée, ce qui les rend aptes à être déployés en toute confiance au sein des écosystèmes de l'« Industrie 4.0 ».

ملخص:

طوّر مشروعنا نظامًا مبتكرًا للصيانة التنبؤية يتميز بانخفاض تكلفته، ويهدف إلى مراقبة أعطال الآلات الكهربائية الدوارة بشكل مستمر وفي الوقت الفعلي. ويسعى النظام إلى تحقيق هدفين رئيسيين: تقليل فترات التوقف الصناعي غير المخطط له، والحد من عمليات استبدال الأجزاء التي تتم بشكل وقائي دون داعٍ فعلي، مما يوفر الموارد. يعتمد النموذج الأولي للنظام على وحدة معالجة من نوع ESP32 تعمل كـ "عقدة حافة"، أي أنها تقوم بمعالجة البيانات محليًا دون الحاجة إلى خوادم خارجية. وتجمع هذه الوحدة بياناتها من ثلاثة أجهزة استشعار رئيسية: مقياس التسارع MPU6050 لرصد الاهتزازات مستشعر درجة الحرارة DS18B20 لمتابعة الحرارة ووحدة قياس التيار ACS712 لمراقبة التيار الكهربائي. بدلًا من إرسال البيانات الخام إلى جهة خارجية لتحليلها، تتم معالجتها مباشرة داخل وحدة التحكم الدقيقة نفسها، حيث يقوم النظام بحساب مؤشرات إحصائية متجددة، مثل الانحراف المعياري ضمن نوافذ زمنية متحركة، والقيمة الفعالة (RMS) تُستخدم هذه المؤشرات بعد ذلك كمدخلات لمحرك قواعد منطقي تم تصميمه وترتيبه حسب الأولوية، وتمت معايرته بالاعتماد على بيانات تجريبية فعلية. ولتقييم أداء النظام، تم اختباره في عدة حالات تشغيلية مختلفة، شملت: التشغيل الطبيعي، والحمل الزائد، والاختلال الهيكلي، وأعطال المحامل. وأظهرت النتائج قدرة عالية على اكتشاف الأعطال وتصنيفها بدقة. وبناءً على هذه النتائج، يخلص المشروع إلى أن أنظمة تشخيص الأعطال يمكن أن تكون فعالة وسهلة التطبيق وتعمل بشكل آلي بالكامل، وهو ما يجعلها قابلة للنشر بثقة ضمن منظومات "الصناعة 4.0".

General Introduction

General Introduction

Electric machines represent critical elements in modern industrial environments. The machines are considered interfaces that convert electromagnetic energy into mechanical energy to operate other devices, such as pumps, compressors, conveyors, fans, and machine tools. Given their extensive utilization in the industry, the reliability of such machines becomes crucial since an unexpected machine breakdown can result in considerable financial losses and damage to the machinery as well as potential safety concerns depending on the type of application and its environment.

Traditionally, there are two types of maintenance applied to industrial machines: corrective maintenance carried out only after a malfunction occurs and preventive maintenance involving planned maintenance interventions regardless of the state of the device. Despite the advantages of the mentioned approaches, their effectiveness appears to be limited because corrective maintenance leads to unplanned downtime and increased costs for maintenance whereas preventive maintenance entails unnecessary maintenance activities and replacement of the working parts.

In response to these challenges, the concept of predictive maintenance gained popularity recently due to its efficiency and intelligence. Predictive maintenance involves the continuous analysis of the machine's health through signal processing or machine learning and alerting about the potential breakdown. As a result, this approach allows not only reducing maintenance costs and increasing the lifetime of the equipment but also avoiding downtime associated with maintenance.

This thesis concerns itself with the creation of a predictive maintenance system for electrical machines. The project entails research encompassing all aspects of the issue, from the theoretical basis to its practical application. The document will be divided into four chapters, each dealing with a specific part of the process.

The first chapter provides a comprehensive introduction to electrical machines. It begins by defining the concept of electromechanical energy conversion and classifying the main types of electric machines encountered in industrial settings, including DC machines, asynchronous motors (induction motors), synchronous machines, and special-purpose motors.

Each machine type is described in terms of its operating principle, construction, and typical field of application. Among these, the asynchronous motor deserves special attention because it is the most widely used motor in industries due to its robustness, reliability, and low

maintenance cost. This chapter discusses the asynchronous motor in greater detail than the other machine types.

The chapter also reviews the key components shared by most machines, such as the stator, rotor, windings, bearings, and shaft, emphasizing their respective functions and the role they play in the overall behavior of the machine. This foundational knowledge is essential to understand how and where faults can originate, which forms the basis for applying predictive maintenance strategies to ensure continuous and reliable operation of industrial machinery.

The second chapter is dedicated to the identification and classification of the most frequent types of faults occurring within electrical machines. It begins with a structured list of possible faults classified by physical location as well as their type: mechanical faults include, among other things, bearing faults and rotor eccentricity; electrical faults involve, for instance, stator winding short circuit and broken rotor bars. Next, the chapter analyzes the reasons behind each type of fault, the physical damage that takes place, and its effect on the functionality and service life of the machine. Finally, data obtained through statistical research in the industry is provided for each fault type, thus supporting the conclusions made in the next chapter.

The third chapter provides a profound academic analysis of various methodologies used for detecting and diagnosing malfunctions in rotating electrical machines. It starts with classical signal-based approaches, including time-domain analysis, Fast Fourier Transform (FFT) for frequency-domain analysis, and Short-Time Fourier Transform (STFT) and Wavelet Transform for time–frequency analysis. It then transitions to non-invasive, current-based diagnostics performed remotely via Motor Current Signature Analysis (MCSA) to identify rotor and stator defects. While classical physical examinations—such as vibration analysis, infrared thermography, and acoustic emissions—are also discussed, emphasis is placed on the technological paradigm shift driven by Industry 4.0. Particularly, the implementation of AI and Deep Learning algorithms for end-to-end fault classification is examined. Furthermore, the chapter explores Industrial Internet of Things (IIoT) technology and Edge Computing, paying specific attention to utilizing the ESP32 microcontroller as an edge node for the on-site processing of acquired signals. Finally, the Digital Twin approach is considered, which integrates the simulation of hidden physical processes using Finite Element Method (FEM) modeling with real-time sensor data streams to estimate the machine’s remaining useful life (RUL).

The fourth chapter will contain all details about developing a predictive maintenance prototype of an electric machine. This will include describing a general scheme of the system and presenting all hardware components: sensors for data collection, signal processing, and the processing unit itself. In addition, it will be necessary to explain the software part of the predictive maintenance system, namely data acquisition algorithms, signal processing, and fault classification algorithms. Tests performed on the real object (electric machine) with simulated faults will be presented and discussed to demonstrate the reliability and efficiency of the developed predictive maintenance prototype.

As a result, it will be proved that it is possible to create an effective and efficient predictive maintenance system to monitor electric machines.

Chapter I:

generalities on electrical machines

I.1. Introduction

Electric motors play an important role in modern-day industries, although often they remain unnoticed by plant workers due to continuous operation in the background of various processes. Starting from morning and up to night time, motors work continuously and help to implement various processes that cannot be performed without using motors in any meaningful scale. The principle of functioning is rather simple – one needs to provide electrical energy in order to receive mechanical motion. However, the variety of functions that can be performed with the help of such motion makes electric motors highly versatile and widely used across different industries. In manufacturing, motors are used in conveyor systems, pumps, fans, compressors, robots, etc. [1]. All these applications have various requirements in terms of speed, torque, and accuracy. Nevertheless, the principle remains the same.

In this chapter, we will present general information about electrical machines, beginning with the main laws of physics that govern their operation. Next, we will list the different types of these machines and their main characteristics. Then, we turn our attention to the construction of these machines whether they are direct current machines or alternating current machines. Finally, we will present the different applications of these machines.

I.2. Physical Principles and Basic Laws

All electrical machines, both static (transformers) and rotating (motors and generators), function based on the basic laws of electromagnetism. The conversion of electromagnetic energy is dependent on the interaction of electricity and magnetism that is continuous and dynamic. In order to understand the functioning of such electrical machines and hence monitor them for purposes of predictive maintenance, it is necessary to formulate the basic physical laws.

I.2.1. Ampere's Circuital Law and Generation of Magnetic Field

Ampere's law describes the basic relation between the electric current and the magnetic field generated by it [3]. This law is used in industrial electrical machines for creating the primary magnetic flux by using the stator/rotor windings [4].

According to Ampere's law, the line integral of the magnetic field intensity H along any closed loop is equal to the total current enclosed within that closed loop I_{enc} [5].

Mathematically, this can be written as:

$$\oint H \cdot dl = I_{enc} \quad (I.1)$$

If N turns of a coil carry current I , the Magnetomotive Force (F) generated by the coil is determined by this law as follows:

$$F = N \cdot I = \oint H \cdot d\ell \quad (I.2)$$

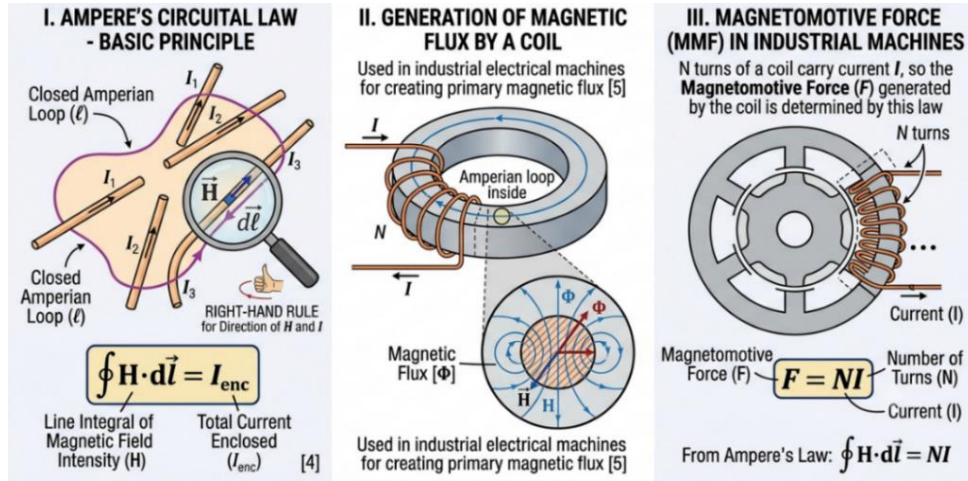


Figure I.1 : Ampere's Circuital Law and magnetic field generation in electrical machines

I.2.2. Faraday's Law of Electromagnetic Induction

Faraday's Law is the fundamental law concerning the production of voltage in electrical machines [4]. This law asserts that whenever there is any change in the magnetic flux Φ passing through a circuit, an electromotive force e is induced in the circuit [3].

The voltage is produced by rotating the coil in a magnetic field using mechanical energy in generators, while it is produced by alternating current causing a changing magnetic flux in the transformer [5]. For a coil having N turns, the induced electromotive force is:

$$e(t) = -N \cdot \frac{d\Phi}{dt} \quad (I.3)$$

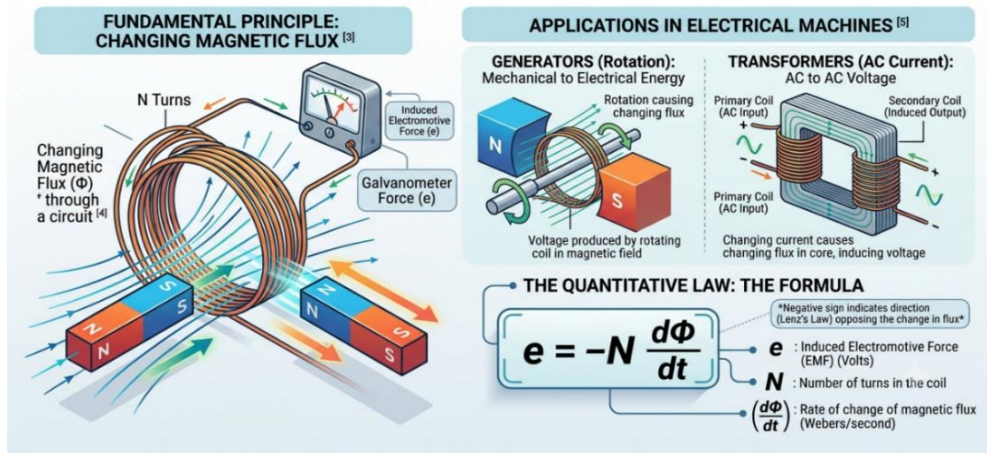


Figure I.2 : Faraday's Law of electromagnetic induction and its applications in generators and transformers

I.2.3. Lenz's Law

Closely related to Faraday's Law, Lenz's Law indicates the direction of the induced electromotive force (EMF) [3]. According to this law, the induced current will always flow in the direction that creates another magnetic field, which opposes the first change in the magnetic flux [4].

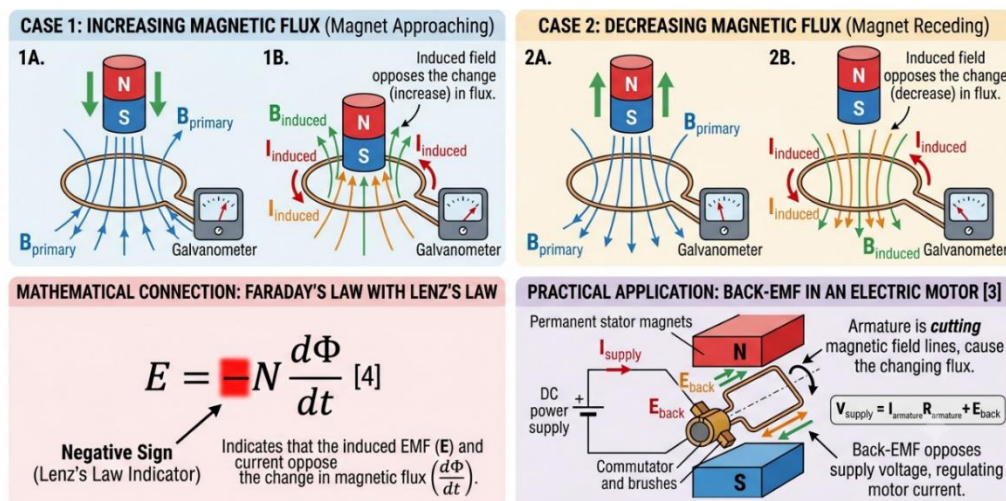


Figure I.3 : Lenz's Law demonstrating the direction of induced EMF and back-EMF in electric motors

It can be observed from the negative sign in the above equation of Faraday's law. The effect of Lenz's Law in practical electromechanical systems finds application in the form of back-EMF (Counter Electromotive Force) in electrical motors, where it automatically controls the current taken by the motor [3].

I.2.4. The Laplace

As Faraday's law explains the production of electrical energy, the Laplace force, which is the macroscopic form of the Lorentz force, is responsible for the production of mechanical energy in electric machines like motors [4]. As the conductor of length L with electric current I is placed in an external magnetic field with flux density B , then it will experience mechanical force F , which will be perpendicular to both the current flow and the magnetic flux [5].

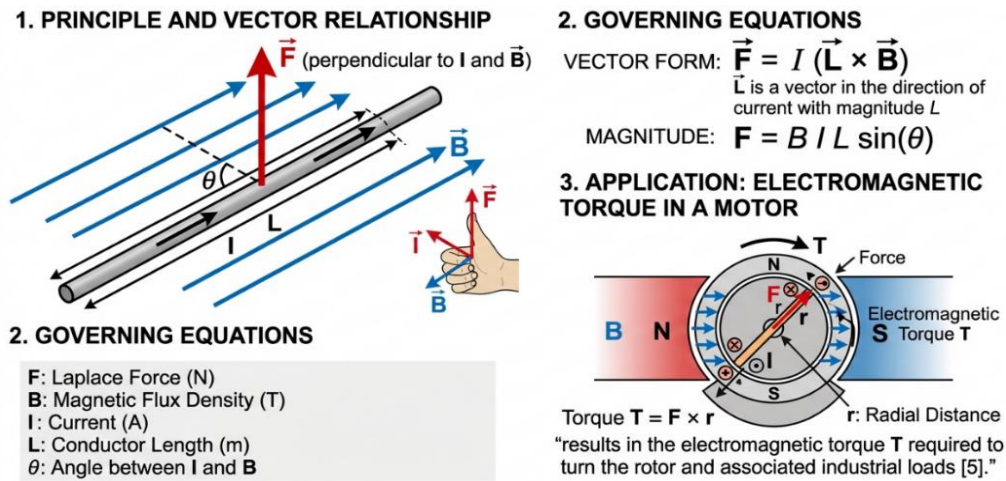


Figure I.4 : The Laplace force principle, governing equations, and electromagnetic torque production in a motor.

The equation for the Laplace force in vector form is:

$$F = I \cdot (L \times B) \quad (I.4)$$

The equation for the magnitude of the force, when the angle between the conductor and the magnetic field is θ , is: [3].

$$F = I L B \sin(\theta) \quad (I.5)$$

In a rotating machine, this basic force, applied at radial distance from the center of rotation, results in the electromagnetic torque T required to turn the rotor and associated industrial loads [5].

$$T = F \times r \quad (I.6)$$

I.3. Classification of Electrical Machines

The basic classification of electrical machines is based on their structure as well as the manner in which the electrical energy is utilized. The most general classification divides electrical machines into static and rotating types, with the latter using mechanical rotation for

energy conversion [3]. In addition to the method of electric energy utilization, the machines can be distinguished by the type of current used DC or AC as well as their synchronization modes [4].

I.3.1. Static Machines:

The static machine refers to an electromagnetic device designed for transferring electrical energy from one circuit to another through magnetic coupling without relative motion between components [5]. The main example of static machines is a transformer.

The core idea behind the operation of transformers is changing the values of alternating voltages and currents, while keeping the same frequency. Changing values is achieved using electromagnetic induction between the windings of the primary and secondary parts that share a common ferromagnetic core [4]. In industry, transformers play an essential part in raising voltages for the effective transmission over large distances and decreasing voltages to match the conditions of industrial distribution systems [5].

I.3.2. Rotating Machines

The rotating electric machine is made up of two main components: the stator, which is stationary, and the rotor, which is rotating. The rotating electric machine works either as a motor, converting electrical energy into mechanical energy, or as a generator, converting mechanical energy into electrical energy [3].

I.3.2.1. Direct Current (DC) Machines

A DC machine is an electromechanical energy conversion system. There are two main types of DC machines : the first one is the DC generator and the second one is the DC motor

The DC generator converts mechanical power into DC electrical power, while the DC motor converts DC electrical power into mechanical power. Although AC motors are commonly used in the industry for converting electrical power into mechanical power, DC motors are preferred in applications requiring a wide range of speeds and precise speed regulation, such as electric traction systems.

There are two main categories by which the DC machine gets excited first one is self-excited and the second one is separately excited.

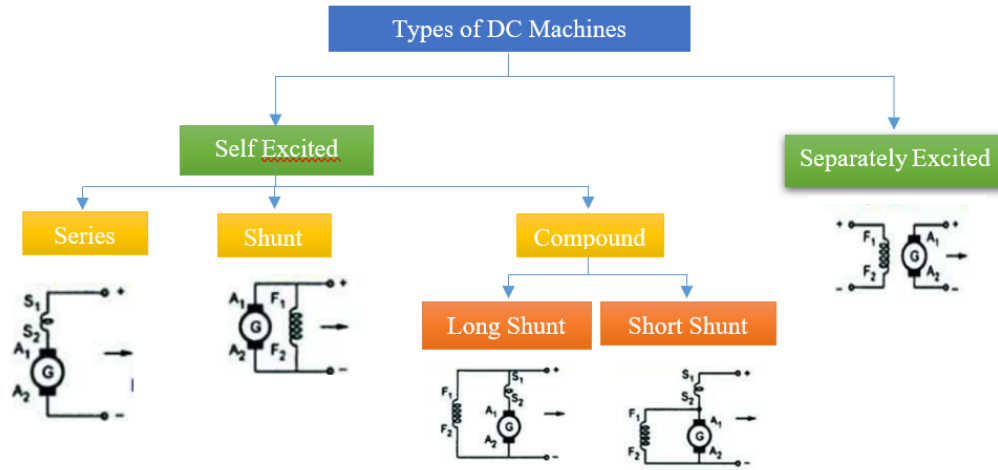


Figure I.5 : Classification of DC machine.

In self-excited machines field current produced by the machines itself while in separately excited machines the field current is provided by the separated source. Due to these two excitations methods, the DC machines are further divided into different types that are described here.

- Compound DC machine.
- Shunt DC machine.
- Separately excited DC machine.
- Series DC machine.

I.3.2.2. Alternating Current (AC) Machines:

AC machines form the major sources of power in today's industries. They can be classified based on the ratio between the speed of the rotor (N) and the speed of rotation of the magnetic field in the stator known as synchronous speed (N_s) [4]. Synchronous speed is expressed mathematically as:

$$N_s = \frac{120 \cdot f}{P} \quad (I.7)$$

Where:

- N_s is the synchronous speed in revolutions per minute (rpm).
- f is the supply frequency (Hz).
- P is the number of magnetic poles in the machine [3].

AC motors are classified into two main types:

- A. Synchronous machine:** These are the motors in which the speed of the rotor is equal to the speed of the rotating magnetic field produced by the stator ($N = N_s$) [3]. They find their extensive applications as generators in power stations and as synchronous motors in industrial applications [4].
- B. Induction (Asynchronous) machine:** In induction motors, the rotor turns at a speed lower than the synchronous speed ($N < N_s$) [3]. It is important to note that this difference in speeds is critical for the generation of torque since the induced current on the rotor is created by the movement of the magnetic field produced by the rotating stator and rotor. The difference in speeds is represented by the slip factor (S) which can be expressed as [4]:

$$S = \frac{N_s - N}{N_s} \quad (I.8)$$

Induction motors (squirrel cage induction motors) are the main players in today's industries. They are used extensively due to their sturdy design, absence of brushes, cheap nature, reliability, and suitability for being run on line or with varying speeds through power electronics.

I.4. Construction of electrical machines

I.4.1. Construction of the Asynchronous Motor

An asynchronous machine, otherwise called an induction motor, is an electrical machine which runs using alternating electric voltage and current. One of the main purposes of the asynchronous machine is energy conversion from electrical to mechanical; if this purpose fails owing to faults, it implies that there is something wrong with the motor. The asynchronous operating phenomena were discovered by Michael Faraday in 1831, and since then many breakthroughs have been witnessed in order to improve this electrical machine till date. An asynchronous machine can be used as a motor in various industries for diverse applications. It consists of different parts (shown in Fig. I.6) that are arranged in three major parts which include the stator, rotor and bearings.

Figure I.6 shows also a fan whose work is to reduce the heat produced during the functioning of the machine. This fan is mounted on the machine shaft and it rotates without electricity. Also, the machine has bearings at the end points of the rotor shaft and their main function is to create a shafting between the fixed stator and rotor shaft in order to reduce friction while rotating.

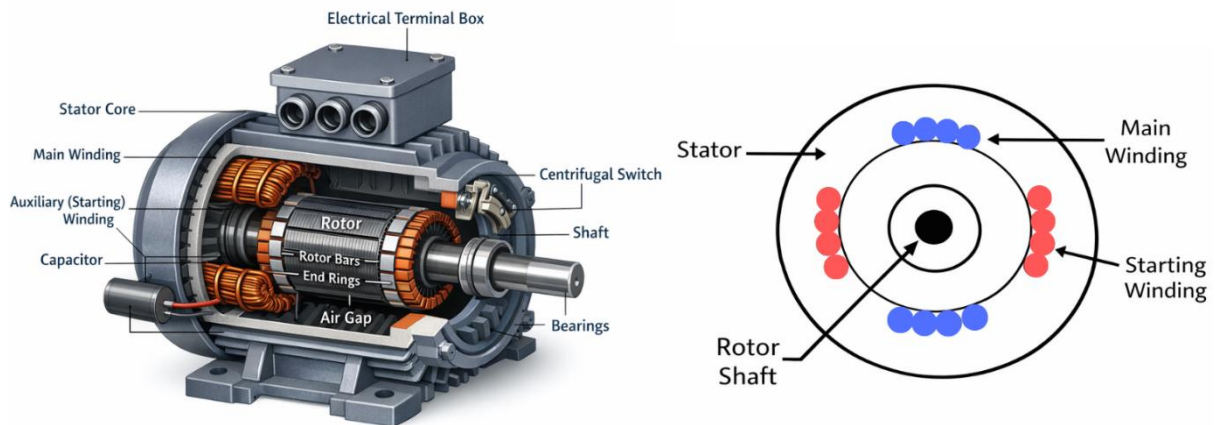


Figure I.6 : Construction of the asynchronous motor

I.4.1.1. The Stator

The stator, or Armature winding, represents the stationary part of the motor, which is meant to create the rotating magnetic field. The device consists of the frame, the core, and the three-phase coil winding located in the slots of a ferromagnetic cylindrical housing to reduce eddy currents. The stator core serves as an element of support and protection of the three-phase stator winding, and it is made by stamping quality silicon steel. The stator winding itself can be separated into two components, namely, the slot conductors and the coil heads. The first creates the magnetic field in the air gap for the electromechanical transformation process to proceed, and the second completes the circuit of current flow between the slot conductors. [6]

The aim here is to achieve a current distribution in the air gap close to the sinusoidal pattern, and hence minimize the ripple in the electromagnetic torque. [7] Figure 1.7 shows the diagram of the stator.



Figure I.7 : Diagram of a stator

I.4.1.2. The Rotor

The rotor is known as the armature, forming the moving part of the electric motor. It consists of the core and the winding, whereby the current in the winding is electromagnetically induced by the rotating magnetic field of the stator.

The cylindrical rotor core made of iron has the semicircular slot on its surface to accommodate the conductors, either copper or aluminum ones. At both ends, the conductors are linked to the short-circuited aluminum or copper rings. The rotor can take two forms, namely the squirrel-cage rotor and wound rotor. Squirrel-cage asynchronous motors are used in industrial applications for their strength, ease of manufacturing, compared to the wound-rotor motors, and affordability.

In the squirrel-cage rotor, the short-circuited rings are responsible for generating the current that flows through the rotor bars. They are uniformly arranged to constitute the rotor circuit [7]. Such cage is incorporated in the magnetic circuit consisting of the stack of laminated discs fixed on the machine shaft similarly to the rotor shown in Figure 1.8.

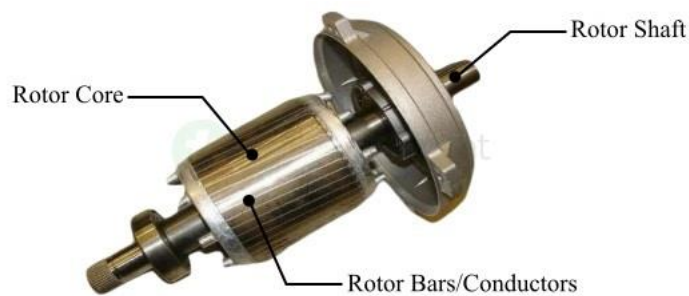


Figure I.8 : Diagram of a rotor

I.4.1.3. Bearings

The bearings represent mechanical parts which shield, support, and make possible the rotation of the motor. These include:

- Housing : which represents a structural element, acts as a casing, and protects the device from the outside world.
- Shaft : represents a transmission element which consists of the main part where the rotor is placed and the shaft end with a half-coupling attached. It is usually made of cast or forged steel.

- The bearings : support the shaft and keep the rotor in place enabling its rotation without hindrances. There is an additional bearing for thermal expansion of the shaft.

- Bearings make sure the shaft rotates freely without any problems.

I.4.2. Direct Current Machine

The structure of DC motor consists of two major elements:

- Stator : stationary element
- Rotor : rotating element

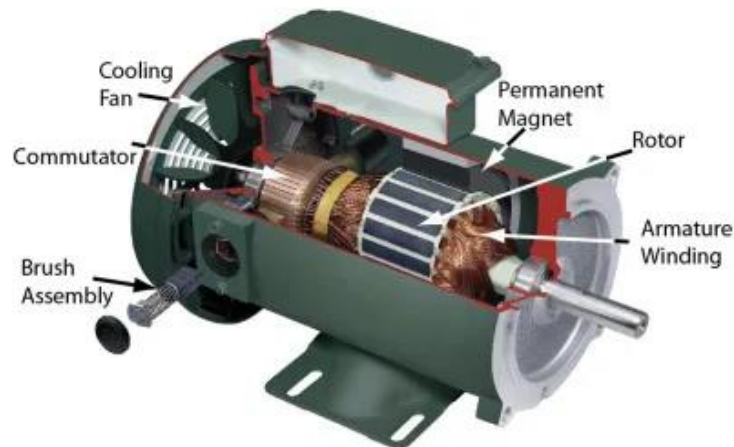


Figure I.9 : Diagram of a DC motor.

I.4.2.1. The stator

The stator produces a magnetic field (or excitation field) using a coil wound and energized by direct current, or using permanent magnets mounted inside the stator[8].

The magnetic lines run from the north pole to the south pole. The poles of excitation windings are set in such a way that the poles adjacent to each other have opposite polarity.

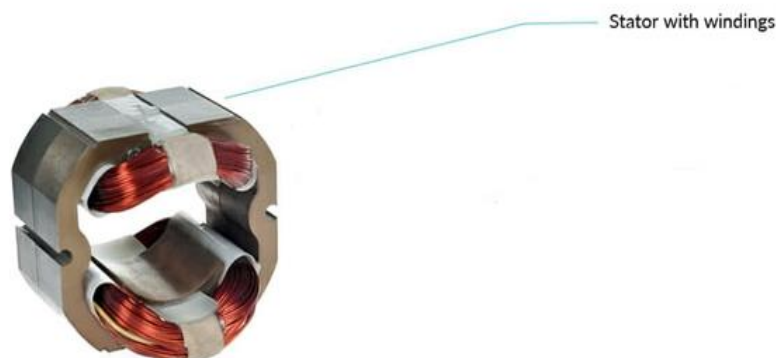


Figure I.10 : The stator of a DC motor.

I.4.2.2. The rotor

Rotor is made of magnetic laminae and torque acts upon it to cause rotation in a magnetic field.



Figure I.11 : Rotor of a DC motor

I.4.3. Synchronous Motor:

A synchronous motor refers to a type of AC motor that rotates in synchronization with the revolving field produced by the stator at exactly the same angular velocity. Contrary to induction motors, synchronous motors do not experience slip during steady state.

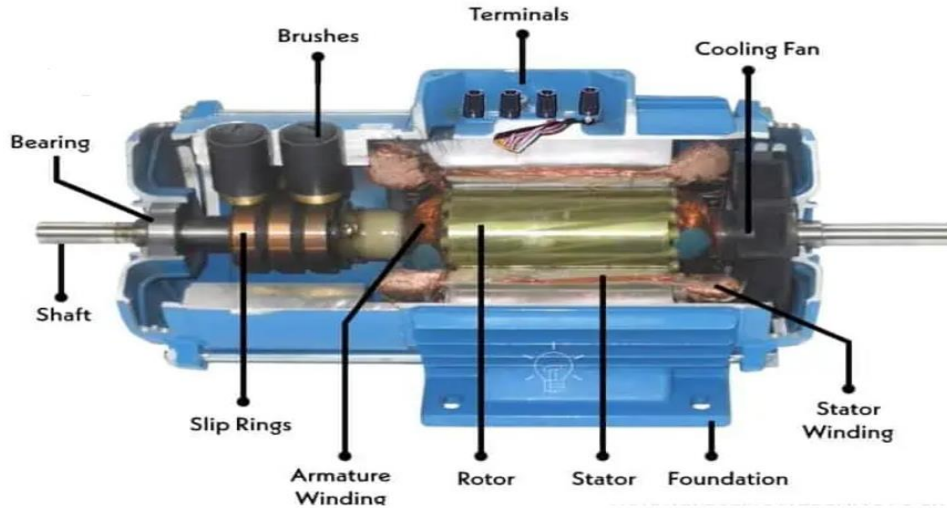


Figure I.12 : Diagram of a Synchronous Motor

A synchronous motor consists mainly of the following parts[9]:

I.4.3.1. The stator

The stator represents the fixed part of the synchronous motor. It comprises a steel framework, laminated magnetic core, and windings of three-phase located inside slots.

Laminations act as a measure of reducing eddy current losses, making the motor efficient. Application of three-phase AC in the stator windings results in the formation of a rotating magnetic field that forms the basic working principle of the motor.

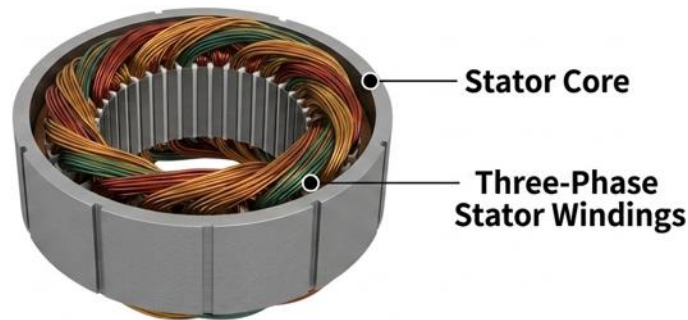


Figure I.13 : stator of a Synchronous Motor

I.4.3.2. The Rotor

Rotor is the rotating part of the synchronous motor. The rotor holds the field coil that receives power from the DC supply source. The constant magnetic field is created by the field coil due to DC excitation.

The rotor runs synchronous with the rotating field produced by the stator and runs with the exact same speed as that of the rotating field. The rotor can either be of salient pole type or cylindrical type[9].

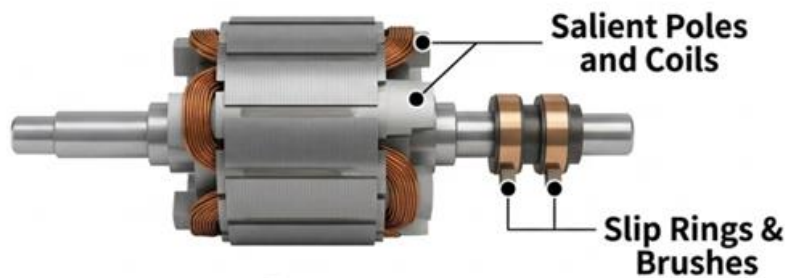


Figure I.14 : Rotor of a Synchronous Motor

I.5. Applications of electrical machines

Electrical machines form a basic element in present-day industrial machinery. One can observe that all those principles of the electromechanical system discussed above are put into practice during material, liquid, and gas transportation in various industries. Under the conditions of high competition on the part of the industry, the reliability of those systems is associated with the overall profitability of enterprises [10].

➤ Pumps

Pumps represent one of the most popular industrial machines which help to move liquids at petroleum plants, water purification stations, and cooling plants in manufacturing enterprises. Pumps are driven with the help of three-phase asynchronous induction motors, which are reliable even under difficult conditions as proven by:

- Water distribution systems (municipal ones)
- Hydraulic systems of manufacturing companies
- Transport of oil and gas through pipelines
- Irrigation systems (agriculture)
- Power plant cooling water systems

➤ Compressors

These machines have the capability to increase the pressure of gases. The use of these machines forms the basis of the pneumatic control system, refrigeration, and gas transmission systems. Operation of these machines involves induction motors and synchronous motors used in large-scale operations such as:

- Pneumatic systems for delivering air under pressure to tools used in industries
- Refrigeration and HVAC systems
- Gas compressions in petrochemical plants

➤ Robotics and Automation

Electrical machines form the primary equipment in present-day robotics and automation, where the conversion of electrical energy to mechanical motion takes place. DC machines are relatively easy to operate and possess good speed control qualities. Synchronous machines with permanent magnets are usually preferred in the field of robotics and servomechanisms due to their compactness and precision capabilities. On the other hand, asynchronous machines are used in larger scale automation, such as the use of conveyor robots and AGVs. Such machines and their control systems make robots capable of executing complex, repetitive operations quickly and efficiently in the automobile, electronics, and logistic industries [11].

➤ **Electrical Power Generation**

Electrical machines are instrumental in generating electricity through the conversion of mechanical energy into electrical energy. Various power stations, such as those based on thermal power, hydroelectric power, nuclear power, and gas, make use of synchronous generators to generate stable AC voltage with constant frequency. For wind energy conversion systems, doubly-fed induction generators are applied to ensure the possibility of variable-speed operation. As for DC machines, their application is rather outdated and limited only to emergency cases[12].

➤ **Conveyors**

Conveyor systems act as vital equipment used in transporting materials in industries. These machines consist of different machines where gear induction motors and direct current motors are commonly utilized. Some of the common uses of these machines include[10]:

- Assembly line transportation of goods in the automotive industry
- Handling luggage in airports

I.6. Conclusion

This introductory chapter provides the basic theoretical and practical foundation necessary for further investigation into the operation of electric machines in modern industry. First of all, the introduction of Ampere's, Faraday's, Lenz's, and Laplace's laws allows the establishment of the basic rules of electromagnetic energy conversion to mechanical energy and back.

Moreover, the structural classification of the technologies in question encompasses both static devices for voltage regulation, like transformers, as well as rotating DC and synchronous machines, focusing on their application in industrial practices through pumps, compressors, robots, power generation, and conveyors.

The most important among static and rotating technologies is the AC asynchronous (induction) machine because of its reliable design without brushes, economical performance, and durable service. The structural composition shows how the rotor, stator, and bearing allow the rotation process; moreover, the consideration of the energy conversion highlights the problems of inherent energy losses, which can be due to copper, iron, and mechanical effects.

Finally, the information provided clearly shows that despite high resistance to wear and tear, there is still considerable sensitivity to both electrical and mechanical damage, meaning

that otherwise the industrial process would be subject to serious disturbances, economic losses, and dangers to employees. Thus, this theoretical knowledge proves the necessity of developing novel concepts in the sphere of monitoring. The next step to accomplish concerns the classification of faults and diagnostic tools.

Chapter II:

different faults in electrical machines

II.1. Introduction

The robustness of an electrical machine in no way guarantees its infinite longevity, since it is constantly subjected to disturbances that lead to the occurrence of electrical, mechanical, thermal, or other failures. The objective is to detect these faults as they develop or, better yet, as they begin to occur. These faults are classified according to their nature or origin. [1]

Motor faults are so varied that specialists in the field are compelled to classify them into two main groups: internal and external. External faults are caused by factors not directly related to the motor, such as supply voltages, mechanical load, and the operating environment of the machine. Internal faults are caused by the machine's components (magnetic circuits, stator and rotor windings, mechanical air gap, rotor cage, etc.) [2].

Numerous factors, such as manufacture flaws, challenging working conditions, overloading, aging, and poor maintenance, can result in electrical machine faults. To guarantee machine dependability, save downtime, and avoid catastrophic failures, early identification and precise classification of these defects are essential. The main types of electrical machine faults, together with their physical mechanisms, causes, and effects, are covered in detail in this chapter.

II.2. Electrical Faults

II.2.1. Stator Faults

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

- Insulation fault
- Turn-to-turn short circuit
- Phase-to-phase short circuit
- Power supply imbalance
- Magnetic circuit fault

II.2.1.1. Insulation faults

In an induction motor, thermal phenomena occur due to various losses (Joule, mechanical, etc.), causing the temperature of the motor's various components to rise. This leads to short circuits that continuously degrade the insulation in the windings, which eventually fail to perform their function. The various causes of this type of fault are:

- Degradation of the insulation from the manufacturing stage.
- Exceeding the voltage limit of the winding insulation material.
- High current in the winding due to a short circuit or overload. This leads to a rise in temperature that prematurely degrades the insulation material.
- Natural aging of the insulation, even when the machine is used correctly.
- Operation in a harsh environment [3].

II.2.1.2. Turn-to-turn short circuit

Increased stator currents in the impacted phase and amplified currents in the rotor circuit can result from several insulation flaws in the winding. This raises the temperature at the winding and accelerates the insulation's deterioration, which can result in a chain fault (the emergence of a second short circuit) or a short circuit between a phase's turns.

II.2.1.3. Phase-to-phase short circuit

The analysis of this type of fault relies on criteria that are difficult to overlook because they depend on its location:

- A phase-to-phase short circuit near the power supply induces very high currents that lead to the melting of the power supply conductors and/or tripping by the protection devices.
- A short circuit between two phases near the neutral causes an imbalance without causing the conductors to melt.

When this fault occurs, the stator currents are completely unbalanced and are proportional to it. The currents in the busbars and also in the rings are increased.

Detection of this type of fault can therefore be based on the imbalance of the phase currents [3].

II.2.1.4. Power Supply Imbalance

Three-phase distribution systems often supply single-phase loads. Any imbalance in impedance or load distribution can cause an imbalance across the three phases. Potential faults may occur in the motor wiring, in its terminals, or even in the windings. This imbalance can

place stress on the entire phase circuit of a three-phase system and cause excessive current flow on one or more phases, which increases operating temperatures and degrades insulation [4].

II.2.1.5. Magnetic circuit fault

The most common causes of this defect are generally related to severe static and/or dynamic eccentricity, which can eventually lead to contact between the stator and the rotor, thereby destroying the magnetic circuit [5].

The projection of foreign objects into the air gap (due to intense local heating in the laminations)

caused by a short circuit in the conductors can lead to abrasion of the laminations and thus short-circuit them [6]. These faults, in turn, can exacerbate the problem through overheating, overvoltage, significant increases in current, etc.

II.2.2. rotor faults

Rotor imbalance in the machine's operation is observed after these defects are identified. This, in turn, can exacerbate problems such as:

- Thermal (overload)
- Electromagnetic (eccentricity)
- Residual (deformation)
- Dynamic (drive shaft)
- Mechanical (bearing)

The most common defects, located in the rotor, can be defined as follows:

II.2.2.1. Bar fractures

Bar fracture or breakage is one of the most frequent defects in the rotor. It is commonly studied in the laboratory due to its simplicity of replication. An increase in oscillation amplitude is synonymous with a reduction in the average value of the electromagnetic torque and an acceleration of the machine's deterioration. This leads to abnormal machine operation (production of mechanical vibrations) and the torque decreases significantly with the number of broken bars [7].

II.2.2.2. Ring Breaks

One flaw that happens just as frequently as bar breakage is the breakage of a ring segment. In fact, it is often mistaken for bar breakage in statistical research, which makes it

challenging to identify [7]. The breakage of a ring segment really results in an imbalance in the distribution of currents in the rotor bars, which has an effect amplitude modulation on the stator currents that is comparable to that caused by busbar breaks.

The primary distinction is that greater currents are carried by short-circuit rings. As a result, the rings may break due to incorrect ring sizing, deteriorating operating conditions (temperature, humidity, etc.), or torque overload [8].

II.3. Mechanical faults

Most of the faults that can affect electrical machines are generally caused by abrasive wear, moisture, corrosion, improper installation, incorrect clearances between the bushings and the shaft or in the bearing, slippage of rolling elements, unforeseen contamination, or failure of the cage, seals, or lubrication, or excessive load [9]. These cause mechanical effects in the machines, such as increased noise levels and the occurrence of vibrations due to the rotor's movement around the machine's longitudinal axis. In the following, we will list the mechanical faults commonly found in induction motors.

II.3.1. Unbalance

It is one of the most common and frequent causes of mechanical failure encountered in rotating machinery. It is caused by an uneven spatial distribution of masses within the structure, resulting in a shift of the center of gravity away from the geometric axis of the rotor. As a result, the rotating shaft is subjected to centrifugal forces that deform it. Unbalance is a mass imbalance that generally stems from defects in machining, assembly, and asymmetric heating of the rotor during operation [3]

The force generated by an imbalance is a function of the mass m and the radius of the circle r on which the rotor rotates. It is proportional to the square of the rotational speed ω and is given by the following equation (II.1) [10]:

$$F = m \cdot r \cdot \omega^2 \quad (\text{II.1})$$

II.3.1.1. Types of Unbalances

A rise in the overall level at low frequencies and, to a considerably greater extent, a high amplitude component at the rotor's rotational frequency in the radial direction are characteristics of the imbalance phenomenon [3]. Three categories of imbalances exist:

➤ **Static imbalance**

It causes a parallel shift of the center of mass relative to the geometric axis. It must be compensated for at the center of gravity. To do this, material must be removed or added on the opposite side to balance the process. (Figure II.1) below shows a diagram of a rotor with static imbalance.

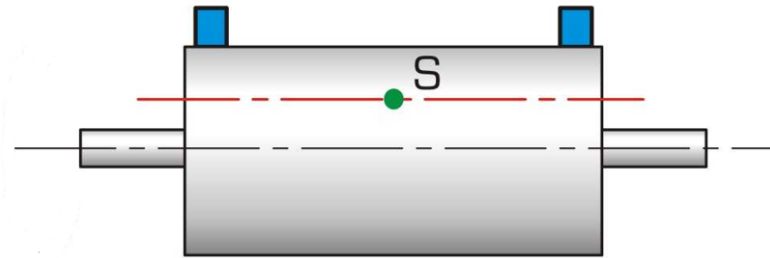


Figure II.1 : Schematic diagram of a rotor with static imbalance...

➤ **Torque imbalance**

Two equal parallel forces acting in opposite directions along the same straight line create a torque imbalance. The torque imbalance becomes apparent only when the part is rotating. Unlike static imbalance, torque imbalance can only be corrected by making balancing adjustments in two planes (Figure II.2).

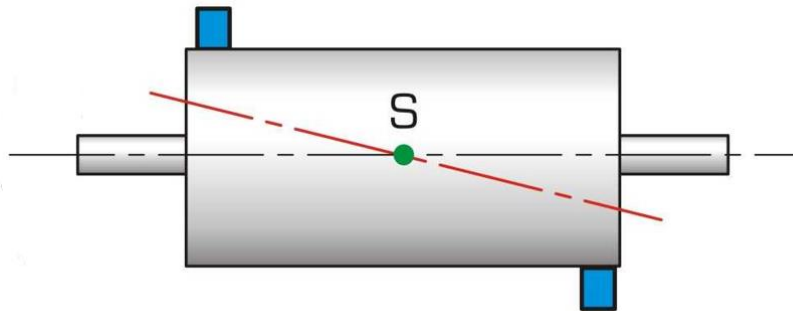


Figure II.2 : Schematic diagram of a rotor with a torque imbalance

➤ **Dynamic imbalance**

In reality, the rotor has several imbalances distributed randomly along the axis of rotation. Dynamic imbalance results from the combination of static and torque imbalances, which shift the center of gravity away from the axis of rotation while tilting it. To completely correct dynamic imbalance, two correction planes are required. Dynamic imbalance occurs in virtually all rotors, which is why both horizontal and vertical balancing machines are used to perform balancing (Figure II.3).

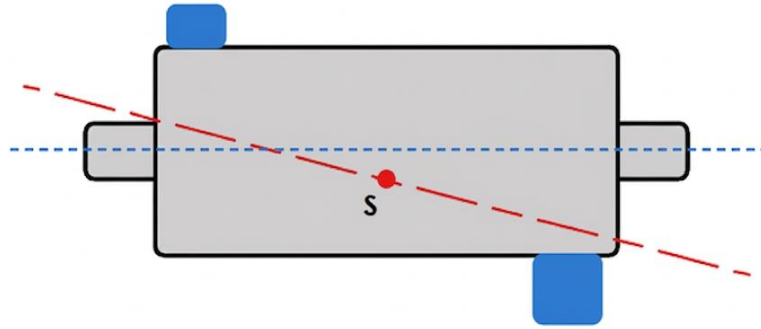


Figure II.3 : *Schematic diagram of a rotor with dynamic imbalance.*

II.3.1.2. The origins of Unbalance

- **Mechanical:** An immediate change in vibrations is observed as soon as a mass of material breaks off or accumulates on the rotor, such as a blade loss, erosion, or material buildup, etc...
- **Thermal:** when rotors are not homogeneous or the temperature is not distributed uniformly, the rotors deform under the effect of thermal stresses:
 - deformation of turbine rotors,
 - deformation of alternator or electric motor rotors.
- **Progressive:** caused by friction between the shaft and one of the machine's bearings, resulting in asymmetric heating [10].

II.3.2. Bearing faults

There can be several causes of bearing failure, starting as early as the manufacturing stage, where an inappropriate choice of material can lead to flaking or cracks that may cause disruptions within the machine. Electrical currents flowing through the bearings can, in turn, cause further deterioration of the bearings. The grease, which ensures lubrication and smooth rotation of the bearings, can harden and create resistance to rotation .

Magnetic imbalance, high temperatures, or a lack of cleanliness also lead to metal loss and cause the balls to repeatedly strike the bearing cage . Fluctuations in the load torque then become apparent.

The rotor's displacement around the machine's longitudinal axis results in vibrations due to increased losses and play between the bearing's inner and outer rings. In the worst situation, this may cause the motor to seize [8]. A ball bearing's internal construction is depicted in Figure

1.4 below. The distinctive frequencies of a spectrum can be used to diagnose bearing failure. The velocities at the locations of contact between the balls and the rings are assumed to be zero in order to calculate these [11]

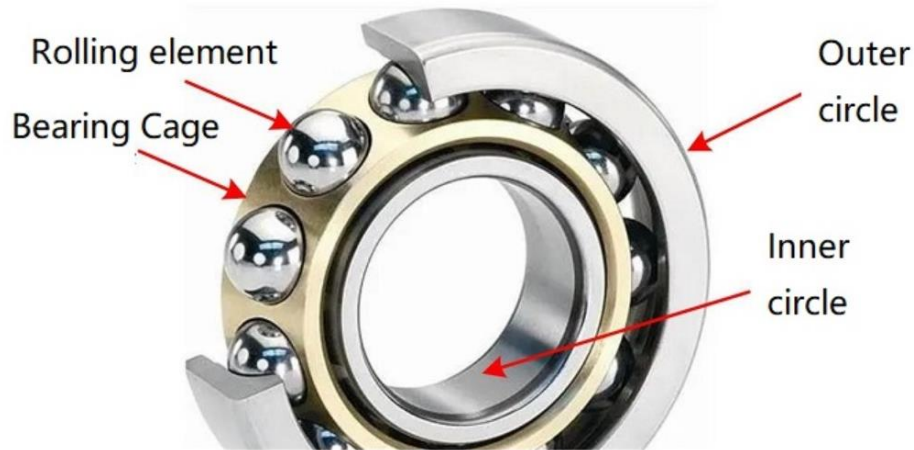


Figure II.4 : *Internal Structure of a Ball Bearing.*

II.3.3. Eccentricity faults

The eccentricity of an electric machine is a phenomenon that evolves over time and exists from the moment of manufacture. It results from a misalignment of the rotor relative to the stator, which manifests as torque oscillations (a misalignment between the shaft's center of rotation and the center of the rotor). The ultimate consequence of eccentricity is stator-rotor rubbing, which leads to rapid machine failure.

There are numerous comprehensive works in the literature that address these various issues[12][13]: Vibration analysis, ultrasonic analysis, and, to a much greater extent, stator current analysis are the techniques used to detect this type of failure. There are three types of eccentricity:

II.3.3.1. Static eccentricity

The rotor's axis of rotation is fixed but does not coincide with that of the stator therefore, the same offset between the rotor and its center of rotation relative to their initial positions is observed [14] (Figure II.5). The air gap thickness does not change over time for a given position.

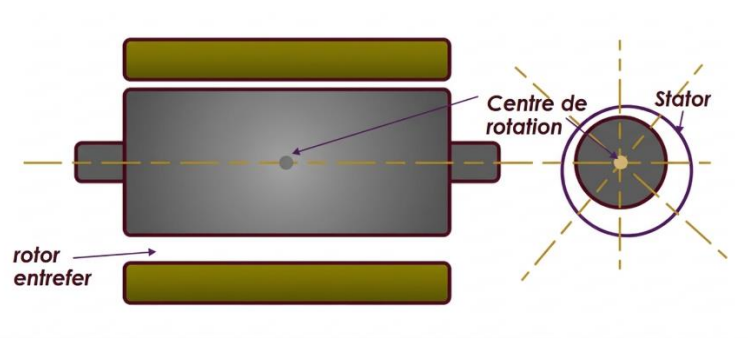


Figure II.5 : Schematic diagram of a static eccentricity defect.

II.3.3.2. Dynamic eccentricity

The rotor's center of rotation differs from the stator's geometric center but rotates around the stator's geometric center. This type of eccentricity is caused by deformation of the rotor or stator cylinder. Since the rotor no longer rotates around its center, the air gap thickness varies over time for a fixed position (Figure II.6) [15].

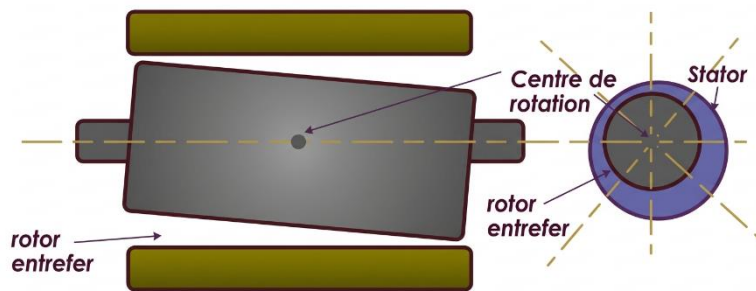


Figure II.6 : Schematic diagram of a dynamic eccentricity defect.

II.3.3.3. Excentricité mixte

The most common case is a combination of the two previous ones, in which not only is the rotor offset from the stator, but its center of rotation is also offset [15] (Figure II.7).

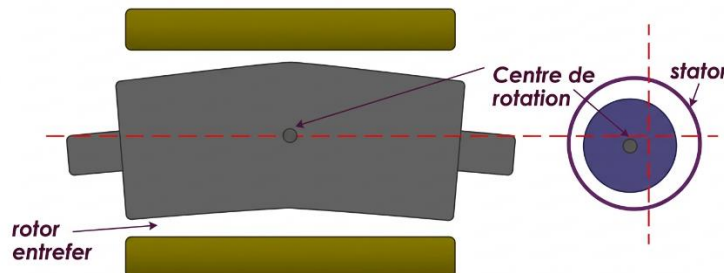


Figure II.7 : Schematic diagram of a mixed eccentricity defect.

Eccentricity is caused by:

- Manufacturing defects (machining).
- Shaft deflection.
- Wear or misalignment of the bearings.
- Incorrect positioning of the rotor, stator, or bearings during assembly
- Ovality of the rotor or the inner part of the stator
- Excessive operating speed of the motor.

II.4. Other defects

II.4.1. Mechanical play (backlash)

Mechanical play sometimes called lash, backlash, or slop is generally associated with improper tightening of one of the motor's components, broken bolts, improper assembly, or wear

Mechanical play generates a distinct noise that can be diagnosed using the second harmonic of the rotational frequency. Sometimes, peaks can also be detected at the half-harmonic ($\frac{1}{2} fr$) and its multiples.

II.4.2. Alignment faults

This is a problem similar to imbalance, because despite the use of self-aligning bearings and flexible couplings, it is virtually impossible to align two shafts and their bearings. Misalignment causes vibrations at rotational frequencies and at the 2nd and 3rd harmonics of the rotational frequency, and sometimes even higher.

II.4.3. Gear Failure

This type of failure is often associated with damage to the gear teeth, such as misalignment, broken or damaged teeth, or other issues.

It can also result from corrosion or friction, which leads to metal removal when the gear is poorly lubricated and subject to high loads. This defect is characterized by a frequency equal to the rotational frequency multiplied by the number of teeth .

II.4.4. Thermal and Insulation Faults

Electric machines are made up of various parts. Temperature causes some of these components to deteriorate quickly. The effects of temperature on the temperature-sensitive parts of permanent magnet machines are covered in this section.

The main parts of an electric machine that are susceptible to heat include bearings, magnets for permanent magnet machines, and insulators (slot insulation, varnishes, resins, and enamels).

II.4.4.1. Insulation degradation

This is generally the component most sensitive to temperature in electric machines. The study conducted here applies equally to the slot insulation, the slot shim, and the slot spacers in the case of a split winding. All these components are generally used as thin as possible to maximize the slot fill ratio. Slot insulators determine the machine's load capacity and thus the temperature limits.

For standard machines, the International Electrotechnical Commission (IEC) standards IEC 85 and IEC 34-1(2008) [16] specify the most commonly used insulation classes.

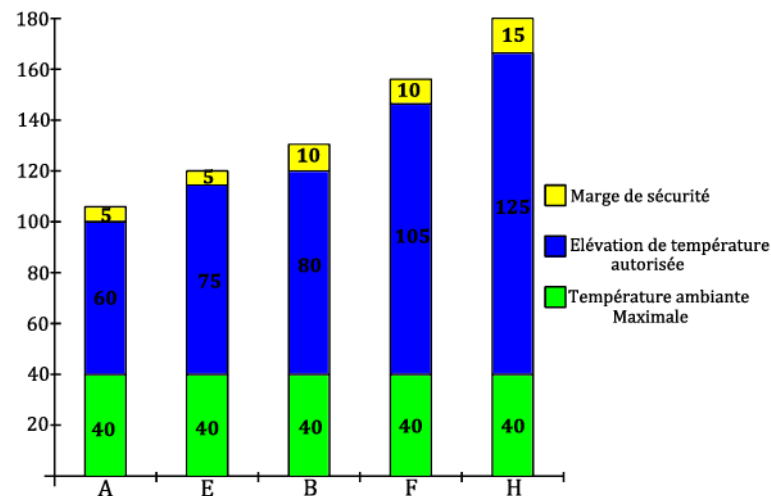


Figure II.8 : Standard insulation classes

The average temperature increase of the windings is represented by the temperature rise. The change in the windings' resistance can be used to determine it. The machine load can be increased if the outside temperature is below 40 °C; otherwise, it must be decreased.

The maximum temperature at the winding's hottest point is determined by the safety margin. If this temperature is exceeded when the machine is operating continuously, the insulation and the machine itself will age more quickly.

The evolution of a machine's service life in relation to the temperature surplus in the winding is depicted in (Figure II.9). The Arrhenius law is the law that describes this curve. The machine's service life is cut in half by a continuous temperature excess of 10 K [16].

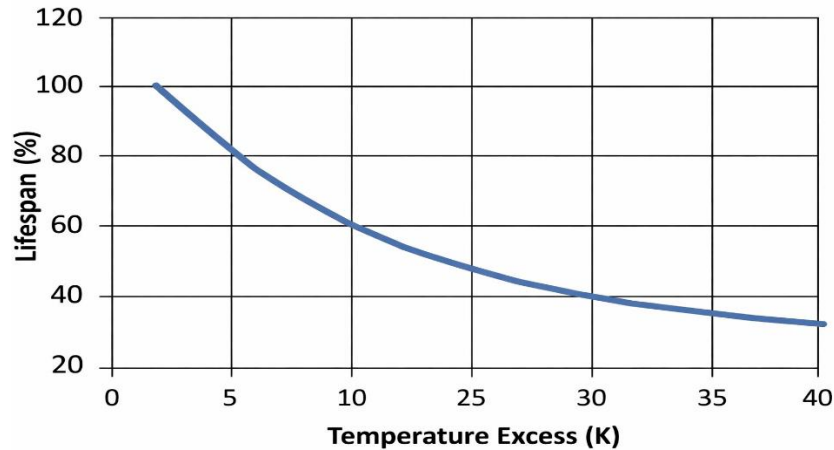


Figure II.9 : *Reduced machine lifespan due to excessive temperature*

Electrical machines used in “sensitive” applications must be able to withstand electromagnetic faults, hence the concept of degraded operation. Possible faults include [17]:

- Open circuit in certain phases
- Short circuit between phases or short circuit between windings of the same phase
- Bearing faults
- Power supply faults
- Overheating of windings
- Control faults.

The most common faults are open-circuit and short-circuit faults. Overheating faults are often a consequence of short-circuit faults. Control faults are faults that can occur in a machine's control system.

II.5. Origins and Causes of Faults

The faults described above result from a combination of numerous stresses that act on the machine. They can be classified according to their origins: thermal, electrical, mechanical, environmental, or manufacturing defects [3].

II.5.1. Thermal

An increase in temperature compared to the machine's normal operating conditions leads to deterioration of the winding insulation in the stator and the wound rotor. It can also affect the lubricant in the bearings. Thermal overload can be caused by unbalanced phase voltage, higher ambient temperature, repeated starts within a short period of time, overloads, etc.

II.5.2. Electrical

Sudden and instantaneous voltage fluctuations lead to the degradation of the dielectric material that insulates the windings. Bearings are most affected by thermal causes because the flow of leakage currents induced by inverters causes their fast aging [3].

II.5.3. Mechanical

Repeated starts cause the temperature in the stator and rotor windings to rise, which could lead to cracks in the insulation that may spread and cause an internal short circuit. Vibrations caused by shaft eccentricity, improper bearing alignment, insufficient ventilation, or insufficient lubrication negatively affect the machine's normal operation.

II.5.4. Environmental

Dusty environments affect the lubrication of certain components, causing wear and corrosion and often leading to their deterioration. The presence of moisture or chemicals in the ambient air can also degrade the quality of the insulation and lead to winding defects.

II.5.5. Manufacturing Defects

Poor welding between the bars and rings, improper tightening, or incorrect installation of bearings or windings have a detrimental effect on the normal operation of the machines and lead to the degradation or even destruction of the machine's components [3].

II.6. Conclusion

This chapter discussed the primary types of faults in electrical machines along with their reasons. These issues encompass stator, rotor, mechanical, and insulation malfunctions, all of which impact machine performance and dependability. It has been demonstrated that elements like temperature, excessive load, inadequate maintenance, and environmental factors significantly contribute to the rapid deterioration of machines.

In summary, grasping the characteristics and processes behind electrical machine faults is crucial for enhancing reliability, optimizing performance, and reducing downtime. This understanding serves as a core foundation for establishing efficient condition monitoring and predictive maintenance systems, essential in contemporary industrial applications.

Chapter III:
fault detection methods in
electrical machines

III.1. Introduction

Electromechanical and rotating electric machinery are important components of today's industrial plants used to produce goods, perform assembly, and, more generally, generate energy globally [1]. This highlights the need for proper maintenance to prevent possible machine failures that can lead to system malfunctions, production interruptions, safety risks for workers, and financial losses [2]. As a result, a maintenance approach has been developed from preventive maintenance to predictive maintenance in order to enhance the efficiency of operation [3].

III.2. Type of Maintenance

Maintenance approaches have developed as manufacturing organizations became increasingly complex [2]. These include:

➤ Reactive Maintenance

Machines are run until a failure occurs, after which maintenance is performed. Although simple, this approach is risky because of possible system failure, extensive machine downtime, high cost of repairs, and mechanical strain caused to neighboring machines.

➤ Preventive Maintenance

Machines undergo inspection based on a predetermined schedule to prevent unforeseen breakdowns. This approach typically surpasses run-to-failure in effectiveness but may be wasteful by requiring maintenance of working machinery, leading to inefficiencies.

➤ Predictive Maintenance

A relatively recent maintenance philosophy that relies on predicting machinery malfunctions through analytical techniques and regular inspections [2].

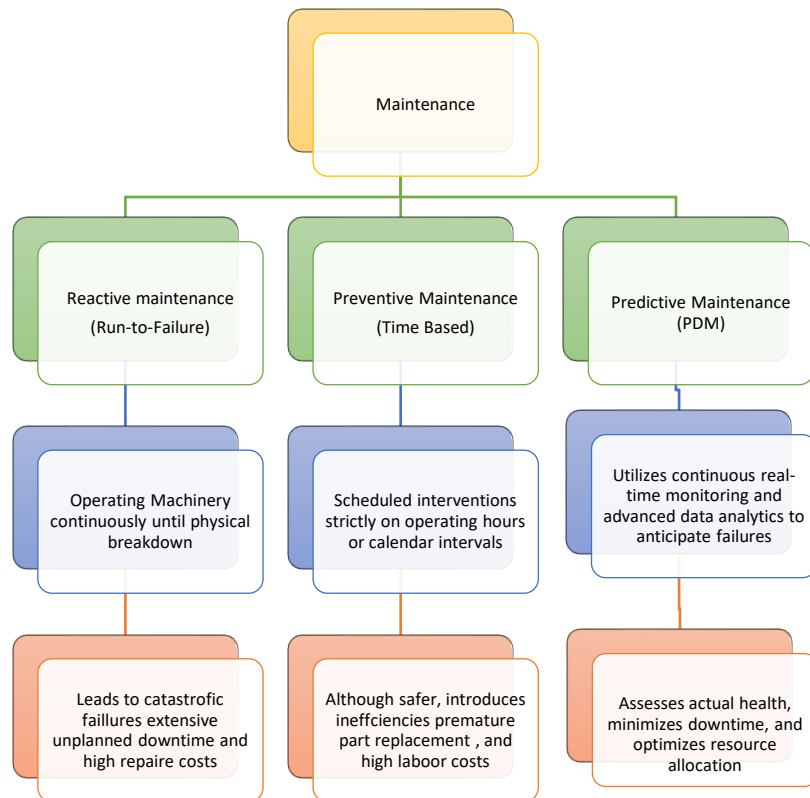


Figure III.1 : Types of Industrial Maintenance

III.3. Prediction of Maintenance Using Mechanisms and Physical Inspection

The first warning signs of degradation of electromechanical devices occur due to mechanisms and physical phenomena that do not result in electrical breakdowns. The study of the physical properties of rotating machines is the most developed prediction maintenance approach. Analyzing mechanical behavior, temperature changes, and sound production allows for detecting problems before a failure occurs [8].

III.3.1. Vibration Analysis

Vibration analysis is considered a versatile method for condition monitoring in electromechanics. All machines have a unique signature vibration pattern. When a change in stiffness and mass takes place due to fault in the system, there is a deviation from this pattern [8 , 9].

III.3.1.1. Signal measurement and collection

➤ Proximity Sensor

The following instrument is used to measure displacement. It consists of a proximity sensor, cables, and an oscillator/demodulator (see Figure III.2).

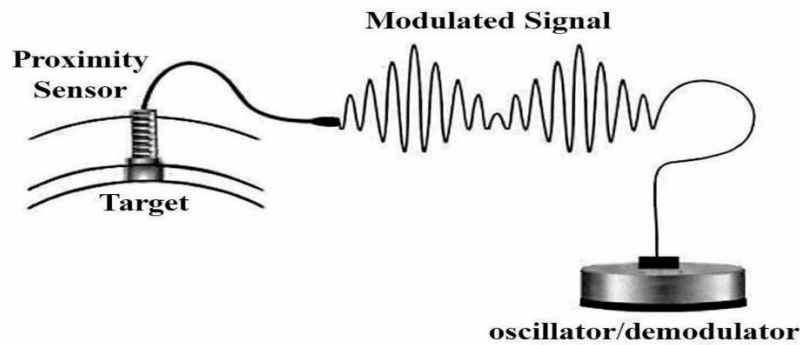


Figure III.2 : Schematic diagram of a proximity sensor works

➤ Speedometer

Transducer which is very common in measuring the speed of rotation of a machine. This is due to its ease of mounting and cheapness. It produces a strong output and, importantly, does not require a power source [11]. Some of the disadvantages associated with it are that it is bulky and heavy as well as sensitive to frequency and magnetic field.

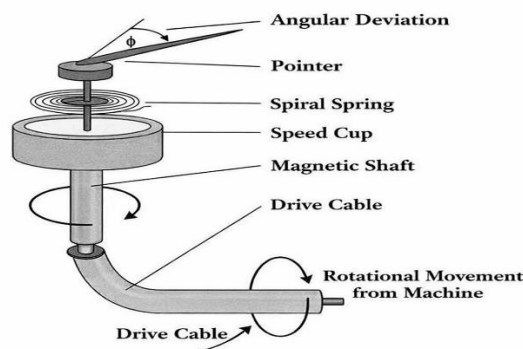


Figure III.3 : Schematic diagram of an accelerometer

➤ The Accelerometer

Because of the wide range of frequencies involved, the piezoelectric accelerometer is the most commonly used sensor [12]. It facilitates monitoring changes in the characteristics of rotating machines that show vibratory characteristics at high frequency levels. The piezoelectric accelerometer is a kind of sensor that produces an electric current output in relation to the acceleration caused by vibrations in the machine. Figure III.4 below shows an example of a piezoelectric accelerometer.

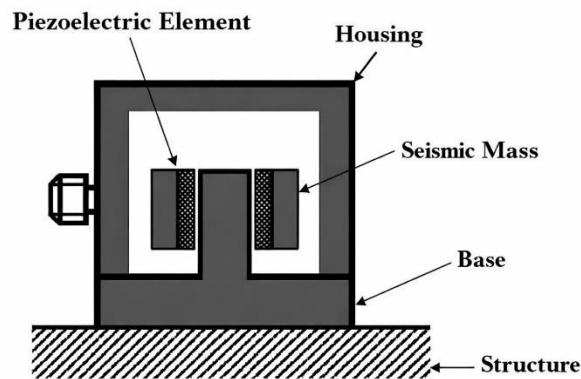


Figure III.4 : Schematic diagram of an accelerometer

III.3.2. Infrared Thermography and Thermal Analysis

It is natural for heat to be generated as a result of energy conversion in electromechanical devices; however, overheating plays the role of a significant contributor to failure mechanisms. Infrared thermography is a non-intrusive test method used for measuring the thermal emissions from the outside of the machine. It provides a real-time spatio-temporal thermal map of the surface temperatures [13].

III.3.2.1. Scope and Anomaly Detection

Thermal testing is good at detecting both electrical and mechanical faults.

- Mechanical faults can easily be found based on detecting a presence of localized hot spots, which are caused by excess friction in case of poor lubrication or damaged bearings.
- Electrical problems can be detected when there are imbalances between phases, overload in the stator windings, partial insulation breakage and high resistance in electrical connections [13].

III.3.2.2. Mechanism

The current approaches to predictive maintenance include usage of either portable infrared cameras for regular testing or installation of stationary thermal sensors like Resistance Temperature Detectors (RTD) into the machine stator. RTDs monitor thermal gradients and trigger automated alerts if the predefined maximum temperatures have been exceeded [5].

III.3.3. Acoustic Analysis and Ultrasonic Emissions

As opposed to traditional vibration analysis, acoustic and ultrasonic analysis focus on monitoring the emissions from high-frequency stress wave transients, which work above 20 kHz, and are therefore inaudible for humans [14].

III.3.3.1. Scope and Anomaly Detection

Ultrasonic analysis is extremely sensitive to developing mechanical issues. For example, it will efficiently help to identify friction due to lack of lubricant, rubbing of metal to metal, and micro-fatigue cracks in roller bearings. Besides that, the ultrasound technology allows detecting early stages of electrical problems, namely corona discharge and tracking inside insulating systems of high-voltage rotating equipment [14].

III.3.3.2. Mechanism

Special acoustic sensors or ultrasonic microphones are used to record these high frequency stress waves. Since high frequency waves attenuate quite fast in physical media, they are highly directional. That way, engineers get the ability to pinpoint the source of a problem and distinguish it from other factory noises.

III.3.4. Detection Methods Based on Electrical Quantities

While mechanical and thermal detectors provide meaningful insight at a macro level into the condition of a machine, the nature of electromechanical devices suggests that almost any fault occurring would change the characteristics of its electromagnetic fields. Hence, monitoring the electrical quantity offers many benefits. One key advantage of this method of testing is that it is non-invasive, making it possible to gather important operational information about the machine through measurements made directly at the Motor Control Center (MCC) from a safe distance, thus not requiring staff to enter the noisy and unsafe factory area [15].

III.3.4.1. Motor Current Signature Analysis

Motor Current Signature Analysis (MCSA) is one of the most efficient and thoroughly researched methods currently used in diagnostics of modern electromechanical machines. According to MCSA, an electric motor can be considered as an active transducer a generator. A machine malfunction electrical or mechanical alters its air-gap magnetic flux, which, in turn, impacts the current in the windings of the stator [15].

➤ Physical Principle

When the machine operates normally, the rotor creates a perfect, symmetrical forward rotating magnetic flux. Appearance of any kind of asymmetry, such as a fracture or breakage of the rotor bar, prevents equal current distribution and results in the generation of secondary, back-rotating magnetic flux against the rotation of the rotor.

➤ Diagnosis:

This unusual back-rotating magnetic flux causes non-harmonic components in the currents of the stator, also known as "sidebands". In the case of a broken rotor bar, these sidebands emerge on both sides of the main frequency (F1). Their positions depend on the slip of the rotor S and are described by the formula:

$$F_{sideband} = F1 \times (1 \pm 2KS) \quad (III.1)$$

Where K is any whole number (1, 2, 3, ...). Using Fast Fourier Transformation (FFT) of the current signal makes it possible to detect these frequencies and predict rotor damages with a high degree of accuracy [16].

III.3.4.2. Instantaneous Voltage and Power Analysis

While motor current signature analysis proves highly reliable, using only stator current alone can result in false alarms under noisy industrial grid conditions. To improve detection, analyzing the instantaneous total power, which incorporates both voltage and current, reflects the real work done by the motor.

➤ The Power Principle

In a three-phase system, the instantaneous electrical power P(t) equals the instantaneous electromagnetic torque of the machine, given as follows:

$$P(t) = v_a \cdot i_a + v_b \cdot i_b + v_c \cdot i_c \quad (III.2)$$

➤ Diagnostic Methodology

An analysis of a motor with faulty mechanics (e.g., bearing of a gearbox, worn seals, misaligned pumps) requires different torque at each point in time. Physical torque ripples travel throughout the electromechanical system, resulting in characteristic low frequency oscillations in the instantaneous power waveforms. Thus, when adding power analysis alongside current measurement, one can distinguish between the mechanical load faults and motor-related or grid supply problems [17].

III.3.5. Magnetic Flux Analysis

Under normal circumstances, a healthy electrical machine creates a perfect symmetry of the magnetic field inside the stator core and air gap. But when electrical internal fault appears, the magnetic field loses symmetry and the flux starts leaking from the enclosure of the machine.

➤ **The Electrical Principle**

A normally balanced motor does not generate any axial magnetic flux (perpendicular to motor's shaft axis). However, once an internal fault occurs, such as a short circuit within a single stator coil (a turn-to-turn fault), the axial shaft axis magnetic flux increases to be non-zero and a radial leakage flux rises significantly.

➤ **Diagnostic Application**

Analyzing magnetic flux is highly efficient in detecting early-stage insulation failures, often discovering the stator shorts before the conventional MCSA. To obtain the magnetic flux data, a technician should place the specially-designed search coils to the external part of a motor housing to detect radial and axial fluxes. Early warning provided by magnetic flux allows timely scheduling of repairs, thus preventing a minor turn-to-turn short from becoming a catastrophic phase-to-phase/phase-to-ground fault [1].

➤ **Partial Discharge Measurement**

The primary cause of damage in medium-high voltage (above 3.3 kV) rotating equipment is the extensive degradation of stator winding insulation made up of epoxy-mica material. In such environments, Partial Discharge (PD) measurement becomes an effective indicator of insulation degradation [18].

➤ **Principle of Operation:**

Since solid dielectric insulation ages when operated in industrial settings, it is subjected to repeated heating and cooling cycles, heavy loading from electrical current, and vibrations. This causes the formation of microscopic cavities, voids, or delamination inside solid epoxy. The gas or air inside these cavities has significantly reduced dielectric strength in comparison with other parts of insulation. When exposed to strong high voltage electric fields, the gas undergoes ionization and breaks down. This results in the formation of a miniature electrical spark in the void called a partial discharge.

➤ **Mechanism and Diagnostics:**

In each case where a micro-spark occurs across a void, a tiny burst of UV energy and heat is released. During thousands of operational hours, repeated micro-sparking damages the epoxy near a void and causes its enlargement. To detect this effect, high frequency capacitive coupling devices are installed on machine terminals. The devices measure high frequency pulse trains generated during partial discharges. Analysis of spark frequency and size of the released charge (in picoCoulombs or PC) gives an accurate picture of aging and RUL estimation.

III.3.6. Advanced Technologies and Latest Works

Traditionally, methods such as spectral balance analysis and manual feature extraction have shown to be highly effective in condition monitoring and fault diagnosis tasks like bearing condition assessment. The major disadvantage of these techniques is that they rely on expert interpretation of complicated data. Although these methods work well with simple rotating machines, modern industrial systems have evolved substantially since then. With the rise of Industry 4.0, the entire paradigm has shifted from being human-intensive to highly automated. This chapter discusses advanced intelligent methods used nowadays for fault diagnosis. [19]

III.3.6.1. Artificial Intelligence and Machine Learning

Modern equipment continuously produces a large volume of data referred to as "Big Data." The amount of data is so huge that humans cannot possibly cope with it. Therefore, artificial intelligence (AI) is crucial because it allows a system to automatically discover and map nonlinear dependencies of healthy operation of equipment and different faults [19, 20].

➤ **Artificial Neural Networks and Support Vector Machines**

These are classic machine learning algorithms used for fault classification. For example, support vector machines show outstanding performance when analyzing extracted features to detect an optimal multidimensional hyperplane, which perfectly divides data corresponding to healthy operations and an inner race fault.

➤ **Deep Learning for Automatic Classification:**

Modern architectures used for deep learning have proved to be the most efficient technique for predictive maintenance in several industries. As opposed to classic machine learning, where manual feature extraction (e.g., identifying fault frequencies in FFT) is required, deep learning methods allow doing all those tasks automatically through end-to-end classification. That means the system takes raw data as an input (e.g., 2D spectrograms of

acoustic emission or vibrations) and automatically learns important features of a fault [21]. This ability makes deep learning-based fault detection extremely precise even when working with highly loaded bearings under mechanical noise interference.

III.3.6.2. The Industrial Internet of Things

As a consequence, the efficiency of predictive maintenance depends on several factors primarily the speed, precision, and continuousness of data acquisition. The advent of the Industrial Internet of Things (IIoT) revolutionizes this notion by decentralizing condition monitoring systems and equipping them with smart sensing units, built right into machinery [22].

➤ Architecture of Continuous Monitoring

There is no place for intermittent and manual monitoring of conditions in the age of Industrial Internet. systems are based on a network of advanced, connected "smart" sensors, facilitating continuous and around-the-clock monitoring of electromechanical equipment within the whole plant.

➤ Edge Computing:

Today's IIoT solutions often involve using efficient microcontrollers with integrated wireless capabilities (such as Wi-Fi or Bluetooth); the ESP32 microcontroller serves as a great example of such technology (see figure 3.5). These controllers act as "Edge Nodes". Instead of transmitting the massive amount of raw analog data to a central node in the cloud, these smart microcontrollers perform a series of important tasks – such as High Dynamic Range Analog-to-Digital Conversion (ADC) and Fast Fourier Transform calculation on-site at the machine itself. As a result, information transfer to the server becomes much less intensive because only the processed diagnostics results or warnings are transmitted to the cloud [22].



Figure III.5 : *ESP32 Microcontroller used as an Edge Computing Node*

III.3.6.3. Digital Twins: Virtual Machine Model

Perhaps, the Digital Twin is the most widely researched modern trend in predictive maintenance. It is crucial to differentiate a digital twin from a traditional static CAD 3D model of an electric machine. A digital twin represents a highly sophisticated virtual machine that precisely reflects all processes going on in the actual electromechanical asset [23].

➤ **Digital Twin Simulation Methodology:**

Creation of a Digital Twin involves the synthesis of the mathematical model of the machine (developed through application of Finite Element Methods, FEM) and a steady flow of real-time operation data obtained from (IIoT) sensors.

➤ **Unseen Process Prediction:**

The key advantage of using a Digital Twin is the ability to observe physical processes that cannot be monitored directly. Thanks to feeding the model with real-time parameters of machine operation (e.g. real-time values of stator current, environmental temperature, vibration due to load change), the DT can calculate phenomena such as thermal spots and stress states within a machine. Importantly, a faster simulation time scale allows to estimate the point of failure in advance [23].

III.4. Comparison between Diagnostic Techniques

A predictive maintenance strategy depends heavily on the appropriate diagnostic technique to be used. There is no universal technique for diagnosing machine breakdowns

since different types function on the basis of diverse physical phenomena and have particular advantages and disadvantages. This will be discussed further in the next section.

The following table synthesizes the core operational characteristics, strengths, and limitations of both the traditional and advanced fault detection methodologies discussed in this study [2, 5].

Table III.1 :fault detection techniques in rotating electrical machines with the primary

Detection Method	Targeted Faults	Academic and Practical Advantages	Primary Limitations	Accuracy	Cost
Vibration Analysis	Mechanical (Wear, Unbalance, Misalignment)	Industry standard; highly effective for early mechanical degradation.	Requires direct physical access; sensitive to external structural noise.	High	Moderate
MCSA	Rotor asymmetries, stator short-circuits	Non-invasive remote monitoring from the Motor Control Center (MCC).	Susceptible to electrical grid noise and load fluctuations.	High	Low
Thermography	Insulation issues, friction hotspots	Non-contact safety; rapid spatial scanning of large surfaces.	Restricted to surface temperatures; typically a late-stage indicator.	Moderate	Mod-High
Acoustic/Ultrasonic	Micro-cracks, lubrication loss, Partial Discharge	Exceptional sensitivity for early-stage	High signal attenuation; generates massive, complex datasets.	Very High	High

		microscopic defects.			
Magnetic Flux	Turn-to-turn shorts, dynamic eccentricity	Rapid response to early electromagnetic asymmetry.	Requires precise sensor alignment; prone to magnetic interference.	High	Low-Mod

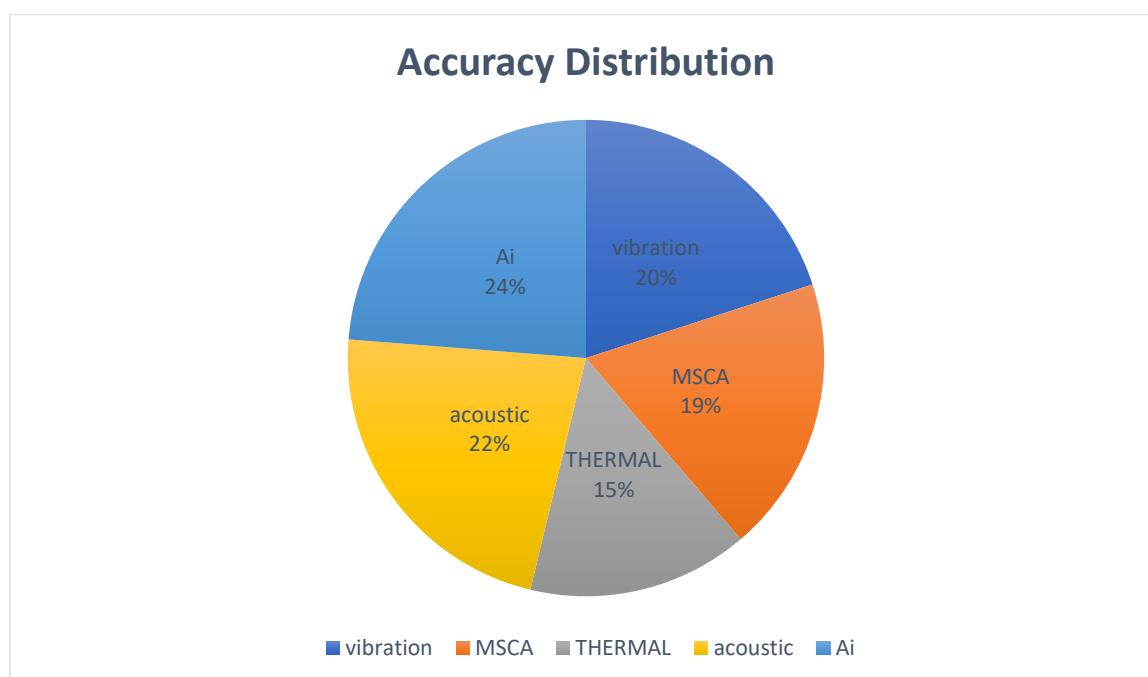


Figure III.6 : Accuracy Distribution of Detection Methods

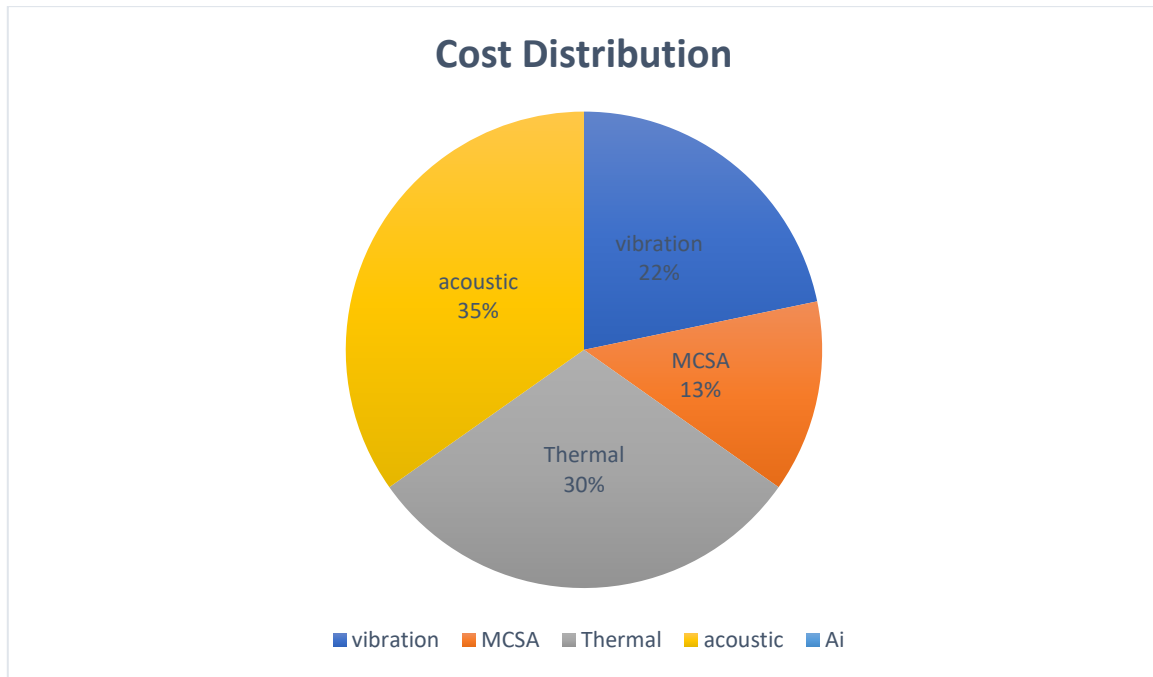


Figure III.7 : *Cost Distribution of Detection Methods*

III.5. Methods Selected

Based on the comparative analysis presented in this chapter, three fault detection methods were selected for implementation in the proposed prototype: vibration analysis, thermal monitoring, and current measurement.

Vibration analysis was chosen because it directly reflects the mechanical condition of the rotating assembly imbalance and bearing faults both produce characteristic changes in vibration amplitude and regularity that are detectable with a low-cost MEMS accelerometer such as the MPU6050.

Thermal monitoring was included because temperature rise is a reliable and universal indicator of overload conditions, friction increase, and general motor degradation, measurable with a simple contact sensor like the DS18B20 without any modification to the motor circuit.

Current measurement was selected because electrical overload produces an immediate and unambiguous increase in RMS current, providing a fast-response fault indicator that complements the slower thermal response. The remaining methods reviewed in this chapter including full spectral MCSA, magnetic flux analysis, acoustic emission, and partial discharge measurement were excluded from the prototype scope due to their requirement for specialized hardware, higher-frequency acquisition systems, or applicability only to three-phase or medium-voltage machines. The three selected methods together cover the primary fault

signatures expected in a single-phase water pump motor operating under real conditions, while remaining implementable on a low-cost embedded platform within the constraints of an end-of-study prototype.

III.6. Conclusion

This chapter has provided a thorough study of the theory and practice of fault detection strategies for rotating machines. As shown through the review presented here, the transition from conventional maintenance strategy to a state-of-the-art Predictive Maintenance (PdM) is not just a beneficial practice anymore; it has become an absolute necessity in modern industrial production.

The comparative discussion in this chapter reveals the presence of machine faults during their initial stages of degradation within several physical and electrical fields. While conventional mechanical methods such as vibration analysis and infrared thermography remain irreplaceable for finding faults in machine structure like bearing or shaft malfunctions, the chapter has also highlighted the significance of detecting electrical faults via monitoring electrical parameters. For instance, Motor Current Signature Analysis (MCSA) and Partial Discharge (PD) measurements have a great potential for diagnostics as they allow catching even microscopic electromagnetic distortions right from the control room. This way, engineers can predict any faults that may occur in a rotor or stator without waiting for them to physically affect the machine.

Therefore, the chapter has concluded that the future of diagnosing faults in rotating machinery lies not only in analyzing data manually. Through incorporating industry 4.0 technologies like Artificial Intelligence (AI), Deep Learning algorithms, and Industrial Internet of Things (IIoT), the field of condition monitoring was radically altered. With the help of intelligent diagnostic systems, which do not rely on human interpretation of data anymore, it is now possible to carry out continuous and automatic monitoring, leading to precise calculations of Remaining Useful Life .

Chapter IV:

pdm prototype realization

IV.1. Introduction

The reliable monitoring of an asynchronous motor's operating conditions requires a carefully selected and integrated set of hardware components, each chosen for its ability to accurately capture specific physical phenomena in real time. This chapter provides a comprehensive presentation of all hardware elements constituting the prototype developed in the scope of this graduation project.

The proposed system targets three fundamental parameters that reflect the health and operational state of an asynchronous motor: mechanical vibrations, surface temperature, and supply current. The acquisition of these parameters is carried out through dedicated sensors interfaced with a central processing and communication module, forming a coherent and functional embedded system.

For each component presented in this chapter, the discussion covers four essential aspects: the role it plays within the overall system architecture, its physical construction and internal structure, the operating principle governing its behavior, and its key technical specifications relevant to the application [1].

IV.2. hardware components

The components are presented in a logical order, beginning with the central microcontroller unit and proceeding through the sensing elements and their associated signal conditioning modules.

Table IV.1 : Hardware components

Component	Role	Interface	Supply voltage
ESP32 Dev Module	Main microcontroller	USB / GPIO	3.3 V / 5 V via USB
MPU6050	3-axis accelerometer + gyro	I2C	3.3 V
DS18B20	Digital temperature sensor	1-Wire	3.3 V
LCD 16x2 with I2C	Real-time display	I2C	5 V

ACS712 5A modul	measure and calculate the amount of current	Analog	5V
4.7 kΩ resistor	DS18B20 data pull-up	-	-
Breadboard + jumper wires	Prototyping connections	-	-

IV.2.1. ESP32 Microcontroller

The ESP32 is a low-cost, low-power System-on-Chip (SoC) microcontroller developed by Espressif Systems. It serves as the central processing unit of the prototype, responsible for acquiring data from all connected sensors, processing the measurements, displaying results on the LCD, and enabling wireless communication via Wi-Fi or Bluetooth for remote monitoring purposes.



Figure IV.1 : ESP32 Development Board

➤ Operating Principle

The ESP32 is built around a dual-core Tensilica Xtensa LX6 32-bit processor running at up to 240 MHz. It integrates all essential RF components on-chip, including a power amplifier, low noise receive amplifier, antenna switch, filters, and RF balun, which greatly simplifies PCB design. The microcontroller communicates with sensors via standard protocols including I2C,

SPI, UART, and 1-Wire, and reads analog signals through its built-in 12-bit ADC for sensors such as the ACS712 current sensor.

For this project, the ESP32 performs the following tasks in a continuous loop: reading vibration data from the MPU-6050 via I2C, reading temperature from the DS18B20 via 1-Wire, sampling the analog output of the ACS712 for RMS current calculation, detecting vibration events from the SW-420, and updating the LCD 16x2 display with current measurements.

IV.2.2. MPU-6050 (Accelerometer)

The MPU-6050 is a 6-axis Inertial Measurement Unit (IMU) manufactured by InvenSense. It integrates a 3-axis accelerometer and a 3-axis gyroscope into a single chip, making it ideal for motion detection and vibration analysis. In this project, the MPU-6050 is mounted on the motor housing to detect abnormal vibrations that may indicate mechanical faults such as bearing wear, rotor imbalance, or misalignment.

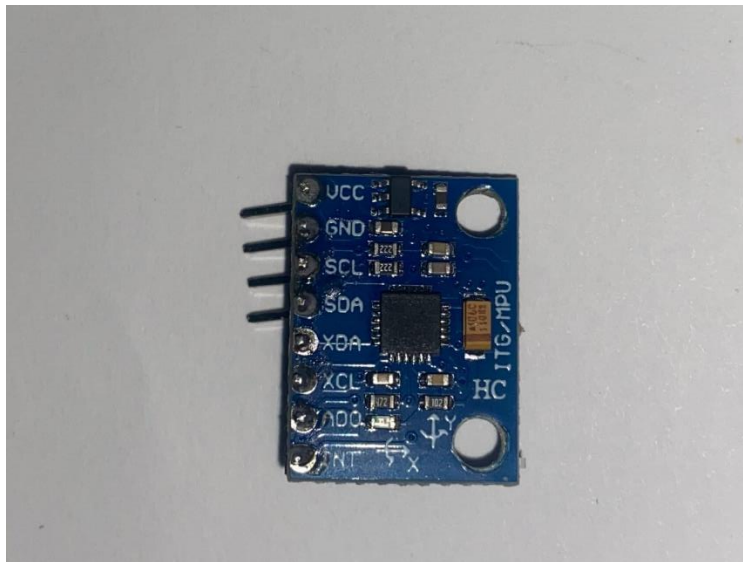


Figure IV.2 : MPU-6050 GY-521 Module

➤ Operating Principle

The MPU-6050 uses Micro Electro-Mechanical Systems (MEMS) technology for both sensing elements. The accelerometer works by measuring the deflection of a small proof mass suspended on springs. When the sensor is accelerated, the mass moves, changing the capacitance between fixed and movable plates; this change in capacitance is proportional to the applied acceleration. The gyroscope operates on the Coriolis Effect: when the sensor is rotated, a vibrating MEMS structure experiences a Coriolis force that is detected and converted to an angular velocity measurement.

The MPU-6050 also includes an onboard Digital Motion Processor (DMP), which can perform sensor fusion algorithms internally, reducing the computational load on the main microcontroller.

Communication with the ESP32 is achieved via the I2C bus at up to 400 kHz, using the default address 0x68 (or 0x69 if the AD0 pin is pulled high). The sensor outputs 16-bit digital values for each of the six axes, as well as a temperature reading.

IV.2.3. DS18B20 Digital Temperature Sensor

The DS18B20 is a digital temperature sensor manufactured by Maxim Integrated (originally Dallas Semiconductor). It provides high-accuracy temperature measurements and communicates over a single-wire 1-Wire bus protocol, which means only one data pin is needed between the sensor and the microcontroller. In this project, the DS18B20 is placed on the motor casing or winding area to monitor operating temperature, as overheating is one of the most common causes of insulation failure in asynchronous motors.



Figure IV.3 : DS18B20 Waterproof Temperature Sensor

➤ Operating Principle

The DS18B20 converts temperature directly into a digital value using a dual-oscillator counting technique. It contains two internal oscillators: a low-temperature-coefficient oscillator that generates a stable reference clock, and a high-temperature-coefficient oscillator whose frequency varies significantly with temperature. The chip counts pulses from both oscillators simultaneously; the ratio between the two counts determines the temperature value. The measurement is stored in a 16-bit scratchpad register and transmitted to the microcontroller on request.

Communication follows the 1-Wire protocol: the ESP32 sends a reset pulse, then issues a ROM command (to select a specific sensor if multiple are on the bus), followed by a Convert T command that triggers the temperature measurement. After a conversion delay of up to 750 ms (at 12-bit resolution), the ESP32 reads the result from the sensor scratchpad. Each DS18B20 has a unique 64-bit ROM code, allowing multiple sensors to share the same data line.

IV.2.4. ACS712 5A Current Sensor Module

The ACS712 is a fully integrated Hall-effect-based linear current sensor manufactured by Allegro MicroSystems. It provides an economical and precise solution for AC and DC current sensing in industrial, commercial, and communications systems. The device is available in three current rating variants 5A, 20A, and 30A with the 5A variant (ACS712-05B) selected for this prototype due to its compatibility with the rated current of the monitored motor (2.0A).

The sensor is packaged as a small module that integrates the sensing element, signal conditioning circuitry, and output stage on a single IC. The primary current path passes directly through a low-resistance internal conductor (typically 1.2 m Ω), which minimizes power dissipation and eliminates the need for external shunt resistors

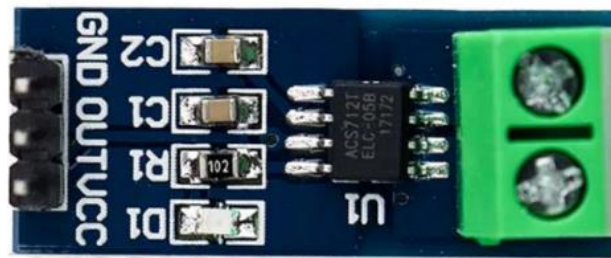


Figure IV.4 : *current sensor ACS721*

➤ **Operating Principle**

The ACS712 operates on the principle of the Hall effect, discovered by Edwin Hall in 1879. When a current-carrying conductor is placed in a magnetic field perpendicular to the current flow, a voltage is developed across the conductor in the third perpendicular direction. This voltage, known as the Hall voltage, is proportional to both the magnetic field strength and the magnitude of the current.

Inside the ACS712, the current to be measured flows through the internal copper conductor, generating a proportional magnetic field around it. A Hall-effect transducer integrated on the same silicon die is positioned to sense this magnetic field. The transducer converts the field into a small differential voltage, which is then amplified and conditioned by the internal signal processing circuitry.

The output is a linear analog voltage centered at $V_{CC}/2$, which equals 2.5V when powered from a 5V supply. This midpoint bias allows the sensor to represent both positive and negative current directions symmetrically around the center point.

IV.2.5. LCD Display

The LCD 16x2 is a standard alphanumeric liquid crystal display module capable of showing 2 rows of 16 characters each, for a total of 32 characters simultaneously. It is based on the Hitachi HD44780 controller IC, which is the most widely used LCD controller in embedded systems. In this project, the LCD provides a local, real-time readout of the monitored parameters (temperature, current, and vibration status) directly on the prototype, without requiring a computer or smartphone.



Figure IV.5 : LCD 16x2 Display

IV.3. Hardware Wiring

Table IV.2 : Hardware Wiring

Sensor	Sensor pinpin	ESP32 pin	Notes
MPU6050	VCC	3.3 V	Do not use 5 V damages the chip
MPU6050	GND	GND	Common ground rail
MPU6050	SDA	GPIO 21	Shared I2C bus with LCD
MPU6050	SCL	GPIO 22	Shared I2C bus with LCD
DS18B20	VDD	3.3 V	
DS18B20	GND	GND	
DS18B20	DATA	GPIO 4	4.7 k Ω pull-up to 3.3 V required

LCD I2C	VCC	5 V (VIN)	Must be 5 V for correct contrast
LCD I2C	GND	GND	
LCD I2C	SDA	GPIO 21	Shared I2C bus with MPU6050
LCD I2C	SCL	GPIO 22	Shared I2C bus with MPU6050
ACS712	VCC	5V	
ACS712	OUT	GPIO 34	At 0.0A $\rightarrow$ VOUT = 2.500V (zero current)
ACS712	GND	GND	
ACS712	IP+	Live wire in	Mains live conductor
ACS712	IP-	Live wire out	To motor

IV.4. Softwar

IV.4.1. Firmware Architecture

The firmware is written in C++ using the Arduino framework for ESP32. It is structured as a single-file sketch divided into clearly separated initialization and measurement phases, with a rule-based fault detection engine running in the main loop.

IV.4.1.1. Library Dependencies

The following libraries must be installed via the Arduino IDE Library Manager before compiling the sketch:

Table IV.3 : Firmware library dependencies.

Library	Author	Purpose
Adafruit MPU6050	Adafruit	IMU driver — accelerometer and gyroscope
Adafruit Unified Sensor	Adafruit	Dependency of the MPU6050 library
LiquidCrystal I2C	Frank de Brabander	I2C LCD driver
DallasTemperature	Miles Burton	DS18B20 one-wire temperature driver
OneWire	Jim Studt et al.	1-Wire bus protocol implementation

IV.4.1.2. Startup Sequence

On power-up, the firmware executes the following initialization steps in order:

Serial initialization: Opens USB serial at 115,200 baud and configures the ADC for 12-bit resolution with full 0–3.3V attenuation.

Bias auto-calibration: Samples GPIO 34 one thousand times over three seconds to compute the true resting voltage of the ACS712 output at zero current. The expected value is 2.5V (ADC raw $\approx$ 3103). The result is stored as `g_bias` and subtracted from every subsequent current sample.

MPU6050 initialization: Configures the accelerometer to ± 8 g range, the gyroscope to ± 500 °/s range, and the digital low-pass filter to 21 Hz.

DS18B20 initialization: Scans the 1-Wire bus and verifies that at least one device is present.

LCD boot screen: Displays system name and initialization status on the 16×2 display.

CSV header: Prints the column names to serial so data loggers and spreadsheets label columns automatically.

IV.4.1.3. Main Loop

Each 500 ms iteration of the main loop executes six tasks in sequence:

Table IV.4 : *the main loop executes*

Step	Task	Output
1	DS18B20 temperature request	tempC in °C, loop aborts if sensor returns -127 °C
2	MPU6050 event read	Acceleration (m/s ²) and angular rate (rad/s) on X, Y, Z
3	ACS712 current measurement	True RMS current in Amperes over a 200 ms window
4	Rolling feature computation	VibMag_std, AccY_std, GyroZ_std over last 10 samples
5	Rule-based fault detection	One of: Normal, Motor_OFF, Imbalance, Bearing_Fault, Overload, Thermal_Fault
6	Serial CSV + LCD update	One CSV row to serial, fault status and sensor readings to LCD

IV.4.2. Current Measurement Algorithm

The ACS712 outputs a DC-biased analog voltage centered at 2.5V at zero current, swinging $\pm 0.185V$ per Ampere. The firmware measures true RMS current using the following steps:

- Sample GPIO 34 continuously for 200 ms, covering ten full 50 Hz AC cycles.
- Subtract `g_bias` from each raw ADC reading to center the signal around zero.
- Accumulate the square of each centered sample into a 64-bit integer (long long) to prevent 32-bit overflow.
- Compute the square root of the mean of squared samples to obtain the RMS ADC count.
- Convert RMS counts to RMS volts:

$$rmsVolts = (rmsRaw / 4095) \times 3.3 \dots\dots\dots(IV.1)$$

- Convert RMS volts to RMS amperes:

$$\text{rmsAmps} = \text{rmsVolts} / 0.185 \dots \dots \dots (\text{IV.2})$$

- Apply a noise floor: readings below 0.02 A are set to zero to suppress idle ADC noise.

The conversion in code:

```
float rmsRaw  = sqrt((float)sumSquares / numSamples);

float rmsVolts = (rmsRaw / (float)ADC_RES) * VREF; // ADC counts → Volts

float rmsAmps = rmsVolts / ACS712_SENS;           // Volts → Amps (÷ 0.185)

if (rmsAmps < NOISE_FLOOR_A) rmsAmps = 0.0f;      // suppress noise
```

IV.4.3. Rolling Feature Computation

Raw sensor samples are noisy and a single reading is insufficient for reliable fault classification. The firmware maintains three circular buffers of length 10 (corresponding to 5 seconds at the 500 ms loop rate). At each iteration, the standard deviation of each buffer is recomputed:

Table IV.5 : *Rolling feature buffers and their associated fault indicators*

Feature	Buffer contents	Fault it detects
VibMag_std	$\sqrt{(\text{AccX}^2 + \text{AccY}^2 + \text{AccZ}^2)}$ per sample	Imbalance (std > 0.40) and Motor_OFF (std < 0.04)
AccY_std	AccY per sample	Bearing fault (std > 0.30)
GyroZ_std	GyroZ per sample	Overload confirmation (std > 0.03)

IV.4.4. CSV Output Format

The system streams one row of data per measurement cycle at 115,200 baud over USB. The first row transmitted after boot is a header line. All subsequent rows carry live sensor readings and the detected fault label, making the output immediately importable into Excel, pandas, or any data analysis tool.

Table IV.6 : CSV column definitions.

Column	Unit	Source	Description
AccX	m/s ²	MPU6050	X-axis linear acceleration
AccY	m/s ²	MPU6050	Y-axis linear acceleration
AccZ	m/s ²	MPU6050	Z-axis linear acceleration
GyroX	rad/s	MPU6050	X-axis angular rate
GyroY	rad/s	MPU6050	Y-axis angular rate
GyroZ	rad/s	MPU6050	Z-axis angular rate
VibStd	m/s ²	Computed	Rolling std of vibration magnitude (window = 10)
AccYStd	m/s ²	Computed	Rolling std of AccY (window = 10)
CurrentA	A RMS	ACS712	True RMS current through monitored conductor
TempC	°C	DS18B20	Motor housing temperature
Fault	—	Rules	Detected condition: Normal / Motor_OFF / Imbalance / Bearing_Fault / Overload / Thermal_Fault

Example output during normal pump operation:

```
AccX,AccY,AccZ,GyroX,GyroY,GyroZ,VibStd,AccYStd,CurrentA,TempC,Fault
-9.2153,-0.2753,0.7398,0.0069,0.0480,-0.0008,0.1123,0.1876,1.1300,49.50,Normal
-9.2129,-0.2394,0.6847,0.0045,0.0437, 0.0005,0.1187,0.1924,1.1280,49.56,Normal
```

IV.4.5. Dataset Description

A labeled dataset was collected from the EMTOP water pump (370 W, 2850 r/min, 220–240 V, 2.0 A rated) using the data acquisition prototype described in the preceding sections.

Data was captured using a Python serial logger running on a host PC, which automatically saved each session to a timestamped CSV file.

Table IV.7 : *Dataset summary.*

Condition	Rows	Duration	How simulated	Current (A)
Normal	1541	~13 min	Pump running under normal load	1.11 – 1.15
Motor_OFF	225	~2 min	Power disconnected, pump stationary	0.00
Overload	646	~5 min	Pump outlet partially blocked to increase load	1.71 – 1.74
Imbalance	401	~3 min	Small weight (nut) attached to motor cooling fan	1.13 – 1.15
Bearing_Fault	540	~5 min	Mechanical constraint applied to shaft rotation	1.13 – 1.14
Total	3353	~28 min	—	—

Normal data was collected over a longer period to capture the thermal warm-up signature of the motor, which rises from approximately 39.8°C at cold start to 54.3°C after 13 minutes of continuous operation. This temperature gradient provides a secondary feature for distinguishing sustained normal operation from fault conditions that produce abnormal heating rates.

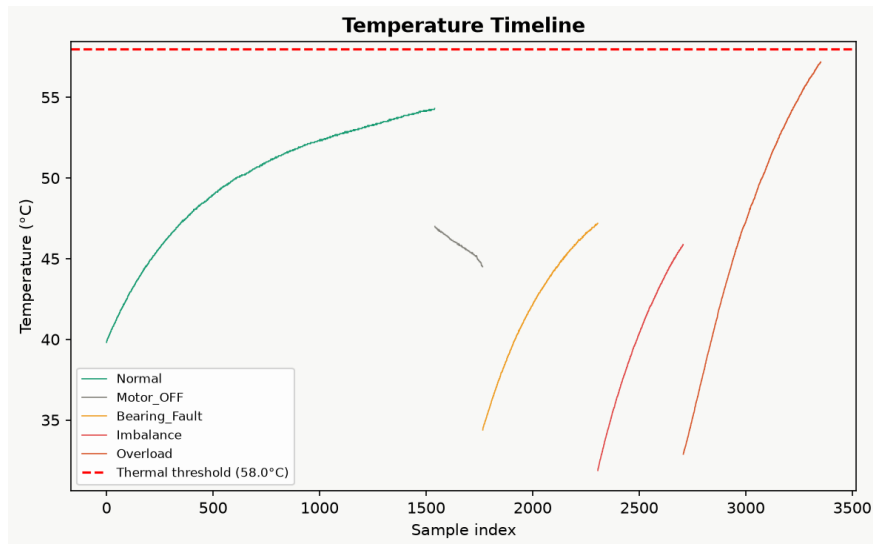


Figure IV.6 : *Temperature recorded by the DS18B20 sensor over the entire dataset*

IV.4.6. Feature Engineering

Raw sensor readings alone are insufficient for reliable fault detection at a 2 Hz sampling rate. Three derived features were computed from the raw columns:

Table IV.8 : *Derived features used for fault detection*

Feature	Formula	Rationale
VibMag	$\sqrt{(\text{AccX}^2 + \text{AccY}^2 + \text{AccZ}^2)}$	Single scalar representing total vibration energy regardless of sensor orientation
VibMag_std	$\text{std}(\text{VibMag}, \text{window}=10)$	Imbalance causes large oscillation → high std; normal operation is steady → low std
AccY_std	$\text{std}(\text{AccY}, \text{window}=10)$	Bearing fault elevates lateral vibration on the Y axis specifically
GyroZ_std	$\text{std}(\text{GyroZ}, \text{window}=10)$	Overload increases rotational irregularity, detected by gyroscope Z-axis std
Temp_rate	$\text{TempC}[n] - \text{TempC}[n-1]$	Fast temperature rise indicates thermal fault before the absolute threshold is reached

All rolling statistics use a window of 10 samples (5 seconds). This window was chosen to be long enough to suppress single-sample noise while short enough to detect a fault within 5 seconds of its onset.

IV.5. Detection Results

The rule-based detection system was evaluated against the full 3,353-row labeled dataset. Each row was passed through the rule engine and the predicted label was compared to the ground truth label assigned during data collection. A rolling majority filter (window = 5, minimum count = 3) was applied to smooth out transient misclassifications before scoring.

Table IV.9 : *Per-condition detection accuracy.*

Condition	Total rows	Correctly detected	Accuracy
Normal	1541	1479	96.0 %
Motor_OFF	225	223	99.1 %
Overload	646	644	99.7 %
Imbalance	401	324	80.8 %
Bearing_Fault	540	286	53.0 %
Overall	3353	2956	88.2 %

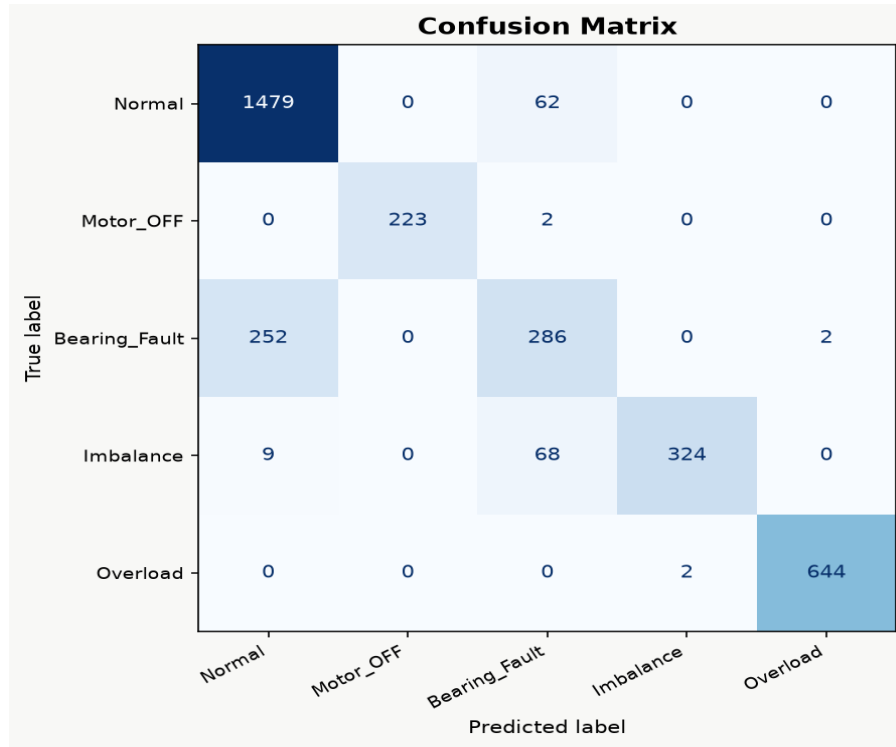


Figure IV.7 : Confusion matrix of the rule-based fault detection system

Confusion matrix of the rule-based fault detection system evaluated on 3,353 labeled samples. The matrix is computed by comparing the predicted label from the rule engine against the ground truth label assigned during data collection for every row in the dataset. Each cell shows the number of samples predicted as the column label when the true condition was the row label. The diagonal cells represent correct detections.

The strong diagonal confirms that Motor_OFF (223/225), Overload (644/646), and Normal (1479/1541) are detected with high confidence. The main source of error is the 252 Bearing_Fault samples misclassified as Normal, reflecting the narrow separation between these two conditions in the vibration feature space at 2 Hz sampling rate.

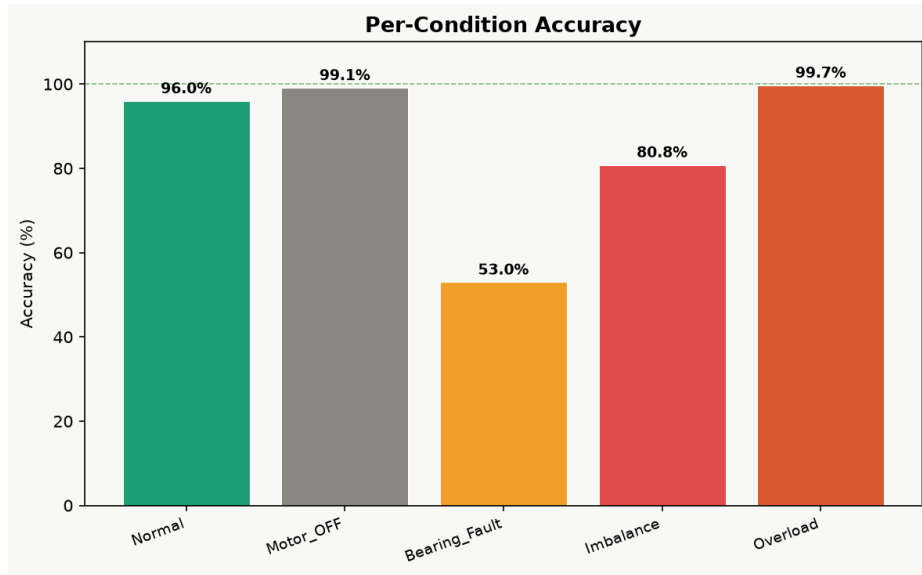


Figure IV.8 : Bar chart summarising per-condition detection accuracy.

Motor_OFF and Overload achieve near-perfect accuracy because their distinguishing features vibration magnitude and motor current respectively — produce large, unambiguous signal changes. Normal condition accuracy of 96.0% indicates that the thresholds are well calibrated to the actual operating envelope of the pump.

Imbalance detection reaches 80.8%. The misclassified rows are concentrated at the beginning of each imbalance session, when the rolling std window has not yet accumulated enough samples to reflect the elevated vibration. After approximately five samples (2.5 seconds) the window fills with imbalance data and detection becomes stable.

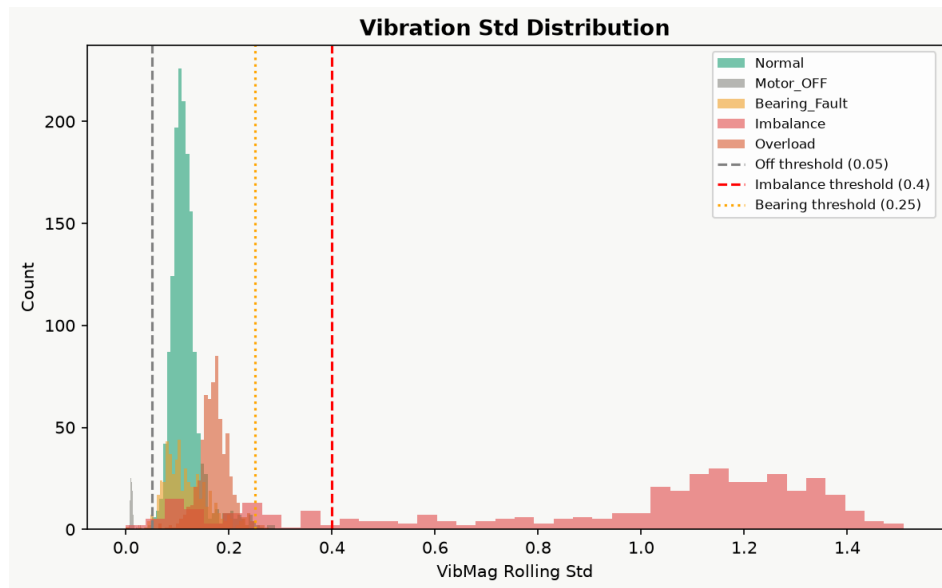
Bearing fault detection at 53.0% is the weakest result and is an expected limitation of the approach. At a 2 Hz sampling rate, the vibration signature of a bearing fault and normal operation are statistically similar the AccY_std threshold of 0.30 lies very close to the upper bound of normal (0.289), leaving a narrow separation margin.

IV.6. Threshold Derivation

Thresholds were derived empirically from the collected dataset using the $\text{mean} \pm 3\sigma$ rule on the Normal condition, which statistically bounds 99.7% of normal readings. Any value outside this range is classified as abnormal. Table IV.10 shows the key statistics per condition and the resulting threshold boundaries.

Table IV.10 : Feature statistics per condition and derived thresholds.

Feature	Normal (mean±std)	Motor_OFF	Imbalance	Bearing_Fault	Overload	Threshold
VibMag_std	0.115 ± 0.076	0.011	0.935	0.116	0.171	< 0.04 → OFF > 0.40 → Imbalance
AccY_std	0.195 ± 0.065	0.011	0.409	0.253	0.451	> 0.30 → Bearing
GyroZ_std	0.011 ± 0.004	0.001	0.014	0.015	0.056	> 0.03 → Overload
CurrentA	~1.13 A	0.00	~1.14	~1.13	~1.73	> 1.50 → Overload
TempC	49.9°C max 54.3	45.9	40.0	42.3	57.2	> 57.0 → Thermal

**Figure IV.9** : Histogram of the VibMag rolling standard deviation for all five conditions.

The threshold values are overlaid as vertical lines: grey dashed at 0.05 (Motor_OFF boundary), orange dotted at 0.25 (Bearing_Fault boundary), and red dashed at 0.40 (Imbalance boundary). Normal, Motor_OFF, Bearing_Fault, and Overload all cluster tightly below 0.30, confirming they cannot be separated by vibration std alone. Imbalance distributes broadly between 0.40 and 1.50, creating a clear gap from all other conditions. The threshold of 0.40 was chosen at the point where the Normal and Overload distributions end and the Imbalance distribution begins.

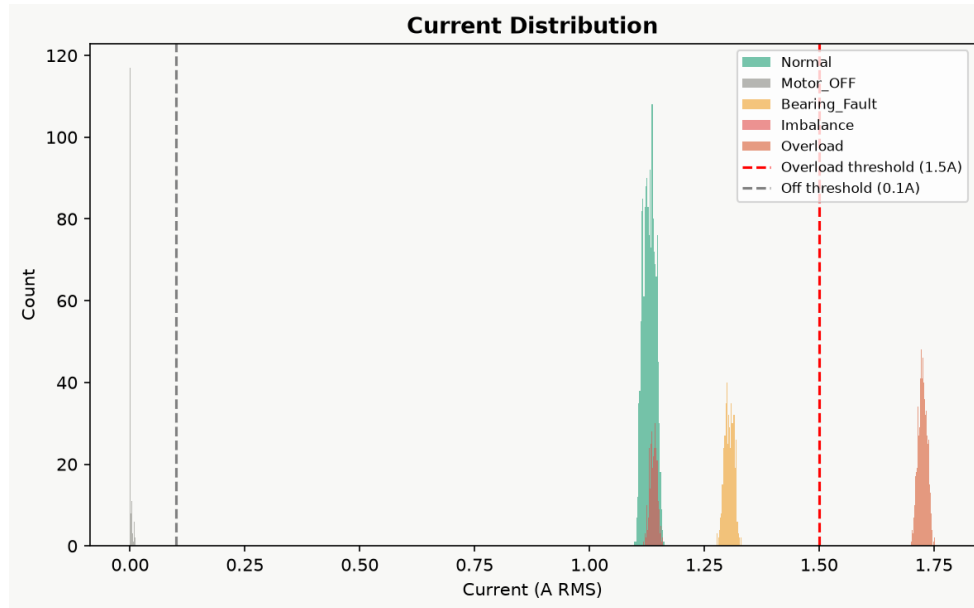


Figure IV.10 : Histogram of the RMS current values for all five conditions.

With the overload threshold (1.50 A, red dashed) and motor-off threshold (0.10 A, grey dashed) overlaid. Normal, Imbalance, and Bearing_Fault all cluster tightly around 1.13 A, confirming that current alone cannot distinguish mechanical faults from normal operation. Motor_OFF sits at 0.00 A and Overload clusters around 1.73 A, separated from the normal group by a clear gap of approximately 0.60 A. The overload threshold of 1.50 A was placed at the midpoint between the two groups, providing a comfortable margin above normal (max 1.15 A) and well below overload (min 1.71 A).

The detection priority order is: Motor_OFF → Thermal_Fault → Overload → Imbalance → Bearing_Fault → Normal. Motor_OFF is evaluated first because a stationary motor would otherwise satisfy the low-vibration condition expected of a healthy running motor, leading to misclassification. Thermal fault is second because overheating is the most safety-critical condition regardless of the vibration signature.

IV.6.1. Real-Time Fault Detection

The fault detection firmware extends the data acquisition code with a rule engine and an active LCD alert system. At each 500 ms loop iteration, the detected fault is displayed on the LCD and streamed to serial. The LCD backlight blinks four times when the detected condition changes, providing an immediate visual alert to the operator.

IV.6.2. LCD Display Layout

The 16×2 LCD shows a different layout depending on the active fault:

Table IV.11 : LCD display layout per fault condition.

Condition	LCD Row 0	LCD Row 1
Normal	Status: NORMAL	V:<std> T:<°C>
Motor_OFF	! Motor OFF	I:<A> T:<°C>
Overload	! Overload	I:<A> T:<°C>
Imbalance	! Imbalance	V:<std> T:<°C>
Bearing_Fault	! Bearing Fault	V:<std> T:<°C>
Thermal_Fault	! Thermal Fault	T:<°C> rate:<°C>

IV.7. Rule Engine

The rule engine is implemented as a single function detectFault() that receives the six computed features and returns a fault string. Rules are evaluated in priority order using early return, so a higher-priority fault always takes precedence:

```
String detectFault(vibStd, accYStd, gyroZStd, currentA, tempC, tempRate) {
  if (vibStd < 0.04 && currentA < 0.10)      return "Motor OFF";
  if (tempC > 57.0 || tempRate > 0.30)      return "Thermal Fault";
  if (currentA > 1.50)                       return "Overload";
  if (vibStd > 0.40)                         return "Imbalance";
  if (accYStd > 0.30)                       return "Bearing Fault";
  return "Normal";
}
```

IV.8. Limitations and Future Improvements

The following limitations were identified during the development and evaluation of the prototype:

- **Low vibration sampling rate:** The 500 ms main loop yields a 2 Hz effective sampling rate for vibration. Industrial bearing fault detection typically requires 1–10 kHz sampling to resolve the characteristic fault frequencies (ball pass frequency, cage frequency, etc.). At 2 Hz, bearing faults can only be detected through statistical features (rolling std) rather than spectral analysis, which limits accuracy to 53%.
- **No persistent storage:** Data is streamed over USB and requires a connected PC running the logger script. Adding an SD card module or MQTT over Wi-Fi would enable untethered continuous monitoring deployable in a real industrial environment.

IV.9. prototype réalisation

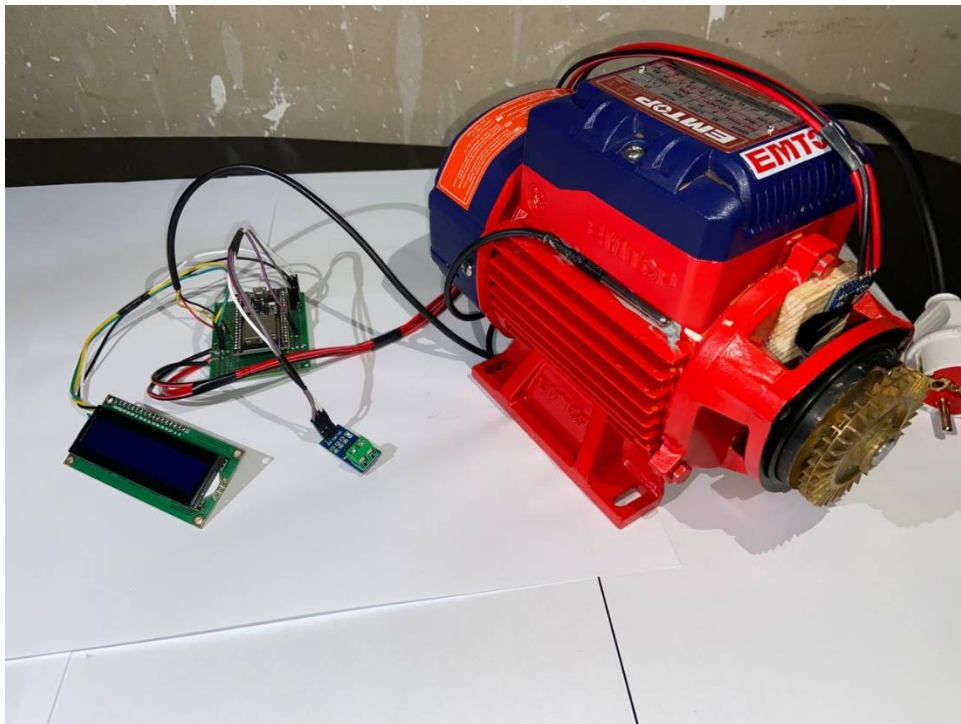


Figure IV.11 : Prototype with the sensors monted on the pump

IV.10. Conclusion

This chapter described the complete construction of a four-sensor PdM data acquisition prototype. Starting from the component selection through hardware wiring, bias circuit design, firmware development, and calibration procedure, each step was motivated by a specific measurement requirement or hardware constraint.

The key engineering decisions were: sharing the I2C bus between the MPU6050 and LCD to minimize GPIO usage, using the ACS712-05B Hall-effect current sensor whose built-in 2.5V bias eliminates the need for an external voltage divider circuit, applying true RMS calculation with a 64-bit accumulator to avoid integer overflow, and implementing runtime label switching to allow multi-class training data collection without reflashing.

The system is now ready to collect labeled CSV data for machine-learning model training. The following chapter describes the feature engineering and classification pipeline that processes this raw data into a deployable fault detection model.

General Conclusion

General Conclusion

The growing complexity of industrial systems together with the demand for reliability in operation has made maintenance management a highly important issue for modern engineering practice. Faults occurring in electrical machines can lead to severe loss of productivity, potential safety hazards, and significant repair costs. To solve these issues, a technique called predictive maintenance was used, which is defined as the ability of a system to predict possible failures before they happen and improve the overall process of maintenance.

The main goal of this Professional Final Year Project (PFE) was the development of a prototype of a predictive maintenance system for electrical machines. With the help of data processing and analysis, it became possible to monitor the health of machines continuously, detect any degradation, and alert the maintenance workers to the problem. Thus, the approach was not based on time-based or reactive methods but rather followed an intelligent and condition-based one.

As part of this work, all types of failures in electrical machines were thoroughly analyzed. On the basis of this analysis, relevant features from sensor signals, such as vibration, temperature, and current, were selected and processed. Afterward, machine learning algorithms trained to detect faults based on the state of the machines were developed using these features. Thus, a complete pipeline from collecting and preprocessing the sensor data to creating predictive models was implemented.

The outcome of this study was highly satisfying as all experiments provided positive results that confirmed the relevance and validity of our research hypothesis. The prototype showed excellent capabilities in detecting faults in their early stages of development, ensuring ample time before approaching a critical situation in the machine operation process. In addition, the classification models proved to be efficient enough in delivering high accuracy, precision, and recall, thus confirming the effectiveness of both the feature selection strategy and the algorithm.

From the perspective of industry, this study helps to save significant amounts of time on unplanned downtime, optimize maintenance activities, and increase the lifetime of electrical machines. This is achieved by substituting traditional maintenance strategies with machine learning and predictive analytics, which helps to reduce operating expenses and improve safety and equipment efficiency. Therefore, the presented prototype can be considered the first step towards the application of artificial intelligence methods in industry maintenance services.

Nevertheless, there are multiple ways in which we can further develop this model and implement more useful modifications. First, we can make the system more versatile to include different types of electric machines and the various faults and anomalies they may experience. Second, we could apply more complex deep learning algorithms such as convolutional neural networks (CNN) or recurrent neural networks (RNN). In doing so, our system could work with raw time-series data, thus avoiding manual feature extraction. Finally, we could integrate the system into an Internet of Things (IoT) environment and deploy it on a much larger scale.

To sum up, the presented project has proven the practicality and effectiveness of implementing predictive maintenance technologies into electrical machine operations. We gained theoretical knowledge and hands-on experience in using machine learning, signal processing, and maintenance engineering methods in practice. Therefore, we can confidently state that the project can become the basis for future research and innovation in the industry.

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