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Development of an STM32 Based Diagnosis Tool for an Induction Motor Faults

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Abstract

This project proposes a novel fault detection tool for Induction Motors (IMs) utilizing an STM32 microcontroller and an ACS712 current sensor. The STM32's high processing speed allows for real-time analysis of stator currents data via simply the Fast Fourier Transform (FFT) technique. By analyzing the frequency spectrum, the tool can identify characteristic signatures of broken bars, a common IM fault. This non-invasive and potentially cost-effective approach leverages the STM32's compact design and FFT's established role in spectral analysis, offering a valuable solution for industrial IM monitoring.

Keywords Induction Motors, Fast Fourier Transform FFT, Fault detection, STM32 microcontroller

ملخص

هذا المشروع يقترح أداة جديدة لاكتشاف الأخطاء في محركات التيار المتردد (IMs) باستخدام متحكم STM32 ومستشعر تيار .ACS712 تسمح سرعة معالجة STM32 العالية بتحليل البيانات الحالية في الوقت الحقيقي باستخدام تقنية التحويل السريع لفورييه .(FFT) من خلال تحليل الطيف الترددي، يمكن للأداة التعرف على التوقيعات المميزة للأعمدة المكسورة، وهي خلل شائع في محركات التيار المتردد. يستفيد هذا النهج غير الغازي والمكلف بشكل محتمل من التصميم المدمج لـ STM32والدور المؤسس لـ FFT في التحليل الطيفي، مما يقدم حلاً قيمًا لمراقبة محركات IM الصناعية .

Résumé

Ce projet propose un nouvel outil de détection de défaillance pour les moteurs à induction (IM) utilisant un microcontrôleur STM32 et un capteur de courant ACS712. La vitesse de traitement élevée du STM32 permet une analyse en temps réel des données de courant statorique via la technique de la transformée de Fourier rapide (FFT). En analysant le spectre de fréquences, l'outil peut identifier les signatures caractéristiques des cassures de barreaux, un défaut courant des IM. Cette approche non invasive et potentiellement rentable tire parti de la conception compacte du STM32 et du rôle établi de la FFT dans l'analyse spectrale, offrant une solution précieuse pour la surveillance des IM industriels.

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As I embark on this new chapter, a profound sense of gratitude washes over me. First and foremost, my deepest appreciation goes to the Almighty, whose divine guidance and unwavering support have been the wind beneath my wings throughout this journey.

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LIST OF SYMBOLS

IM	Induction Motor
CM	Condition Monitoring
RMS	Root Mean Square
FFT	Fast Fourier Transform
MCSA	Motor Stator Current Signature Analysis
AC	Alternating Current
BRB	Rotor Broken Bar
Pdm	Predictive Maintenance
CMe	Corrective Maintenance
PM	Preventive Maintenance
CBM	Condition-Based Maintenance
RUL	Remaining Useful Life
ML	Machine Learning
Ai	Artificial Intelligence
A/D	Analog to Digital Converter
WT	Wavelet Transform
STFT	Short-Time Fourier Transform
CWT	Continuous Wavelet Transform
DWT	Discreet Wavelet Transform
DAQ	Data Acquisition
ADC	Analog to Digital Conversion
DFFT	Digital Fast Fourier Transform
FPU	Floating Point Unit
IDE	Integrated Development Environment

INTRODUCTION

1.1 Background

An Induction Motor is an essential part of any rotating machine since it is its heart. According to (Gundewar and Kane, 2021) almost 90% of machines across all industries use an Induction Motor(IM) as their prime mover. Powering countless applications ranging from manufacturing and production lines to powering pumps, fans, and conveyors, it is the machine's key driving component due to their simplicity, robust design, reliability, and relatively low maintenance requirements which make them a popular choice for diverse industrial needs. However, like any machine, they are susceptible to faults that can lead to downtime, loss of production, and even equipment damage. Early detection and diagnosis of these faults in Induction Motors, particularly for the most common issues like bearing degradation, broken rotor bars, and stator winding insulation shorts, are crucial for maintaining efficient operation and preventing catastrophic breakdowns. Consequently, ensuring their continued health through condition monitoring is paramount to preventing these issues and subsequent production stoppages. The consequences of IM failure are far-reaching, encompassing significant financial losses due to unexpected downtime and costly repairs (Choudhary et al., 2019).

Extensive research has been conducted on condition monitoring (CM) systems and fault diagnosis techniques for Induction Motors. Various CM techniques have been explored, analyzing diverse parameters such as thermal, chemical, acoustic, torque, induced voltage, partial discharge, vibration, and motor current signature. The reliability of condition monitoring systems is based on understanding the behavior of the machine in healthy and faulty status working under different conditions, this seeks to lower costs, boost machine availability, and improve production process (Dash et al., 2016; Terron et al., 2021).

These CM techniques are processed to detect and diagnose faults using different signal processing techniques such as root mean square (RMS), frequency domain analysis such as Fast Fourier Transform (FFT), and time-frequency domain analysis such as wavelet technique.

In order to diagnose motor faults in this study, motor’s stator current signature analysis (MCSA) is selected, it involves analyzing the current signal of one phase, typically through a Fast Fourier Transform (FFT). This spectrum reveals the magnitude and frequency of each individual component within the complex current waveform. By identifying characteristic patterns in the motor signature, as a non-invasive online monitoring approach, MCSA provides numerous advantages including avoiding the need for additional sensors, simplifying implementation and reducing costs in industrial settings (Bonaldi et al., 2012; Guo and Liu, 2018).

1.2 Format of the dissertation

The dissertation is divided into five chapters: Chapter 2 dives into the machine itself, detailing its failure modes and current techniques for monitoring their condition to detect these failures. The chapter three presents the experimental methodology for detecting faults in Induction Motors. It outlines the experimental setup, which utilizes an STM32 (F4 series) microcontroller to acquire current data. Chapter four analyzes and discusses both frequency and time domain simulation results obtained through spectral analysis (FFT), comparing them to experimental results obtained from the developed tool. Finally, Chapter 5 contains the conclusion and recommendations for further research.

Chapter 1 INDUCTION MACHINE, FAULTS AND MAINTENANCE

1.1 Induction Motor construction

An Induction Motor, also known as an asynchronous motor is an AC (alternating current) electric motor in which electrical energy is converted into mechanical energy. It operates on the principle of electromagnetic induction, where a rotating magnetic field is generated in the stator (stationary part) of the motor, which induces current flow in the rotor (rotating part), causing it to rotate. Induction Motors are widely used in various industrial, commercial, and residential applications due to their simplicity, reliability, and robustness(Cavallo, 2020).

The structure of an Induction Motor consists of several key components, each one playing a crucial role in its operation. An overview of the main components in an induction machine is given

- The stator serves as the stationary part of the Induction Motor.
- The rotor (rotating part) carries bars permanently short-circuited by the end rings.
- The mechanical components responsible for both rotor rotation and the upkeep of various sub-assemblies

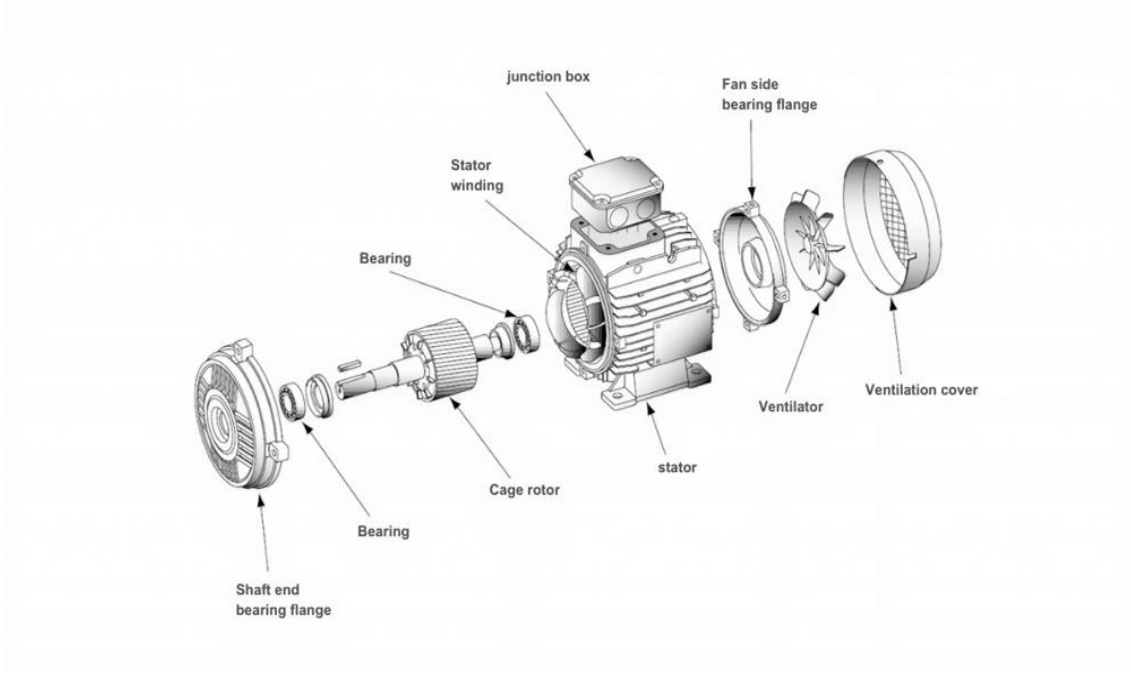


Figure 1-1:*3-phase Induction Motor(https://en.itafran.com/synchronous-and-asynchronous-motors-what-are-the-differences.html)*

1.1.1 The stator

The stator is the stationary part of the motor and is typically made of laminated steel sheets stacked together to reduce eddy current losses. It consists of a cylindrical frame or core with slots for housing insulated copper or aluminum windings.

When alternating current flows through the stator windings, it generates a rotating magnetic field that interacts with the rotor to produce motion.

1.1.2 The rotor

The rotor, constructed from thin laminations of the same material as the stator comprises a laminated cylindrical core directly affixed to the shaft. These laminations feature outer slots designed to accommodate the conductors. The IM rotors are found into two types: wound or squirrel cage rotor,

1.1.2.1 Wound rotor

A wound-rotor motor, also known as a slip ring-rotor motor, is a type of Induction Motor characterized by its phase wound rotor configuration. The rotor comprises a laminated cylindrical core with semi-closed slots to accommodate 3-phase insulated windings. These windings are connected to slip rings mounted on the shaft, with brushes in contact with them. The brushes are linked to a variable resistor, allowing for adjustment of each rotor phase's resistance. This setup facilitates multiple functions: Firstly, it enhances starting torque while decreasing starting current, resulting in smoother motor start-up. Secondly, it enables precise speed control by adjusting the resistance, thus meeting specific operational requirements or load conditions (bhakti, 2016).

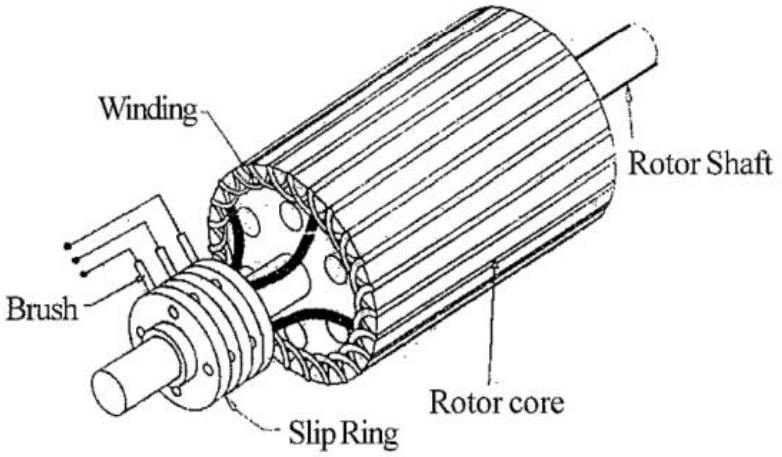


Figure 1-2:*wound-rotor motor(https://www.electrorules.com/slip-ring-induction-motors/)*

1.1.2.2 Squirrel cage rotor

A squirrel cage rotor, the predominant type found in Induction Motors, boasts a construction characterized by conductors, typically copper or aluminum bars, embedded within semi-closed slots of a laminated rotor core. These bars are short-circuited at both ends by end rings, forming a closed circuit within the rotor. Unlike other rotor types, the squirrel cage rotor does not possess a fixed number of poles; instead, the same number of poles as the stator is induced in the rotor through electromagnetic induction.

This rotor design offers several distinctive features. Notably, it exhibits very low leakage reactance owing to the absence of separate windings, leading to efficient power transmission. While the squirrel cage rotor may yield low starting torque, it compensates with maximum running torque. During start-up, however, it tends to have a poor power factor.

To enhance starting performance, rotor bar skewing is often employed. This technique elongates the effective length of the bars, thereby increasing rotor resistance and improving starting torque. The skewed rotor configuration offers several advantages, including reduced humming and noise, uniform torque output across rotor positions, diminished locking tendency between rotor and stator teeth, and heightened rotor resistance.

The squirrel cage rotor presents numerous advantages over alternative designs. Its cost-effective construction and robustness make it an economical choice, while the absence of brushes reduces the risk of sparking and lowers maintenance requirements. Additionally, the squirrel cage rotor exhibits higher power factor and efficiency, further solidifying its appeal in Induction Motor applications.

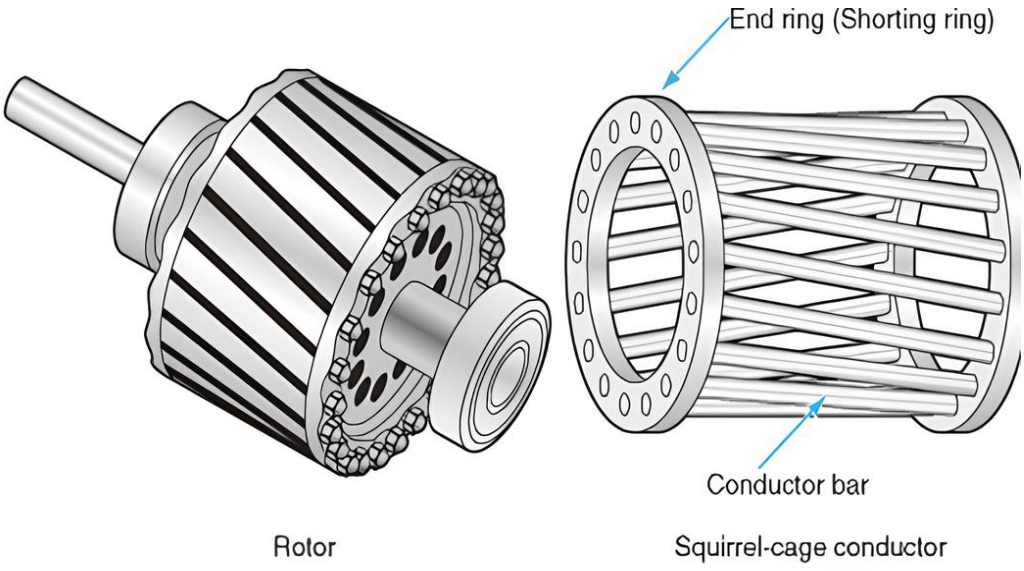


Figure 1-3:*Squirrel cage*

1.1.3 The mechanical components

The most important mechanical component that plays a crucial role in both rotor rotation and the maintenance of various sub-assemblies is bearing.

1.1.3.1 Bearing

In the realm of machinery, bearings serve as essential components designed to support rotating shafts. These mechanical elements play a pivotal role in constraining relative motions while effectively reducing friction between moving parts. Bearings function to support, guide, and restrain moving elements within a machinery setup, with the bearing itself serving as a stationary member responsible for bearing the load. The portion of the shaft upheld by the bearing is known as the journal, constituting the moving member within the system.

Bearings are categorized based on the type of operation they facilitate, including the motions allowed and the directions of the applied loads or forces. Serving as fundamental components, bearings establish a movable connection between rotating mechanisms, facilitating relative rotation with precision and minimal friction under load. Among the various types of bearings, ball bearings stand out as the most prevalent in industrial applications, renowned for their exceptional performance(Ibrahim, 2009).

A typical bearing comprises three primary elements

1) Two concentric steel rings, namely the inner and outer rings, featuring raceways surfaces upon which the rolling bodies traverse.

2) Rolling bodies, typically balls or rollers crafted from steel, which facilitate smooth movement between the two rings with minimal friction. These rolling bodies rotate within the raceways embedded inside the rings.

3) A cage, constructed from materials such as polyamide, sheet steel, brass, or resin, serves the critical function of separating and guiding the rolling bodies within the bearing structure.

By seamlessly integrating these elements, bearings ensure the efficient operation of rotating shafts, facilitating smooth and precise motion while minimizing frictional losses.

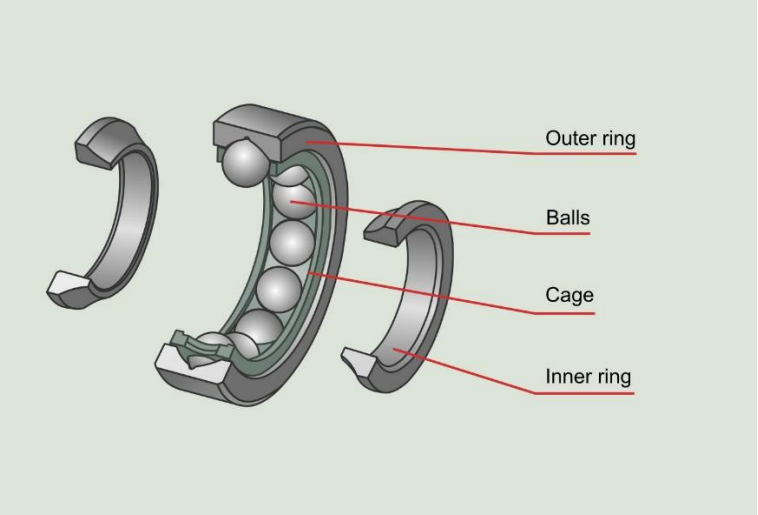


Figure 1-4:*Rolling element Bearing parts*

1.2 Major faults in induction machine

Induction Motors play a vital role across multiple industries, with their daily operation necessitating proper maintenance and early detection of faults to prevent significant damage and industrial shutdowns. Among the most prevalent faults in Induction Motors are bearing faults, broken rotor bar faults, and short-circuit insulation faults, emphasizing the importance of detecting and categorizing these issues at an early stage. Despite their widespread use due to cost-effectiveness, robustness, and reliability, induction machines are susceptible to failures arising from internal, external, or environmental factors. The literature offers various perspectives on categorizing these faults, such as classifying internal faults based on their origin (electrical or mechanical) or their location (stator or rotor). However, faults in IMs are typically categorized into two main groups electrical and mechanical faults.

Figure (2.5) shows the occurrence percentages of potential fault classes in induction machines (IMs). Among these potential fault classes, bearing faults have the highest occurrence percentage at 44%, followed by stator faults at 26%, broken rotor bar faults at 16%, and other types of faults at 12%. Effective bearings can increase power consumption of IMs whereas efficiency decreases. As such, the literature focuses on the condition monitoring systems and the development of fault diagnosis techniques with the aim to detect these faults at an early stage and to track their evolution. This approach allows for the scheduling of maintenance tasks and reduces outage time caused by sudden breakdowns (Terron *et al.*, 2021; Yatsugi *et al.*, 2023).

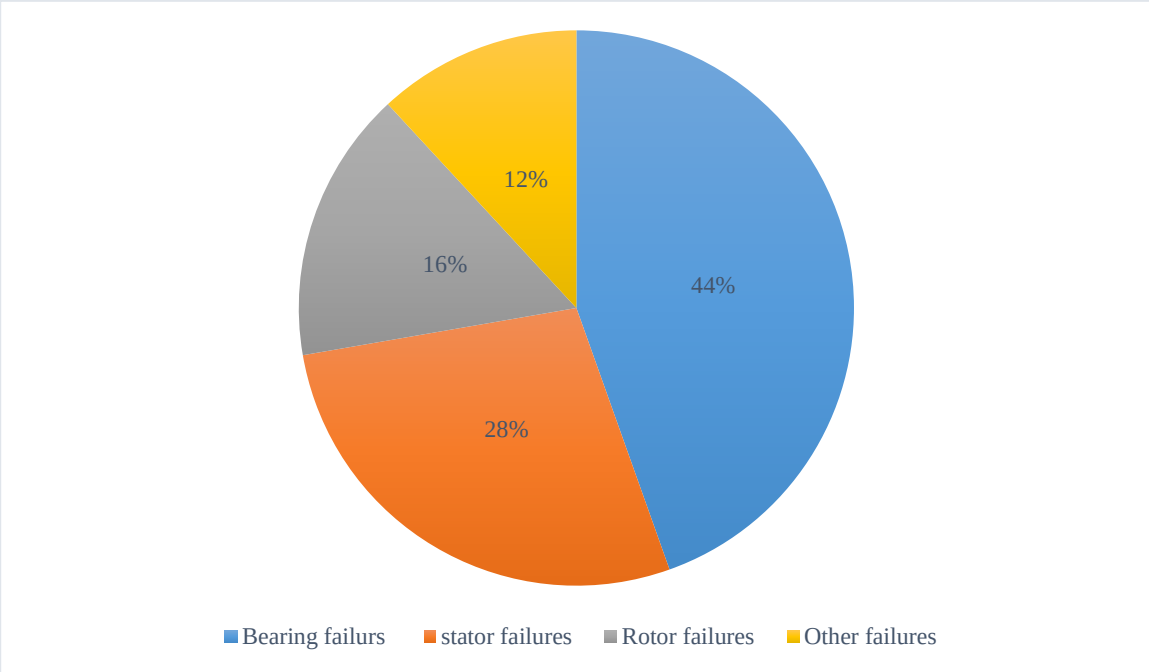


Figure 1-5:*Major failures in IM.*

1.2.1 Mechanical failure mode

Mechanical components represent a critical aspect of electrical motors and are subject to continuous wear and tear. Numerous studies have substantiated this observation, with research indicating that approximately 70% of motor failures stem from mechanical issues.

1.2.1.1 Eccentricity Related Fault

The air gap between the stator and rotor in an Induction Motor (IM) is a critical parameter that significantly influences its operational integrity. An uneven air gap can lead to what is known as eccentricity fault, which induces unbalanced radial forces, resulting in the rotor rubbing against the stator. This rubbing action can lead to faults in both the stator and rotor components.

Eccentricity faults typically manifest in two forms: static eccentricity and dynamic eccentricity as shown in figure 6 . In static eccentricity, the location of the minimum air gap remains fixed in space. This can occur due to improper rotor installation or ovality in the stator core. On the other hand, dynamic eccentricity occurs when the center of the rotor does not align with the center of rotation, causing the position of the minimum air gap to shift with rotor rotation. Dynamic eccentricity can be triggered by various factors such as resonance at critical speeds, rotor shaft bending, bearing wear, or misalignment(Yassa, Rachek and Houassine, 2019; Gundewar and Kane, 2021).

The mixed eccentricity is the existence of both static and dynamic eccentricity. In this case, the symmetry axis of the rotor and stator and the rotation axis of the rotor are displaced.

Industry standards typically permit up to 10% air gap eccentricity. In IMs, both static and dynamic eccentricities often coexist. Monitoring and detecting these eccentricities can be achieved through Motor Current Signature Analysis (MCSA) (Nandi, Toliyat and Li, 2005), which identifies specific frequency components associated with static and dynamic eccentricities based on fundamental supply frequency, slip, number of pole pairs, and other parameters. The sideband frequencies associated with an eccentricity using Motor Current Signature Analysis are

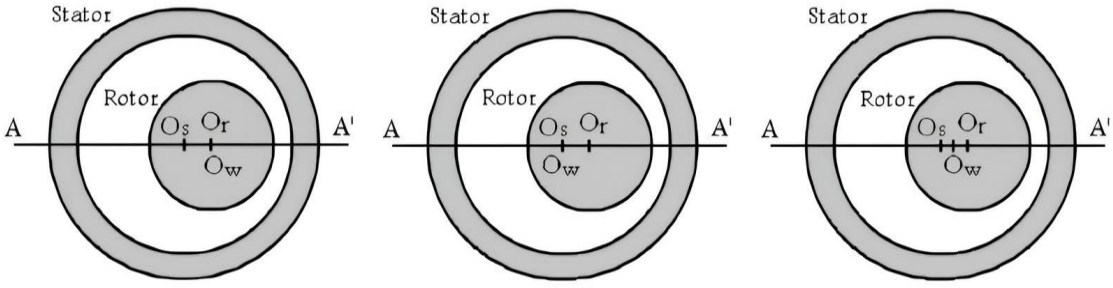
$$f_1 = \left[(kN_r \pm n_d \frac{(1-s)}{p} \pm v\right] f_s$$

Where f_s is fundamental supply frequency, s is the slip, p is the number of pole pairs, k is an integer, n_d = 0 in case of static eccentricity and n_d = 1, 2... represents the dynamic eccentricity, v is the order of stator time harmonics present in power supply which drive the motor In case both static and dynamic eccentricity coexist together, then the low-frequency component is found closer to the fundamental frequency component is given by

$$f_1 = kf_r \pm f$$

where f_r is the mechanical rotational frequency which is given by

$$f_r = (1-s)\frac{f_s}{p}$$



(a) Static eccentricity (b) Dynamic eccentricity (c) Mixed eccentricity

Figure 1-6: *Cross-section of motor for three types of eccentricities: (a) static eccentricity; (b) dynamic eccentricity; and (c) mixed eccentricity(Faiz and Ojaghi, 2009*)

1.2.1.2 Bearing failure

In the intricate world of electric motors, particularly in Induction Motors (IM), bearings stand as indispensable components, providing crucial support to the rotor within the motor housing. Both ball bearings and roller bearings are extensively utilized for this pivotal task. However, despite their fundamental importance, bearings are susceptible to faults, playing a significant role in motor failures, with statistics revealing that bearing faults contribute to a substantial 40–45% of IM failures.

Enduring continuous loading and enduring shock loadings caused by factors like unbalance and misalignment, bearings within IMs are subjected to gradual wear and tear over time. These faults often present themselves in two primary forms: localized faults, which are confined to specific areas, and distributed faults, spanning the entire bearing surface. Common localized faults include inner race defects (IRD), outer race defects (ORD), ball defects (BD), and cage defects (CD)(Gundewar and Kane, 2021)

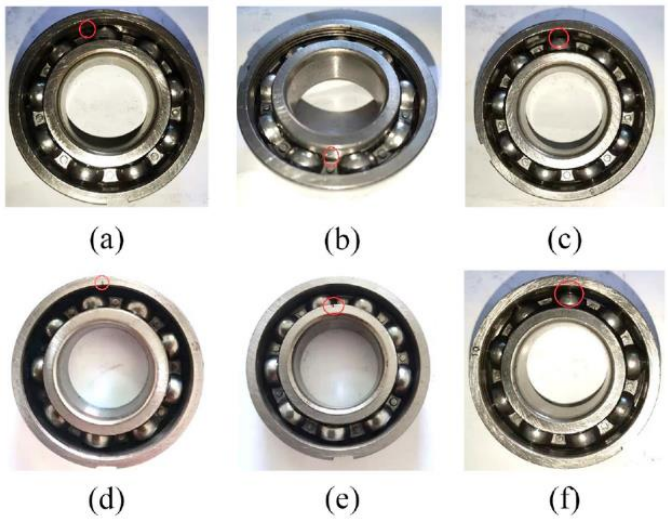


Figure 1-7:*Types and positions of bearing faults: (a) outer raceway pitting, (b) inner raceway pitting, (c) rolling balls pitting, (d) outer raceway crack, (e) inner raceway crack and (f) rolling balls crack(Chen et al., 2023)*

The formulas for the evaluation of characteristic defect frequencies in the vibration spectrum as addressed in(El Bouchikhi, Choqueuse and Benbouzid, 2015)

Table 1-1:Bearing faults and their matching fault frequency

Bearing fault	Fault related frequency
Cage defect	$f_c = \frac{f_r}{2}\left(1 - \frac{d}{D}\cos(\alpha)\right)$
Ball defect	$f_{bd} = \frac{Df_r}{d}(1 - \frac{d^2}{D^2}\cos^2(\alpha))$
Inner raceway	$f_{id} = \frac{nf_r}{2}(1 + \frac{d}{D}\cos(\alpha))$
Outer raceway	$f_{od} = \frac{nf_r}{2}(1 - \frac{d}{D}\cos(\alpha))$

Where, f_r is the rotor speed, D is the pitch diameter of the bearing, d is the ball diameter, α is the contact angle and n is the number of balls.

Many of these failures stem from material fatigue during normal operation, leading to cracks on bearing tracks and logs, as well as chipping and material pulling that accelerate bearing wear. Even with balanced loads and proper alignment, fatigue failures can manifest as increased vibration and noise levels.

External factors can further exacerbate bearing faults, such as contamination, corrosion, improper lubrication, and installation errors. Abrasive particles or corrosive substances and inadequate lubrication contribute to heating and abrasion, compromising bearing integrity. Improper installation practices, including misalignment-induced indentations, can result in brinelling of the raceways.

These bearing-related defects may also manifest as rotor asymmetry faults or fall into categories such as outer bearing race defects, inner bearing race defects, ball defects, and train defects. Therefore, meticulous attention to bearing maintenance and monitoring is paramount to mitigating the risk of motor failures and ensuring uninterrupted machinery operation.

1.2.2 Electrical failure mode

1.2.2.1 Rotor Broken Bar Fault(BRB)

The rotor bar serves as the primary driving shaft in Induction Motors (IM), facilitating the transfer of torque and speed. Literature indicates that faults related to rotor bars account for approximately 8–10% of IM failures. The rotor is supported by two bearings, located at the drive end and the fan end.

There are various reasons for rotor bar and end-ring breakage, including(Nandi, Toliyat and Li, 2005)

1) Thermal stresses resulting from thermal overload, unbalance, hot spots, excessive losses, and sparking (especially in fabricated rotors).

2) Magnetic stresses caused by electromagnetic forces, unbalanced magnetic pull, electromagnetic noise, and vibration.

3) Residual stresses originating from manufacturing issues.

4) Dynamic stresses arising from shaft torques, centrifugal forces, and cyclic stresses.

5) Environmental stresses such as contamination and abrasion of rotor material due to chemicals or moisture.

6) Mechanical stresses due to loose laminations, fatigue of parts, bearing failure.

Rotor bar breakage can lead to undesirable consequences, such as decreased motor efficiency and increased harmonics in the slip torque characteristic. BRB is responsible for increasing the severity of the fault. In the current spectrum, This may result in the appearance of distinguishing characteristic frequencies (sideband frequencies around the supply frequency) that are given by

$$f_b = (1 \pm 2ks) f_s \quad k=1,2,3, \ldots \qquad (1.1)$$

The upper sideband $f_b=(1 + 2ks)f_s$ is due to consequent speed oscillation, while the lower sideband $f_b=(1 - 2ks)f_s$ is specifically due to broken rotor bars.

The per unit slip is calculated as follows

$$s = \frac{\Omega_s - \Omega}{\Omega_s} \qquad (1.2)$$

where f_s is the supply frequency, Ω_s is the synchronous speed and Ω is the rotor speed and p is the number of poles.

For the reasons outlined above, damage to rotor bars can occur, potentially leading to an unbalanced rotor situation. Asymmetry in the rotor cage results in uneven distribution of rotor currents. Consequently, damage to one rotor bar can propagate to adjacent bars, causing multiple bar fractures. In the case of a crack in a bar, overheating will occur, eventually leading to bar breakage. This heightened thermal stress can also induce cracks in surrounding bars, which now carry higher currents due to the failure of the adjacent bar. Moreover, the increased current flowing through the remaining bars may lead to thermal stress-induced damage to the rotor laminations. The temperature distribution across the rotor laminations is altered due to rotor asymmetry. Cracks in the bars may manifest in various locations, including the slot portion and end rings of bar joints. The likelihood of cracking in the region of end rings of bar joints is

highest during prolonged startup times and frequent starts of the machine. (Gangsar and Tiwari, 2019),

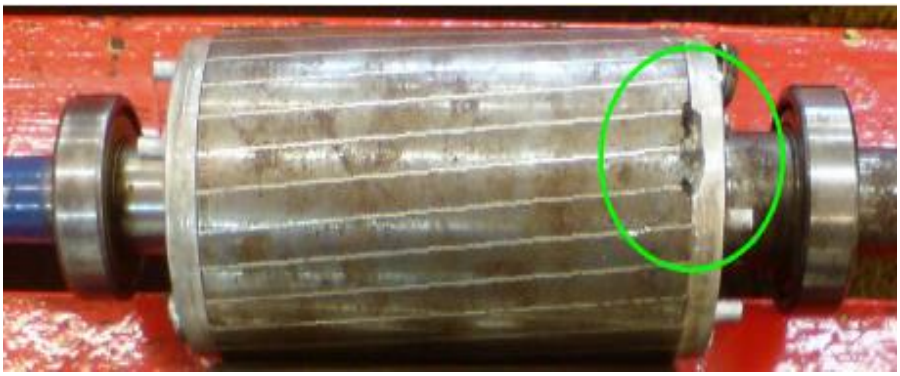


Figure 1-8: *Actual broken bar fault.*

1.2.3 Stator Faults

The stator plays a pivotal role as it generates the rotating magnetic flux responsible for inducing electromotive force in the rotor. Consequently, any faults in the stator can significantly impact motor performance and reliability. Studies indicate that stator faults are accountable for a substantial proportion, ranging from 30% to 40% of IM failures. These faults are usually related to insulation failure, Stator faults can be categorized into several types, including those affecting the stator winding, winding laminations, and the stator frame. Out of these, the first one is the most commonly occurring fault . The different types of faults in stator winding such as turn to turn, coil to ground faults, coil to coil, phase to phase are shown in figure 2-9 (Karmakar *et al.*, 2016; Choudhary *et al.*, 2019)

The frequency component on the axial flux, and thus stator current due to turn fault is given by

$$f_{stator} = \left(k \pm \frac{n(1-s)}{p}\right) f_s \qquad (1,3)$$

Where, k is an integer, s is the slip of motor, p is the number of poles, and f_s is the supply frequency.

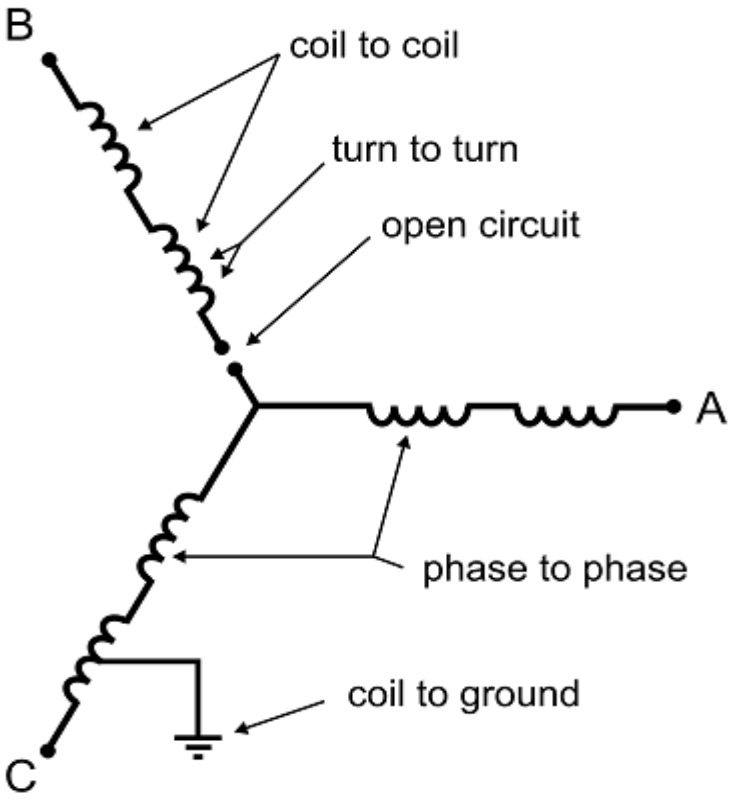


Figure 1-9: *Types of stator winding faults.*

Causes of stator faults can be summarized as

- loose bearing for end rings,
- high stator core and winding temperature,
- slack core lamination, slot wedges, and joints,
- contamination due to oil, dirt, and moisture,
- leakage in the cooling system

Although, other work shows that the stator winding faults can arise from a variety of stresses, including mechanical, electrical, thermal, and environmental factors. Mechanical stress typically results from the movement of stator coils, driven primarily by the substantial current flowing through them. Additionally, mechanical vibration within the motor can contribute to mechanical stress. Electrical stress occurs when transient disturbances affect the supply voltage. Thermal stress, often a consequence of thermal overloading, is a major contributor to insulation deterioration in stator windings. Thermal overloading can occur due to factors such as motor overcurrent, unbalanced supply voltage, inadequate ventilation, or high ambient temperatures. A notable guideline suggests that for every 10°C increase in ambient temperature, insulation life decreases by approximately 60%. Furthermore, environmental

stress may impact the motor if it operates in hostile conditions, such as extreme heat, cold, or humidity. Identifying and addressing these various stresses are essential for preventing stator winding faults and ensuring the reliable operation of Induction Motors(Karmakar *et al.*, 2016; Gundewar and Kane, 2021)

1.3 Introduction to Predictive Maintenance (PdM)

According to the European standard PN-EN 13306, maintenance is characterized as " a combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it, or restore it to a state, in which it can perform the required function''. (Theissler *et al.*, 2021)

In today's competitive industrial landscape, pressure to maintain high production efficiency and low operational costs necessitates robust production systems. However, unexpected machine failures can significantly disrupt system function, leading to transient operational states and extended downtime, both of which negatively impact throughput and product quality.

Effective maintenance strategies are crucial for minimizing disruptions, enhancing system reliability through proactive maintenance, and ensuring consistent output levels and product quality by maintaining optimal machine performance.

Predictive maintenance, a highly effective and cost-efficient strategy, utilizes real-time or historical data to predict potential failures before they occur, enabling condition-based decision-making. This proactive approach translates to reduced unscheduled downtime through timely identification and mitigation of potential issues, and optimized maintenance interventions by eliminating unnecessary disruptions to production schedules.

While advantageous in single-stage systems, implementing predictive maintenance in multistage production systems presents unique challenges due to machine interdependencies. These challenges include cascading effects of failures, where a single machine failure can disrupt interconnected machines, potentially leading to system-wide production losses, and the complexity of decision-making, which requires considering not only individual machine health but also the interconnectedness of the entire system and potential cascading effects. (M. Feng and Y. Li, 2022)

The preeminent maintenance methodologies widely acknowledged in industrial settings are categorized into three principal classifications: Corrective Maintenance (CM), Preventive Maintenance (PM), and Predictive Maintenance (PdM).

As depicted in Figure(2-10), these strategies offer organizations a comprehensive framework for asset maintenance, elucidating their respective advantages and limitations.

Corrective Maintenance (CM) often referred to as reactive or run-to-failure maintenance, embodies a conventional paradigm focused on addressing equipment failures post-occurrence.

Preventive Maintenance (PM) constitutes a systematic regimen involving periodic maintenance interventions, irrespective of the current health status of the equipment. The primary objective is to preemptively rectify potential issues, thereby minimizing the likelihood of breakdowns. Essentially, preventive maintenance entails the inspection and upkeep of operational equipment.

Predictive Maintenance (PdM) emerges as a forward-looking approach that centers on proactively foreseeing equipment malfunctions. This is achieved through the continuous collection and analysis of real-time data from devices, allowing the detection of potential failures before they manifest. Predictive maintenance leverages diverse data analytics and prognostic techniques to unveil latent patterns and interconnections within the device's data.(O. Manchadi, F. -E. Ben-Bouazza, and B. Jioudi, 2023)

Although "condition-based maintenance (CBM)" and "predictive maintenance (PdM)" are sometimes used interchangeably, a distinction exists within the broader classification of PdM.

CBM can be viewed as a subcategory of PdM, further dividing it into two distinct approaches which are 1) Statistical PdM; this approach relies on data not directly linked to the individual state of a specific machine. Examples include historical maintenance data, or data from a broader vehicle fleet or entire population. This approach leverages statistical methods and analysis of historical trends to predict potential failures.

Condition-based; PdM; this approach emphasizes real-time data monitoring of the system's health to inform maintenance decisions. By continuously collecting and analyzing real-time data from individual machines or equipment, potential failures can be identified and addressed proactively. This approach often utilizes advanced data analytics and sensor technology to gain deeper insights into the machine's condition.(Theissler *et al.*, 2021)

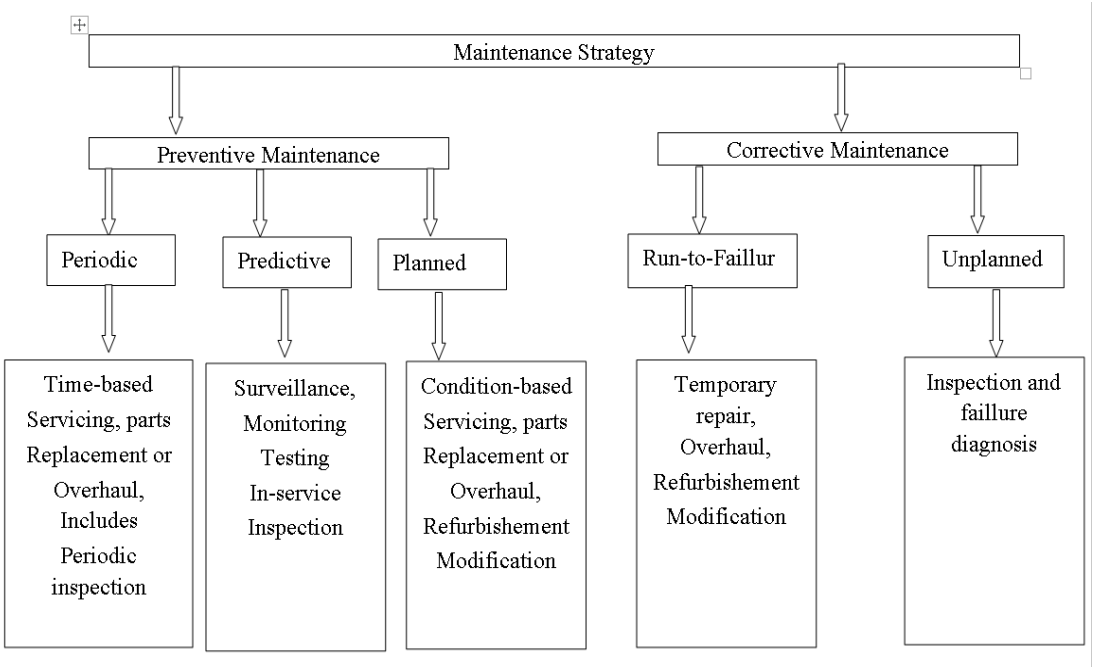


Figure 1-10:*Maintenance strategies, RD/GD-210, 2007.*

1.3.1 Exploring the Rise of Predictive Maintenance

The field of maintenance management has witnessed a remarkable evolution, continuously adapting and evolving to meet the needs of modern equipment and production systems. This section delves into this historical progression, exploring the transition from reactive approaches to the more proactive and data-driven strategies of today.

1.3.1.1 Run-to-failure maintenance (CM)

The dominant strategy until the 1960s, involved reacting to equipment breakdowns rather than anticipating them. This reactive approach, often referred to as "fix it when it breaks," presented significant limitations, leading to increased downtime, reduced equipment life, and higher overall costs. The emergence of preventive maintenance (PM) in the 1960s marked a significant shift towards a more proactive approach. PM involves scheduled maintenance activities based on predetermined time intervals, equipment usage, or historical data analysis. This strategy aimed to prevent unexpected failures by addressing potential issues before they manifested, leading to improved equipment longevity and reduced downtime. However, PM faced criticism for its potential to be overly proactive, resulting in unnecessary part replacements and increased maintenance costs.

1.3.1.2 The Rise of Condition-Based Maintenance

The late 1980s witnessed the introduction of condition-based maintenance (CBM), driven by advancements in sensor technology and condition monitoring capabilities. CBM focuses on monitoring the actual health of the equipment using sensors and diagnostics, triggering maintenance interventions only when there are clear indications of deterioration. This approach eliminated unnecessary scheduled tasks, optimizing maintenance efficiency and minimizing costs compared to PM. However, CBM requires continuous equipment monitoring, making it challenging to schedule maintenance activities proactively.

1.3.1.3 Predictive Maintenance the Future of Maintenance Management

Building upon CBM principles, the concept of predictive maintenance (PdM) emerged in recent years. By incorporating prognostics (predicting future faults) into its decision-making process, PdM offers a more sophisticated approach.

PdM leverages data from sensors and historical records to predict potential failures with greater accuracy, allowing for proactive maintenance planning. This strategy enables the estimation of remaining useful life (RUL) of equipment, facilitating optimized resource allocation and minimizing downtime. PdM represents the culmination of advancements in maintenance management, offering a data-driven and cost-effective approach to maintaining critical assets.(O. Manchadi, F. -E. Ben-Bouazza, and B. Jioudi, 2023)

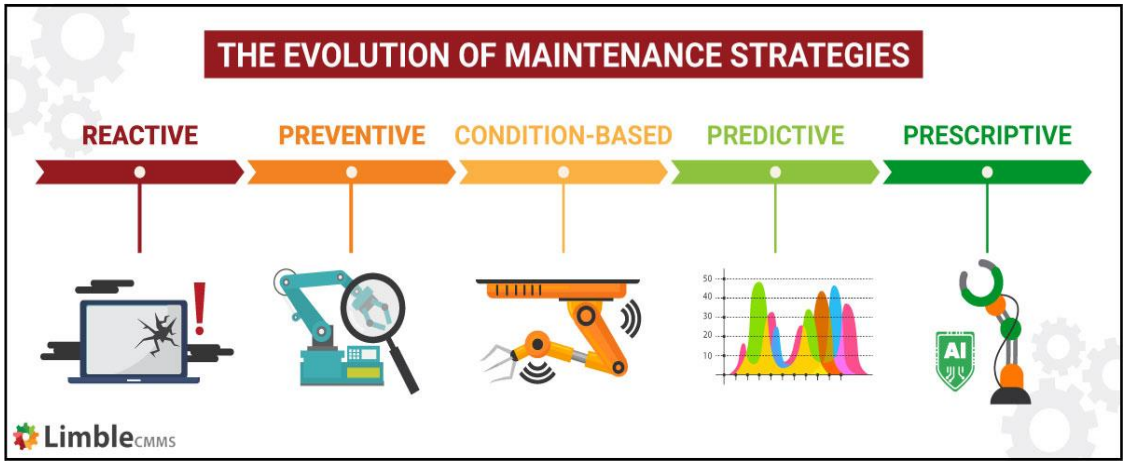


Figure 1-11:*Maintenance evolution through time.(https://limblecmms.com.)*

1.3.2 Advantages of Predictive Maintenance

Predictive maintenance prioritizes minimizing operational costs, preventing disruptive downtime, and ensuring both system availability and reliability.(O. Manchadi, F. -E. Ben-Bouazza, and B. Jioudi, 2023).

1.3.2.1 Machine Uptime and Reliability

Availability, often measured as uptime, refers to the percentage of time a machine is operational and ready for production. Predictive maintenance (PdM) systems achieve increased availability by enabling early detection of potential failures through continuous data monitoring and advanced prognostic techniques. This proactive approach significantly reduces unplanned downtime and minimizes the occurrence of catastrophic breakdowns. Minimizing downtime directly translates to reduced operational costs and increased production efficiency. Consequently, improving equipment availability and reliability are intertwined goals that PdM effectively addresses.

1.3.2.2 Extending Equipment Lifespan

Predictive maintenance (PdM) systems offer a crucial benefit: prolonging the lifespan of equipment. This is achieved through continuous monitoring of the machine's health condition and the ability to predict its remaining useful life (RUL). Early detection of potential issues allows for timely interventions and reduces the risk of catastrophic breakdowns that can significantly shorten equipment life. Additionally, by enabling targeted maintenance based on actual machine health, PdM eliminates unnecessary maintenance activities, which can stress the equipment and potentially lead to premature wear and tear.

1.3.2.3 Cost Optimization; a Long-Term Investment

While the initial setup costs of implementing a predictive maintenance (PdM) system might seem significant, it offers a compelling long-term business case due to its ability to optimize several cost factors. By enabling proactive maintenance and minimizing unplanned downtime, PdM directly contributes to reduced maintenance costs associated with reactive repairs.

1.3.2.4 Enhancing Employee Safety

Predictive maintenance (PdM) systems play a critical role in prioritizing the safety of employees who work directly with or near equipment. By continuously monitoring the machine's health condition, PdM allows for the early detection of potential failures, ultimately preventing catastrophic breakdowns. This proactive approach significantly reduces the risk of accidents and injuries that could occur during unexpected equipment malfunctions.

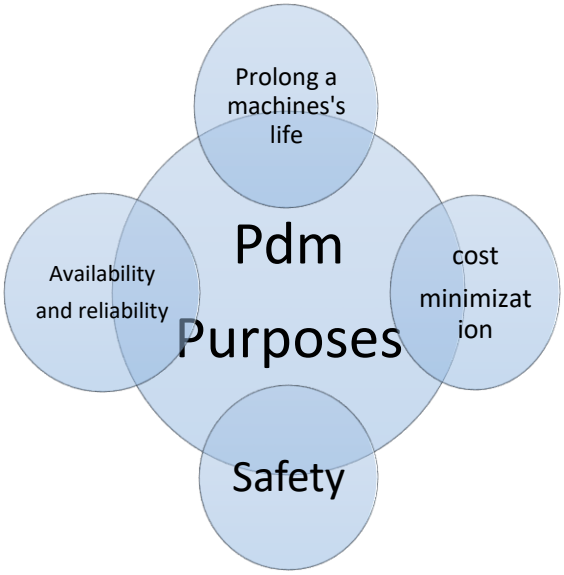


Figure 1-12:*Purposes of predictive maintenance.(O. Manchadi, F. -E. Ben-Bouazza, and B. Jioudi, 2023)*

1.3.3 Leveraging Machine Learning for Predictive Maintenance

Machine learning (ML), a subfield of artificial intelligence (AI), has emerged as a fundamental pillar supporting the advancements and efficacy of predictive maintenance (PdM) technology. ML algorithms possess the remarkable capability to learn and extract valuable insights from vast datasets, a characteristic ideally suited for the data-driven nature of PdM. (Theissler *et al.*, 2021)

1.3.3.1 Early Anomaly Detection

One of the principal contributions of ML in PdM lies in its ability to facilitate the early detection of anomalies. By meticulously analyzing sensor data and historical trends, ML models can effectively identify subtle deviations from the established normal operating patterns of equipment. These deviations often serve as early indicators of potential equipment failures, allowing for timely intervention and preventative maintenance before the occurrence of catastrophic breakdowns.

1.3.3.2 Enhanced Prediction Accuracy

The iterative learning process inherent to ML algorithms enables them to continuously refine their capabilities and improve the accuracy of their predictions over time. This translates to enhanced precision in predicting equipment failures within the PdM context. As a result, proactive maintenance interventions can be strategically planned, minimizing the risk of unexpected downtime and its associated disruptions to production or service delivery.

1.3.3.3 Optimized Resource Allocation

ML algorithms can be employed to analyze and interpret maintenance data, empowering the estimation of the remaining useful life (RUL) of equipment. This crucial information facilitates the development of prioritized maintenance schedules and the efficient allocation of resources. By directing maintenance efforts towards equipment nearing the end of its useful life, organizations can optimize resource utilization and minimize the potential for unexpected equipment failures

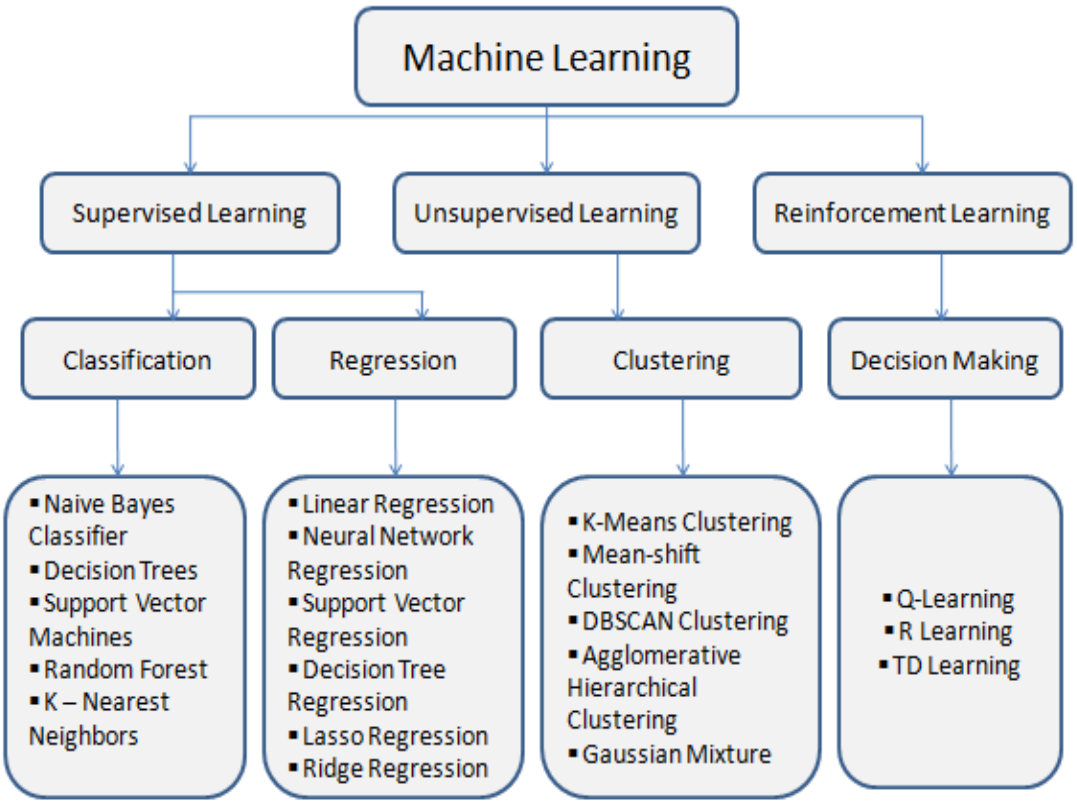


Figure 1-13:*Common categorization of machine learning with the ML tasks(https://www.analyticsvidhya.com/machine-learning/).*

Building upon the discussion of machine learning's role in PdM, we now explore specific ML tasks commonly employed in this context (Figure 2-14). This section will provide a concise explanation of each task.(Theissler *et al.*, 2021)

1.3.3.4 Clustering

The most prevalent unsupervised learning technique, plays a vital role in exploratory data analysis (EDA). Its primary function is to uncover hidden patterns or groupings within data sets (see top left quadrant of Figure 2-14). Unlike supervised learning methods that require labeled

data, clustering algorithms operate on unlabeled data, seeking to automatically identify similarities between data points and subsequently group them into distinct clusters.

1.3.3.5 Classification

Supervised learning encompasses a broad range of techniques, and classification is one of its fundamental pillars. In contrast to unsupervised learning methods like clustering, classification algorithms rely on labeled data to establish a mapping between input features and categorical class labels (see top right quadrant of Figure2-13). During the training process, the model learns a decision function that enables it to classify new, unseen data points into the appropriate category based on the patterns identified in the labeled training data.

1.3.3.6 Regression

Regression analysis falls under the umbrella of supervised learning techniques. It leverages paired data sets consisting of input variables and their corresponding continuous output values (see bottom left quadrant of Figure2-14). The core objective of regression algorithms is to learn the underlying relationship between the input features and the continuous outputs. Through this learning process, the model establishes a predictive function that allows it to estimate the continuous output value for new, unseen input data points.

1.3.3.7 Anomaly detection

The ISO-26262 standard defines an anomaly as any deviation from expected behavior, as outlined in various sources like requirements, specifications, design documents, user manuals, industry standards, or past experience. In the context of remaining useful life (RUL) estimation, anomalies can serve as valuable indicators of equipment degradation.

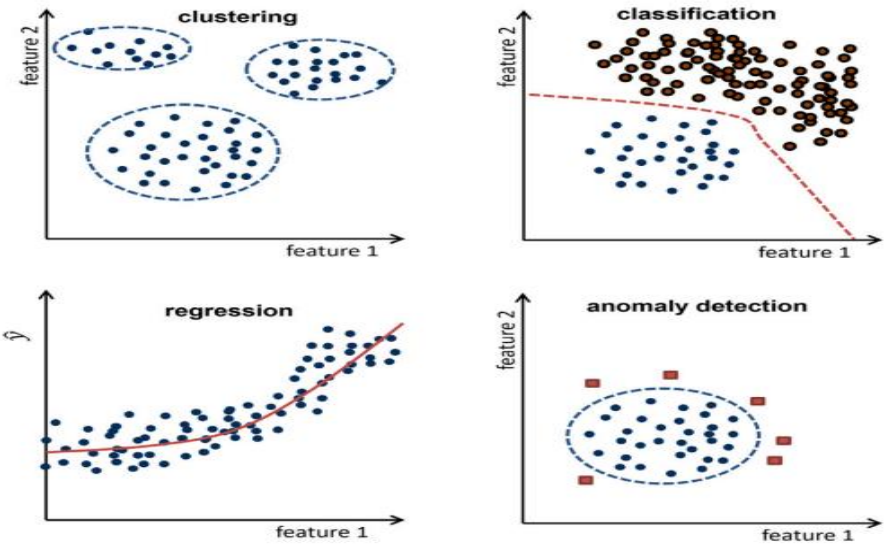


Figure 1-14:*Machine learning tasks most relevant for PdM.*

1.4 Faults Detection Techniques

Modern monitoring techniques have revolutionized the field of induction machine health assessment. Combining sophisticated measurement tools, advanced data processing, and computerized data acquisition, these techniques unlock novel approaches based on spectral analysis of operational parameters like temperature, pressure, and steam flow. Time-domain analysis utilizing characteristic values and trends, spectrum analysis focusing on frequency, amplitude, and phase relations, and spectrum analysis delving deeper into the frequency spectrum itself, offer a comprehensive and data-driven perspective on machine health. While vibration monitoring remains valuable for incipient fault detection, these advanced techniques provide a broader and more insightful picture.

The following section will delve into some of the key stator-current-signature-based techniques used for induction machine monitoring.(M. El Hachemi Benbouzid, 2000)

1.4.1 Classical Fast Fourier Transform (FFT) for Stator Current Monitoring

The Classical Fast Fourier Transform (FFT) approach to stator current monitoring, depicted in figure 2-15 employs a four-step process

1.4.1.1 Sampling

This stage focuses on a single-phase stator current. A low-pass filter removes the 50Hz excitation component, followed by a 50Hz notch filter on the current (sensed by a current transformer) to further reduce the fundamental component. Amplification and low-pass filtering follow. Amplification maximizes the analog-to-digital (A/D) converter's input range, while the filtering eliminates unwanted high-frequency components that could cause aliasing during

sampling. Finally, the A/D converter samples the filtered current signal at a predetermined sampling rate, an integer multiple of 50Hz, and continues for a period sufficient to achieve the desired FFT resolution.

1.4.1.2 Preprocessing

The sampled signal is converted into the frequency domain using an FFT algorithm, generating a spectrum containing only the magnitude information for each frequency component. To reduce signal noise, the calculated spectrum is averaged across a predetermined number of generated spectra, either from multiple sample sets or from multiple sections (windows) within a single large sample set. The chosen sampling rate and desired frequency resolution determine the number of frequency components generated, typically reaching several thousand.

1.4.1.3 Fault Detection Algorithm

This step aims to reduce the vast amount of spectral data. An algorithm, essentially a frequency filter, eliminates components lacking valuable fault information. It retains components corresponding to characteristic frequencies in the current spectrum known to be associated with specific motor faults. Since slip isn't constant during normal operation, some retained components appear as bands in the spectrum, with the width determined by the maximum variation in motor slip

1.4.1.4 Postprocessor

As a fault is a continuous degradation process, the postprocessor diagnoses and classifies the identified frequency components (for each specified fault).

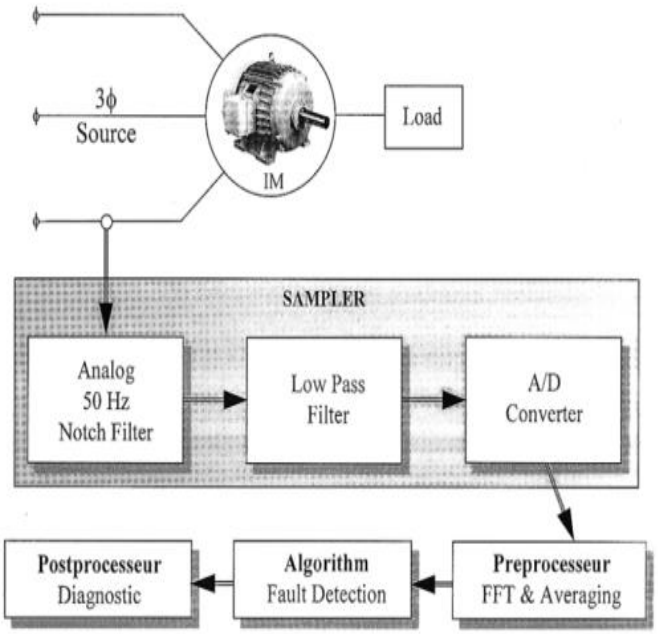


Figure 1-15:*Single-phase stator current monitoring scheme (M. El Hachemi Benbouzid, 2000)*

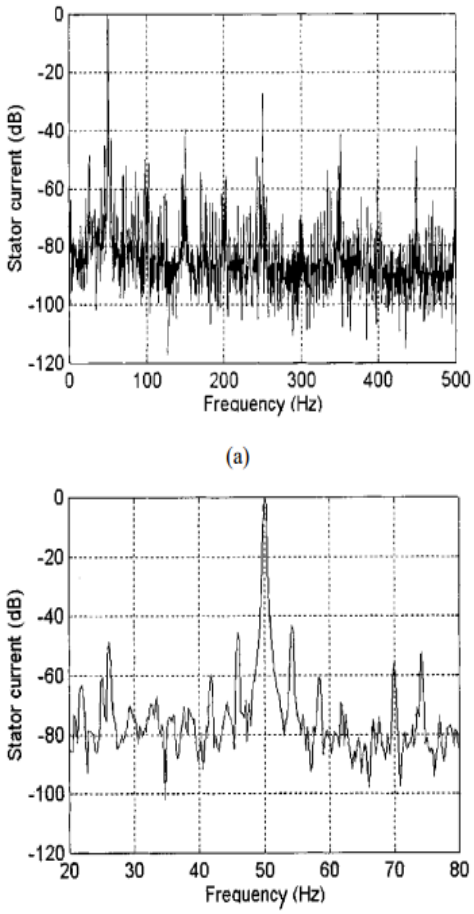


Figure 1-16:*Stator current power spectra of supposedly healthy motor (M. El Hachemi Benbouzid, 2000)*

1.4.2 Instantaneous Power FFT (IP-FFT)

An alternative approach to stator current monitoring utilizes Instantaneous Power FFT (IP-FFT) for motor signature analysis, specifically targeting mechanical fault detection within a drive system. Research suggests that the information content carried by instantaneous power, the product of supply voltage and motor current, surpasses that of the current alone.

This is because the IP-FFT spectrum, in addition to the fundamental and sideband components found in the current spectrum, reveals an additional component directly at the modulation frequency. This additional component offers valuable insights for fault detection. as illustrated in the following equation

$$P(t) = P_0(t) + \frac{MV_{LL}I_L}{2}\left\{\cos[(2\omega + w_{osc})t - \varphi - \frac{\pi}{6}] + \cos[(2\omega - w_{osc})t - \varphi - \frac{\pi}{6}] + \cos\left(\varphi + \frac{\pi}{6}\right)\cos(w_{osc}t)\right. \qquad (1,4)$$

Where

P instantaneous power;

M modulation index;

V_{LL} RMS value of the line-to-line voltage;

I_L the line current

w_{osc} radian oscillation frequency;

1.4.3 Bispectrum

Emerging from the realm of higher-order statistics, the bispectrum offers a powerful tool for motor condition monitoring by capturing non-linear relationships within signals. Mathematically, it is defined as the two-dimensional Fourier transform of a signal's third-order moment sequence, enabling the extraction of both magnitude and phase information beyond the capabilities of traditional Fast Fourier Transform (FFT) analysis. This additional information significantly enriches the process of fault detection and diagnosis.

As illustrated in Figure 2-17, the bispectrum effectively reveals a correlation between the dominant component's magnitude (associated with machine rotation) and the severity of the fault. This demonstrates the potential of stator current bispectrum analysis for comprehensive motor health assessment. Furthermore, the bispectrum exhibits particular strength in detecting electrical-based faults, such as stator voltage unbalance, which often lack distinct harmonic frequency components, rendering them invisible to conventional FFT methods

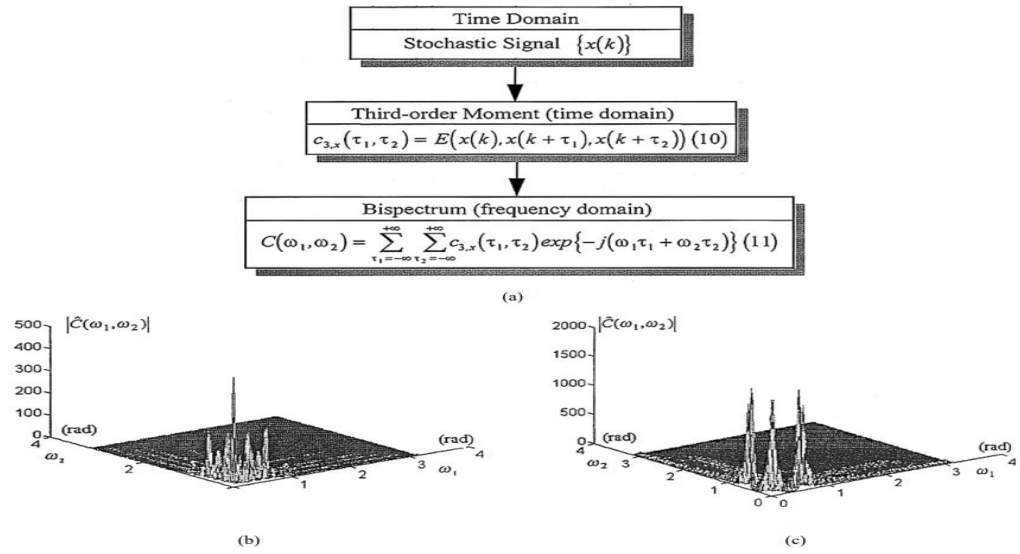


Figure 1-17:*Bispectrum. (a) Bispectrum evaluation from the discrete time-domain signal. (b) Reference condition (healthy machine). (c) Stator winding faults(M. El Hachemi Benbouzid, 2000)*

While computationally efficient, traditional spectral estimation techniques like the Fast Fourier Transform(FFT) suffer from a significant drawback (side lobe leakage). This

phenomenon arises due to the inherent windowing applied to finite datasets. Windowing functions aim to mitigate the abrupt truncation of data at the beginning and end, but they introduce artifacts in the frequency domain known as side lobes. These side lobes can obscure weaker spectral components, hindering accurate analysis.

To overcome the limitations of classical methods, researchers have explored high-resolution spectral analysis techniques. These techniques aim to improve the resolution of the estimated spectrum, allowing for better distinction between closely spaced frequency components. This often comes at the expense of increased computational complexity compared to the FFT

1.4.4 Wavelet Analyses

The Wavelet Transform (WT) emerges as a powerful tool for analyzing non-stationary signals, overcoming a key limitation of the Short-Time Fourier Transform (STFT). Unlike STFT, which employs a window of fixed length for analysis, resulting in constant resolution across frequencies, the WT utilizes a multi-resolution technique. This allows for analyzing different frequency components with windows of varying lengths, achieving better resolution for the signal.

The core concept of WT lies in the mother wavelet, a basis function used for decomposition. The equation bellow mathematically defines the Continuous Wavelet Transform (CWT) of a signal x(t). Here, ψ(t) represents the mother wavelet, and the integral calculates the similarity between the signal and scaled, shifted versions of the wavelet function.(I. Atoui *et al.*, 2013)

$$X_{WT}(\tau, t) = \frac{1}{\sqrt{|S|}} \int x_v(t) \Psi^* \left(\frac{t-\tau}{\varsigma}\right) dt \qquad (1,5)$$

The Wavelet Transform (*WT*) utilizes two key variables: scale *(s)* and translation *(τ).* These variables play a crucial role in analyzing the signal's frequency content at different time instances.

Scale *(s):* This parameter controls the dilation or compression of the mother wavelet function. A larger scale value stretches the wavelet, allowing it to capture broader frequency components within the signal. Conversely, a smaller scale value compresses the wavelet, enabling it to analyze finer details and higher frequency components.

Translation *(τ):* This parameter represents the temporal shift of the wavelet function along the time axis. By shifting the wavelet across the signal, the WT examines the frequency content at different time locations.

The term √s serves a vital purpose in the WT equation. It acts as a normalization factor, ensuring that the energy of the wavelet remains consistent across different scales. This normalization is crucial for meaningful comparison of the wavelet coefficients obtained at various scales.

$$\Psi(t) = \frac{1}{\sqrt{|s|}} \Psi\left(\frac{t-\tau}{\varsigma}\right) \qquad (1,6)$$

In practical applications of wavelet analysis, the wavelet function (ψ(t)) typically possesses a characteristic that simplifies the admissibility condition. This characteristic is the sufficient decay of its Fourier transform (*Ψ(w))* at high frequencies *(w).* Due to this decay, the admissibility condition, which ensures the wavelet is suitable for wavelet analysis, often reduces to a simpler requirement:

$$\int \Psi(t).dt = 0 \qquad (1,7)$$

1.4.5 Demystifying the Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) offers a powerful tool for analyzing digital signals, built upon the concept of sub-band coding. This technique efficiently computes a time-scale representation of the signal, significantly reducing computational time and resources compared to the continuous wavelet transform (WT).(I. Atoui *et al.*, 2013)

1.4.6 Historical Roots

The groundwork for DWT was laid in the mid-1970s. Croiser et al. introduced a method for decomposing discrete-time signals, while Crochiere et al. explored similar ideas for speech signal coding using sub-band coding. In 1983, Burt introduced the concept of multiresolution analysis, closely related to sub-band coding, under the name pyramidal coding. Finally, Vetterli and Le Gall [1989] refined the sub-band coding scheme by eliminating redundancies present in the earlier pyramidal coding approach.

1.4.7 Sub-band Coding Explained

DWT utilizes digital filtering techniques to achieve a time-scale representation. The signal is passed through filters with varying cutoff frequencies, enabling analysis at different scales. This process involves successive low-pass and high-pass filtering of the discrete signal. This technique, known as the Mallat algorithm or Mallat-tree decomposition, bridges the gap between continuous-time multiresolution analysis and discrete-time filters.

1.4.8 Reaching the Desired Level

The filtering and decimation (removing redundant samples) process continues until the desired level of decomposition is achieved.

1.5 Chapter summary

This chapter lays the groundwork by exploring the fundamental components of the asynchronous squirrel cage motor (induction motor). It delves into the most common faults that can plague this machine, detailing their impact on its operation. Additionally, the chapter sheds light on various diagnostic techniques currently employed to identify these faults.

Chapter 2 **METHODOLOGY**

2.1 Introduction to Data Acquisition

Data acquisition (DAQ) stands as the cornerstone of digital measurement in various scientific and engineering disciplines. It entails transforming real-world phenomena (temperature, pressure, light, etc.) into a computer-readable format via sensors and analog-to-digital converters (ADCs). This computer-driven automation not only enhances data collection speed and accuracy but also facilitates the management of vast datasets. Furthermore, DAQ systems enable real-time analysis and control based on the acquired information, creating a powerful link between the physical world and the domain of digital computation.

To be recorded and understood by a computer, data must be in digital form. Unlike continuous analog signals, digital waveforms consist of discrete values, meaning they can only hold specific values at specific points in time. These values and sampling points are typically separated by a constant time interval, resulting in the characteristic "stepped" appearance seen in digitized waveforms. However, as the sampling rate (the number of samples taken per unit time) increases, the digital representation becomes a remarkably accurate approximation of the original analog waveform. Provided to have a thorough understanding of the sensor's transfer function and any intervening analog instrumentation, the resulting digital waveform can be a highly accurate representation of the time-varying quantity under measurement. The process of converting an analog signal into a digital one is known as analog-to-digital conversion (ADC), performed by a dedicated device called an analog-to-digital converter. Modern DAQ systems often employ high-speed, state-of-the-art ADCs to capture rapid changes with exceptional fidelity.(Austerlitz, 2003)

2.2 Elements of a monitoring system for predictive maintenance

2.2.1 Analog Signal Transducers

A transducer is a device designed to monitor input values such as current, voltage, acceleration, or temperature at its entrance, and it outputs a conditioned signal sent to the acquisition system for processing. Within measurement and control systems, transducers play a vital role in converting energy from one form to another, effectively facilitating signal transformation between different energy domains.

The main transducers used in the monitoring and processing electric machines includes; 1) temperature measurement where three primary sensors are utilized thermocouples, thermistors, and RTDs (Resistance Temperature Detectors). 2) For vibration analysis, two types of transducers are employed absolute transducers, which require contact and measure the actual movement of the machine, and relative transducers, which operate without contact and measure

the movement of one machine element relative to another. The accelerometer stands out as the predominant absolute sensor in the market and 3) Electric and magnetic values are typically measured by transforming voltage and current, which are integral components of protection systems. However, additional measurements may be necessary, such as determining magnetic flux density within the machine, which can be achieved using a Hall-effect device.(Austerlitz, 2003; Bonaldi *et al.*, 2012)

In our case, we are using Motor Current Signature Analysis, MCSA is a condition monitoring technique used to diagnose problems in any dynamic energized system by monitoring the stator current (more precisely the supply current). By utilizing existing current and voltage sensors installed for control, safety, and energy management purposes, MCSA minimizes the need for additional sensors. This approach not only detects electrical faults but also identifies mechanical issues within system components.(Yakhni *et al.*, 2023)

Current sensor (**ACS712)**

The ACS712 module presents a cost-effective solution for precise current measurement within circuits. This sophisticated sensor accurately detects current levels, offering a voltage output proportional to the current consumed. Its integration into a compact module streamlines connectivity, featuring intuitive connection tabs and all necessary components for seamless integration. Operating on the Hall effect principle, it enables comprehensive measurement of magnetic fields and currents. By leveraging this technology, the module detects current-carrying conductors and their interaction with vertically circulating magnetic fields, producing an output voltage proportional to the magnetic field strength and current flow. With a robust capacity to measure up to 30A, it stands as a reliable tool for intricate circuitry.

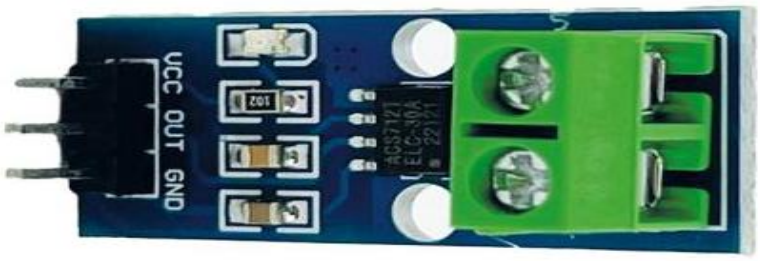


Figure 2-1:*Current sensor (ACS712, 30A)*

2.2.2 Analog/Digital Conversions

Data conversion stands as the core process within data acquisition systems. Analog signals from the real world undergo transformation into binary representations through an analog-to-digital converter (ADC). An ADC converts continuous voltage values into a binary

representation that digital circuits can process. The conversion process involves several key characteristics including resolution, and sampling rate.

Resolution plays a crucial role in determining the fidelity of a digitized signal to its analog counterpart. When digitizing an analog waveform obtained from a sensor, the process involves breaking down the waveform's amplitude into several discrete steps based on the resolution of the DAQ device. The number of steps is determined by the ADC's resolution, which represents the number of discrete binary levels available to represent the analog signal. An n-bit ADC has 2^n possible output values and a resolution of 1 part in 2^n this resolution, also referred to as granularity, dictates the precision with which changes in the signal are measured.

During digitization the ADC returns the highest possible level without exceeding the actual voltage level of the analog signal. This ensures that the digitized representation closely mirrors the original analog waveform.

ADC sampling rate known as the conversion rate, is a critical specification frequently scrutinized. It indicates the number of readings completed per second, making it particularly vital for capturing rapidly changing signals. If the signal frequency surpasses the sampling rate, swift signal variations may go undetected between consecutive ADC samples. This holds true regardless of the ADC's method of operation. Whether it performs an instantaneous analog measurement using a sample-and-hold amplifier to maintain the value constant during the conversion cycle, or if it averages the signal value with an integrator throughout the conversion process, the risk of missing rapid signal changes persists. In fact, even a successive-approximation ADC can yield highly erroneous results if the input signal fluctuates significantly during a conversion cycle.(Austerlitz, 1991b)

The Nyquist Theorem states that to accurately convert an analog signal into digital form using an ADC, the signal must be sampled at a rate at least twice the frequency of its highest frequency component. In simpler terms, only signals with frequency components lower than half the sampling frequency can be precisely digitized. The highest frequency that can be accurately captured is termed the Nyquist frequency, and this principle is known as the Nyquist theorem.

2.3 Implementation set-up

The experimental setup designed to evaluate fault detection in an Induction Motor using an STM32(F4 series) microcontroller relies on current data acquisition. A strategically positioned sensor measures stator current, which is then converted to a digital representation through the microcontroller's ADC. This digital data is stored in a buffer for further processing. Subsequently, a Digital Fast Fourier Transform (DFFT) analysis transforms the filtered data

into the frequency domain, revealing the spectral signature of the motor's current. Deviations from the expected spectrum, established through a reference profile (potentially obtained from a MATLAB simulation of a healthy motor) as illustrated in previous theses presented in (Bayou 2021, Ait Mouloud 2020), serve as indicators of potential faults. A multi-level classification approach is implemented based on the DFFT results. If the spectrum aligns with the healthy reference, an LCD display signals "Motor is Healthy." Conversely, detected anomalies trigger a secondary classification stage to pinpoint the specific fault and potentially update the LED display with a more detailed message like "Anomaly Detected." The success of this methodology hinges on meticulous selection of FIR filter coefficients, proper DFFT configuration, and the establishment of a reliable reference spectrum for fault identification.

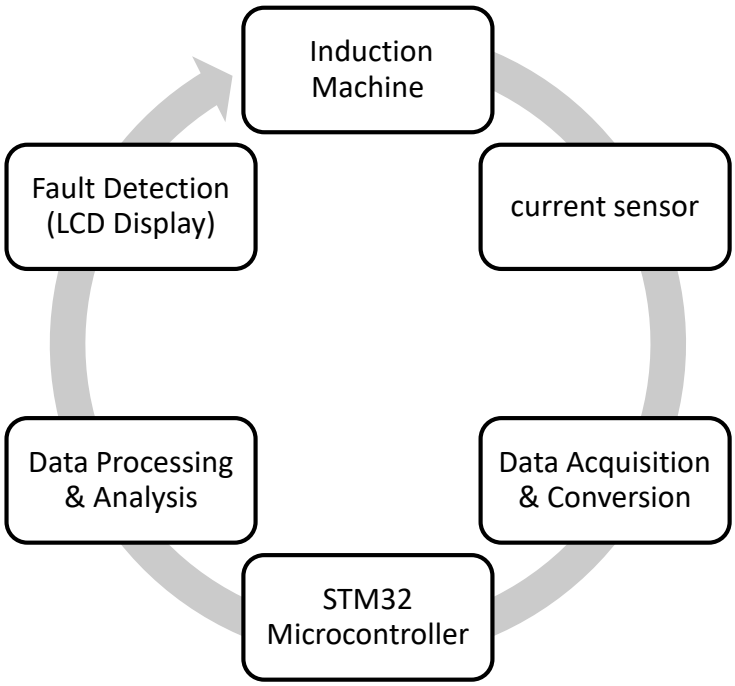


Figure 2-2:*Implementation Setup Process*

As illustrated in figure 3-3, the key components of the implementation setup are

- Induction motors
- Clamper to block the rotor
- STM32F4 discovery board
- Current sensor ACS712

- Personal computer

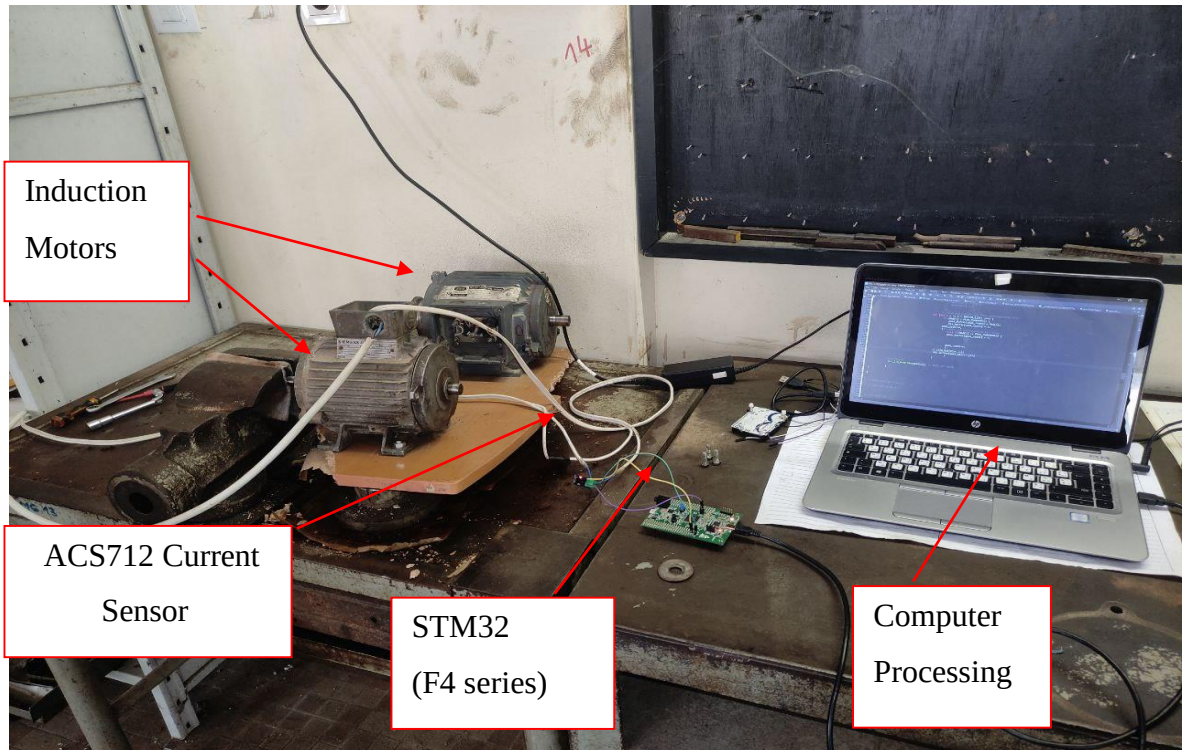


Figure 2-3:*Implementation Setup*

2.3.1 Characteristics of the Motors.

Table 3-2 presents the main specification of the utilized induction machines

Table 2-1: Induction Motors specifications

	Power(kW)	**Speed(Rpm)**	**Rated Current (A)**
Motor 1	0.38	1375	1.09
Motor 2	3	1400	1.57
Motor 3	4.7	1420	6.1

The figures (3-4,3-5,3-6,3-7) illustrate the induction motors utilized for testing the developed tool within the Mechanical laboratory department at Dergana Higher National School of Advanced Technology.



Figure 2-4:*0.38kW motor.*



Figure 2-5:*3kW motor.*



Figure 2-6:*4.7kW motor*



Figure 2-7: *Multi-Motor Testing*

2.3.2 Digital Fast Fourier Transform (DFFT) in Embedded System Fault Detection

Digital Fast Fourier Transform (DFFT) plays a pivotal role in embedded system applications involving signal analysis, particularly for tasks like fault detection in machinery. The DFFT is a computationally efficient algorithm that transforms a signal from the time domain (representing its variation over time) into the frequency domain (representing the distribution of its constituent frequency components). Mathematically, the DFFT can be expressed as

for k = 0, 1, ..., N-1

$$x[k] = \sum \left(x[n] * e^{-\frac{j2\pi kn}{N}} \right) \qquad (1,8)$$

Where,

x[k] represents the signal's frequency domain representation at the k-th frequency bin.

x[n] represents the original signal in the time domain at the n^{th} sample point.

J is the imaginary unit.

N is the total number of data points in the signal.

$e^{-\frac{j2\pi kn}{N}}$ is the twiddle factor, a complex exponential term crucial for efficient computation.

Embedded systems, due to their resource constraints, often rely on optimized implementations of the DFFT algorithm. These implementations leverage techniques like code optimization and hardware acceleration (if available) to achieve fast execution while maintaining acceptable accuracy. By analyzing the frequency spectrum obtained from the DFFT, embedded systems can identify characteristic frequency components indicative of normal operation or potential faults within the system under observation. This information serves as a valuable input for anomaly detection algorithms and subsequent decision-making processes within the embedded system.

2.3.3 STM32F407 Discovery Board

The STM32F407 Discovery Board, depicted in Figure 3.8, belongs to the family of 32-bit microcontroller integrated circuits. These microcontrollers are built around the high-performance Arm® Cortex®-M4 32-bit RISC core and can operate at speeds of up to 180 MHz. Setting it apart, this series is the first in the STM32 lineup to feature DSP instructions and a Floating Point Unit (FPU) for single precision, significantly boosting the speed of tasks like FFT analysis. Additionally, it boasts high-speed embedded memories, including Flash memory up to 512 Kbytes, SRAM up to 128 Kbytes, and up to 4 Kbytes of backup SRAM. The STM32 board is equipped with an integrated ST-LINK/2-1 debugger and programmer, eliminating the need for a separate probe. Moreover, it provides access to the STM32 comprehensive software HAL library and various pre-packaged software examples. Furthermore, users can benefit from direct access to the Arm® Mbed™ online resource.

Furthermore, the STM32F4 series offers enhanced features such as the ART Accelerator™ for zero-wait-state execution from internal Flash memory, up to two USB2.0 OTG FS/HS ports, SDIO, USART, SPI, I²C interfaces, 16-bit and 32-bit timers, up to three 12-bit ADCs, up to two 12-bit DACs, an external memory controller, and a wide operating voltage range from 1.7V to 3.6V.

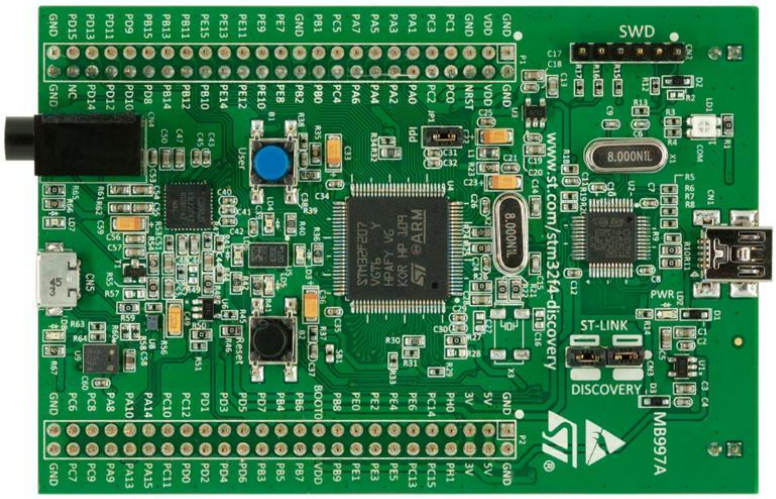


Figure 2-8:*STM32F4 Discovery Board*

2.3.3.1 STM32F4 Discovery Board ADC modules

This development board is equipped with an ARM Cortex-M4 based STM32F407VG chip, which offers numerous user-programmable peripherals, including ADC modules. The STM32F407VG microcontroller features three successive approximation type ADC modules, namely ADC1, ADC2, and ADC3. These ADC modules collectively provide 16 analog input channels, making them available for use on the STM32F4 discovery board.

Regarding ADC functionality, the STM32F407VG6T microcontroller ADC supports configurable resolutions of 6-bit, 8-bit, 10-bit, and 12-bit. Additionally, it offers three modes of A/D conversion: single, continuous, and scan or discontinuous mode. The resulting ADC values are stored in either left or right-aligned 16-bit data registers.

The ADC resolution can be defined as the smallest input voltage at the analog pin that an ADC can identify and increments its digital value. The maximum and minimum digital output value of ADC depends on the number of bits of the ADC**,** the resolution used in this project is of 8 bits.

2.3.4 Pin Assignments

The following table shows the pinouts of the STM32 that has been assigned for the current sensor to acquire the data and the LCD used to display the status of the motor.

Table 2-2: Pins assignement

PIN	Definition	Purpose
GND	GROUND	
Vcc	5V, 3V	
PA8	SDA	LCD
PA9	SCL	
PA1	Current	Current sensor input

2.3.5 STM32CubeIDE (integrated development environment (IDE))

STM32CubeIDE is an all-in-one development tool, which is part of the STM32Cube software. STM32CubeIDE is an advanced C/C++ development platform with peripheral configuration, code generation, code compilation, and debug features for STM32 microcontrollers and microprocessors. It is based on the Eclipse®/CDT™ framework and GCC tool chain for the development, and GDB for the debugging. It allows the integration of the hundreds of existing plugins that complete the features of the Eclipse® IDE.

STM32CubeIDE integrates STM32 configuration and project creation functionalities from STM32CubeMX to offer all-in-one tool experience and save installation and development time. After the selection of an empty STM32 MCU or MPU, preconfigured microcontroller or microprocessor from the selection of a board or the selection of an example, the project is created and initialization code generated. During the development, the user can return to the initialization and configuration of the peripherals or middleware and regenerate the initialization code with no impact on the user code.

STM32CubeIDE also includes standard and advanced debugging features including views of CPU core registers, memories, and peripheral registers, as well as live variable watch, Serial Wire Viewer interface, or fault analyzer.

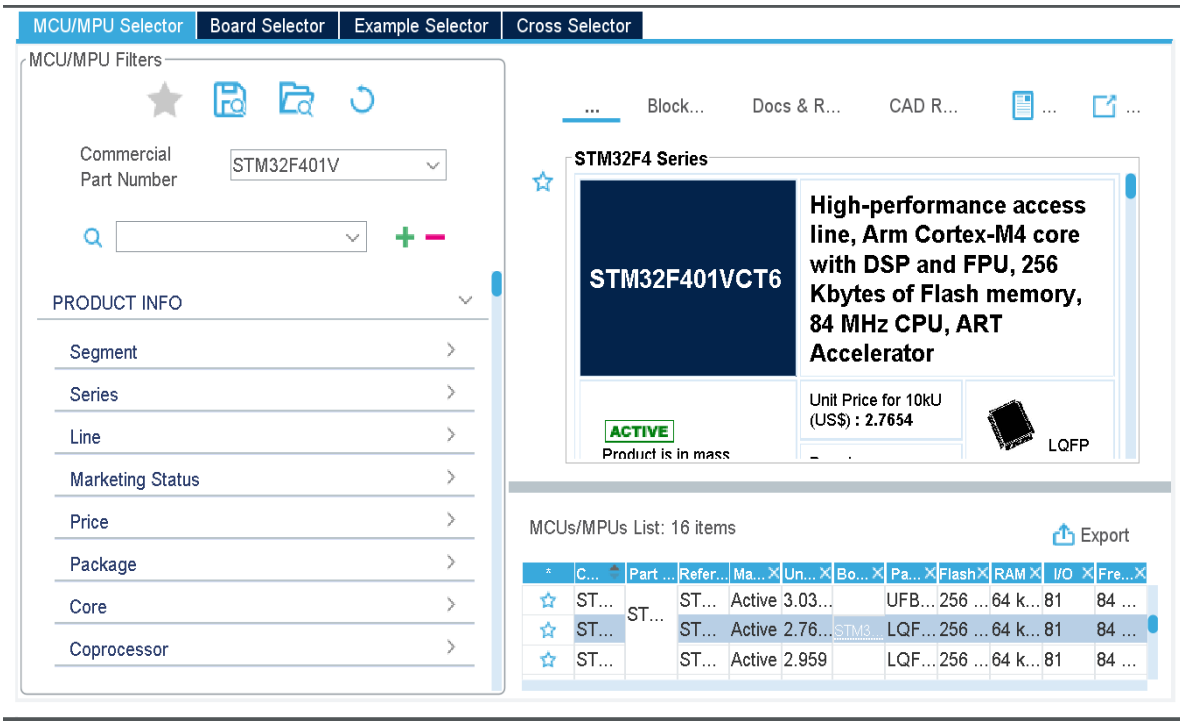


Figure 2-9: *STM32CubeIDE software interface.*

2.3.6 Experiment procedure

The procedures of the experiment in order to detect the faults in the induction machine were, first, testing the tool and recording the current of one phase while the machine is healthy.

Secondly, the rotor faults were created by drilling the one rotor bar on the motor as presented in figure 3-10 and thirdly, the bearing was pulled out and a slot on its outer race is created as making a hole on it was not achievable.



Figure 2-10:*1 BRB Fault*



Figure 2-11:*outer race fault*

2.3.7 Core Algorithm Blocks

The following flowchart shows the algorithm procedure that has been developed to detect the failures in the IM. A series of blocks are algorithmically devised to first steam the current data, store in buffer. Once the buffer is filled, the digital FFT is calculated to sort real and imaginary parts of the signal. Then, the magnitudes of the signal are calculated and sorted with their corresponding frequencies in another buffer. A threshold point is set within the algorithm to detect anomalies in the machine where the LCD will display the status.

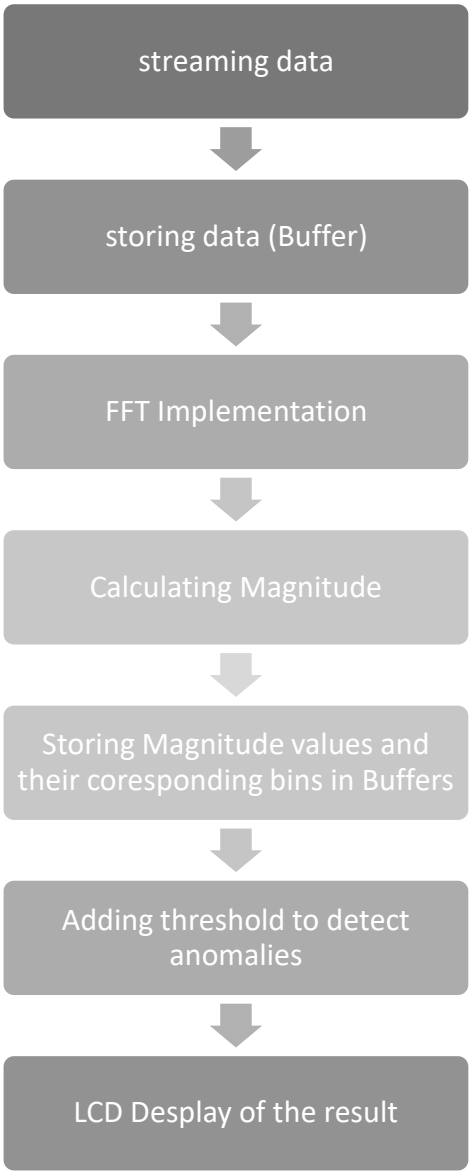


Figure 2.12: *Algorithm procedure*

2.4 Chapter summary

Chapter 3 lays out the foundation for the fault detection experiments on the induction motor. It unveils the intricate details of the experimental setup, where the STM32 (F4 series) microcontroller plays a starring role. acting as the brain of the operation. Its primary function is to acquire current data from the induction motor. This data acquisition process is essential, as it provides the raw information needed to identify and classify potential faults within the motor.

Chapter 3 **RESULTS AND DISCUSSION**

3.1 Introduction

This chapter presents a summary of the experimental findings obtained from stator current of the induction machines. Due to the challenges faced to record and plot the data via embedded system (STM32), data acquisition based on Arduino Uno board is used in this project.

Three Induction Motors with different power ratings were utilized in the current study : 0.38 kW, 3 kW, and 4.7 kW. The sampling time for data collection was selected to be 1ms. The acquired data was subsequently processed using MATLAB for spectral analysis. The results obtained from this analysis are then compared with the outputs generated by the developed diagnosis tool.

3.2 Recorded current data

The following section presents the recorded current data from one phase of the motors at 1ms sampling time using Arduino Uno. The results are unfolded into time domain and its corresponding frequency domain (FFT Analysis using MATLAB software) also the experiment are conducted within the steady state.

3.2.1 Healthy case without load (Unclamped case)

The following results represent the healthy cases that have been studied on three different rating power motors mentioned earlier. For the 0.38 kW, the fundamental frequency peak component having a magnitude of **0.26899** appears at 51.237 Hz (Figure 4-1, 4-2), it is noticeable that additional harmonic components appear at 150Hz and 250hz (at the 3^{rd} and the 5^{th} harmonics), having a magnitude of **0.00735** and **0.02104,** respectively.

Similarly, for the 3kW motor, the fundamental frequency component having magnitude of **0.3160** appears at **51.39**Hz (Figure 4-4, 4-3), again, it is noticeable also that additional

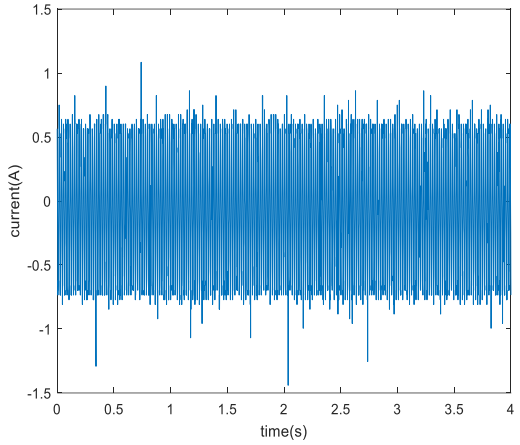


Figure 3-1: *Time domain stator current*

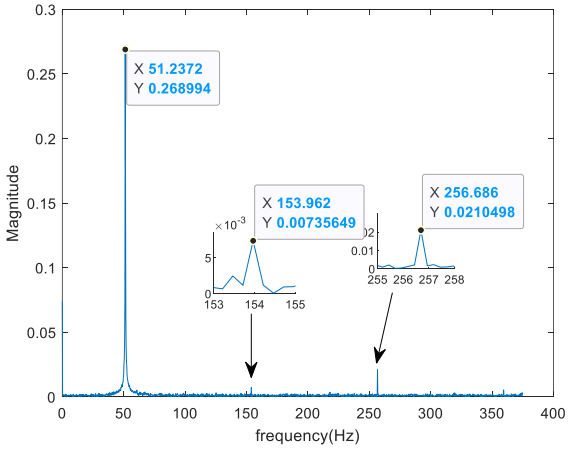


Figure 3-2:*Corresponding spectrum*

harmonic components appear at 150HZ and 250HZ(the 3rd and the 5th harmonics), having magnitude of **0.00621** and **0.01725** ,respectively. This is mainly due to the supply line frequency.

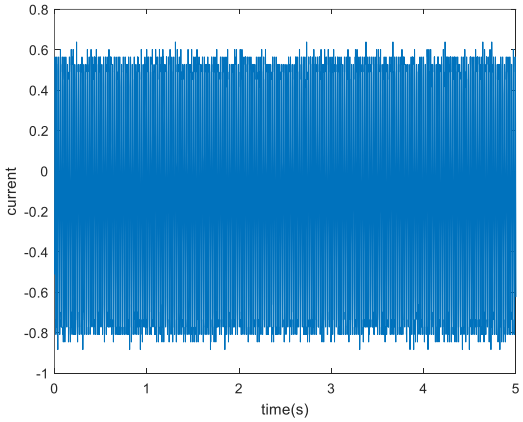


Figure 3-3: *Time domain stator current*

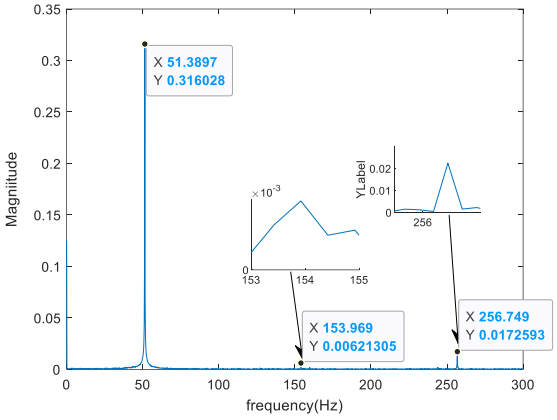


Figure 3-4 *Corresponding spectrum*

For the 4.7Kw motor, the current amplitude reaches 2.2A and the fundamental frequency component having a magnitude of **0.7060** appears at **51.49**Hz, it is noticeable also that additional harmonic components appear at 150HZ and 250HZ(the 3rd and the 5th harmonics), having a magnitude of **0.00748** and **0.07503;** respectively. This confirms that the supply line is the cause of the additional peak frequencies.

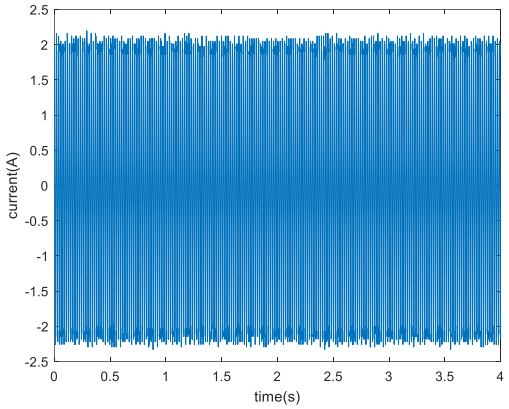


Figure 3-5 *Time domain stator current*

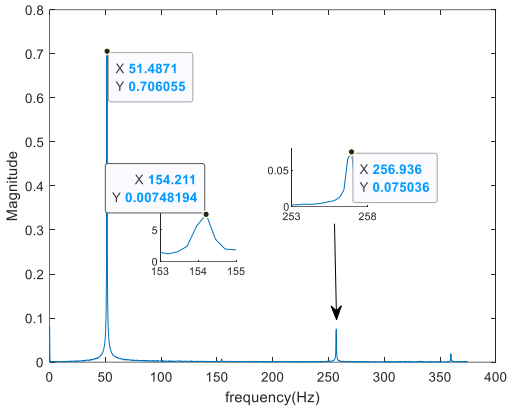


Figure 3-6 *Corresponding spectrum*

In summary, the above results confirmed that the 3rd and 5th harmonics are related to the supply line for the three motors. In the following results, only the 0.38kW motor is chosen to conduct the remaining experiment, as presented in the previous chapter, the experimental setup includes a clamper which is used as load in this experiment to partially/fully clamp the rotor in order to visualize its effect on the phase current of the IM.

3.2.2 Semi blocked rotor

Setting up a specific load on the induction motor in this study was not achievable due to equipment shortage. Therefore, the clamper is used to slightly release the rotor to turn (semi blocked rotor), hence applying a certain load on the IM.

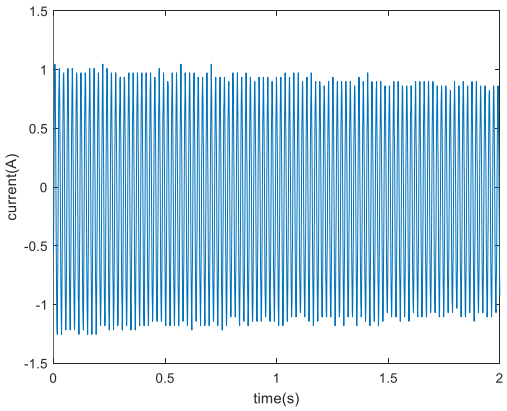


Figure 3-7 *Time domain stator current*

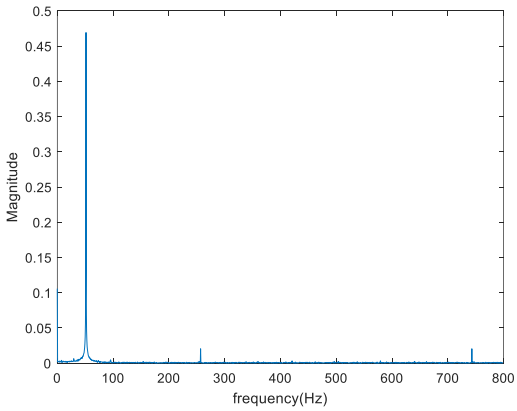


Figure 3-8 *Corresponding spectrum*

3.2.3 Fully blocked rotor

The other fold of the experiment is totally blocking the rotor by the clamper and making it stationary (rotor speed = 0). This is to verify the changes in the phase current spectrum.

In this case, the magnitude of the fundamental frequency component reaches 1.2, while it is clear that the magnitude of the other harmonics (3^{rd} and 5^{th}) are slightly increased compared to the semi blocked rotor.

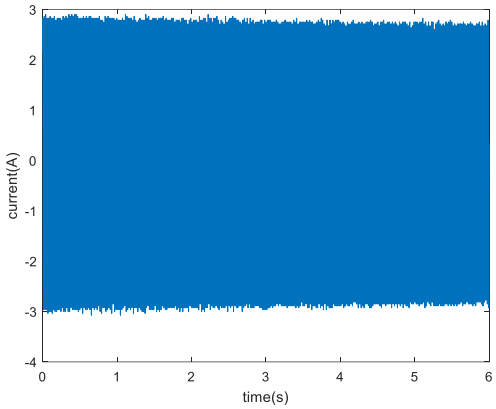


Figure 3-9 *Time domain stator current*

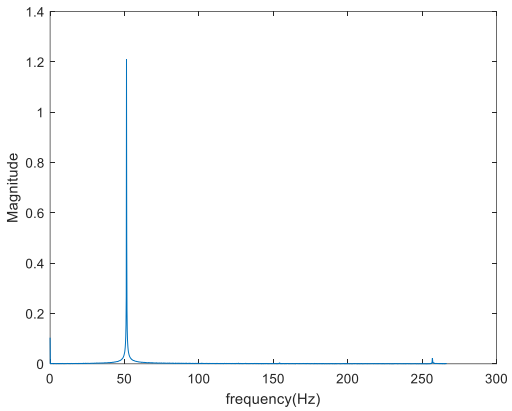


Figure 3-10 *Corresponding spectrum*

In time domain, the current results show that the current value went from 0.6A (refer to Figure 4-1) to 1.1A in the semi blocked rotor case (Figure 4-7) and to 3A in the fully blocked rotor (Figure 4-9)

3.2.4 Faulty case

To analyze the effect of rotor's broken bars on the phase current, one bar within the rotor slots is drilled as presented in the previous chapter. Again the experiments were carried out under three conditions; 1) without load, 2) semi blocked rotor and 3) fully blocked rotor.

3.3 One Broken Bar (BRB)

The recorded current data was taken at 1ms sampling time from the 0.38kW motor with one broken bar.

3.3.1 Without load

In this case the rotor of the machine was unloaded (free rotation). From the frequency spectrum presented figures (4-11;4-12), it is hard to visualize the effect of the broken bar when there is no load applied to the motor. Again the supply line exhibits two peaks at the 3^{rd} and 5^{th} harmonics.

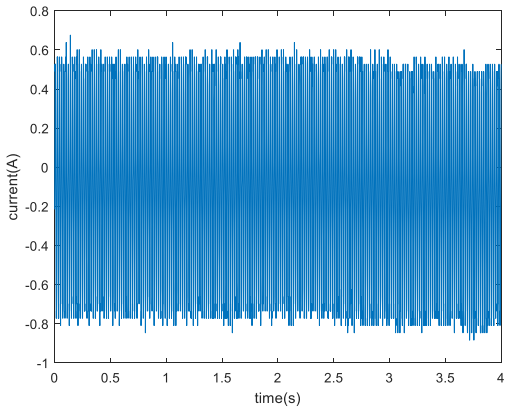


Figure 3-11 *Time domain stator current*

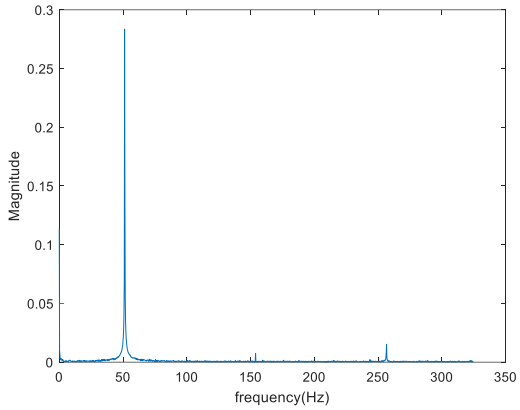


Figure 3-12 *Corresponding spectrum*

3.3.2 Semi Blocked Rotor with one broken bar

In this case of experiment, the rotor of the machine was liberated slowly using the clamper, hence applying a certain load on it. However, the speed and the torque stay unknown parameters.

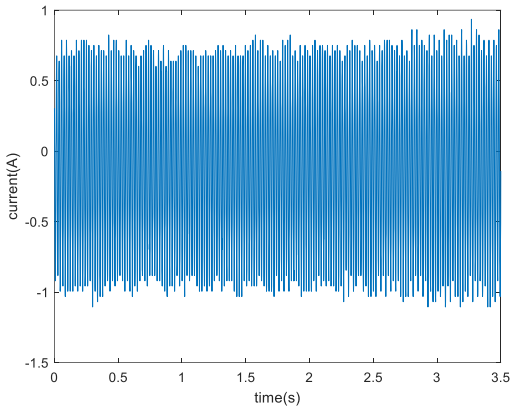


Figure 3-13 *Time domain stator current*

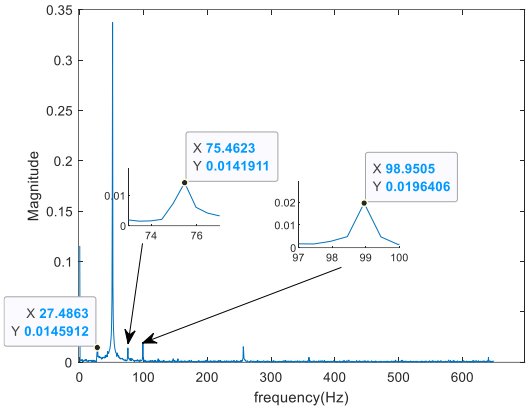


Figure 3-14 *Corresponding spectrum*

Figures (4-13; 4-14) illustrate the results of spectral analysis applied to the motor with broken bar. The results clearly show sidebands of type $f_b=(1\pm 2ks)\ f_s$ which are due to rotor faults around the fundamental frequency, these frequencies have the following values (27.48, 75.46, 98.95) [Hz] with the following magnitudes; respectively (0.0145, 0.0149, 0.0196). Based on the frequency of a slot harmonic (in this case f_b=75HZ), the rotor speed is determined.

By substituting the given slot harmonic frequency (fb = 75 Hz) and assuming k = 1, we can solve for the slip (s):

75 Hz = (1 + 2s) * fs

Solving for s, we get:

s = 0.25

once we have the slip we can determine the rotor speed as follow

$s = \frac{\Omega_s - \Omega}{\Omega_s}$ = 0,25

3.3.3 Fully Blocked Rotor with one broken bar

As the rotor of IM is fully blocked the slip (s) is equal to 1, hence the equation (2.1) becomes 3**fs* which corresponds to the the 3rd harmonic of the spectral. This means that the effect of the broken bar is exactly aligned with the 3rd harmonic. In this case when one bar is broken, the magnitude has increased compared with the healthy case.

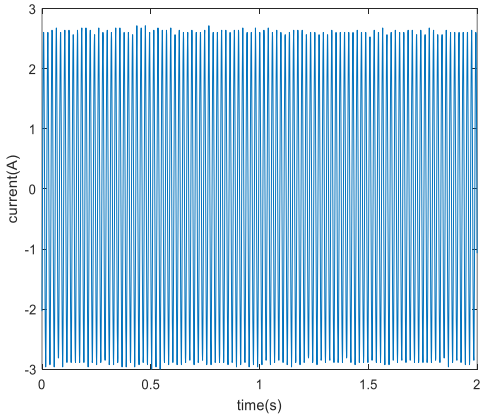


Figure 3-15: *Time domain stator current*

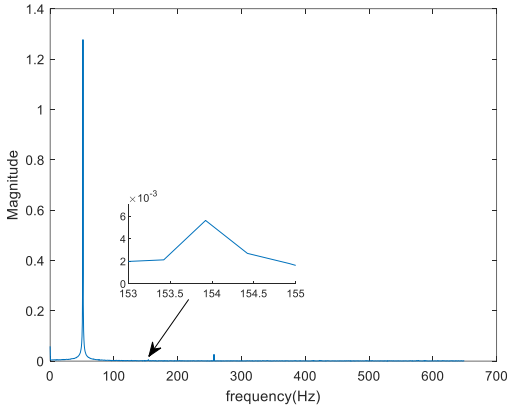


Figure 3-16: *Corresponding spectrum*

3.3.4 One broken bar and the bearing being faulty

Moreover, an additional experiment was carried out with one broken bar on the rotor and the bearing on the shaft being defected on its outer race as presented in the previous chapter.

With the bearing being defected, it is clear that the spectrum of the current phase exhibits extra noises even without load being applied to the machine.

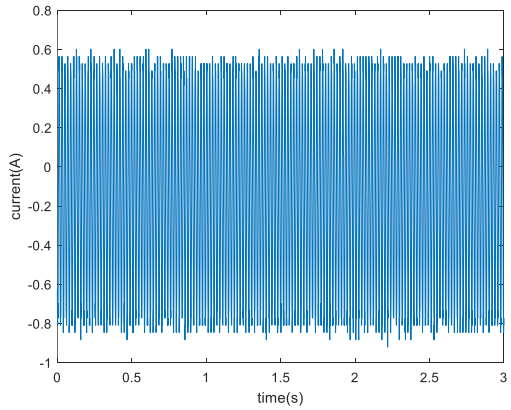


Figure 3-17: *Time domain stator current*

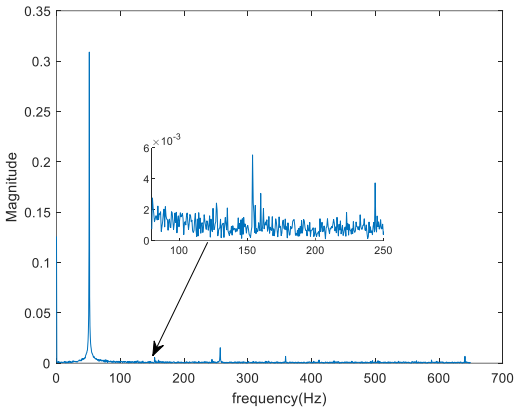


Figure 3-18: *Corresponding spectrum*

3.4 The developed tool

This section presents a novel diagnostic tool for induction motors developed based on STM32 microcontroller. The tool leverages the Motor Current Signature Analysis (MCSA) technique, where current data from a single phase is acquired, stored in a buffer, and processed using the Fast Fourier Transform (FFT) algorithm. This approach facilitates the detection of Broken Rotor Bar (BRB) faults. Future development and experimentation aim to expand the tool's capabilities to diagnose bearing and end ring faults as well. The following section presents a comparison between simulated and experimental results, validating the effectiveness of the MCSA-based diagnosis for BRB faults tool.

3.4.1 Free Rotor (without load)

When the rotor is free to rotate, a comparison between the magnitude of the calculated DFFT using MATLAB as mentioned earlier and the calculated magnitude using the tool along with their corresponding frequencies is made. This is achieved on the three cases i.e. healthy, one broken bar and bearing being defected (see Table 4.1). it is clear that the magnitudes of both tool and the MATLAB based calculation are close. However, their corresponding frequency bins are slightly different (51.23Hz (MATLAB) and 49,21Hz(tool)). This is basically referring to the sampling time using Arduino and STM32 (set to be 1ms) and in reality the two board(arduino and the STM32F4) cannot match exactly with the accuracy due to the clock setting.

Table 3-1:Free Rotor results comparison.

Case	FFT Magnitude -Matlab Calculation-	FFT Magnitude - Experiment-	Frequency(Hz) - Matlab Calculation -	Frequency(Hz) - Experiment-
Healthy	0.2689	0.3622	51.2343	49.2187

BRB	0.2835	0.0194	51.2372	49.2187
Bearing	0.3090	/	51.47	/

3.4.2 Semi Blocked Rotor

Similarly, the tool's results are verified with MATLAB FFT results for the second set of experiment (semi blocked rotor). Notably, the peaks appear in both MATLAB and the tool's where these latter get closer to the fundamental frequency (sideband frequencies) when one bar is broken within the rotor.

Table 3-2: Semi Blocked Rotor Results Comparison.

cases	FFT Magnitude - Matlab Calculation -	FFT Magnitude - Experiment-	Frequency(Hz) - Matlab Calculation -	Frequency(Hz) - Experiment-
Healthy	0.4692	0.6012	51.4743	49.2187
	0.0145	0.0190	27.4836	24.6093
	0.3371	0.3951	51.4743	49.2187
BRB	0.0141	0.0131	75.4623	73.8281
	0.0196	0.0257	98.9505	94.3359

3.4.3 Fully Blocked Rotor

In the fully blocked rotor, again the tool's results are verified with MATLAB FFT calculation as presented in the table 4-6.

Table 3-3: Blocked Rotor Results Comparison.

Case	FFT Magnitude - Matlab Calculation -	FFT Magnitude - Experiment-	Frequency(Hz) - Matlab Calculation -	Frequency(Hz) - Experiment-
Healthy	0.0035	/	154.308	/
BRB	0.0055	0.0111	153.923	147.6562

Figures 4(19-20) presents the effectiveness of the tool in detecting one broken bar in the machine. Notably, the highest peak (0.377) which corresponds to the fundamental frequency appears at 49.21Hz as always, while the second highest peaks (0.02, 0.023) appear at around a frequency of 98Hz refer to the broken bar (highlighted with blue box).

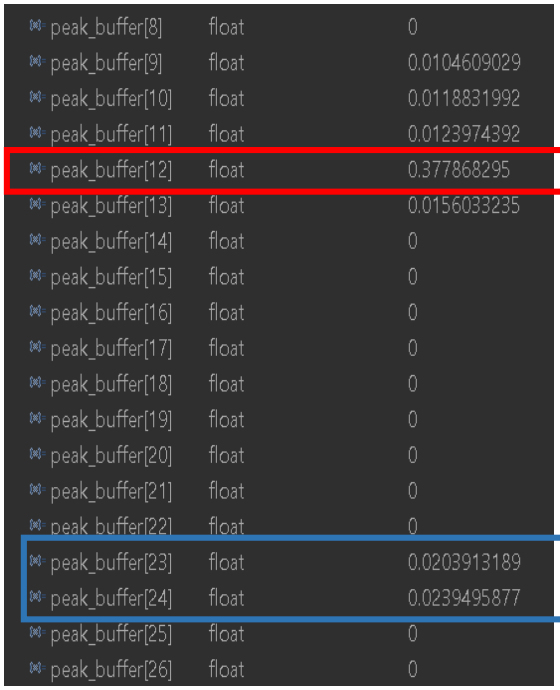


Figure 3-19:*BRB detected in the tool*

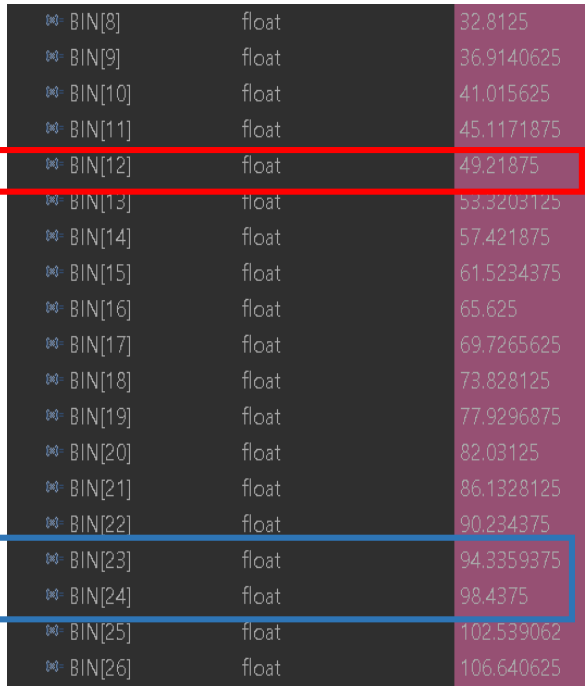


Figure 3-20:*Corresponding BIN buffer*

3.5 Chapter Summary

This chapter presents the results of spectral analysis based on Fast Fourier Transform applied to induction machine phase current's signal in both cases: healthy and faulty as well as the comparison with the results obtained from the developed tool. The results prove the effectiveness of the developed tool in detecting faults by spotting abnormal frequencies with different amplitudes in faulty machine compared with a healthy one.

Chapter 4 **CONCLUSION**

This project explores the development of a novel fault detection tool for Induction Motors (IMs) utilizing an STM32 microcontroller and spectral analysis. Traditional diagnostic techniques often require specialized equipment or invasive procedures. This project investigates a non-invasive and potentially cost-effective alternative tool.

The initial phase focused on establishing a theoretical foundation. Chapter 2 delved into the operating principles of squirrel cage IMs, exploring their key components and functionalities. It further investigated common fault types such as broken rotor bars, bearing faults, and winding faults, analyzing their impact on motor performance. Additionally, existing diagnostic techniques like Motor Current Signature Analysis (MCSA) and vibration analysis were reviewed, highlighting their limitations and potential drawbacks.

Chapters 3 and 4 focused on the development and implementation of the proposed fault detection tool. The core of the system revolved around an STM32 microcontroller, functioning as the central processing unit responsible for data acquisition. Chapter 3 detailed the intricate details of the experimental setup. An ACS712 current sensor interfaced with the STM32, acquiring current data from the IM under test. This data serves as the raw material for fault identification. The chapter also explained the signal conditioning techniques employed to prepare the acquired data for subsequent analysis.

Chapter 4, likely focusing on the core functionality of the tool, we delve into spectral analysis using the Fast Fourier Transform (FFT) technique. The FFT transforms the current signal from the time domain to the frequency domain, allowing for the identification of characteristic spectral signatures associated with specific fault types. This chapter would elaborate on how these signatures are extracted and utilized to develop classification algorithms for fault detection within the IM.

The proposed approach offers several advantages. Firstly, it is non-invasive, requiring no physical modification of the motor. Secondly, the STM32 microcontroller provides a compact and embedded solution. Finally, the FFT technique is a well-established and reliable method for spectral analysis, making it suitable for various fault detection applications.

This project establishes a foundation for further development. Expanding the tool's capabilities to detect additional fault types, such as bearing and end ring faults, presents an exciting avenue for future research. Furthermore, incorporating predictive maintenance functionalities aligns with current industry trends, enabling the detection of faults before they cause significant damage or downtime. By building upon this project's framework, future

efforts can propel fault detection in IMs to a new level, ensuring optimal performance and efficiency in industrial settings.

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