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Advanced intelligent diagnostic approach for induction machines, based on experimental analysis of residual mechanical vibrations for detection and classification of incipient faults

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Abstract

This article presents a vibration-based method for early detection and classification of incipient faults in induction machines. Gyroscope signals are acquired with an Arduino/Raspberry Pi platform on a laboratory test bench, were recorded under three health conditions (normal, stator phase fault, and misalignment). Fast Fourier Transform (FFT) features were used to train and test four classifiers on these laboratory measurements: support vector machine (SVM), Random Forest (RF), Decision Tree (DT), and XGBoost. A previously published COMSOL finite-element simulation framework, serves only as a physics-based reference for interpreting the fault signatures. XGBoost performed best, reaching 80% or higher accuracy across all performance indicators, outperforming the other models overall. Ultimately, on the laboratory dataset considered in this study, this method enables fault detection with high confidence, which may help reduce downtime and maintenance costs, while supporting the development of predictive maintenance algorithms suitable for industrial environments.

Keywords: *AI-based predictive maintenance, mechanical vibrations, COMSOL Multiphysics, XGBoost algorithm*

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Highlights

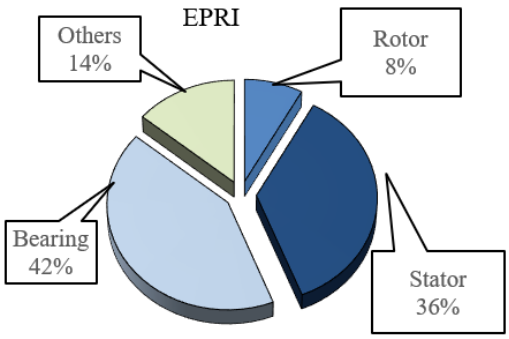
- An innovative diagnostic approach using residual mechanical vibrations.
- The XGBoost algorithm outperforms SVM and Random Forest for fault detection.
- The method discriminates the investigated health states under the laboratory conditions studied.
- The results are validated experimentally on a comprehensive, controlled test bench.
- The system enables predictive maintenance, reducing costs and machine downtime.

1. Introduction

1.1. Background and motivations

Squirrel Cage Induction Machines (SCIMs) are widely used in various industries due to their reliability, efficiency, and low cost [1,2]. In addition, these machines represent a significant percentage of the equipment installed in many industries, including manufacturing, energy production, and transportation [2,3]. Nevertheless, their prolonged operation makes them subject to a variety of faults, whether mechanical (misalignment, bearing abrasion, unbalanced rotor) or electrical (stator phase faults, inter-turn short-circuits faults, overloading) [4,5]. The Electric Power Research Institute (EPRI), the Institution of Electrical and Electronics Engineers (IEEE), and the Asea Brown Boveri (ABB) have performed statistical analyses on IM failure [6,7]. Figure 1 depicts the most common IM failures, according to their statistical study. The causes of defects in these subsystems are briefly described in Figure 2 [7]. This figure shows that the most common faults encountered on induction machines are due to mechanical stress. These faults occupy the highest percentages compared to the other classical types of defects. These defects are initially incipient, but when they persist, they become large and consequently dangerous. In

summary, machine faults can be classified into four categories [8,9]. However, these defects, when not detected in time, may lead to costly breakdowns, unexpected interruptions, and major losses in production.



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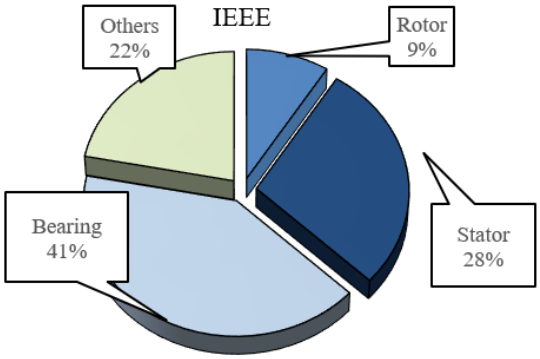

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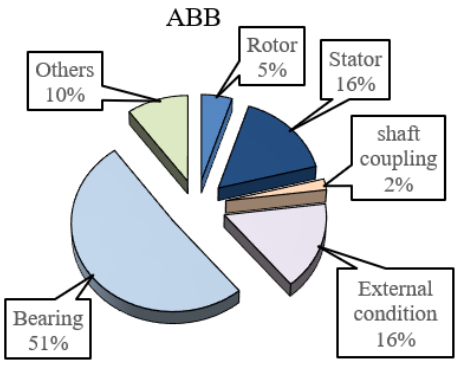

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Figure 1. Induction machine fault appearance percentage: (a) ERPI, (b) IEEE, (c) ABB.

For these reasons, Traditional maintenance strategies, such as corrective and preventive maintenance, often fall short in preventing sudden failures [10,11]. Corrective maintenance is reactive and expensive, while preventive maintenance may involve unnecessary interventions and overlook emerging issues [12]. This has led to a growing interest in predictive maintenance, which uses real-time data to detect early signs of faults before they cause major disruptions [13]. To this end, several diagnostic methods have been developed and cited in the literature, based on the analysis of various data, including vibrations, acoustical emissions, thermal variations, electrical signals, and non-destructive testing (NDT) [14].

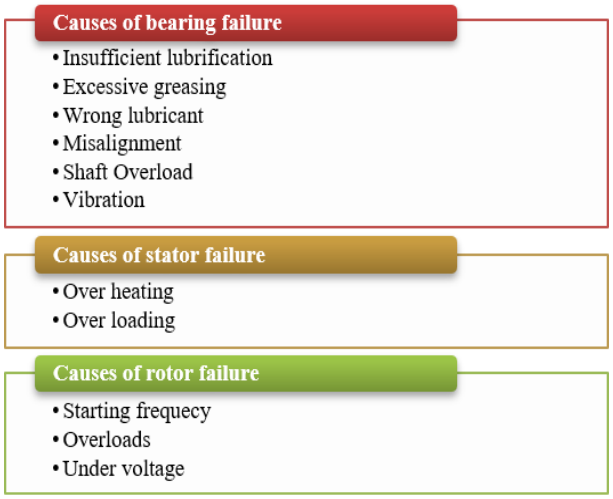


Figure 2. The causes of bearing, stator, and rotor defects.

Vibration analysis is a popular technique in predictive maintenance, enabling the detection of irregular mechanical behaviour. However, interpreting this data manually is time-consuming and often imprecise [15]. This is where Machine Learning (ML) can significantly improve the process. By automating the analysis, AI-based systems can quickly and accurately identify potential issues, allowing for timely and targeted maintenance actions [16–19].

Technological advances in sensors and data processing, as well as the rapid development of Artificial Intelligence (AI) [20,21], are providing the opportunity to perform real-time monitoring of the operating status of machines and to predict potential failures before they actually happen [13].

The motivation behind this solution lies in enhancing predictive maintenance for induction machines by combining vibration analysis with advanced machine learning models [22]. This approach seeks to improve fault detection, reduce downtime, and lower maintenance costs, contributing to more reliable and efficient industrial operations.

In this way, focusing on detecting faults in induction machines is a direct solution to the challenges facing industrial maintenance in the present context, while at the same time contributing innovative new techniques to make operations

more reliable, effective, sustainable, and to avoid the secondary effects of an undetected fault [9,23]. Table 1 summarizes the causes of faults and their generated secondary effects, where vibratory analysis is omnipresent.

Table 1. Causes of faults, their generated secondary effects, and diagnosis methods.

Faults	Reasons	Effects on the system	Diagnostic Method
Support vibration [24-27]	-A magnetic imbalance -An unbalance in the power supply -Overload -Bad installation -Contact with the rotor	Mechanical vibrations	- Vibration analysis (FFT, time-domain analysis) - Spectrum envelope analysis
Rotor misalignment (eccentricity) [25,28-30]	-Manufacturing defects/assembly defects -Magnetic unbalance -Bearing defects -Wear of the bearing -Incorrect bearing position	-Torque oscillations -Speed oscillations -Increase the current - Bearing defects	-Air-gap flux analysis. -Vibration analysis. - Acoustic emission monitoring

1.2. Literature review

In the recent literature, there are several reviews on the diagnostic methods of defect and their implementation. However, these reviews are restricted to the detection of developed or advanced defects with a high level of severity.

In general, these diagnostic methods are categorized into two types: those that use an analytical model of the system and those that do not use a model. These diagnosis methods are listed in Figure 3.

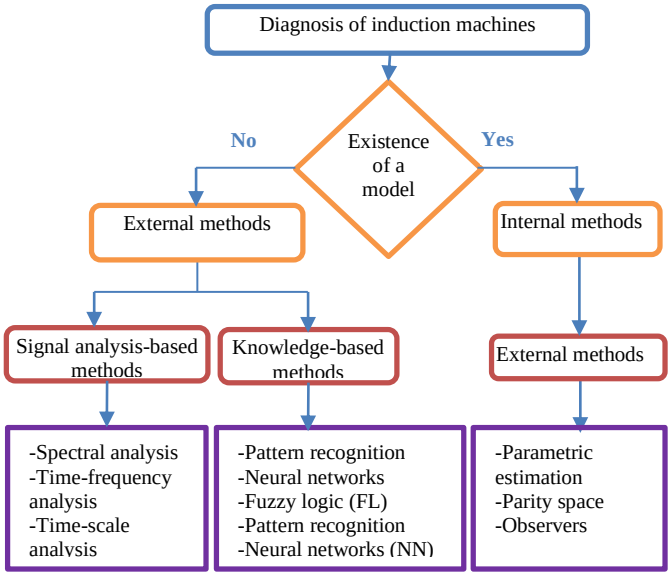


Figure 3. Diagnosis of induction machines: an overview of methods.

This section reviews diagnostic approaches and techniques for fault detection, which rely on the use of external methods that are not based on a well-defined mathematical model [31,32], because of the important role they play in maintenance based on life-cycle management and decision-making in industrial maintenance operations. The CM is one of the most important elements of maintenance. CM has emerged as an effective means of implementing predictive maintenance of induction motors in industrial situations [33]. CM intends to define the operation of a system through characterizing incipient faults by identifying the type and origin of each fault, as well as how each fault interacts with the performance of the device [34]. A thorough review of the literature on existing techniques has identified different diagnostic and predictive maintenance techniques for induction machines, specifically how to utilize vibration, electrical, acoustic, and flux signal analysis. Figure 4 illustrates the main analytical approaches (vibration, electrical, acoustic, flow) applied to the input signal to locate faults, which then guide the condition-based maintenance (CM) strategy. In terms of new digital technologies used to enhance the maintenance practice of Induction machines, there is a growing trend to use diagnostic and predictive maintenance data analytics technology. Vibration analysis is a well-understood process for diagnosing faults in rotating machinery based on the frequency and amplitude of vibration. The standard of practice was to decompose the vibrations signals using traditional techniques, such as Fast Fourier Transform (FFT), to illuminate fault signatures.

These traditional methods, like Hilbert Transform, Statistical Analysis, Wavelet Transform, Fast Fourier Transform (FFT), and Short Time Fourier Transform (STFT), can be challenged with complex fault detection under various conditions [8,35]. To handle varying fault conditions, several Artificial Intelligence (AI) and Machine Learning (ML) techniques were examined [36]. The process for early fault detection was organized around a process cycle to include data collection, detailed analysis with an anomaly detection phase for fault detection, and, in the end, a proactive tendency for

maintenance [37]. Figure 5 shows the process used to improve the reliability of induction machines and reduce downtime.

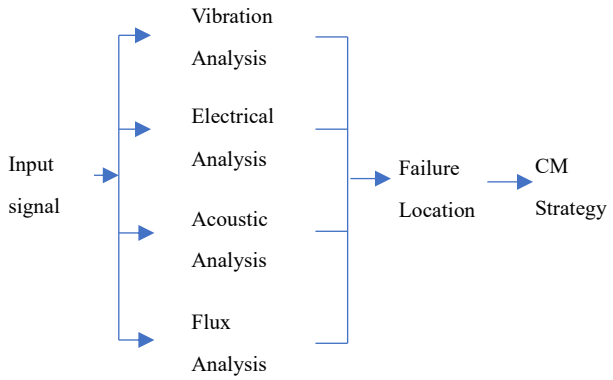


Figure 4. Input signal analysis-based fault location.

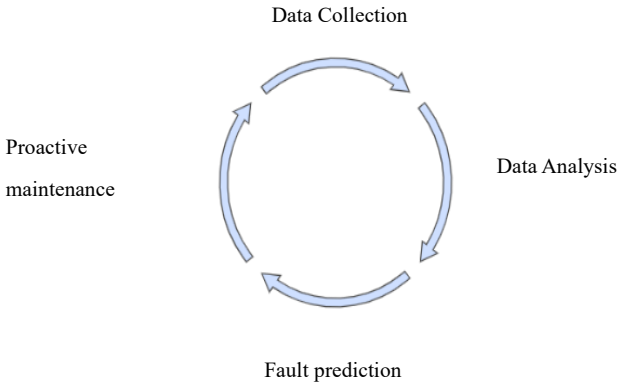


Figure 5. Proactive maintenance and fault prediction cycle.

Table 2. Summary of method characteristics: function, early detection, data, and resolution.

Method	Function	Early fault detection	Dataset	Resolution
Hilbert Transform (HT)	Signal conditioning	Possible	Medium	High
Statistical Analysis (SA)	Extraction of Feature	Possible	Low	Rely on data
Discrete Wavelet Transform (DWT)	Signal conditioning	Yes	Low/ Medium	Medium
Fast Fourier Transform (FFT)	Extraction of Feature	No	Medium	High
Short-Term Fourier Transform (STFT)	Extraction of Feature	Possible	High	Medium
Model-Based techniques (MBT)	Extraction of Feature	Yes	Medium/High	Rely on data
Stator current signature analysis (MCSA)	Extraction of Feature	No	Medium	High
Artificial Intelligence Applications	Extraction of Feature diagnosis and prognosis	Possible	High	Rely on data

This review describes the shift from conventional diagnostic paradigms to AI-enabled predictive maintenance (PdM), realizing better machine reliability, efficiency, and cost savings, where labelled data is lacking. Table 2 summarizes the characteristics of the diagnostic methods used, including their function, early detection, data, and resolution [37]. Table 3 captures the different signals utilized for fault surveillance and diagnostic applications and highlights the advantages and disadvantages, and limitations of the signals [38-47].

This paper will focus on improving the reliability and safety of induction motors through a literature study. Specifically, it will emphasize advanced predictive maintenance to avoid costly repairs and minimize downtime. Detecting motor faults or failures in the early stages, such as phase deficiency or misalignment, is important to help prevent destruction or damage to motor stator windings.

More recent studies have shown that incorporating Artificial Intelligence (AI) and machine learning (ML) can greatly assist in finding faults in asynchronous motors. For example, Benbouzid [48] reviewed methods of diagnosing induction motors and found that using more sophisticated algorithms has far healthier results when categorically detecting faults earlier. Henao et al. [49] demonstrated that a combination of traditional signal processing and neural networks improves the classification of faults for a motor at the start-up period.

In this study, vibration analysis, with Fast Fourier Transform, was applied to identify fault-specific frequency peaks. The objective of this study is to create more effective predictive maintenance by involving machine learning modelling techniques (e.g., Support Vector Machines, Random Forest, and XGBoost). XGBoost, in particular, demonstrated superior success in classifying faults (phase deficient, misalignment, healthy) because it provided the greatest accuracy in comparison to different models [50,51].

This review of the literature looked at using COMSOL Multiphysics and AI-based techniques for the earliest diagnosis of induction machines [52,53]. COMSOL Multiphysics has been widely used to model and simulate designs of electric machines because of their electromagnetic performance. Research indicates that COMSOL can be used to model mechanical defects more specifically, magnetic rotor types of faults. These research efforts help establish the diagnosis and effects of such failures through the evaluation of electromagnetic imperfections imposed by failures like

magnetic rotor failures [48]. Simulation tools such as COMSOL Multiphysics will be used to simulate motor behaviour (section 3), whereas the AI-driven predictive maintenance system is trained and evaluated on laboratory measurements (section 4). The combination of simulated data and experimental data provides a basis for developing the fault detection models and increasing the reliability of the overall system [54,55], and combining simulated data with experimental data as an integrated simulation takes predictive maintenance to the next level and allows for predictive maintenance based on real time data for asynchronous motors, and this method is based on the premise of reducing downtime, maintenance costs, and increased productivity.

Table 3. Summary of defect, causes, input signal, and detection methods used for induction machine diagnosis fault.

Features	Methods	Pros	Cons	Limitations
Vibration **[25-27]**	Spectral analysis (FFT)	-Mostly dominated method -Reliable -Standardized (ISO10816)	- Costly maintenance - Frequent calibration	-Expensive -Complexity -Difficult implementation of sensors - Susceptible to sensor failure - Non-detection of incipient defects
Acoustic Emission (AE) **[38,39]**	Analysis of acoustic emissions	- Detect defects at an early stage - High SNR - Suitable for low-speed conditions - Frequency range away from load disturbances	- Difficulty filtering out background noise	-Costly -Complex -Requires a very high sampling rate
Temperature **[40,41]**	Monitoring thermal gradients	-Reliable -Cost-effectiveness -Standardized (IEEE 841)	- Low sensitivity to early defects	-Embedded thermal sensor needed -Inaccurate defect localization -The sensors are fragile in harsh environments
Lubricating Oil **[42]**	Infrared spectroscopy, particle analysis, and viscosity measurement	-Early detection of defects -Direct determination of the bearing status	- Dependent on used type of lubricant used	-Restricted to bearings using oil in a closed circuit -The online operation is expensive.
Magnetic Flux **[30,43]**	Magnetic flux analysis using Hall sensors, demodulation methods	-Detect a large number of defects	- Impacted by external electromagnetic fields	-Expensive -Sensitive -It is difficult to place sensors in restrictive environments.
Non-destructive inspection **[44]**	Ultrasound (A-scan and B-scan), digital radiography, eddy current, active thermography	-Detection of hidden structural defects	- Specific expertise required	-Needs costly instruments
Electrical Signal **[29,43]**	Motor Current Signature Analysis (MCSA), electrical harmonic analysis, FFT, and Wavelet Transform	-Popularly applied technique -Detection of defects at an early stage -Reduced equipment complexity -Cost-effective -No supplementary sensors are needed -Non-invasive and easy to implement.	- Limited due to some mechanical defects	-It is difficult to detect incipient faults -Sometimes low signal-to-noise ratio.
Artificial Intelligence **[45-47]**	Machine learning (SVM, RF), neural networks (CNN, LSTM), XGBoost, etc.	- High accuracy in fault detection - Adaptability to complex and non-linear data - Early anomaly detection - Reduced human intervention	- Requires AI expertise - High cost of computing infrastructure	- Requires significant computational resources - Dependent on data quality - Implementation complexity

Zachariades and Xavier [56] suggest that the combination of artificial intelligence with simulation-based techniques would accurately contribute to improved fault detection capabilities. The objectives of this project are to combine contemporary simulation tools and novel AI-based techniques to provide a complete solution for early fault detection, thereby also contributing to improved operational reliability of industrial applications. There is currently little detailed literature surrounding the extent of COMSOL Multiphysics and artificial intelligence-based methods for the earlier diagnosis of such

failure [57]. Future works should try to develop the aspects of each of these methods that could be combined, and then fully leverage such technologies to explore further the reliability of induction motors [58–61].

1.3. Contribution

In this paper, a new diagnostic method was proposed for the early detection of vibrations in induction machines. This method aims to identify and classify vibration defects at their beginning, minor stage, under the laboratory conditions investigated. Motor defect diagnosis is generally done by vibration signal analysis and frequency domain analysis; however, there is a gap in the literature regarding the use of advanced machine learning algorithms for this purpose. This gap motivates this work as different defect types, such as stator phase fault and misalignment, will be analysed. Various conventional methods presented in the literature indicated a lack of sensitivity and reliability in correctly identifying such defects, as they often resulted in false alarms in industry. Thus, the new diagnosis strategy, as proposed by this paper, used XGBoost for classifying the vibration signals accurately. Support Vector Machines (SVM) and Random Forest (RF) were initially used for comparison, but XGBoost performed the best, as no other method obtained the highest accuracy was chosen as the algorithm. The proposed method here concentrates on extracting the correct features from the frequency (spectrum) for improved sensitivity in the detection of faults. The proposed diagnostics strategy is evaluated on the laboratory dataset considered in this study for accurate identification of defects while the motor remains running. The key contributions of this study include:

- Enhanced sensitivity in detecting incipient defects, under the laboratory conditions investigated.
- Effective classification of multiple defect types with high accuracy using advanced machine learning techniques.
- A straightforward implementation that requires minimal computational resources and can operate with readily available vibration data.
- The advanced diagnostic strategy is intended to support the early identification of motor defects, particularly in environments focused on improving operational efficiency and reducing downtime.

Finally, the experimental analysis is supported by the COMSOL finite-element framework previously reported in our conference work [62], which provides a physics-based reference for interpreting the investigated fault signatures.

1.4. Paper organization

The rest of the article is organized as follows. Section 2 is devoted to the overall architecture of the proposed diagnostic approach, specifying the fundamental steps for extracting the vibration signal and then processing the data. Section 3 addresses the simulation of the asynchronous machine, considering both the healthy machine and the machine with faults, followed by upstream analysis of the corresponding vibration signals. Section 4 presents the experimental results obtained on the test bench developed, highlighting the accuracy and performance of the artificial intelligence techniques used. Section 5 concludes with a general assessment and the prospects for extending the methodology to other types of faults and deploying it in a real industrial environment.

2. Structure of the suggested new method

The objective of this section is to introduce some mathematical notions of the signal processing tools, which are exploited to build the new diagnosis technique.

2.1. Vibrational signal extraction for early fault diagnosis in induction machines

Mechanical disturbances and changes in load placed upon an induction machine influence its operation, creating non-stationarity in the vibrational signals it generates. This paper aims to take advantage of that nonstationary behaviour to assist in the diagnosis of motor health. A specific tool will be designed and developed to process the vibrational waveform to permit detection and awareness of factors such as stator phase fault, misalignment, and other common faults. Key vibrational defect signatures can be identified based on their characteristic frequencies. Table 4 presents the signature characteristics of various types of faults.

These characteristic frequencies serve to accurately identify which defects are present in the motor and facilitate what we refer to as fault classification. The RESE method segregates fault signals by synchronising and averaging the signal and then

subtracting non-fault signals to isolate the defect signature.

Table 4. Signatures and characteristics of different types of faults.

Defect Type	Defect Signatures
Bearing defect **[36]**	$f_{int} = 0{,}4\,\frac{n_b}{p}\,(1-s).f_s$
	$f_{ext} = 0{,}6\,\frac{n_b}{p}\,(1-s).f_s$
Stator Inter-Turn Short Circuit fault (ITSC) **[63]**	$f_{cc} = \left(K \pm \frac{n}{p}\,(1-s)\right).f_s$
Eccentricity defect **[64]**	$f_{exc} = \left(1 \pm n.\,\left(\frac{1-2.s}{p}\right)\right).f_s$
Rotor fault (broken bar or inter-turn short circuit) **[29]**	$f_r = (1 \pm 2.n.s).f_s$

2.2. Machine learning approach for fault diagnosis and data collection

In this paper, a machine learning method was developed to diagnose faults in induction motors, namely stator phase faults, misalignment, and healthy power supply operations. First, it was necessary to collect data, enabling an accurate and reliable diagnostic system. To collect the dataset, an experimental environment was built in which the vibration signals from the induction machine operating under different health conditions, representing both healthy and faulty operation, were recorded. The vibration dataset was collected on the laboratory test bench described in Section 4, and the machine was also tested with a known mechanical fault (misalignment). Once the data had been collected, it was pre-processed to eliminate noise and outliers and to obtain clean, high-quality input data for the algorithms. Data processing involved extracting features from the time domain into the frequency domain using the Fast Fourier Transform (FFT). This process enabled the separation of the critical frequency peaks corresponding to the motor faults specified by the theoretical models and experiments performed. These characteristics were used as input data for our classification model.

Several machine learning algorithms are used to find the one best suited to our dataset. The feature vectors were effective in feeding numerous classifiers in the field of machine learning (SVM, Random Forest, Decision Tree, XGBoost) that were trained using an 80/20 split of the data (training/testing). The models were validated using standard metrics (accuracy, precision, recall, F1-score).

2.3. Fast Fourier transform

The Fast Fourier Transform is one of the most applied techniques to Control monitoring (CM) of the IM in the manufacturing industry. This technique will analyse the vibration signal and is the most useful technique for finding faults. The method that uses the FFT analysis is a principal signal processing tool for signature extraction. The FFT algorithm is applied to analyse the vibration signal waveforms. A Hanning window will be used in convolution with these vibration signals [9]. The coefficients of the Hanning function of length N_L are calculated by the following equations:

$$w(n) = w_0.\left(\frac{N_L}{N}\left(n - \frac{N}{2}\right)\right) \tag{1}$$

$$w_0(x) = \begin{cases} \frac{1}{2}\left(1 + cos\,\left(\frac{2\pi x}{N_L}\right)\right) = cos\left(\frac{\pi x}{N_L}\right), |x| \le \frac{N_L}{2} \\ 0, |x| > \frac{N_L}{2} \end{cases} \tag{2}$$

$$w(n) = \frac{1}{2}\left(1 - cos\left(\frac{2\pi n}{N}\right)\right), 0 \le n \le N \tag{3}$$

where N+1 is the number of samples, and the integer N can be an odd or even number.

Once this method is implemented, the frequency components with a high magnitude in the spectrum are extracted to identify the defect. These components are mathematically related to any failures of the investigated IM. For this reason, this method applied to the vibration signal shows a pulsation with the characteristic frequency of the defect.

2.4. The new advanced approach

To overcome the insufficient accuracy and sensitivity of conventional FFT method to classify directly the detect, a new method combining vibration analysis with advanced machine learning models is constructed. The main steps and the flowchart of the new algorithm are illustrated in figure 6.

3. Simulation results and validation

3.1. Simulation platform

To complete the theoretical concept presented in section 2, the present study builds upon the COMSOL Multiphysics finite-element model previously developed and reported in our conference work [62]. In that work, the induction machine model was used to investigate the behaviour of the system under healthy and stator-fault conditions. In the present article, the model is retained as a physics-based reference for interpreting the fault signatures subsequently investigated through laboratory measurements and machine learning based diagnosis.

The induction machine model is defined from the geometrical and electrical characteristics of its principal components, while COMSOL Multiphysics employs the finite element method to solve the governing equations over the computational mesh [48,54,55] We first used the model COMSOL to simulate the performance of the Induction Machines in the "Normal" (healthy) state to establish a reference operating condition. Its behaviour under a stator phase fault is then examined to characterise the associated variations in quantities such as current, electromagnetic torque, rotational speed, and efficiency. These simulation results provide the physical context for the experimental analysis presented in subsequent section. The specifications of the machine's various variables for the final design are detailed in Table 5.

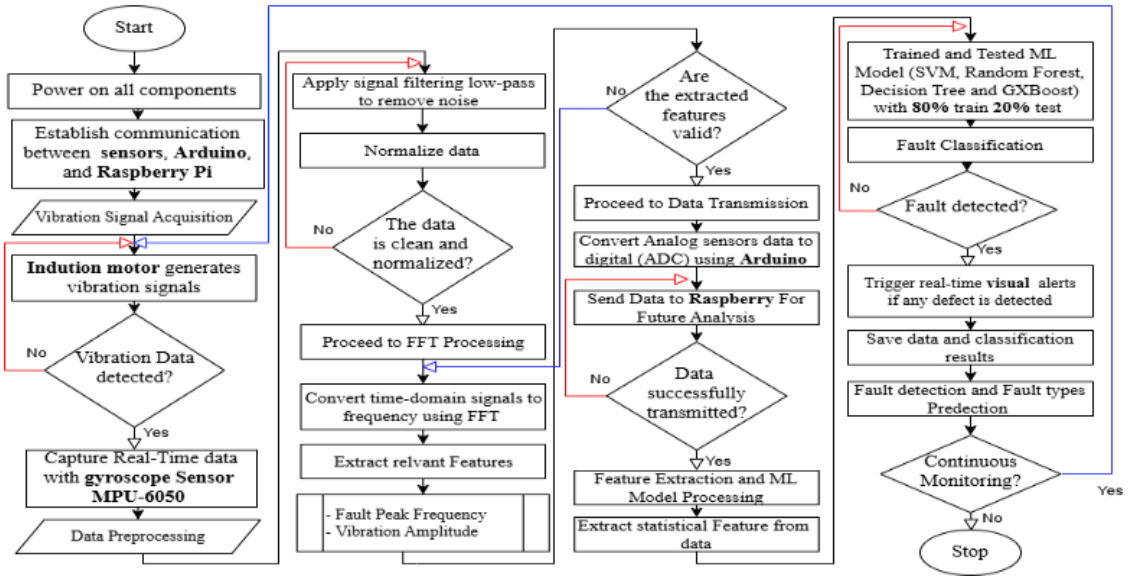


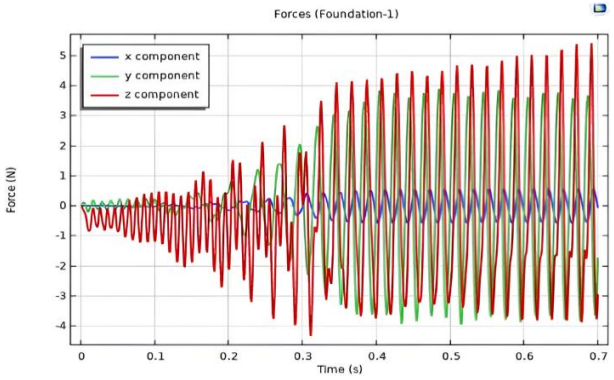
Figure 6. Flowchart of the proposed algorithm.

Table 5. The specifications of the implemented machines.

Machine Parameters	Value
Rated output power	$P = 1.5$ kW
Number of pole pairs	$N_p = 2$
Rated Stator Frequency	$F_s = 50$ Hz
Rated Stator Phase Voltage	$U_s = 400$ V
Rated Stator Current	$I_s = 3.4$ A

3.1.1. Temporal analysis

After running the simulation, the vibration graphs for the three axes, in the healthy and faulty cases, are shown in Figure 7. This figure shows the evolution of vibration forces along the x, y, and z axes of the induction machine in the healthy case and in the presence of the fault.



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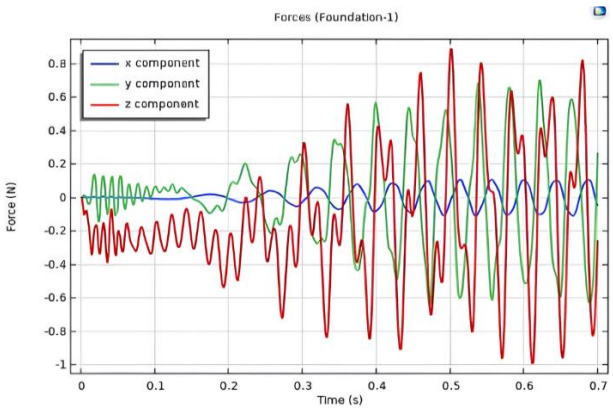


(b)

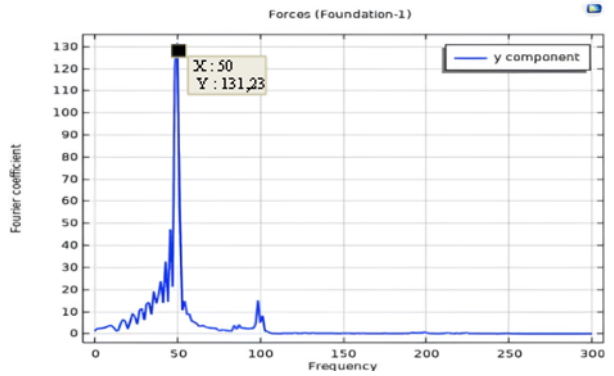
Figure 7. The evolution of vibration forces in the x, y, and z axes as a function of time in the absence of a fault (a) and in the presence of a fault (b).

Figure (7-a) shows a healthy state of the asynchronous machine with regular and stable oscillations, while Figure (7-b) shows irregular and less stable oscillations, characterizing the presence of a fault in the induction machine. In Figure (7-a), the x, y, and z components show regular, periodic oscillations with constant, well-defined, high amplitudes. Thus, the stable signal indicates a normal operating state. Compared with figure (7-a), the x, y, and z components in figure (7-b) show oscillations that

are chaotic and less stable, with small, irregular maximum amplitudes. This is due to the machine not operating at full potential. Consequently, this signal instability suggests the presence of a fault.

3.1.2. Frequency analysis

Time analysis of induction machine vibration signals provides a means of observing instantaneous signal variations. However, to accurately identify faults such as stator faults, it is absolutely imperative to move on to spectrum analysis. Fast Fourier Transform (FFT) splits the time signal into its frequency components, revealing the typical frequencies of the various anomalies. As indicated in section 2, this transition can be used to provide an accurate diagnosis and effective detection of potential failures. Since all axes show the presence of a potential defect, the Y vibration component is selected for analysis in the next steps. The spectrum of Fourier coefficients as a function of frequency for the y-component, in the healthy case (a) and in the presence of the out-of-phase fault (b), is depicted in Figure 8.



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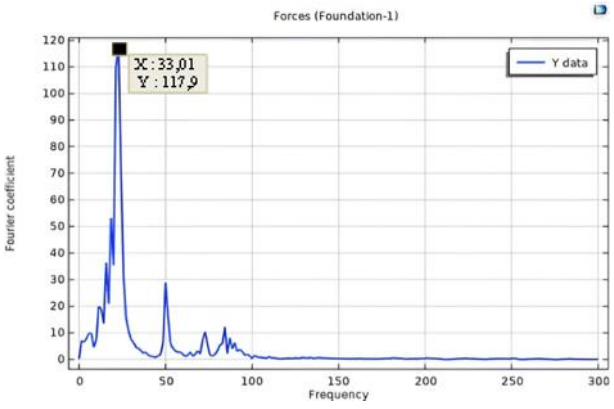
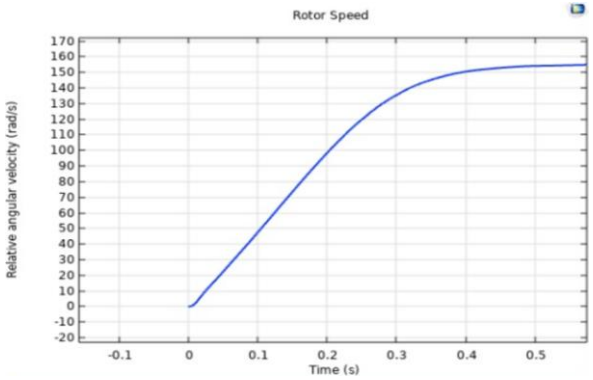


(b)

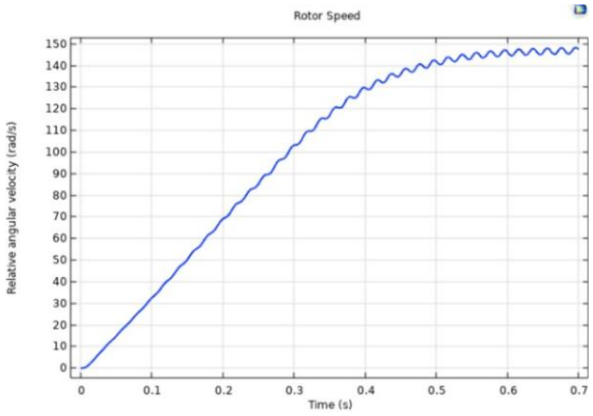
Figure 8. Spectrum of Fourier coefficients as a function of frequency for the y axis in the healthy case (a) and in the presence of the fault (b).

The results of this simulation confirm that the spectra in the healthy and defective cases are not identical. Figure (8-a) shows the spectrum of Fourier coefficients, i.e., vibration amplitudes as a function of frequency for force components in the Y direction. The Fourier coefficients show several small peaks at different frequencies, with a notable peak around 50 Hz. Effectively, no signature is observable, excluding the 50 Hz frequency component, which is most prominent in the spectrum of the healthy case.

Figure (8-b), showing the frequency peaks on the y-axis, reveals a very high peak at approximately 33 Hz. This indicates the frequency at which the vibrations are strongest. These peaks, whose amplitude decreases rapidly at higher frequencies, provide information about the behaviour of the induction machine in the presence of a stator fault. The peak value of the fault in the simulation results matches exactly with the theoretical value found using the formula from the table.



(a)



(b)

Figure 9. Velocity evolution as a function of time in the healthy case (a) and in the presence of the fault (b).

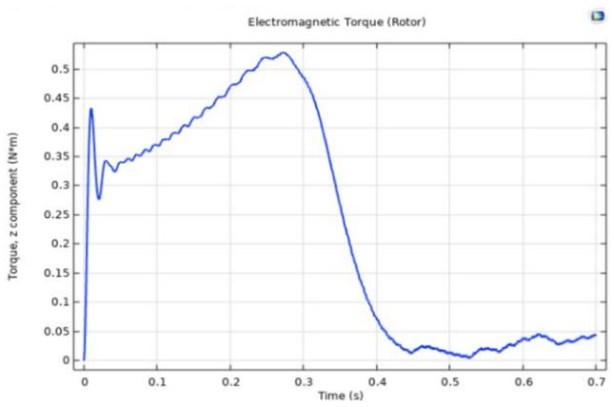
3.1.3. Analysis of the speed

Analysis of the speed curve is fundamental for assessing the performance of an induction machine, both in normal operation

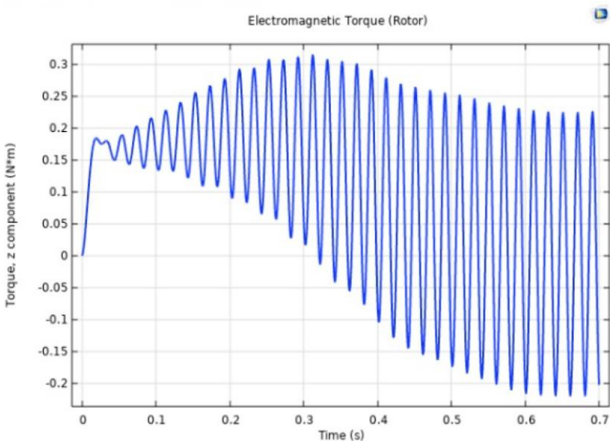
and in the presence of faults. The results are illustrated in Figure 9.

Figure (9-a) shows a rapid increase in rotor angular velocity, starting at 0 rad/s and reaching around 1432 at 0.3 seconds. This phase represents the rotor's initial acceleration when the machine is energized. Then, from 0.3s to 0.7s is the stabilization phase, when the curve begins to stabilize, reaching a no-load angular speed of around 1432 RPM. This curve contains no oscillations around this value, indicating that the rotor has reached an almost constant rotational speed and that the machine is not effective.

The angular velocity curve of the induction machine in the fault case, figure (9-b), illustrates oscillations over the simulation time. These oscillations are mainly due to the imbalance created by the fault. This imbalance generates pulsating electromagnetic forces and mechanical torque variations, leading to angular velocity oscillations and mechanical vibrations.



(a)



(b)

Figure 10. Torque evolution as a function of time in the healthy case (a) and in the presence of the fault (b).

3.1.4. Analysis of the torque

Analysis of the torque curve is fundamental for assessing the performance of an induction machine, both in normal operation and in the presence of faults. The results are illustrated in Figure 10.

Figure (10-b) illustrates the considerable and irregular fluctuations in electromagnetic torque that have been identified as characteristic of a stator fault. These oscillations are an indication of machine instability resulting from stator phase imbalance. The amplitudes of these oscillations tend to become larger over time, which may lead to excessive vibration and probable damage to the machine's mechanical components.

In Figure (10-a), the electromagnetic torque increases exponentially, then decreases and stabilizes. In contrast to the stator unbalance fault conditions, the absence of significant oscillations shows that the machine is operating correctly and offering constant performance. Consequently, the machine operates correctly with perfect phase balance.

3.1.5. Analysis of the magnetic field behaviour

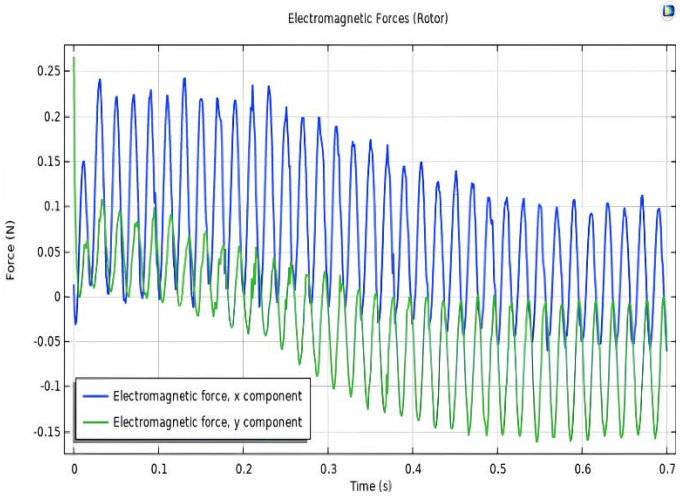
Understanding the efficiency of an induction machine relies on analysing the behaviour of the magnetic field, both in normal operation and in the event of a fault. In-depth analysis of this machine behaviour provides a better understanding of the varying effects of the magnetic field on overall performance. Magnetic field curves on the X and Y axes, in the healthy and faulty cases, are shown in Figure 11, outlining the differences between normal and faulty operation of the machine under test.

In figure (11-b), the electromagnetic forces produce regular oscillations, resulting from a perfect balance of well-distributed electromagnetic forces, giving rise to regimes of relatively constant amplitudes. In contrast, the signals in Figure (11-a) are typical of a major imbalance in electromagnetic forces due to a stator fault. Indeed, its amplitudes vary more than usual, which is characteristic of an imbalance resulting from a fault on the stator phase, and itself at the origin of irregular oscillations.

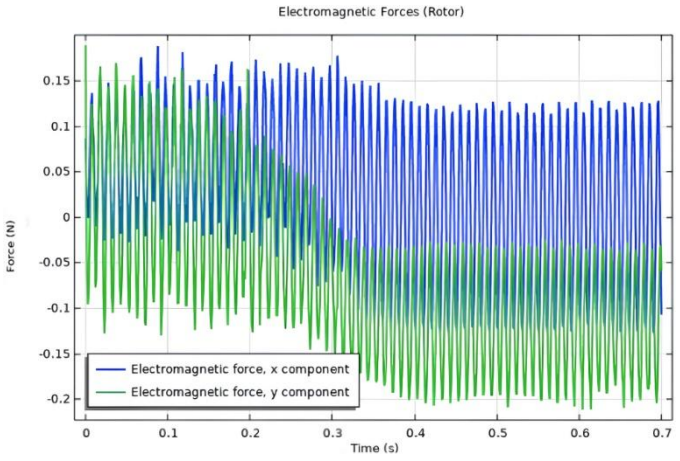
3.1.6. Von Mises' stress distribution in the induction machine

The distributions of von Mises stresses, depicted in Figure 12, offer detailed information about the stress states to which the components are subjected. Such an analysis assists design optimization, failure prevention, and the overall reliability and

durability of the machines, thus rendering the machines efficient and operationally safe.



(a)



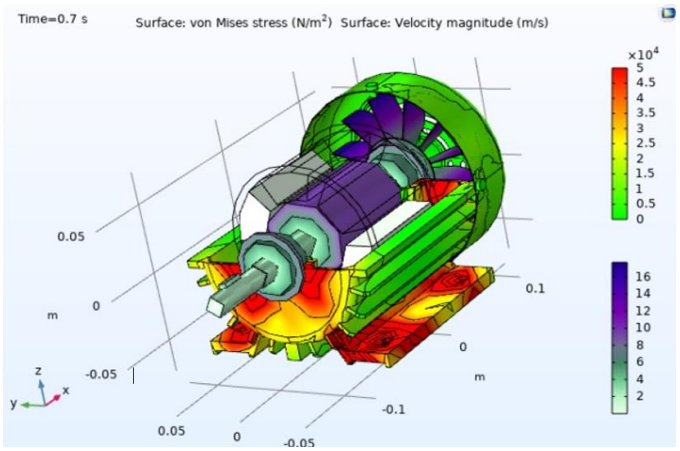
(b)

Figure 11. The electromagnetic forces in the healthy state (a) of the machine and in the fault condition (b).

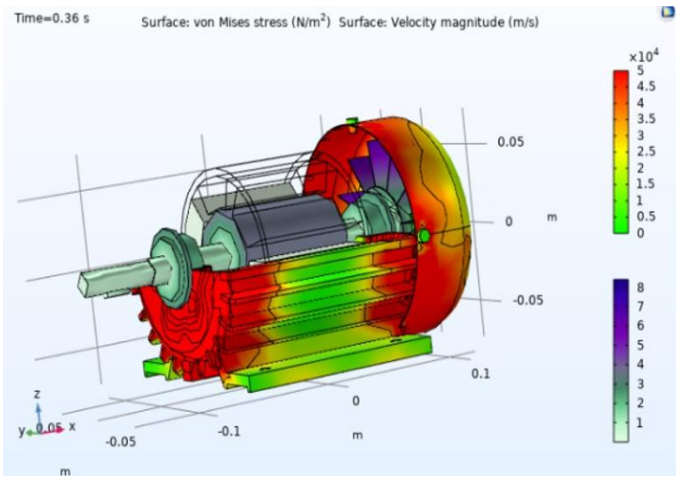
The distribution of von Mises stresses in the induction motor when healthy is shown in Figure (12-a). Those areas with high stress, mainly located in the stator, are lower than those identified in fault conditions.

Figure (12-b), however, indicates the stress distribution in the motor under fault conditions, due to the interaction between the magnetic fields of the rotor and stator. High-stress regions in red (stator) could indicate fault points, whilst low-stress areas represented in blue (rotor) denote regions that are slightly less critical under fault conditions.

In both figures, the most prominent high stress concentrations appear around the stator yokes, rotor teeth, and air gap regions. This is consistent with expected stress distributions for an induction machine. This is due to highly intense electromagnetic interactions in those areas, where currents and magnetic fields generate significant forces. The stator yokes are under electromagnetic forces due to windings, and the rotor teeth undergo cyclic forces due to the rotating magnetic field. The air gap, being the area wherein energy is exchanged between the stator and rotor, experiences high localized mechanical forces. The electromagnetic drives intense magnetic fields, which, in turn, create large stresses on rotor-stator faces close to the air gap. Further dynamic vibrations and material properties of the components amplify these stresses, and the outrageously vulnerable nature of these areas in the induction machine design life.



(a)



(b)

Figure 12. The distribution of von Mises stresses in the healthy state (a) and in the presence of the fault (b).

4. Experimental results and validation

4.1. Experimental test

The test rig designed for this project comprises an asynchronous machine coupled to a DC generator, which allows load values to be emulated. A gyroscope is installed on the machine to

measure vibrations along the three axes X, Y, and Z, providing precise data on machine dynamics. An Arduino Uno board plays the role of acquisition, and a Raspberry Pi 4 board plays the role of a small control unit for managing and processing the data collected, as well as for monitoring the status of the various components of the induction machine contained in the test bench afterwards. Two pull-up resistors are used to stabilize the sensor signals, ensuring accurate measurements. Finally, a screen is provided to show the measurement and analysis results in real-time, providing an overview of the tests so that they can be monitored and adjusted as necessary. The complete test bench allows assessment of asynchronous machine performance under two forms of emulated fault, specifically stator phase failure and mechanical misalignment at the coupling with the DC generator.

Figure 13 shows the overall process of monitoring vibration for an induction machine to determine its operating mode as a motor or generator. The vibration signal from the motor is first captured and converted into a digital signal (digitized data) using an Arduino UNO board, which acts as an Analog-to-Digital Converter. This digitized data is then transmitted to a processing unit, in this case a Raspberry Pi 4, which analyses the vibratory signal. This processing generates a graph of the motor's vibration signal, representing variations in vibration over time. Afterwards, a frequency analysis using FFT is performed to identify the dominant characteristic frequencies of the signal, thus facilitating the detection of potential anomalies.

Finally, a machine learning-based model is built for the early prediction of the nature of the fault, to ensure accurate predictive maintenance of the motor. Figure 14 shows the test bench used to validate the results experimentally.

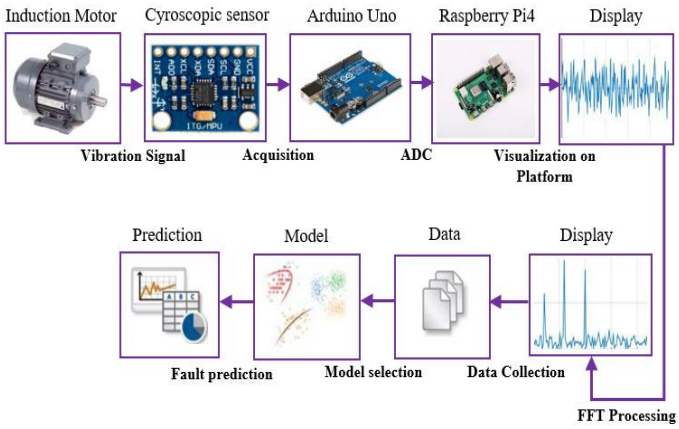


Figure 13. Schematic description of the experiment.

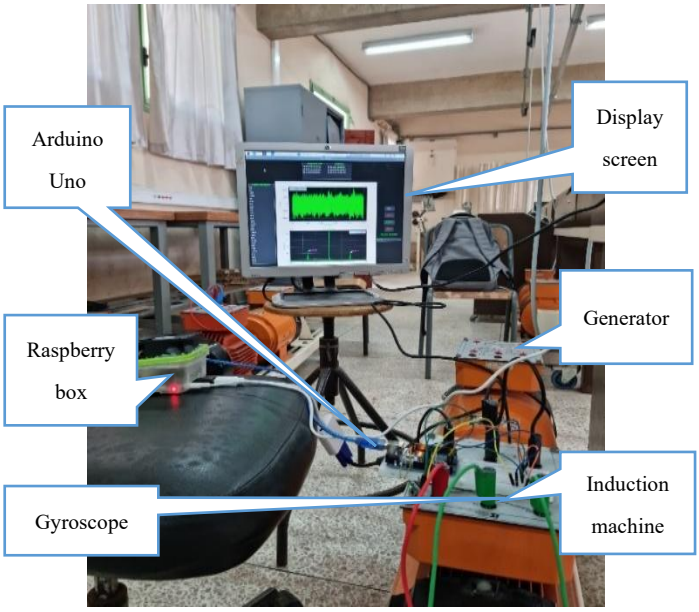


Figure 14. The experiment test bench.

To enhance and facilitate user interaction, an innovative Graphical User Interface (GUI) has been created on the Raspberry Pi4. Figures 15 and 16 show the welcome window and main window of the elaborate interface, respectively. This sophisticated interface displays the vibration signal in real time, along with its FFT. In addition, a table displaying the amplitudes and frequencies of the four largest frequency peaks has been added to facilitate data collection, which will be used to model the intelligent monitoring and diagnostic system. It also includes buttons such as “Start”, “Clear”, “Exit”, and “Stop” for flexible control of the monitoring process. Before this, a welcome window has been created in which the interface name is displayed, as well as a “Start analysis of your machine” button and an “Exit” button. The main functions of this interface are listed as follows:

- Start button: Starts real-time collection and display of vibration data.
- Clear button: Resets graphs for a new monitoring session.
- Stop button: Stops data collection without quitting the application.
- Exit button: Closes the graphical interface and stops data collection.
- Number of points: Allows you to define the number of data points to be displayed on the time graph, offering flexibility in visualization.
- Field for entering file name: The user can enter a file name to save the diagnostic session data. This feature

maintains a machine monitoring history, facilitating data management and engine performance monitoring.

- Gyroscope value display bar: Displays in real time the values collected by the gyroscope, enabling immediate visualization of vibration data.

In the data collection phase, a short message is displayed as a priority to inform the user that the acquisition system is in the process of collecting the indicated number of data points. In this way, the user is informed that the acquisition system is actively operating and that the user should wait until the end of this phase before continuing with any other operation.

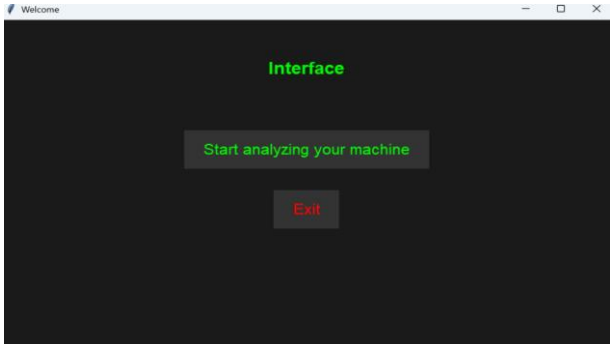


Figure 15. Graphical user interface home window.



Figure 16. Graphical user interface main window.

4.2. Results and discussion

4.2.1. Temporal and frequency analysis

The experimental set-up was designed to ensure continuous monitoring of the machine concerned, with features such as display of gyroscope values, the ability to start and stop data collection, and saving of results for historical follow-up.

The various phases of data collection and processing, as well as the resulting graphics, are presented in Figure 17 for the healthy case, in Figure 19 for the stator fault case, and in Figure 21 for the misalignment fault case, respectively, to illustrate the system's performance.

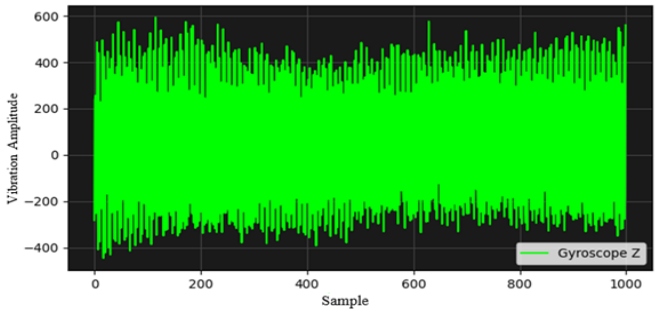


Figure 17. Vibratory signal in the healthy case.

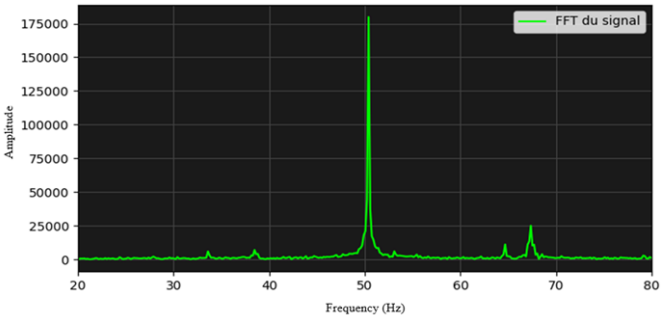


Figure 18. The spectrum of the vibration signal in the healthy case.

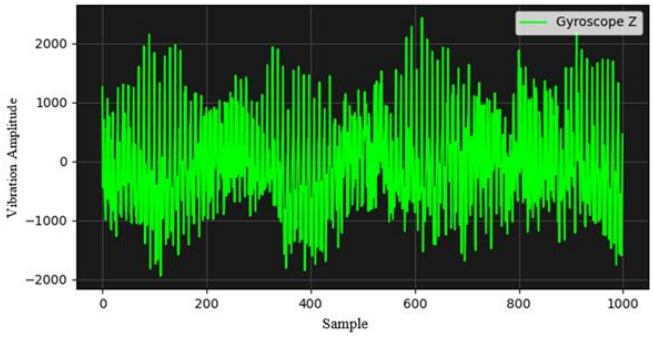


Figure 19. Vibration signal in case of stator fault.

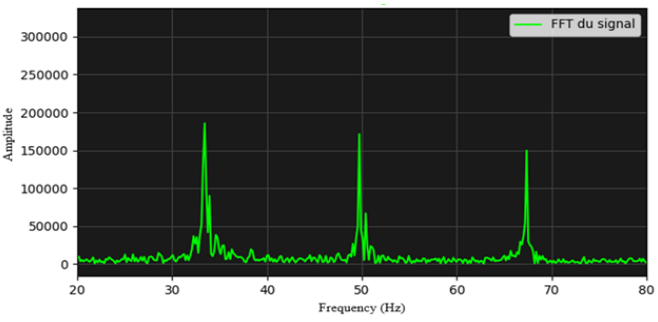


Figure 20. The spectrum of the vibration signal in the case of a stator fault.

Figure 17 shows that the vibration amplitude is low, which indicates that the machine is operating normally and without fault. Unfortunately, the fault cannot be deduced directly from the vibration signal, so frequency analysis is carried out on the platform to find the characteristic peaks of the fault. In Figure

18, the spectrum shows several small peaks at different frequencies, with a significant peak appearing around 50 Hz. No signature is detectable except for the 50 Hz frequency component, which is the most prominent in the spectrum of the healthy case.

Unlike Figure 17, in Figures 19 and 21, the vibration amplitude is high, indicating that the machine is operating abnormally and is probably affected by an incipient fault. To confirm the presence of the fault and detect its exact type and nature, frequency analysis is presented, for both cases of defect, in Figures 20 and 22, and the frequency spectrum shows a significant peak located at the characteristic frequency of a stator phase fault. When a stator phase fault occurs, it is difficult to measure the rotational speed, which is not fixed, as it is always oscillating due to the vibrations generated by the fault. Based on experience and the frequency spectrum in the event of a fault, the slip in the event of a fault is calculated to deduce the theoretical frequency of the fault. Given that the sector frequency is 50 Hz, the synchronizing speed of the machine is 1500 rpm, and the number of pole pairs is p=2, the calculated slip is s = 0.172.

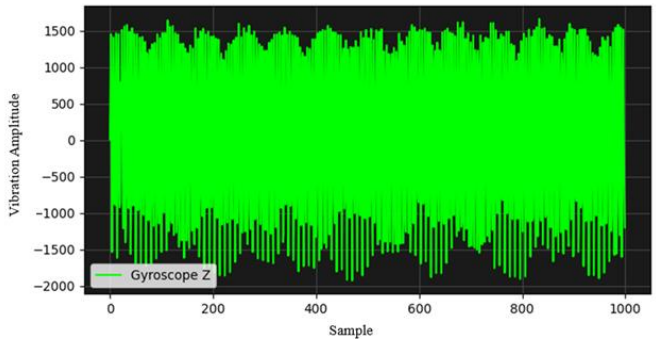


Figure 21. Vibration signal in the case of misalignment.

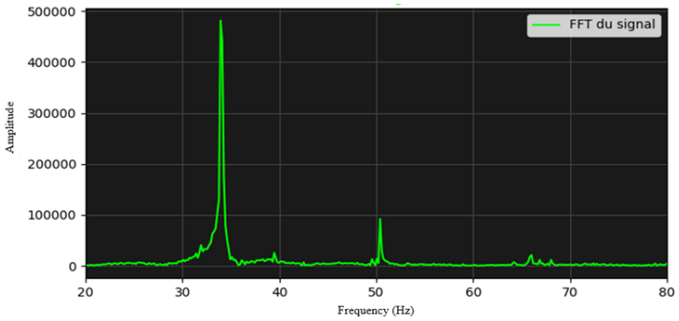


Figure 22. The spectrum of the vibration signal in the case of misalignment.

The theoretical values of the signatures, of the two bandwidths, of the two defects calculated from the equations given in Table 4, coincide to the nearest point with the values of the signatures found experimentally in Figures 20 and 22. The values are summarized in Table 6.

Table 6. The theoretical and experimental values of the defect signature.

		stator fault (Hz)	misalignment fault (Hz)
No-load IM (0%)	Theoretical fd frequency (Hz)	fd1=33,60 Hz fd2 = 66.4 Hz.	fd1=33,1 Hz fd2 = 66.9 Hz.
	experimental fd frequency (Hz)	fd1=33,60 Hz fd2 = 67.54 Hz	fd1=33,26 Hz fd2 = 67.87 Hz

The spectral analysis of vibrations does not allow accurate identification of defects, due to the high similarity between the frequency signatures of the various anomalies. This limitation makes it difficult to detect faults early using conventional methods alone. Consequently, the integration of artificial intelligence algorithms is becoming essential to improve fault prediction and diagnosis.

4.2.2. Artificial intelligence-based prediction

This subsection presents the findings of the detailed analysis and conclusions resulting from the application of machine learning techniques to predict the behaviour and faults of induction motors. This study aims to demonstrate the discrimination capability of these models under the laboratory conditions investigated. A detailed analysis of the results is carried out, examining accuracy, precision, recall, and F1 score to give a complete picture of predictive maintenance models.

The dataset used in the present study consists of 60,000 samples collected directly from an induction machine on the laboratory test bench described in Section4, in three different health states (clases): healthy, misalignment (mechanical fault), and stator phase fault (electrical fault). Each class comprises the same number of samples. In total, we allocated 20,000 samples to each class, for a total of 60,000 samples. A split of 80% training data and 20% test data was used to ensure robust model training and evaluation. This means that a total of 48,000 samples were applied to model training (16,000 samples allocated to each of the healthy, misalignment, and stator phase fault classes). The test set consists of 12,000 samples, i.e., 4,000 samples assigned to each class.

The performance of the used algorithms is easily evaluated using standard metrics such as accuracy, recall, and F1-score to see which of these techniques correctly predicts the type of

defect.

To evaluate and compare the performance of the different machine learning models applied to the prediction of defect categories, graphical representations are depicted in Figures 23 and 24.

These figures simultaneously display several performance metrics, such as precision, recall, and F1-score, for each of the models studied (SVM, Random Forest, Decision Tree, and XGBoost). These graphical comparisons provide a clear and intuitive overview of the strengths and weaknesses of each model, facilitating interpretation and the choice of the method best suited to our problem.

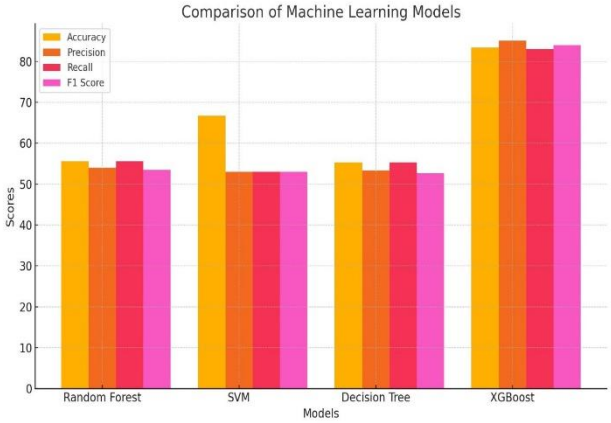


Figure 23. Comparison between the different models used.

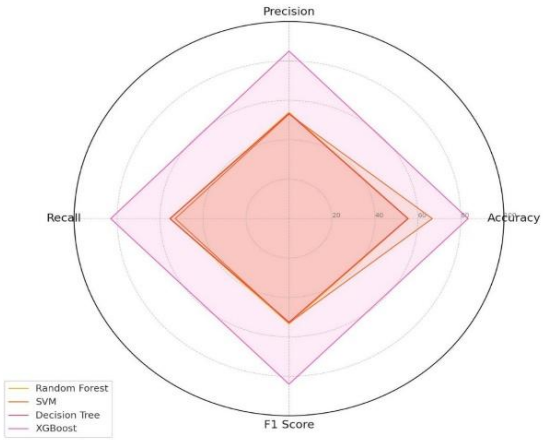


Figure 24. Performance measurement comparison.

The XGBoost model stands out with the best performance across all metrics, achieving scores above 80%, confirming its discrimination capability for the induction machine health states investigated. In comparison, the SVM model shows good precision (68%) but recall and F1 scores similar to other classical models (53%), indicating an imbalance between correct detection and false predictions.

Random Forest and Decision Tree models show similar performance, with moderate scores overall (55% for all metrics). This suggests that these methods are not powerful enough to capture the complexity of vibrational signals.

These results confirm that conventional learning approaches, such as decision trees, are limited for reliable fault prediction. By contrast, XGBoost appears to be the most suitable tool for accurate diagnosis on the laboratory dataset considered, thanks to its ability to generalise better on complex data.

To provide a more in-depth evaluation, model performance was also measured for each defect class individually.

Figure 25 illustrates, in the form of spider diagrams, the comparison of the performance of Random Forest, SVM, Decision Tree, and XGBoost models for predicting faults in an induction machine. Three health classes are considered: CS (Healthy Case), DD (Misalignment Fault case), and MP (Stator Phase Fault case). The metrics used, once again, to evaluate the models are Precision, Recall, and F1 Score.

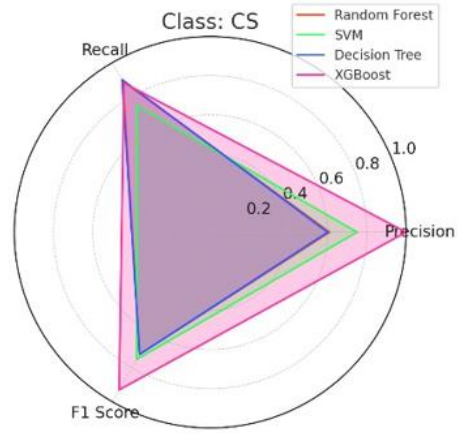
For the Healthy case class, the XGBoost model shows the best overall performance, with values close to 1 for all metrics, outperforming the other algorithms. SVM also performs well, albeit slightly worse than XGBoost, while Decision Tree and Random Forest perform less well.

As far as the Misalignment Fault class is concerned, all performances are generally weaker than those of the Healthy case class. Nevertheless, XGBoost maintains a significant advantage, achieving better accuracy and a better F1 score than the other models. The Decision Tree and Random Forest are relatively close in terms of performance, but remain insufficient for reliable detection.

For the Stator Fault class, the best SVM model achieved both the best precision and recall, demonstrating that it was able to identify this defect type correctly. XGBoost performed well, also, whereas Random Forest and particularly Decision Tree performed modestly in general and very poorly in terms of F1 score.

The results indicate that traditional methods, such as vibration analyses alone, do not provide sufficient separation between faults. However, the results imply that there is significant power in incorporating machine learning models where it relates to accurately predicting and detecting faults in

induction machines, especially SVM and XGBoost.



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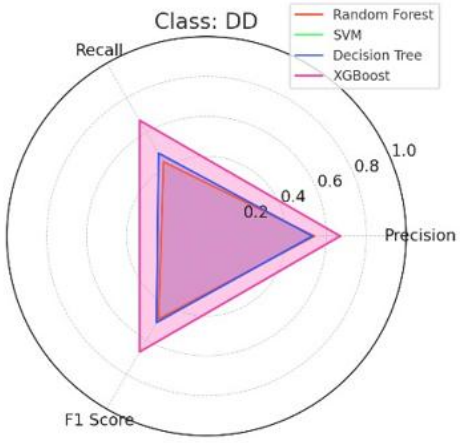

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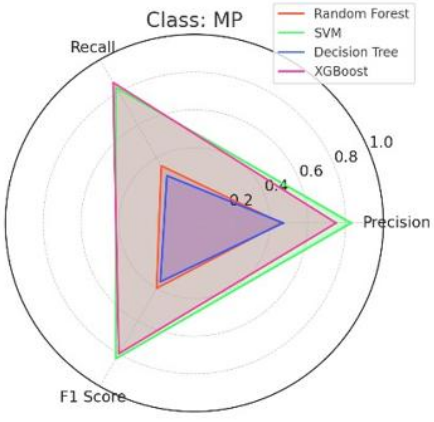

(c)

Figure 25. Comparison of precision, recall, and f1 score for each class and model (spider chart), a) healthy case (CS), b) misalignment fault case (DD), c) stator fault case (MP).

5. Conclusion

In this paper, a new approach to fault diagnosis on induction machines based on machine learning and vibration analysis is developed. The results demonstrate that vibration analysis does not provide reliable fault diagnosis, justifying the use of advanced artificial intelligence techniques to improve prediction reliability.

Four models were described: Random Forest, SVM, Decision Tree, and XGBoost, and several performance measures (precision, recall, F1 score, and accuracy) were used to define and evaluate the models. The evaluation concluded that XGBoost was significantly better than the other algorithms, with performance reliability in excess of 80%. Based on these results, this model can successfully classify highly complex features that represent the information behind variations in vibration signals.

The first step towards our goal of eliminating the limitations of all conventional methods of vibration analysis is the application of machine learning.

In conclusion, on the laboratory dataset considered in this study, this method shows potential for overcoming the constraints associated with rapid and reliable fault diagnosis, and thus for supporting the reliability, availability, and durability of induction machines.

Although these results are promising, we recognize that this study examined only two representative faults, namely misalignment and stator phase fault, in order to demonstrate the feasibility and effectiveness of the proposed approach. This is a limitation that we will strive to address in our future research. The proposed method may be extendable to other common faults, such as bearing failures or broken rotor bars, which will be evaluated in our future investigations.

In the future, research may be carried out to incorporate more advanced models (“Neural Network,” hybrid models), as well as to extend the approach to include other electrical and mechanical failures, including combined defects. To assess the approach's robustness, validation using real industrial data and multi-sensors will be conducted in order to anticipate real-time implementation for predictive maintenance. In addition, research will focus on developing multi-core datasets across multiple machines and in different operational contexts to improve robustness and generalization, as well as exploring more advanced options, including domain adaptation or federated learning, to reduce data dependency.

Acknowledgment

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