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Revolutionizing motor maintenance: a comprehensive survey of state-of-the-art fault detection in three-phase induction motors

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ABSTRACT

This comprehensive review delves into electrical machine fault diagnosis techniques, with a particular emphasis on three-phase induction motors. It covers a variety of faults, including eccentricity, broken rotor bars, and bearing faults. It also covers techniques like motor current signature analysis (MCSA), partial discharge testing, and artificial intelligence (AI)-based approaches. This review focuses on fault diagnosis techniques for electrical machines, specifically eccentricity faults, squirrel cage rotor faults, and bearing faults. It discusses their efficacy, applications, and limitations, as well as the role of AI and neural network techniques in modern fault detection applications. The review covers not only eccentricity faults, but also stator or armature faults caused by insulation failure, as well as bearing faults classified as ball, train, outer, and inner races. It focuses on early detection to ensure optimal machine performance and reliability, while also providing insights into fault detection mechanisms. Modern ways of finding problems with machines, like non-negative matrix factorization, rectified stator current analysis, incremental broad learning, and AI-based methods, make machines work better and stop money from being lost. The review is a valuable resource for practitioners and researchers in the field, allowing them to make better decisions about maintenance strategies and increase machine efficiency.

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1. INTRODUCTION

The increasing complexity of electrical machines and their growing integration into critical infrastructure have heightened the demand for robust fault diagnosis techniques to ensure operational reliability, safety, and efficiency. Overcurrent, overvoltage, and earth-fault protection have been used as standard safety measures for decades. However, faults that are not found can disrupt operations, cause schedule delays, and result in large financial losses, so we need more proactive and accurate fault detection methods. The significance of three-phase induction motors in various industries lies in their high motive power generation, durability, and low maintenance costs. Approximately 90% of industrial equipment worldwide uses these motors as the prime mover, highlighting their critical role in industrial operations [1]–[4]. They are known for their robust nature and reliable performance, making them indispensable for industrial processes. Additionally, a wide range of industrial applications favor these motors for their ability to provide flexible production control and soft motor start-up, making them a versatile and efficient solution.

Electrical machine faults can be roughly grouped into five areas: problems with the stator, bad connections between the stator windings [5]–[9], changes in the air gap that are either dynamic or static, shorted rotor field windings, and bearing and gearbox failures. These faults can manifest in various forms, including overheating, vibration, noise, and changes in motor current signatures. Early detection and accurate identification of these faults are crucial for implementing timely maintenance strategies, preventing catastrophic failures, and ensuring optimal machine performance. The challenge of fault detection in electrical machines has led to the development of numerous diagnostic techniques. We can broadly classify these techniques into two categories: non-invasive and semi-invasive methods. Non-invasive techniques do not require direct contact with the machine, relying instead on external measurements such as temperature, vibration, acoustic noise, and radio frequency (RF) emissions. Examples of non-invasive techniques include temperature measurement, infrared thermography, vibration analysis, acoustic noise analysis, and RF emission monitoring [6]. Semi-invasive techniques, on the other hand, require some level of physical access to the machine, such as partial disassembly or the insertion of probes. Examples of semi-invasive techniques include motor current signature analysis (MCSA), online partial discharge (PD) testing, and axial flux component analysis [9].

In recent years, advanced diagnostic approaches based on artificial intelligence (AI) and neural network techniques have emerged as promising tools for fault detection in electrical machines [10]–[15] These methods use machine learning algorithms to look at complicated patterns in motor data. This allows them to find small problems that may indicate a problem more accurately and sensitively than other methods. AI-based fault diagnosis techniques are particularly well-suited for large datasets of motor data, allowing them to continuously monitor machine health and detect trends that may lead to future faults. This comprehensive review article provides a detailed overview of the diverse range of fault diagnosis techniques for electrical machines, examining their effectiveness in detecting and classifying various types of faults. We will delve into the principles, applications, and limitations of each technique, highlighting the advantages and disadvantages of each approach. We will also talk in depth about the growing role of AI and neural network techniques in modern fault diagnosis applications. We will look at how they can improve the accuracy of fault detection, give us more information about what might go wrong, and help us come up with proactive maintenance plans. Through this comprehensive review, we aim to provide a valuable resource for engineers, researchers, and practitioners involved in the design, operation, and maintenance of electrical machines. By understanding the strengths and limitations of each fault diagnosis technique and the potential of AI-based approaches, we can make informed decisions about selecting the most appropriate methods for specific applications and achieving optimal machine reliability and performance.

The review article revolves around the comprehensive exploration of various fault types and the corresponding detection methods employed in three-phase induction motors. The article delves into the adverse impact of eccentricity faults on motor efficiency, with a focus on the use of MCSA for static and dynamic eccentricity detection. The article also carefully talks about faults in the stator or armature that happen because of insulation failure. It does this in a number of ways, such as using PD tests, axial flux component analysis, and statistical process control. Furthermore, the article delves into the intricate domain of bearing faults, classifying them into ball defects, train defects, outer bearing race defects, and inner bearing race defects, and provides a comprehensive overview of advanced fault detection methods for three-phase induction motors that incorporate artificial intelligence-based approaches. The review article conducted a comprehensive exploration into various fault types and the corresponding detection methods employed in induction motors. Their research looked at how eccentricity faults hurt motor efficiency, how to find broken rotor bars using MCSA and sideband component analysis, and how to fix stator or armature faults caused by insulation failure in a number of different ways. Additionally, the contributors delved into the intricate domain of bearing faults, categorizing them into distinct categories such as ball defects, train defects, outer bearing race defects, and inner bearing race defects. They showcased a comprehensive overview of advanced fault detection methods for three-phase induction motors, incorporating artificial intelligence-based approaches. This collaborative effort consolidated a wealth of insights into fault types and their detection mechanisms, providing a valuable resource for practitioners, researchers, and enthusiasts in the realm of induction motors. The review article conducted an in-depth exploration into various fault types and the corresponding detection methods employed in induction motors. Their findings encompassed a comprehensive understanding of fault types such as eccentricity faults, squirrel cage rotor faults (broken bars and end rings), and bearing faults. They delved into the causes, detection techniques, and effects of each fault type, providing valuable insights for practitioners, researchers, and enthusiasts in the realm of induction motors. Furthermore, the authors presented cutting-edge methods for finding faults in three-phase induction motors that use artificial intelligence and up-to-date diagnostic techniques.

2. THE COMPREHENSIVE THEORETICAL BASIS OF IM FAULTS

Figure 1 serves as a visual compass, offering a comprehensive overview of the myriad fault types and the diverse array of detection methods applied in the intricate realm of three-phase induction motors. These faults have ramifications that extend beyond mere operational glitches, potentially culminating in both reduced efficiency and the specter of catastrophic failure. This review aims to highlight a specific facet of this complex landscape, focusing on internal mechanical faults and the cutting-edge realm of AI-based methods meticulously designed for fault detection.

As we navigate through the complexities of AI-infused fault detection, our journey will delve into not only the merits and advantages of these methodologies, but also candidly address their limitations and the challenges that lie ahead. The following sections of this review article will serve as an exploratory voyage, shedding light on the nuanced landscape of internal mechanical fault detection with a keen eye on AI-based techniques. Furthermore, we will cast our gaze toward the future, outlining potential directions for advancements and innovations in the realm of fault detection methods.

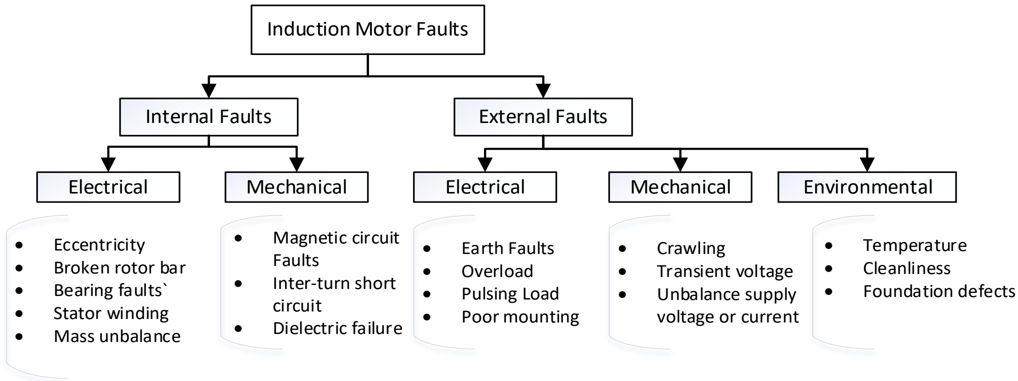

Figure 1. Classification of the most frequent induction motor faults [16]

The expansive landscape of three-phase induction motors unfolds within the purview of this reviewed article, where a comprehensive exploration ensues into a spectrum of faults that can disrupt their seamless operation. These include the elusive eccentricity, intricacies within the squirrel cage rotor, potential stator or armature aberrations, and the critical domain of bearing faults. Table 1, a trove of insights, serves as a structured repository that meticulously dissects the causes, detection techniques, and ripple effects each fault can induce. The intricate dance of eccentricity, the subtleties within the squirrel cage rotor, and the vulnerabilities embedded in the stator or armature find their place under the scrutiny of this article's lens. Delving into the root causes, the article unravels the mechanisms and intricacies involved in the detection of these faults, ensuring a comprehensive understanding of their manifestations. Dedicated attention is paid to bearing faults, which are essential to the operation of induction motors. Table 1 shows the complex landscape of their causes, how to find them, and the effects they have on motor performance. As we traverse the contents of Table 1, a mosaic of insights emerges, offering not only a panoramic view of fault intricacies but also a practical guide for engineers, researchers, and enthusiasts navigating the labyrinth of three-phase induction motor faults. This review article, through its meticulous exploration and presentation, endeavors to contribute to the collective knowledge base, fostering a deeper comprehension of the challenges and solutions within this dynamic realm.

2.1. Eccentricity faults

Diving into the wealth of insights provided by studies conducted by the IEEE-industry applications (IAS), the intricate landscape of failure mechanisms in induction machines comes to light. These studies reveal a breakdown of common failure types, with stator faults accounting for 38%, rotor defects at 10%, bearing defects taking a significant share of 40%, and the remaining 12% attributed to various other defects [9]. This comprehensive breakdown serves as a valuable benchmark, providing a nuanced understanding of the vulnerability points within these motors.

Eccentricity is a common mechanical problem that can happen in induction motors [11], [17]–[19]. It can show up in static, dynamic, or mixed forms, as shown in Figure 2. Static eccentricity, a notable subtype, finds its origins in the stator core's ovality or improper rotor and stator alignment during the commissioning phase. On the other hand, dynamic eccentricity, another part of this fault, occurs when bearings wear out, mechanical resonance occurs, or a bent rotor shaft causes rotational misalignment. The interplay of these factors culminates in a nonuniform air gap, triggering instability in air-gap voltage and line current.

The consequences of eccentricity extend beyond the mechanical intricacies, directly impacting the motor's efficiency. As eccentricity worsens, the average motor current and losses increase. This shows that there is a direct link between how bad the fault is and how badly it affects the motor's performance. This phenomenon underscores the importance of vigilance in monitoring and addressing eccentricity in induction motors, as it plays a pivotal role in maintaining operational stability and efficiency. The insights gleaned from these studies not only shed light on the prevalence of eccentricity but also emphasize its critical role in the broader landscape of induction motor performance [20].

Eccentricity turns out to be a key factor in how failures show up in three-phase induction motors, having a big effect on how well they work. The consequences of eccentricity extend beyond mere performance degradation, as it induces vibration and uneven magnetic forces (UMF), thereby shortening the machine's lifespan. The mechanical stress that eccentricity puts on different machine parts, especially making bearing wear worse, makes its bad effects even worse [21].

In the complexities of real-world scenarios [22], a notable observation emerges: both static and dynamic eccentricities often coexist within induction machines. Even in the nascent stages of machine life, static eccentricity, an inherent byproduct of production and assembly processes, is prevalent. This results in a consistent unbalanced magnetic pull (UMP) in a specific direction, laying the groundwork for potential issues such as accelerated bearing wear or a misaligned rotor shaft. Simultaneously, these natural causes have the potential to lead to dynamic eccentricity. Failure to fix these issues can lead to a severe machine breakdown, such as a stator-to-rotor hub failure. MCSA emerges as a crucial diagnostic tool for identifying both static and dynamic eccentricities. The (1) encapsulates the essence of MCSA, providing a framework for detecting relevant frequency components [23].

$$fh = (k * Z2 \pm nd) * fr \pm \upsilon * fs \tag{1}$$

Here, f_h denotes the frequency of the shaft's lateral vibration, f_r represents the rotor frequency, fs represents the frequency of stator vibration, and *nd* denotes the frequency of the bearing's outer race defect. *Z2* denotes the bearing's characteristic frequency; k serves as a variable multiplier dependent on the bearing type and operating conditions; and υ accounts for any misalignment between the shaft and bearing.

Various models, including the DFT and Modified Prony's Method, are instrumental in discerning eccentricity faults. While DFT is user-friendly, its drawback lies in being time-consuming and ill-suited for dynamic models. On the other hand, the Modified Prony's Method shows promise as a practical alternative, accurately identifying fault characteristic frequencies based on the stator's power and current outcomes [24].

Table 1. IM faults, causes, detection techniques, and effects

Fault	Cause	Detection techniques	Effect
Eccentricity faults	Static eccentricity caused by ovality of the stator core or improper rotor or stator alignment and dynamic eccentricity resulting from bearing wear, mechanical resonance, or rotational misalignment due to a bent rotor shaft.	MCSA, Vibration analysis, AI-based methods, Harmonic analysis at stator terminal voltages, NFM-IBL, Measurement of space and time dependencies of air gap flux	Vibration and imbalance, increased stress on bearings, shaft misalignment, reduced performance, heat generation, increased noise
Squirrel cage rotor faults (broken bars and end rings)	Broken rotor bars caused by electromagnetic forces, residual tensions, thermal strains, mechanical strains, environmental stressors, and dynamic stresses.	MCSA, Vibration analysis, AI-based methods, discrete Fourier transform (DFT), modified Prony’s method, Online PD test methods, statistical process control (SPC), rectified stator current analysis, artificial intelligence-based stator winding fault estimation in three phase induction motor, asynchronous motor’s fault detection using artificial neural network (ANN) and fuzzy logic methods.	Increased vibration, altered magnetic fields, overheating, abnormal noise, reduced torque and power output, electrical unbalance, increased current and energy consumption
Stator or armature faults	Stator faults caused by insulation failure, such as phase-to-ground or phase-to-phase faults.	MCSA, vibration analysis, AI-based methods, online PD test methods, rectified stator current analysis, artificial intelligence-based stator winding fault estimation in three phase induction motor, asynchronous motor fault detection using ANN and fuzzy logic methods.	Abnormal current flow, unbalanced magnetic fields, motor overheating, voltage imbalance, reduced motor efficiency, risk of electrical hazards
Bearing faults	Bearing failures due to fatigue, improper lubrication, inadequate placement, contamination, or corrosion.	MCSA, vibration analysis, AI-based methods, SPC, empirical mode decomposition (EMD), sample entropy (SampEn), hall effect flux sensors.	Increased vibration, excessive noise, reduced efficiency.

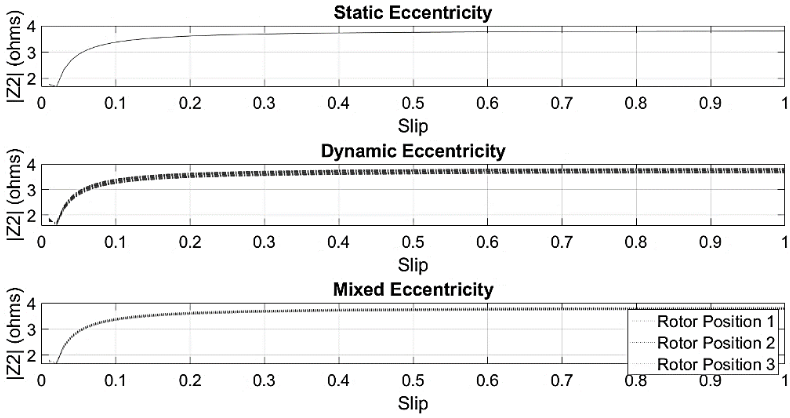

Figure 2. Rotor position effect on stator

2.2. Squirrel cage rotor faults: broken bars and end rings

Furthermore, delving into the complexities of rotor failures reveals a nuanced dichotomy between cast and fabricated rotors. Cast rotors, renowned for their enhanced durability [25]–[27], have witnessed an expanded domain of application, particularly in larger machines reaching power capacities up to 3000 kW, courtesy of innovations like cast ducted rotors. In contrast, fabricated rotors find their niche in larger or specialized application machines, delineating a tailored approach based on specific operational requirements.

Mechanics, electromagnetic forces, residual tensions, thermal strains, mechanical strains, environmental stressors, and dynamic stresses all play a part in how rotor malfunctions happen, especially when rotor bars and end rings break. Cast rotors, while celebrated for their durability, pose a unique challenge when afflicted with faults such as cracked or fractured rotor bars, rendering them practically impossible to repair [28]. Within the diagnostic realm, MCSA emerges as a key methodology for detecting broken rotor bars. This technique relies on identifying sideband components, denoted as 'fb,' around the fundamental frequency, as encapsulated in the (2). The lower sideband signifies the presence of broken rotor bars, while the upper sideband is indicative of speed oscillations. The (3) further underscores the versatility of this approach by allowing multiple sidebands to occur due to broken bars, each corresponding to different values of 'k' (1, 2, 3, and so forth).

$$fb = (1 \pm 2s)\, f \tag{2}$$

$$fb = (1 \pm 2ks)\, f \tag{3}$$

A notable advancement in this field is the integration of a soft sensor [29]–[32] designed to identify broken rotor bars. This new idea uses a group learning method called dynamic weighted majority (DWM) and combines drift detection with automatic structure evolution based on the entropy criterion. The membership degree of the fuzzy classifier is important for figuring out entropy for drift detection. This makes for a sophisticated and flexible way to find rotor faults [33]. It is important to note that uninsulated rotor cages, which feature robust contact between the rotor core and bars, may pose challenges in accurately pinpointing broken bars. To complement these advanced techniques, diagnostic tools such as harmonic analysis at stator terminal voltages after motor shutdown offer additional insights into the intricacies of rotor health [34]. This holistic exploration not only reveals the complexities of rotor failures but also underscores the imperative for sophisticated diagnostic approaches to ensure the reliability and longevity of induction motors.

2.3. Stator or armature faults

When you look more closely at stator faults, you can see that they are very common and cause a lot of induction motor failures [35]. Because of this, you need to fully understand them and be proactive about diagnosing them. These faults, often stemming from insulation failure, unfold in the form of phase-to-ground or phase-to-phase faults, gradually evolving from minor aberrations to major disruptions. The multifaceted etiology of stator or armature insulation failure encompasses a variety of contributing factors, including but not limited to short circuits during motor startup, environmental stressors, insufficient bracing of end windings, compromised core lamination, leaks in the cooling system, electrical arcing, and elevated temperatures within the stator core or winding [36].

The diagnostic arsenal deployed to identify these insidious faults is as diverse as the faults themselves. While online PD test methods are reliable stalwarts, especially for large generators and motors with stator windings rated at 4 kV and above, a conspicuous gap exists in standardized stator defect detection methods for low-voltage motors. To bridge this gap, innovative techniques involve the analysis of the machine's axial flux component through a strategically positioned large coil wound tightly around the shaft, as demonstrated by the work of [37]. The (4) governs the installation of four symmetrically positioned coils in each of the motor's quadrants, further refining the pinpointing of fault location.

$$\left(k \pm \frac{n(1-s)}{p}\right) f \tag{4}$$

Insightful research, as conducted by [10], has identified errors causing machine impedance asymmetry leading to unbalanced phase currents, while [38] attributed such imbalances to negative sequence currents. A modeling endeavor has meticulously mapped these imbalances, revealing a "bolted" flaw among 648 turns. Building on these foundations, [39] proposes a diagnostic index based on the ratio of faulty to healthy positive sequence current. In addition to these methods, techniques like SPC and signal processing [40] help find stator problems more reliably. This shows how important it is to use a flexible and multifaceted approach to fault diagnosis in the ever-changing world of induction motor operations. This thorough study not only sheds light on the complexity of stator faults, but it also stresses how important advanced diagnostic methods are for making sure that induction motors are reliable and last a long time in a wide range of operating conditions.

2.4. Bearing faults

In the intricate realm of electrical machines, the ubiquitous use of ball or rolling element bearings with an inner and outer ring, housing a set of rolling components rotating within raceways, is a common design paradigm [41]. Despite efforts to maintain load balance and alignment, the specter of fatigue failures looms, potentially giving rise to heightened vibration and noise levels [42]. External factors such as improper lubrication leading to abrasion and heating, suboptimal bearing placement resulting in raceway indentations, and the insidious influence of contamination or corrosion by water and abrasive particles can precipitate these often insidious and multifaceted failures. Such failures extend beyond the mechanical intricacies of the bearings, as they have the potential to cause substantial damage to the overall motor system. The detection of faults associated with bearings, a critical yet under-documented aspect, assumes paramount importance due to their significant contribution to motor failures, accounting for a staggering 40–50% of reported cases. Ball defects, train defects, outer bearing race defects, and inner bearing race defects systematically categorize the intricate landscape of bearing-related faults, which manifest as rotor asymmetry, often symptomatic of eccentricity.

Understanding the nuanced manifestations of these faults becomes imperative for maintaining the operational integrity of electrical machines. Ball defects, which arise from anomalies within the rolling components, can introduce irregularities in the rotational motion, resulting in a cascade of detrimental effects. Train defects, which are characterized by issues throughout the entire set of rolling components, present a broader challenge that necessitates comprehensive diagnostic strategies. Outer bearing race defects, which occur in the outer ring raceway, and inner bearing race defects, which manifest in the inner ring raceway, represent distinct fault categories, each with its own unique set of challenges and diagnostic considerations. As the need for more comprehensive diagnostic methodologies in bearing fault detection becomes evident, it underscores the urgency for further research and development in this domain. The intricate interplay between mechanical factors, external influences, and fault manifestations necessitates a holistic approach to ensure the reliable and efficient operation of electrical machines across a variety of applications and operating conditions.

3. METHODS FOR ADVANCED FAULT DETECTION

In this section, we present a MATLAB-created M-file that allows for the visualization and comparison of various fault detection methods for induction motors. This tool streamlines the analysis process, enabling researchers to assess the effectiveness of different techniques efficiently. By synthesizing findings from diverse studies, it offers valuable insights into the most suitable IM fault detection method for specific industrial applications. In the realm of advanced fault detection techniques for 3-phase induction motors, a diverse array of methodologies emerges, each contributing to the evolving landscape of motor diagnostics. One such approach entails the use of incremental broad learning and non-negative matrix factorization. This advanced method combines the power of incremental broad learning with the insights gained from non-negative matrix factorization in order to improve the ability to find faults. The fusion of these methodologies aims to provide a comprehensive and nuanced understanding of motor faults, enabling more accurate and timely detection [43], [44].

Rectified stator current analysis stands as another noteworthy methodology in the arsenal of fault detection techniques. By scrutinizing the stator current in a rectified manner, this approach provides unique insights into the motor's health and performance. The rectification process allows for a more granular examination of the current waveform, facilitating the identification of subtle deviations that may indicate underlying faults. This method proves to be a valuable tool in the diagnostic toolkit for 3-phase induction motors [45], [46]. The measurement of the air gap flux's space and time dependencies represents a cutting-edge approach to fault detection. By analyzing the intricate interplay of spatial and temporal variations in the air gap flux, this methodology unveils valuable information about the motor's condition. This holistic perspective allows for the identification of faults that may manifest in complex ways, contributing to a more comprehensive understanding of motor health [47], [48].

The three-phase induction motor utilizes artificial intelligence to estimate and predict faults in the stator winding. The motor takes advantage of artificial intelligence's prowess to predict and estimate faults in the stator winding. Leveraging advanced algorithms and machine learning techniques, this approach offers a predictive framework for fault estimation that enables proactive maintenance and minimizes downtime [49]. ANN and fuzzy logic methods tackle fault detection for asynchronous motors. Intelligent systems, designed to learn and adapt, offer a dynamic approach to fault detection in asynchronous motors. By combining ANN and fuzzy logic, the diagnostic system can handle the complicated and changing nature of asynchronous motor faults, which makes the system more reliable overall.

A comprehensive framework, encompassing feature extraction, broad learning, and incremental broad learning, outlines a diagnostic methodology for 3-phase induction motor (TPIM) faults [50]. We train the system using processed experimental data, highlighting its adaptability through retraining with incremental learning. The study underscores the effectiveness of incremental broad learning and advocates for future research to focus on improving feature extraction and developing automatic selection methods for incremental nodes. This approach's versatility extends beyond TPIM faults, making it applicable to a range of motor diagnostic issues with the potential for increased accuracy through the augmentation of feature nodes or inputs. Because they focus on always getting better and being able to adapt, these advanced fault-finding methods are at the top of the list for making sure that 3-phase induction motors work well and reliably in a wide range of situations.

3.1. Incremental broad learning and non-negative matrix factorization (NFM-IBL)

TPIMs stand as intricate machinery, subject to an array of potential faults arising from the dynamic interplay of stator and rotor conditions. The complexity inherent in these motors necessitates a diagnostic system that can swiftly and accurately respond to emerging issues [50], [51]. While machine learning-based diagnostic systems have been developed for induction motors, their intricate design often entails prolonged training times and necessitates complete retraining in the event of inaccuracies. To address the nuanced challenges posed by TPIM faults, a novel approach is proposed, leveraging the adaptable incremental broad learning (IBL) method. This method encompasses the integration of NMF-IBL, along with feature extraction techniques employing empirical mode decomposition (EMD) and sample entropy (SampEn). The amalgamation of these methodologies forms the backbone of the proposed TPIM fault diagnostic framework, which comprises four essential sub-modules: data collection and processing, broad learning, incremental broad learning, and structure simplification by non-negative matrix factorization (NMF) [52].

The diagnostic framework relies on the first sub-module, data collection and processing, which systematically collects and processes relevant data related to the TPIM's operational conditions and performance. This crucial step lays the groundwork for subsequent analysis and fault detection. The second sub-module, Broad learning, involves the application of advanced learning algorithms to glean insights from processed data. This phase aims to build a foundational understanding of the motor's normal behavior and performance, serving as a reference point for anomaly detection. The third sub-module, incremental broad learning, introduces adaptability into the diagnostic system. This incremental approach allows the system to learn and adjust over time, avoiding the need for extensive retraining in the face of inaccuracies or evolving motor conditions. This flexibility is particularly crucial in addressing the dynamic nature of TPIM faults. The NMF's final sub-module, structure simplification, adds a layer of sophistication to the diagnostic framework. We employ non-negative matrix factorization to simplify the complex data structure, enabling a more streamlined and interpretable representation. This step enhances the diagnostic system's ability to identify and isolate faults accurately.

The suggested TPIM fault diagnostic framework uses an all-around and flexible approach to find faults. It is based on simulating the findings in [53] using the m-file shown in Figure 3. By integrating innovative methodologies and leveraging adaptability through incremental learning, this framework aims to overcome the challenges associated with TPIM faults. As the diagnostic landscape continues to evolve, the emphasis on real-time responsiveness, accuracy, and adaptability positions this framework at the forefront of ensuring the reliable and efficient operation of three-phase induction motors in diverse operational scenarios [54].

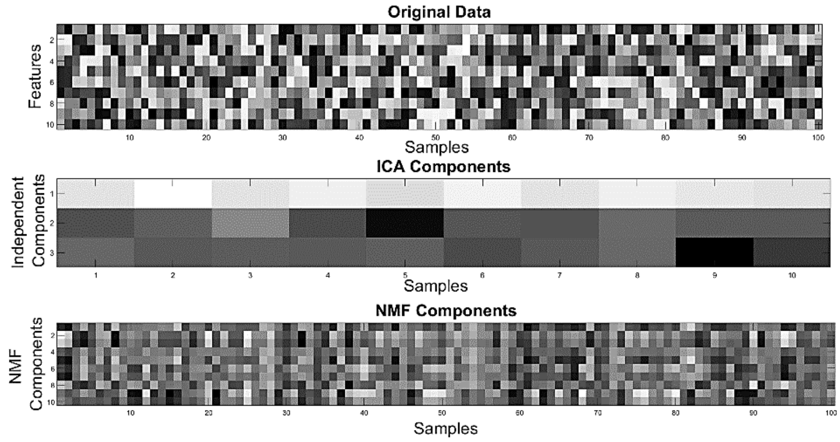

Figure 3. Feature extraction by IBL and NMF [53], [55]

3.1.1. Data acquisition

The proposed TPIM fault diagnostic system has a lot of moving parts. The data acquisition sub-module is the most important part because it lets you learn more about how the motor works. The design of this sub-module includes the detection and capture of four crucial signals: sound waves and the currents in windings A, B, and C, represented as x1, x2, x3, and x4, respectively. However, due to the inherent involvement of only two stator currents in TPIM operation, we strategically select only three signals (x1, x2, and x3). We judiciously apply a band-limiting filter to further refine the data and mitigate interference, enhancing the accuracy and reliability of the subsequent diagnostic processes.

The sound signal, denoted as x1, assumes a pivotal role in the diagnostic framework. In alignment with best practices gleaned from studies [56], this signal is meticulously divided into distinct training, validation, and test datasets. This segmentation is a very important step that helps train and test the diagnostic system thoroughly, making sure that it can correctly identify the subtleties of TPIM faults. The judicious selection and processing of signals within the data acquisition sub-module laid the groundwork for subsequent phases of the diagnostic framework. This sub-module improves the accuracy and dependability of the TPIM fault diagnostic system as a whole by focusing on important signals and taking steps to cut down on interference. Paying close attention to signal processing based on previous research shows a dedication to a method that is based on science and has been proven to work in the real world when trying to understand three-phase induction motor faults [54].

3.1.2. Data Processing

When it comes to TPIM fault diagnosis, the EMD technique is one of the most important steps in figuring out what the raw signals mean [57]. This technique yields three distinct datasets: xk-EMD-Train, xk-EMD-Vali, and xk-EMD-Test. These datasets, each encapsulating unique insights derived from the raw signals, lay the foundation for a more nuanced and granular understanding of the motor's operational dynamics. We enlist the Sample Entropy (SampEn) statistical approach to distill pertinent information and eliminate redundancy within these datasets. SampEn effectively extracts relevant features, focusing subsequent analysis on the most discriminative and informative aspects of the signals. We then subject the resultant features to normalization, a crucial step that ensures each feature contributes equally to the diagnostic process. We store these normalized features as xk-SE-Train, xk-SE-Vali, and xk-SE-Test, respectively, encapsulating the refined and normalized representations of the original signals.

Understanding the importance of domain knowledge (DK) in improving defect detection, we strategically incorporate domain knowledge-informed attributes into the processed datasets. These DK attributes serve as additional layers of information, enriching the datasets with insights that complement the statistical features derived from EMD and SampEn. In the final stages of preprocessing, the datasets undergo a renaming process, signifying the completion of the intricate signal processing journey. We now denote the preprocessed datasets as xk-Proc-Train, xk-Proc-Vali, and xk-Proc-Test. This nomenclature reflects the comprehensive nature of the datasets, encompassing the insights derived from EMD, SampEn, and domain knowledge attributes. The preprocessed datasets are ready for deeper analysis, paving the way for the next stages of the TPIM fault diagnostic framework. This careful and organized preprocessing pipeline, which is based on tried-and-true methods and statistical approaches, shows how dedicated the team is to finding the causes of TPIM faults with precision and accuracy. The diagnostic framework leverages the power of EMD, SampEn, and domain knowledge to establish a robust and comprehensive understanding of the underlying signals for the subsequent analysis.

3.1.3. Board learning [54]

The most important part of the TPIM fault diagnostic framework is model training, which comes after signal processing and preprocessing. A wide learning model, trained using the meticulously prepared xk-Proc-Train dataset, serves as the initial foray into understanding and predicting the intricacies of motor faults. We rigorously evaluate this model, scrutinizing its accuracy to determine whether it aligns with the predetermined goal percentage. The evaluation of the wide learning model serves as a crucial checkpoint, ensuring that the initial training phase meets the desired level of accuracy. However, if the model fails to meet the predetermined goal percentage, we initiate a strategic pivot. The diagnostic system seamlessly transitions into the incremental broad learning phase, an adaptive approach designed to enhance the model's performance dynamically.

In the incremental broad learning phase, a pivotal adjustment is made by increasing the number of enhancement nodes. This augmentation is a strategic intervention aimed at refining the model's understanding and predictive capabilities. The model gets a better understanding of the underlying patterns in the data by adding more nodes. This lets it change and adapt to the changing nature of TPIM faults. This iterative and adaptive process exemplifies the commitment to continuous improvement within the TPIM fault diagnostic framework. The seamless transition from wide learning to incremental broad learning highlights the diagnostic system's flexibility, ensuring that it can effectively navigate evolving motor conditions and fault manifestations. With a goal-oriented approach and an adaptive learning strategy, the TPIM fault diagnostic framework is a strong and flexible tool for making sure that three-phase induction motors work reliably and efficiently in a wide range of operational situations.

3.1.4. Incremental broad learning [54]

Within the TPIM fault diagnostic framework, the IBL submodule assumes a crucial role in refining the accuracy of the model. Using the information from the xk-Proc-Vali dataset, this submodule changes the number of enhancement nodes on the fly. This is done on purpose to make the model better at making predictions over time. However, the adaptive nature of the IBL submodule brings forth a challenge—the potential for overfitting. If the number of nodes is excessively high, the model may start fitting the training data too closely, leading to a reduction in its generalization capabilities. To circumvent this issue, a meticulous trial-and-error process is instituted. This process is geared towards determining the optimal number of nodes, denoted as N, striking a delicate balance between enhancing accuracy and preventing overfitting. The trial-and-error methodology is a nuanced approach that involves systematically experimenting with different node configurations until the desired validation accuracy is achieved. This iterative process is informed by insights presented in a comprehensive review article, providing a theoretical and empirical foundation for optimizing the IBL submodule.

The overarching goal is to harness the model's adaptability and dynamic learning capabilities without compromising its ability to generalize to new data. The IBL submodule aligns with the broader objective of the TPIM fault diagnostic framework by fine-tuning the number of enhancement nodes through a systematic trial-and-error approach, resulting in a robust and accurate model that can effectively detect and predict motor faults. The focus on avoiding overfitting, along with the evidence-based approach described in the review article, shows that the TPIM fault diagnostic system is dedicated to accuracy and dependability. With its iterative nature, the trial-and-error process encapsulates the adaptive spirit of the diagnostic framework, making sure that it always changes to meet the complex and challenging needs of three-phase induction motor faults.

3.1.5. Structure simplification [53]

In order to optimize the TPIM fault diagnostic system, a critical post-processing phase comes into play. The learning system, having undergone the adaptive and dynamic processes of wide learning and incremental broad learning, may inadvertently harbor redundant nodes. To streamline and refine the model, a systematic approach is employed to identify and eliminate these redundancies, ensuring the efficiency and interpretability of the diagnostic system. Node reduction involves simplifying the learning system through low-rank approximations, a technique aimed at retaining the essential features while discarding unnecessary redundancies. This reduction not only enhances the computational efficiency of the model but also contributes to a more interpretable and streamlined representation. We introduce non-negative matrix factorization (NMF) as a compression mechanism to further optimize the IBL structure. NMF is a strong mathematical tool that makes it easier to find meaningful patterns in the learning system. This leads to a clearer representation without lowering the accuracy of the diagnosis [58].

Using NMF to compress the IBL structure is a smart way to cut down on system errors and make the TPIM fault diagnostic system better at finding problems. However, the pursuit of optimal diagnostic accuracy remains paramount. The incremental broad learning submodule initiates an additional layer of compression if the diagnostic accuracy exceeds the predefined range of [TP 0.025]. This iterative compression process ensures that the TPIM fault diagnostic system continually adapts to achieve the delicate balance between model complexity and diagnostic precision. By using these compression techniques that are based on well-known mathematical methods, the TPIM fault diagnostic system works in a way that is efficient, easy to understand, and flexible. The iterative nature of compression, along with the strategic use of NMF and incremental broad learning, makes the commitment to constant improvement in the diagnostic framework even stronger. This careful post-processing step is an important part of making sure that the TPIM fault diagnostic system is a strong, useful, and correct way to figure out what's wrong with a three-phase induction motor.

3.2. Rectified stator current

In the realm of fault detection for induction motors, stator current analysis [59] stands as a prominent and widely employed technique. Renowned for its simplicity and the minimal hardware and software prerequisites it demands, this non-invasive method has proven effective across various motor sizes and operational conditions. However, the practical application of stator current analysis encounters challenges, particularly when dealing with large induction motors operating at extremely low slip rates.

One of the primary challenges inherent in stator current analysis is the potential concealment of fault harmonics by the fundamental component, particularly in situations where the motor operates at extremely low slip. This concealment phenomenon poses a significant obstacle, often resulting in delayed fault detection until the damage reaches a severe stage. In response to this limitation, a novel approach based on rectified motor current analysis emerges as a pragmatic and effective solution. The proposed rectified motor current analysis approach introduces a simple yet powerful strategy to overcome the challenges associated with fundamental component leakage. By rectifying the motor current, the fault harmonics are distinctly revealed at a lower frequency, untethered from the interference of the fundamental component. This innovative method not only circumvents the delayed detection issue but also offers a versatile solution that can be seamlessly implemented through both software and hardware.

The practical efficacy of the proposed approach is robustly demonstrated through experimental verification [60], wherein the method proves instrumental in detecting a broken bars defect in a large induction motor. This empirical validation underscores the real-world applicability and effectiveness of the rectified motor current analysis, positioning it as a valuable addition to the arsenal of fault detection techniques for large induction motors. Stator current analysis remains a stalwart in fault detection, the proposed rectified motor current analysis emerges as a complementary and pragmatic approach tailored to address the nuances of large induction motors operating at extremely low slip rates. Its simplicity, effectiveness, and demonstrated success in real-world scenarios mark it as a noteworthy advancement in the pursuit of reliable and timely fault detection strategies for induction motors.

3.3. Measuring the variations of air gap flux with respect to both space and time

Ensuring the efficient and dependable operation of induction motors hinges on robust condition monitoring systems, a critical facet addressed in this section. Contemporary diagnostic systems predominantly rely on external measurements such as current, voltage, vibration, or flux to glean insights into the motor's health. However, this study advocates for a groundbreaking online fault diagnostic method, as proposed in [52], [61]–[64], which introduces a paradigm shift by utilizing an array of Hall effect flux sensors to measure the internal main air gap flux density of induction motors.

The crux of this method lies in its applicability to specialized motors with elevated reliability requirements. Unlike traditional diagnostic approaches, the proposed method offers a comprehensive solution for diagnosing induction motor failures by tapping into the internal dynamics of the motor's air gap flux density. This internal measurement not only provides a unique perspective but also allows for the detection of issues at an early stage, enabling timely intervention to prevent the escalation of faults.

A distinctive feature of the proposed method is its capability to not only detect faults but also identify their precise location and gauge their severity [58]. This granular level of diagnostic information is instrumental in formulating targeted maintenance strategies, enhancing the overall reliability and lifespan of the induction motors. To substantiate the efficacy of the proposed method, the study undertakes extensive simulations and develops a prototype online condition monitoring system based on the National Instruments real-time platform [65]. The results of these simulations and the functioning prototype serve as empirical evidence, confirming the effectiveness of the proposed method in real-world scenarios. This empirical validation reinforces the viability of integrating Hall effect flux sensors for online fault diagnosis, establishing it as a potent tool for ensuring the health and longevity of induction motors.

This section not only highlights the pivotal role of condition monitoring in induction motor operation but also introduces a pioneering online fault diagnostic method that leverages Hall effect flux sensors. The method's applicability to specialized motors, early fault detection capabilities, and the ability to pinpoint fault location and severity underscore its significance in advancing the field of induction motor diagnostics. The combination of theoretical proposals, simulations, and a functional prototype serves as a robust foundation for considering the proposed method as a valuable addition to the repertoire of condition monitoring techniques for induction motors.

3.3.1. Faulty stator winding

Stator winding shorts pose a severe threat, with the potential to rapidly escalate into catastrophic failures [60]. When a single turn of the stator winding is shorted, it becomes disconnected from other turns within the same phase coil. This disconnection induces a shift in the phase magnetomotive force (MMF), altering the magnetic field distribution. Simultaneously, the isolated turn carries a loop current that exceeds the rated current, resulting in excessive heating. The swift identification and localization of stator winding problems is imperative, as evidenced by an alarming experiment in which the temperature of a shorted turn soared from 60 °C to 120 °C in just 6 seconds. This stark reality emphasizes the critical need for effective fault diagnosis methods.

A groundbreaking study [61] proposes an innovative fault diagnosis method capable of detecting and precisely locating stator winding problems. This method functions by measuring the distortion that stator shorts cause directly within the main air gap flux. It provides a direct and efficient means of identifying faults in the stator winding. Furthermore, the proposed method excels at pinpointing the exact location of the fault by analyzing the rise in primary wave magnitude during rotation. This strategic approach not only mitigates the uncertainties associated with time harmonic interpretation, but it also optimizes the use of extensive instrumentation in investigative processes.

We wrote an m-file to simulate the experimental results [66] in Figure 4, which show a substantial increase in the primary wave's magnitude during the short rotation. This remarkable rise acts as a reliable indicator, allowing for precise fault location. The implications of this method go beyond just finding faults; it provides a complete answer to the urgent need to quickly identify and pinpoint problems with stator windings, which can prevent disastrous outcomes in induction motors.

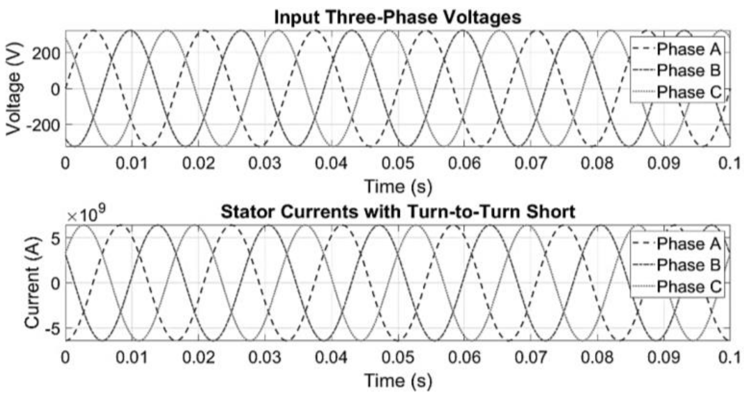

Figure 4. Stator winding with a turn-to-turn short

3.3.2. Eccentricity, both static, and dynamic

This groundbreaking article [67] introduces a pioneering approach aimed at improving the instrumentation critical for effective induction motor operation. The key innovation is the use of a Hall effect sensor array strategically positioned around the stator circumference within the motor air gap. This strategic placement enables the sensor array to capture vital information about the motor's internal dynamics and performance. We dedicate our study to unraveling the fundamental theory underlying AC motor faults, specifically focusing on detecting critical issues like stator winding defects, static and dynamic eccentricity, and rotor bar faults [67].

The proposed approach extends beyond theoretical considerations, providing concrete algorithms designed for the accurate detection of these various faults. Notably, the study employs a comprehensive condition monitoring system, leveraging the capabilities of the National Instruments Compact RIO real-time platform. This system has demonstrated exceptional fault sensitivity, noise immunity, and dynamic variation tolerance, making it a robust tool for diagnosing and monitoring the health of induction motors.

This approach's empirical validation further solidifies its credibility. The study underscores that this innovative methodology is particularly well-suited for dynamic applications involving inverter-fed large induction motors with elevated reliability requirements. This approach's systematic development and validation contribute significantly to the field of fault diagnosis in induction motors [7]. It not only enhances the understanding of motor faults but also presents a practical and effective solution for real-world applications, promising heightened reliability and performance in dynamic settings.

3.4. Estimation of stator winding fault in three-phase induction motors using artificial intelligence

The challenge of detecting faults in induction motors through multiple optimization techniques has spurred innovative research. In an interesting study [68], researchers came up with a smart way to find short-circuit faults in the stator winding of a three-phase induction motor by using fuzzy logic. This method is different because it uses a fuzzy logic controller to carefully look at the stator current and give clues about the type of motor failure based on a clear set of rules and an inference mechanism [69]–[71]. MATLAB-Simulink software facilitates the implementation of this intelligent approach, enabling the simulation of both healthy and short-circuit fault conditions in a three-phase induction motor, as illustrated in Figure 5. The fuzzy logic-based approach has a unique benefit in that it can find faults based on the inputs that are available. This makes it an intelligent and flexible way to keep an eye on motor condition and analyze faults.

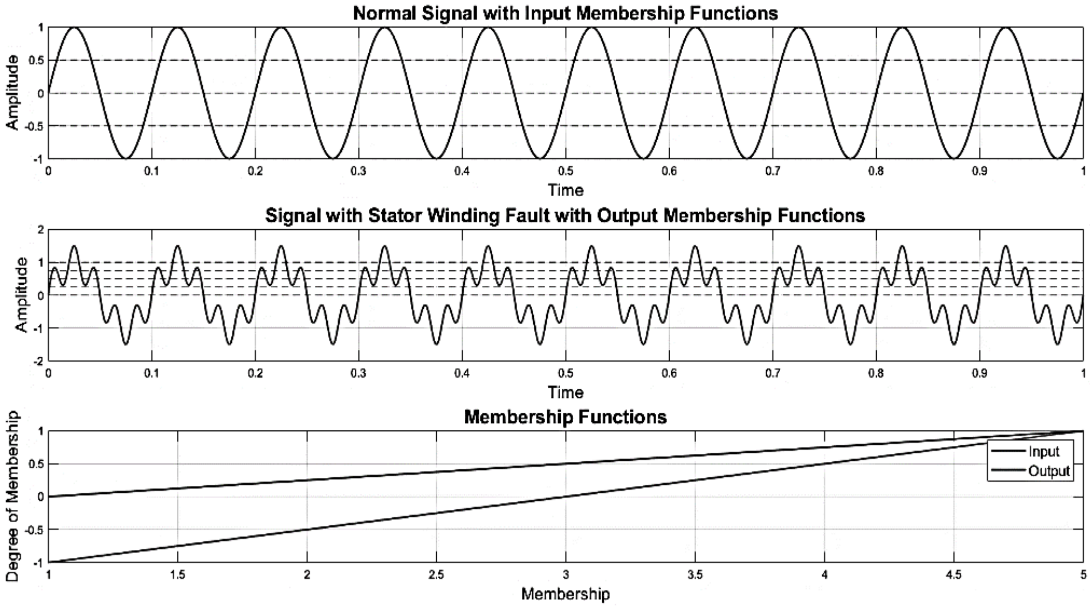

Figure 5. Membership functions for both input and output variables

The significance of this approach goes beyond its technical prowess. By facilitating the detection of faults at an earlier stage, it contributes to the establishment of a safer working environment in industries. The proactive nature of fault detection aligns with the broader goal of ensuring the reliability and safety of induction motors in industrial settings. This study not only introduces an intelligent methodology for fault detection but also underscores its potential impact on industrial operations, emphasizing the importance of early fault detection in maintaining a secure and efficient working environment.

To lessen the impact of load changes on defect detection, researchers propose artificial intelligence (AI) algorithms for detecting interturn short circuit (ITSC) faults in three-phase induction motor stators, with a focus on the use of ANN and fuzzy logic systems [72]. The ANN algorithm is capable of detecting and locating ITSC faults, while the fuzzy method can diagnose the severity of ITSC defects. Simulation and experimental results validate the effectiveness of both techniques under ITSC fault and load change conditions.

In order to achieve reliable stator defect detection even under load changes, a combination of ANN and Fuzzy Logic System (FLS) is proposed. Specifically, this research [73] utilizes a feedforward multi-layer perceptron (MLP) Neural Network trained with the back propagation (BP) algorithm to automatically detect and locate ITSC faults. The suggested approach and neural network architecture are illustrated in Figure 5, with the NN's output number set at three to correspond with the three phases of the induction motor where the ITSC fault could potentially occur.

The selection of fault indicators is a crucial step in developing a monitoring and diagnostic system. Induction motors often detect interturn short-circuit (ITSC) faults using the phase shifts between line current and phase voltage, which offer a wealth of fault information. Healthy motors exhibit identical phase voltage and line current magnitudes, offset by 120 electrical degrees. However, faulty operations can result in changes in magnitudes and phase shifts. We simulated the faulty stator model from Section II under different load torques (T=3 and 7 N.m.) to investigate the behavior of three-phase shifts under various ITSC faults. The output of the m-file that was used to simulate the three-phase shifts [74] is shown in Figure 6. It shows how the results change with the number of short-circuited turns and a 5 N.m. load. The results reveal that load changes have an impact on the ITSC fault detection technique.

This study [75] presents two AI-based techniques for robust stator failure detection in the presence of load variations. Artificial neural networks and fuzzy logic are utilized to eliminate the need for an induction motor model during fault detection, resulting in adaptable and easily deployable systems. The ANN technique identifies the faulty phase, while the fuzzy logic-based detector determines the severity of the problem. These smart techniques have various applications, including alerting the workforce of a dangerous condition and facilitating the repair of a defective stator.

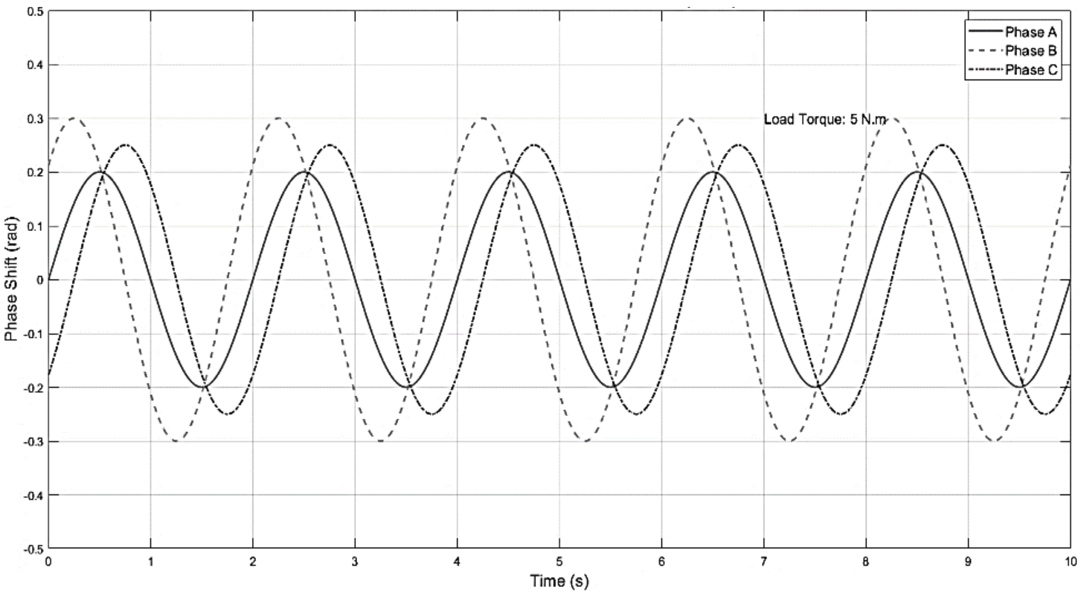

Figure 6. The characteristics of phase shift due to interturn short circuit (ITSC) faults are observed for phase A, phase B, and phase C under a load torque of 5 N.m.

4. MODELLING APPLICATIONS

As the popularity of artificial intelligence-based condition monitoring systems rises, fault detection systems [10], [31], [65], [73], [76], [77] utilizing support vector machine (SVM), ANN, nave bayes classifier, ensemble, and K-nearest neighbors (KNN) have become more prevalent. These systems can detect faults and determine their severity level, but they require extensive data to train and malfunctioning machines are scarce. Numerical methods can simulate faulty conditions that are difficult to test in the field or lab, providing fault data for machine learning algorithms. Accurate induction motor (IM) malfunctioning models can minimize harmful testing, lower costs, and validate new fault detection techniques [78], [79], making them beneficial for training and testing artificial intelligence-based condition monitoring systems. This section covers recent developments in IM models, which are categorized into electrical circuits, magnetic circuits, numerical approaches, and hybrid models, and provides an overview of various fault diagnosis methods [80] as shown in Figure 7.

The coupling circuit model (MCC) represents a wide variety of fault modes, such as stator open circuit, stator short circuit, broken rotor bar, broken end ring, static eccentricity, dynamic eccentricity, mixed eccentricity, and defective bearing. In contrast, the d-q model simplifies the representation of faults and reduces the number of equations required for simulation, but it does not provide specific information about individual rotor bars or end ring currents. The magnetic circuits (MEC) model provides detailed magnetic modeling with reluctances and permeances to accurately simulate faults. The mathematical procedures (FEM) approach, on the other hand, requires a lot of computing power but can accurately model faults in induction machines by taking into account the nonlinearities of magnetic materials and reproducing the machine's performance.

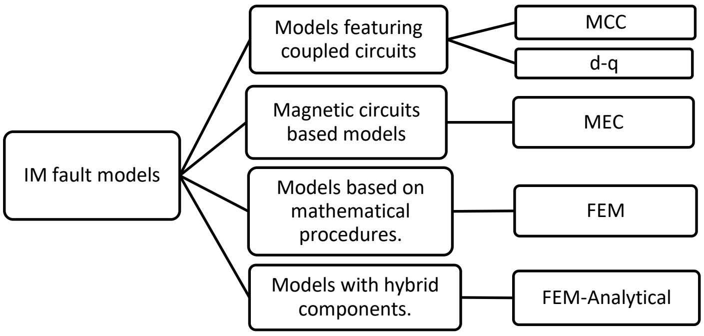

Figure 7. Recent developments in IM models

4.1. Models featuring coupled circuits

The d-q model is a widely used coupling circuit model that assumes symmetrical motors, linear iron permeability, uniform air-gap, and no tangential induction. These simplifications allow for a fast and accurate mathematical model but are problematic when dealing with faulty equipment. This section discusses recent breakthroughs in MCC and d-q models illustrated on Table 2.

Table 2. compiles references addressing outlining methods for incorporating specific faults into MCC, d-q, MEC and FEM models

Faults	MCC Reference	d-q Reference	MEC Reference	FEM Reference	Remarks
Stator open circuit	[81]	[82]	N/A	N/A	d-q Model: More effective (MEC) Model: More accurate
Stator short circuit	[72], [83], [84]	[85]–[87]	[88]	[71], [89]–[91]	d-q Model: More effective (FEM): More suitable
Broken rotor bar	[83], [84], [92]–[95]	[77], [85], [96]	[88], [97], [98]	[71], [99], [100]	(MCC) Model: More comprehensive d-q Model: More effective (MEC) Model: More accurate
Broken end ring	[101], [102]	[96]	N/A	[58], [103], [104]	(MCC) Model: More comprehensive d-q Model: More effective (FEM): More suitable
Static eccentricity	[18], [19], [105]	[35], [106]	[92], [107]	[20], [108]	(MCC) Model: More comprehensive d-q Model: More effective (FEM): More suitable
Dynamic eccentricity	[18], [19]	[55], [105]	[107]	[49], [99]	(MCC) Model: More comprehensive d-q Model: More effective Mathematical Procedures (FEM): More suitable
Mixed eccentricity	[18], [109]	[105]	[110]	[17], [26]	(MCC) Model: More comprehensive d-q Model: More effective Mathematical Procedures (FEM): More suitable
Defective bearing	[35], [42], [46], [111], [112]	[113]	[114]	[115]–[117]	(MCC) Model: More comprehensive d-q Model: More effective Mathematical Procedures (FEM): More suitable

4.1.1. Multiple coupled circuit models

After determining model parameters, the expressions characterizing IM behavior (related to rotor conductors) and requiring stator solving are known as in (5) to (8) [84].

$$[u_s] = [R_s][I_s] + \frac{d}{d_t}[\emptyset] \tag{5}$$

$$[Qs] = [L_{5s}][I_s] + [L_{5r}][I_r] \tag{6}$$

$$[u_r] = [R_r][I_r] + \frac{d}{d_t}[\phi_s] \tag{7}$$

$$[\phi_r] = [l_{rs}][I_s] + [L_{rr}][I_r] \tag{8}$$

The equations consist of various vectors and matrices, including [Us] for stator voltage, [Is] for stator currents, [Ir] for rotor loop current, [Øs] for stator flux linkage, [Rs] for stator phase resistances, [Lss] for stator windings inductance, and [Lsr] for stator to rotor mutual inductance. Additionally, [Ur] denotes the rotor voltages vector, [Ir] the rotor currents vector, [Ir] the rotor loop currents vector, [Ør] the rotor flux linkages vector, [Rr] the rotor resistance matrix, and [Lrr] the rotor inductance matrix.

4.1.2. d-q model

The implementation of the space vector transformation technique is beneficial for depicting an induction machine with structural symmetry in simulations. By utilizing this method, it is possible to represent such machines using only four differential equations that are linked together. This leads to a reduction in the overall number of equations that are required for simulation purposes. Consequently, the equations that define the stator voltage can be expressed as:

$$[v_{ds}] = \frac{1}{w_b}\frac{d^{Q}\,ds}{dt} - \omega_{\emptyset}q + Rs_i\,ds \tag{9}$$

$$\left[v_{qs}\right] = \frac{1}{w_b}\frac{d^{Q}\,ds}{dt} - \omega_{\emptyset}q + Ri_{QS} \tag{10}$$

The variables in the aforementioned equation 9 and 10 can be defined as follows: wb refers to the base per-unit electrical speed, while Øds, Øqs, and Ø0s represent the d-axis, q-axis, and zero-sequence stator flux connections. The stator resistance is denoted by Rs, and the d-axis, q-axis, and zero-sequence stator currents are respectively represented by ids, iqs, and i0s. Additionally, vdr and vqr refer to the d-axis and q-axis rotor voltages, while φdr and φqr are the d-axis and q-axis rotor flux linkages. Furthermore, ω denotes the per-unit synchronous speed, and ωr refers to the per-unit mechanical or rotational speed.

4.1.3. Models based on magnetic circuits (MEC)

In this approach, discrete winding distributions, stator and rotor slotting, and magnetic material saturation-induced saliency effects related to space harmonics are taken into account [113]. The nodal magneto-motive forces [F] are connected to the reluctances [R] in the (11), which represent the fluxes of the rotor and stator [Ø].

$$[\phi] = [F][R] \tag{11}$$

In conclusion, the MEC-based framework has demonstrated high precision in predicting machine performance across diverse operating points, load conditions, and even unbalanced excitation and faulty conditions. Its accuracy and computational efficiency make it an ideal alternative between the standard lumped parameter models and FEM-based approaches [114]. The MEC technique has also proven effective in modeling a range of induction motor faults.

4.1.4. Models based on mathematical procedures (FEM)

By utilizing the machine's actual magnetic and geometric properties, this technique calculates the distribution of the magnetic field [85]–[103]. In general, faulty induction motor models are created in 2D, which offers excellent accuracy in terms of magnetic phenomena. However, these models do not consider the rotor's skewing behavior or the end rings, and the connection of the rotor bars is typically addressed through an ideal current source in the electrical circuit [89]. The magneto-dynamic field equation for a standard induction motor in 2D is defined as:

$$\frac{d}{dx}\left(\frac{1}{v}\frac{dAz}{d+}\right) + \frac{d}{dy}\left(\frac{1}{v}\frac{dA_z}{dy}\right) = -J_0 + \sigma\frac{dA_2}{d_t} - \sigma^{\vec{v}\times(\nabla y\vec{A})} \tag{12}$$

In the given (12), $(A)^{\rightarrow}$ represents the magnetization potential, Az is the z-component of the magnetic vector potential, J_0 refers to the applied density current source, $v^{\rightarrow}$ represents velocity, σ is the electric conductivity, and v represents permeability

4.2. Models with hybrid components

Recent research suggests that combining FEM and analytical methodologies can generate models with FEM level accuracy, which can be executed in real-time simulators [58]. A hybrid model based on the d-q method and finite element analysis has been proposed to model short circuit defects in IM drives. In this model, sparse identification is utilized to minimize the number of FEM simulations needed to compute the IM coupling parameters. FEM is used to solve the entire geometry of the IM, and the coupling parameters are then imported into the machine's analytical model [58]. The sparse identification method is effective in obtaining a defective IM model while minimizing the number of FEM simulations needed, thus reducing computing expenses by over 99.9%. However, the full FEM analysis is still required for each failure scenario, resulting in extensive simulation periods and expensive computational costs. TSFEM-based models require lengthy simulation times for small simulated spans, whereas hybrid models require approximately 25 minutes [104]. Even when the time to execute one simulation is factored in, the time savings exceed 98%.

5. CHALLENGES AND FUTURE DIRECTIONS

The existing challenges in fault detection for three-phase induction motors encompass a range of factors [118], including the limitations of current signature analysis (CSA), the need for specialized diagnostic methodologies, and the impact of variable frequency drives (VFDs). Furthermore, the reliance on Fourier analysis for signal interpretation and feature extraction presents certain drawbacks, such as the lack of transient information and the absence of spectrum content variations over time. These challenges have fostered the exploration of various data-driven prognostics and health management (PHM) methodologies driven by artificial intelligence, machine learning, and deep learning, aiming to leverage current, vibration, and thermal signals for effective fault detection and isolation

The challenges in fault detection for three-phase induction motors can include issues with accurately identifying incipient faults, distinguishing between various fault types, and dealing with the effects of operating conditions and external disturbances. Additionally, extracting fault signatures from noisy measurements and developing reliable and automated fault detection methods also present significant challenges in this domain [31]. The existing challenges in fault detection for three-phase induction motors are multifaceted and encompass various aspects of signal analysis, system complexity, and operational conditions. Some of the prominent challenges include:

(a) Complex operating conditions: Induction motors operate in diverse industrial environments where operating conditions such as variable loads and speeds, temperature variations, and mechanical stresses can influence the manifestation of faults and complicate the diagnostic process [119].
(b) Incipient fault detection: Early detection of incipient faults, such as broken rotor bars, poses a significant challenge due to the limited availability of diagnostic techniques capable of identifying subtle changes in motor behavior at the initial stages of fault development [120].
(c) Signal interpretation: The interpretation of motor current and vibration signals to differentiate between normal and faulty conditions requires accurate analytical models and sophisticated signal processing techniques to extract relevant fault signatures and mitigate false alarms [121].
(d) Transient regimes: Fault detection during transient regimes, such as startup and shutdown, presents challenges due to signal variations and the need for suitable methods to differentiate between normal transient behavior and actual fault conditions [122].
(e) Noise and interference: The presence of electrical and mechanical noise, as well as interference from external sources, can mask fault signatures in the acquired signals, making it challenging to extract relevant diagnostic information [102].
(f) Operational dependence: The effectiveness of fault detection techniques can be influenced by the operational characteristics of induction motors, necessitating robust diagnostic methods capable of accommodating varying operating conditions and loads [32].
(g) Need for expert identification: Traditional fault detection in induction motors often relies on the expertise of skilled engineers to interpret diagnostic data, highlighting the need for automated and intelligent diagnostic systems to overcome human-related limitations [123].
(h) Inadequate diagnostic techniques: The limitations of conventional diagnostic methods in detecting specific fault types, such as broken rotor bars, and the lack of comprehensive fault detection solutions present challenges in ensuring reliable and accurate fault diagnosis in induction motors.
(i) Varied operating conditions: The fault detection process can be complicated due to the diverse operating conditions experienced by induction motors, such as variable speeds, load variations, and environmental factors [85].
(j) Dynamic stresses: Induction motors used in variable-speed applications undergo dynamic stresses at high power levels, leading to reduced lifetimes compared to constant-speed motors, adding complexity to fault detection [124].
(k) Non-deterministic fault characteristics: Some faults, such as eccentricity and certain rotor faults, may manifest in non-stationary and intermittent characteristics, making them challenging to detect and diagnose accurately [85], [125].
(l) Reliability and complexity of parameters: Parameters such as induced rotor voltage exhibit non-reliability and complexity, posing challenges for their usage in condition monitoring and fault diagnosis [126].

To get around these problems, we need to keep studying and creating more advanced diagnostic methods that use cutting-edge signal analysis, machine learning, and artificial intelligence to make fault finding in three-phase induction motors more accurate and reliable. Furthermore, integrating comprehensive fault diagnostic systems that account for various operational scenarios and noise sources can significantly contribute to improving the effectiveness of fault detection methodologies.

6. CONCLUSION

In conclusion, the landscape of fault diagnosis techniques for electrical machines has undergone significant evolution to ensure the secure and reliable operation of these critical systems. The comprehensive exploration within this review article has delved into a myriad of diagnostic techniques, ranging from traditional methods like temperature measurement and infrared recognition to more advanced approaches such as vibration analysis, MCSA, and artificial intelligence and neural network techniques. The article provides a comprehensive exploration of numerous fault detection techniques for electrical machines, covering advancements in traditional methods and cutting-edge approaches. The article talks about advanced techniques such as AI-based methods, rectified stator current analysis, incremental broad learning (IBL), non-negative matrix factorization (NMF), talking about how air gap flux changes over time and space, and other machine learning and signal processing methods. The article underscores the paramount importance of fault detection methods tailored for different types of faults inherent in electrical machines. The article focused on a variety of fault categories, such as eccentricity, rotor faults (broken bars and end rings), stator or armature faults, and bearing faults. Recognizing the dynamic nature of modern electrical machines, the article delved into advanced fault detection methods. These included cutting-edge technologies like non-negative matrix factorization and incremental broad learning, as well as methods based on artificial intelligence and measuring how air gap flux changes over time and space. These advanced techniques' efficiency lies in their ability to provide robust fault detection solutions. By enabling the timely identification of faults, they play a pivotal role in preventing unexpected machine downtime and mitigating potential financial losses. However, the article aptly acknowledges that the field is a dynamic one, and it advocates for continued research and development. This call to action emphasizes the need for ongoing efforts to enhance fault diagnosis capabilities for electrical machines, ensuring that diagnostic methodologies stay ahead of evolving challenges in the ever-changing landscape of electrical engineering.

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