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A COMPREHENSIVE SURVEY ON REAL TIME INDUCTION MOTOR FAILURE DIAGNOSIS AND ANALYSIS

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Graphical abstract

Abstract

The efficient and reliable operation of induction motors is of paramount importance in industrial processes, commercial applications, and residential settings. The timely detection and diagnosis of failures in these motors are crucial for preventing costly downtime and optimizing maintenance strategies. This review article presents a comprehensive survey of real-time induction motor failure diagnosis and analysis techniques. The article begins by outlining the significance of induction motors in various sectors and the economic implications of motor failures. It then delves into the various types of faults that can affect induction motors, including electrical, mechanical, and thermal anomalies. A detailed exploration of the state-of-the-art diagnostic methods follows, encompassing both traditional and modern approaches. The survey covers a wide range of diagnostic techniques, including vibration analysis, current and voltage signature analysis, thermal imaging, acoustic monitoring, and artificial intelligence-based methods. The strengths and limitations of each approach are discussed, along with their applicability to different types of faults. Moreover, the integration of multiple techniques into hybrid systems is explored as a means to enhance diagnostic accuracy. Real-time monitoring and data acquisition play a pivotal role in the proposed diagnostic strategies. The article provides insights into sensor technologies, data acquisition protocols, and the utilization of Machine Learning.

Keywords: Induction Motor, Vibration, Diagnosis, Fault, Real Time

1.0 INTRODUCTION

Induction motors stand as the backbone of modern industrial processes, residential appliances, and commercial activities, powering a myriad of applications across diverse sectors [1]. The uninterrupted and reliable operation of these motors is not only pivotal for ensuring seamless functionality but also for preventing costly downtimes and mitigating potential economic losses [3]-[6]. As these motors operate under varying conditions and loads, they are susceptible to a range of electrical, mechanical, and thermal faults, emphasizing the critical need for robust failure diagnosis and analysis techniques. The majority of the faults, witnessed by the induction motor, are bearing faults as per the data provided by IEEE and EPRI, which has been depicted in Figure 1.

The ability to promptly detect and diagnose faults in real time has become an indispensable requirement for maintaining the efficiency and longevity of induction motors. Traditional maintenance practices, such as periodic inspections or scheduled replacements, are gradually being overshadowed by data-driven and condition-based approaches that offer a higher level of precision and cost-effectiveness.[2] Real-time failure diagnosis not only enhances the reliability of induction motors but also facilitates the optimization of maintenance strategies, thereby reducing operational costs and improving overall system performance. [7]-[9].

This survey article embarks on a comprehensive survey of the latest advancements in real-time induction motor failure diagnosis and analysis. By amalgamating a diverse array of diagnostic methods and techniques, this study seeks to provide a holistic understanding of the state-of-the-art technologies in this vital field. The survey encompasses both established techniques and cutting-edge technologies, shedding light on their respective strengths, limitations, and practical implications.

Throughout this survey, various diagnostic approaches, including vibration analysis, current and voltage signature analysis, thermal imaging, acoustic monitoring, and artificial intelligence-based methods, have been discussed. [10]-[25]. Each method's applicability to different types of faults and operational scenarios is examined, accompanied by a critical assessment of their effectiveness in real-world scenarios. Furthermore, hybrid systems that incorporate numerous diagnostic approaches have been investigated, highlighting the potential for increased diagnostic accuracy and reliability.

The advent of real-time monitoring and data acquisition technologies has significantly transformed the landscape of induction motor diagnostics. This article addresses the pivotal role of sensor technologies, data acquisition protocols, and the utilization of cloud computing in enabling real-time diagnosis, as shown in Figure 2. However, the implementation of real-time diagnostic systems is not without challenges. Issues related to data processing, communication latency, and algorithm robustness have been discussed to provide a well-rounded perspective on the practical implications of these technologies [9]-[12].

In summary, this survey aims to consolidate and present an encompassing overview of the current advancements in real-time induction motor failure diagnosis and analysis. By disseminating the knowledge and insights gained from the amalgamation of various diagnostic methods, this article contributes to the enhancement of induction motor reliability, operational efficiency, and performance across industries and applications.

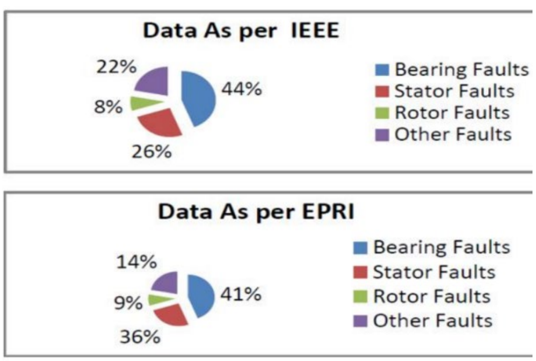

Figure 1 Fault factors in AC induction motors as a percentage (IEEE & EPRI) [2]

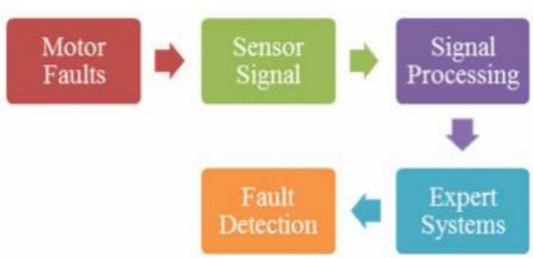

Figure 2 Monitoring of Induction motor faults

2.0 MOTIVATION

The ubiquitous presence of induction motors across industrial, commercial, and residential domains underscores their critical role in powering essential machinery and appliances. As these motors operate under diverse conditions and loads, they are inherently susceptible to a wide array of faults that can compromise their efficiency, reliability, and even lead to catastrophic failures. The consequences of motor failures extend beyond the immediate disruption, often resulting in substantial economic losses due to unplanned downtime, increased maintenance costs, and reduced productivity.

Traditional maintenance practices, such as routine inspections and preventive replacements, have proven inadequate in addressing the dynamic nature of induction motor faults. Reactive approaches to maintenance not only result in inefficient resource utilization but also fail to capitalize on the potential benefits of advanced monitoring and diagnostic technologies. The need for real-time fault detection and diagnosis has emerged as a paramount requirement for ensuring the seamless and cost-effective operation of induction motors.

The advent of sensor technologies, data acquisition systems, and computational tools has paved the way for transformative advancements in the field of motor diagnostics. These technologies enable the acquisition of real-time data, facilitating the identification of emerging faults at an early stage. This paradigm shift towards condition-based and predictive maintenance strategies offers the promise of maximizing operational uptime, optimizing maintenance schedules, and ultimately contributing to improved industrial efficiency. However, the landscape of real-time induction motor failure diagnosis and analysis is characterised by a multitude of diagnostic methods and techniques, each with its own merits and limitations. Navigating through this intricate array of options and discerning the most appropriate approach for a specific context poses a significant challenge. Furthermore, the fast-paced evolution of technologies demands constant monitoring of emerging trends and innovative solutions in order to effectively harness their potential for motor diagnostics.

This comprehensive survey seeks to address these challenges by providing a holistic overview of the current state-of-the-art in real-time induction motor failure diagnosis and analysis. This study critically evaluates a wide range of diagnostic methods, from traditional techniques to cutting-edge artificial intelligence-driven approaches, to empower researchers, engineers, and practitioners to make informed decisions about the implementation of diagnostic strategies that meet their specific needs. Through this endeavour, it is aspired to facilitate the transition towards proactive and data-driven motor maintenance practices, thereby enhancing the reliability, efficiency, and longevity of induction motors across industries.

3.0 INDUCTION MOTOR FAULTS AND ANALYSIS TECHNIQUES USING DIFFERENT METHODOLOGIES

3.1 Common Faults in Induction Motors

The performance and dependability of induction motors could be affected by a variety of defects. Understanding these common faults is essential for developing effective fault detection techniques. Problems with the rotor bars, stator windings, bearings, and eccentricity are among the most common induction motor defects.

Rotor bar faults occur when the rotor bars become damaged or broken, leading to unbalanced magnetic fields and resulting in abnormal vibrations and torque fluctuations. Stator winding faults, such as insulation degradation or short-circuits, can lead to increased winding currents, overheating, and reduced motor efficiency. Bearing faults, including defects in the rolling elements or lubrication issues, can cause abnormal noise, increased friction, and mechanical vibrations. Eccentricity refers to a non-uniform air gap between the rotor and stator, resulting in magnetic imbalances, increased losses, and motor performance degradation [2]-[6].

These faults can have severe consequences if they are not detected and addressed in a timely manner. They can lead to increased energy consumption, decreased motor efficiency, premature component failure, and even catastrophic breakdowns. Therefore, effective fault detection techniques are essential to ensuring the reliable and efficient operation of induction motors.

3.2 Existing Fault Detection Techniques

Numerous fault detection techniques have been proposed in the literature for induction motors. These techniques can be broadly categorized into two main approaches: model- based methods and signal-based methods. Each approach has its advantages and limitations, and the choice of technique depends on various factors, including the available resources, the type of faults to be detected, and the desired level of accuracy.

3.2.1 Model-based Methods

Building mathematical models of the induction motor and comparing it to the actual motor behaviour is an example of a model-based approach. These methods often require accurate knowledge of motor parameters, such as resistances, inductances, and mechanical characteristics[1]. The comparison between the model and the measured data can reveal deviations indicative of faults.

One popular model-based technique is parameter estimation, which aims to estimate the motor parameters based on measured data and known system dynamics. Extended Kalman filtering (EKF) is commonly used for online parameter estimation in induction motors. Extended Kalman filtering combines measurements from sensors with the motor model to iteratively update and refine the parameter estimates [15]-[18]. Adaptive observer-based methods are another class of model-based techniques that estimate the motor states and parameters by minimizing the estimation error.

Model-based methods offer the advantage of being able to detect faults even in the absence of fault signatures in the measured signals. They rely on the comparison between the model predictions and the measured data to identify deviations caused by faults. However, these methods often require accurate motor models, which may not be readily available or may vary with operating conditions. Additionally, model-based methods can be computationally intensive, especially for large-scale systems, and may not be suitable for real-time applications.

3.2.2 Signal-based Methods

Signal-based methods focus on analysing the electrical and mechanical signals from the induction motor to identify fault signatures. These methods exploit the characteristic changes in the signals caused by different faults. Signal-based methods are generally more practical and widely used in industrial applications due to their simplicity and real- time monitoring capability.[18].

One commonly used signal-based technique is current analysis, which involves monitoring the electrical currents in the motor windings. Faults such as rotor bar faults and stator winding faults lead to distinctive changes in the current waveform, including increased harmonics and amplitude variations. Current analysis techniques include Fourier analysis, wavelet transform, and statistical analysis methods to extract fault-related features from the current signals.[20]

Total Harmonic Distortion (THD) analysis is another widely applied signal-based technique. THD analysis involves quantifying the harmonic content in the motor currents or voltages. The presence of harmonics indicates abnormalities in the system, which can be attributed to various faults. THD analysis is non-intrusive and can be easily implemented using power quality analysers. It provides valuable information about the electrical condition of the motor and can detect faults such as rotor bar faults and bearing faults.[13]

Vibrational analysis is a powerful signal-based technique that focuses on monitoring the mechanical vibrations of the motor. Faults such as bearing defects, unbalanced rotor conditions, and misalignments cause specific vibration patterns that could be detected and analysed. Vibrational analysis techniques include FFT (Fast Fourier Transform) analysis, envelope analysis, time-domain analysis, and statistical analysis methods. These techniques enable the identification of fault-related frequencies, amplitudes, and other characteristics in the vibration signals. [13]

Signal-based methods offer the advantages of simplicity and real-time monitoring capability, making them suitable for online fault detection. However, these methods are susceptible to noise and may require advanced signal processing algorithms to extract fault signatures effectively. Additionally, some techniques may only be applicable to specific fault types, limiting their overall effectiveness in detecting multiple faults simultaneously.[21]

3.3 Limitations of Existing Techniques

While existing fault detection techniques have shown promising results, they also have certain limitations that need to be addressed to enhance their effectiveness and applicability. These limitations stem from various factors, including the complexity of induction motor systems, the presence of noise and uncertainties in the measurements, and the challenges associated with real-time implementation.

Model-based methods heavily rely on accurate motor models and knowledge of system parameters. However, obtaining precise motor models can be challenging due to variations in operating conditions, ageing effects, and manufacturing tolerances. Estimating the motor parameters online can help overcome some of these challenges, but it introduces additional computational complexity and may require additional sensors[26].

Signal-based methods are susceptible to noise and measurement uncertainties, which can hinder the accurate detection of fault signatures. Noise sources can include electrical noise in the measurement system, mechanical vibrations from external sources, and variations in the operating conditions. Advanced signal processing techniques, such as adaptive filtering, wavelet denoising, and statistical analysis, can mitigate the effects of noise. However, the performance of these techniques depends on the quality of the measured signals and the chosen analysis parameters[24]-[27].

Another limitation of existing techniques is their specificity to certain fault types. Some methods are more suitable for detecting specific faults, such as rotor bar faults or bearing faults, while being less effective in detecting other fault types[12]. Achieving comprehensive fault detection for multiple fault types remains a challenge, especially when considering the practical constraints of implementation, computational complexity, and real-time monitoring.

Real-time implementation is a critical requirement for fault detection systems in industrial applications. However, many existing techniques may not meet the real-time constraints due to computational complexity or the need for extensive processing of large amounts of data. Real-time implementation necessitates efficient algorithms and hardware platforms capable of handling the computational load within the desired time frame. To overcome these limitations, ongoing research focuses on developing advanced fault detection techniques that integrate multiple approaches, exploit the benefits of machine learning and artificial intelligence, and leverage advanced signal processing algorithms.

These advancements aim to enhance the accuracy, reliability, and real-time capability of fault detection systems for induction motors.

4.0 STUDIES ON FAULT DETECTION IN INDUCTION MOTORS

4.1 Detection of Broken Rotor Bar

Faults in the rotor cage, specifically cracked rotor bars or end rings, are associated with 5-10% of all induction motor failures. Due to the high thermal loads on the rotor, medium-voltage motors are more prone to rotor cage defects compared to small motors [3]-[6]. Rotor cage overheating causes mechanical strains due to thermal expansion. The following are some of the most common causes of a broken rotor bar:-

1) Thermal stresses owing to thermal overload.
2) Magnetic strains due to electromagnetic forces, a magnetic pull that is out of whack, and torques on the shafts, which cause dynamic stresses
3) Environmental stressors brought on by things like pollution and rotor material wear;
4) Mechanical stresses from things like loose laminations, etc.

High thermal stresses at the beginning are a common source of fractured rotor bar/end-ring failures in medium voltage motors. As a result, medium voltage motors have a limited number of starts before the rotor cage fails, compared to standard motors [7]. When a motor's rotor cage cracks or breaks, rotor bars form and must be replaced. Shaft vibration due to the rotor cage fault can cause bearing failures, air gap eccentricity, and other issues. In order to protect the rotor and reduce the likelihood of other types of motor failure, it is crucial to discover the broken rotor bar/end-ring as soon as possible.

An uneven rotor flux might result from damaged rotor bars or end rings, which prevent current flow. The imbalanced rotor flux can be defined as the sum of the positive and negative sequence rotor fluxes that spin in the opposing directions at the same slip frequency. Since the slip frequency is twice the input frequency, the current harmonics appear at the two times the frequency as

$$f_b=(1\pm 2ks)f \tag{4.1}$$

Where s is the slip, f is the input frequency, and f_b is the current frequency associated with a broken rotor bar/end-ring fault. It is suggested that the detection reliability of a broken rotor bar be enhanced by using the high-frequency harmonics. The unbalanced rotor flux induces the $(1-2s)f$ component, whereas the speed and torque oscillation from a broken rotor bar induces the other sidebands, which are sensitive to the motor's inertia. Motors with a damaged rotor bar are introduced as a model. It is shown that the major issue with existing spectrum-based approaches is that load oscillation can also cause the current harmonics at the same frequencies. The current envelop spectrum, the maximum covariance method, the short-time Fourier transform, wavelet transformations, the MUSIC transform, and other signal processing techniques are used to monitor current harmonics at certain frequencies, as shown in [3]. Air gap torque, total or partial instantaneous power, and other similar fault symbols are just a few of the many possible current harmonic symbols. It has been shown that instantaneous power-based approaches provide increased sensitivity to a broken rotor bar problem. Measuring the energy of the stator current across a specific frequency range is presented as an alternative way for identifying rotor bar failure. The use of demoded analysis helps locate damaged rotor bars. Several decision-making systems rely on the monitoring of defect signs. These methods include neural networks, fuzzy logic, multiple discriminant analysis, and the Bayes minimal error classifier. The effectiveness of current-based broken rotor detection methods is limited by their low detection sensitivity, despite the fact that they are easy to develop. Because current harmonics are also produced by intrinsic rotor unbalance at the same frequency, a reliable detection approach is required to tell the difference between the two types of rotor unbalance. To avoid false alarms produced by inherent rotor unbalance, a variety of fault severity techniques are provided for estimating the number of damaged rotor bars. This facilitates the accurate early diagnosis of rotor cage defects.

Easy implementation characterises contemporary spectrum-based approaches and associated methodologies, such as instantaneous power-based methods. It is also proposed that the induced voltage upon switch off and the start-up current function as indicators of defects. On the other hand, these security and monitoring measures will not last forever. As measuring flux or voltage requires a dedicated search coil, the methods provided here are largely ineffective.

Suppressing current harmonics at characteristic frequencies by the current regulator reduces the performance of motors fed by closed-loop drives. It is suggested that rotor saliency be monitored through the insertion of high-frequency signals. However, because the characteristic frequencies are so close to the injected high-frequency signal, the data collection hardware must adhere to stringent restrictions. The suggested model-based approaches likewise centre on motors that are fed by closed-loop drives. For drive-fed motor systems using field-oriented control, the authors of present a time-domain demodulation analysis. In, the author proposes estimating the rotor's position as a means of detecting broken rotor bars. These methods are unable to differentiate between load oscillations and broken rotor bar defects.

Existing approaches for detecting broken rotor bars suffer from a key flaw that has yet to be fixed: they are very sensitive to load oscillations. Motors with a damaged rotor bar are introduced as a model[1]-[4]. It is shown that the major issue with existing spectrum-based approaches is that load oscillation can also cause the current harmonics at the same frequencies.

Some of the methods used for broken rotor bar detection include the "swing angle" approach, the parameter estimation method, and the rotor resistance method. The instantaneous power-based methods and other comparable systems, which are based on the current spectrum, are easier to implement. Additionally, the startup current and the induced voltage after switch off should be used as the defect indicator. However, this type of monitoring and defence cannot be provided indefinitely by these techniques. Since a separate search coil is needed to measure flux or voltage, the approaches presented and have limited utility[6].

Closed-loop drive-fed motors suffer from diminished performance due to the current regulator's suppression of current harmonics at characteristic frequencies. High-frequency signal injection has been proposed to monitor rotor saliency. However, because the characteristic frequencies are close to the injected high-frequency signal, strict limitations must be placed on the data gathering equipment. Closed-loop drive-fed motors are also the focus of suggested model-based approaches. Demodulation analysis in the time domain has been proposed in for drive-fed motor systems with field-oriented control. Estimating the rotor's position is proposed in as a method for identifying damaged rotor bars[15]. Broken rotor bar faults cannot be distinguished from load oscillations using these techniques.

Existing approaches for detecting broken rotor bars suffer from a key flaw that has yet to be fixed: they are very sensitive to load oscillations.

4.2 Detection of Air Gap Eccentricity

When the distance between the stator and the rotor is not the same, a condition known as "air gap eccentricity" exists. It is possible for stator and rotor cores to sustain significant damage from stator to rotor friction if the air gap is extremely eccentric.

The eccentricity of an air gap can be either static or dynamic. Even brand-new motors have a slight amount of static eccentricity. Static eccentricity causes an mbalanced magnetic force, which can result in a bent rotor shaft, bearing failures, dynamic eccentricity, and stator to rotor friction, which can lead to a complete breakdown of the motors. Since the air gap in MV motors is lower in per-unit values than in small motors, even a little amount of eccentricity might cause catastrophic motor failure. Therefore, it is crucial to safeguard the motor system by catching air gap eccentricity early on.

Harmonics in the rotor flux and the resulting harmonics in the stator current are induced by the air gap eccentricity at certain frequencies. It has been suggested to simulate eccentric motors using either numerical models or the finite element approach. It is demonstrated that when modelling motors with eccentricity, a special winding function must be utilized[28]. Current harmonics occur at frequencies given by

$$fe = [1 \pm m\left(\frac{(1-s)}{\frac{p}{2}}\right)]f \qquad (4.2)$$

A positive integer *m*, the frequency f, the slip *s*, the number of pole pairs *p*, and the frequency associated with eccentricity *fe* are all parts of this expression. For a few pole pairs and rotor slots, the indicated current harmonics may be weak. There are more applications that have been proposed, such as the park vector of the current, the instantaneous power spectrum, and the instantaneous reactive power. The instantaneous power-based approaches are identical, but the current spectrum-based methods have a different signal-to-noise ratio. Load oscillation can create current harmonics at frequencies, illustrating a major challenge with eccentricity detection methods.

Although suggests a way to remove load effects from eccentricity detection, its sensitivity to motor parameter alterations limits its usefulness. Separating load effects from eccentricity detection using the motor's inherent unbalancing is proposed in. However, the method's effectiveness depends on the load.

In [23], a signal injection-based method is described for using the zero-sequence voltage as the fault indicator in induction motors that are fed by closed-loop drives. The approach can only be used on motors that have access to the neutral, and it disrupts motor operation by injecting a periodic signal at regular intervals. By injecting voltages at predetermined frequencies, the current regulator considerably reduces the current signature, much like a stator inter-turn fault. It is proposed in [29] that a neural network be used to keep an eye on both the current and voltage harmonics in order to identify air gap eccentricity. However, its usefulness is constrained by the need for training data in a variety of real-world settings. Method's usefulness is constrained by its inability to offer continuous security.

4.3 Detection of Bearing Failure

Different types of sensors have been developed for use in various condition-monitoring procedures for bearings. Bearing failures can be detected with the help of vibration sensors. Using vibration sensors is common since it is apprehended to be an accurate indicator of bearing failure. Access to the motor is necessary for this method to work, and the expense of the sensor and its installation reduces its utility. The vibration sensors also occasionally break and need servicing[23].

In addition to vibration sensors, bearing defects can be detected with thermal sensors by keeping an eye on the bearing's temperatures. Induction motors also make advantage of these techniques, as the stator winding temperature is tracked by incorporated thermal sensors. However, the bearing failures themselves aren't the primary reason of a spike in bearing temperature; a hotter rotor can have the same effect. Magnitude and frequency of vibration depends on the type of bearing damage, location of the damage and the intensity of the damage as depicted in Figure 3 and Figure 4 respectively [13].

Bearing failures can also be detected by the use of other types of analysis, such as chemical analysis, acoustic emission monitoring and sound pressure measurements [14]. The need for specialized gadgets and sensors, however, restricts their usefulness. A certain vibration frequency can result from a single point failure in a single part of the rolling ball bearings which is given by

$$fo = \left[1 - \left(\frac{\mathrm{Db}}{\mathrm{Dc}}\cos\beta\right)\right] Nf/2 \quad (4.3)$$

$$fi = \left[1 + \left(\frac{\mathrm{Db}}{\mathrm{Dc}}\cos\beta\right)\right] Nf/2 \quad (4.4)$$

$$fb = \left[1 - cos^{2}\beta\left(\frac{D_b^2}{D_c^2}\right)\right]\frac{\mathrm{Dc}}{\mathrm{Db}} f \quad (4.5)$$

Db is the diameter of the ball, *Dc* is the diameter of the bearing pitch, and is the contact angle of the balls on the races, *N* is the number of bearing balls, *f* is the mechanical rotor speed, and *Dc* and *Db* are the diameters of the ball and bearing pitch, respectively.

The current spectrum can also be used to detect bearing flaws since bearing vibration causes the motor's output torque to vibrate and, as a result, the current harmonics at a given frequency.

Analysing the stator current using signal processing methods involves keeping an eye on the current spectrum and utilising techniques such as statistical signal processing, wavelet transformations, the current park vector, and the extended park vector[20]-[23].Furthermore, decision-making is based on the observation of particular current harmonics and neural networks are used for this purpose. The rotor eccentricity and other harmonics in the current spectrum are known to originate from bearing problems. It is generally acknowledged that bearing failure with single point flaws occurs at a later, more advanced stage, and thus fault detection becomes crucial when overall roughness is included. This emphasizes the importance of keeping an eye on the bearing's overall roughness in order to anticipate bearing failures and plan for repairs ahead of time. The output torque and, consequently, the motor current can be affected by vibration signals; thus, it is recommended that, similar to vibration-based methods, the current spectrum's standard deviation be carefully monitored. It is essential to eliminate power supply harmonics, load oscillation, rotor eccentricity, broken rotor bars, and other sources of current distortion if want current standard deviation has to be lowered. A Wiener filter-based noise cancellation method is developed to enhance the signal-to-noise ratio. A statistical method has been devised to calculate the increasing spread of the current spectrum due to bearing deterioration. These approaches have not been submitted to thorough field testing to establish their robustness, which is a major limitation given that the standard deviation of the current can be created by a broad variety of other factors in practical applications.

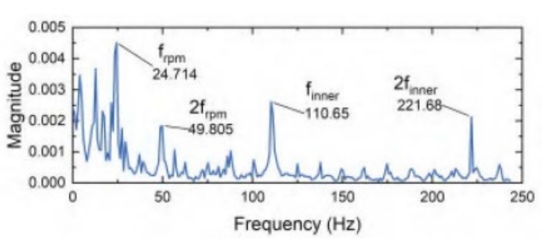

Figure 3 Characteristic vibration frequencies for inner race bearing fault [13]

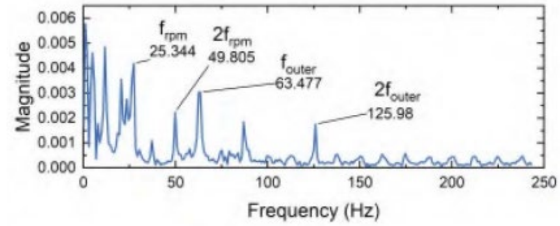

Figure 4 Characteristic vibration frequencies for outer race bearing fault [13]

4.4 Detection of Stator Insulation Failure

Stator insulation monitoring still requires special attention due to the catastrophic effects of insulation failures, even though the stator windings of MV motors are often better protected with sophisticated insulation materials than those of small motors.

Long-term thermal ageing or contamination are frequent causes of form-wound motor stator failure. Due to chemical reactions, the high stator winding temperature, which is also influenced by the insulation class, finally causes insulation failures by gradually lowering the bonding and insulation materials' electrical and mechanical capabilities. Additionally, with MV motors, partial discharge (PD) also happens as the insulation ages and eventually erodes it [20]-[22].

Inter-turn short circuits are typically the first sign of insulation failure because they cause exceptionally large current flows because of the great voltage potential differences between adjacent coils. After that, the short circuit's high current output generates a tremendous amount of heat, which causes the insulation in nearby windings to burn. The stator core eventually suffers damage as a result of this insulation failure, which quickly spreads to the stator core and causes stator core-ground insulation failure. Small low-voltage motors typically require 20–60s to complete this operation. Due to the high voltages between neighboring spins in Medium voltage motors, this process can accelerate significantly.

An analysis of the similarities and differences between several fault detection systems has been presented in Table 1 and Table 2 respectively. In most cases, the methods that include the utilisation of sensors such as flux sensors, eddy current sensors, and rotary encoders are expensive. Methods such as laser modules, accelerometers (two- and three-axial), and spectrometers are among the more expensive approaches. Because of the electrical circuitry that they include, the majority of sensors are vulnerable to issues such as excessive temperatures and circuit failures. In order to prevent catastrophic motor failures, accurate stator insulation failure diagnosis and stator insulation condition monitoring are essential and spectrometers are among the more expensive approaches. Because of the electrical circuitry that they include, the majority of sensors are vulnerable to issues such as excessive temperatures and circuit failures. In order to prevent catastrophic motor failures, accurate stator insulation failure diagnosis and stator insulation condition monitoring are essential.

Table 1 Comparison Of Different Sensors used for Fault Detection

Method	Faults Identified	Measured Signal	Sensor Used
Eddy Current analysis[13]	Inner Race	Vibration	Eddy Current Sensor
Sound Analysis[16]	Bearing defect, imbalance, and a broken Rotor bar.	Sound	Condenser Microphone
Analysis of Motor Current Signature[15]	Bearing Defect	Current	Current Sensor
Analysis of Speed[5]	Bearing Defect	Rotor speed	E60H NPN type Rotary Encoder
Wireless Multi-sensor system[28]	Air-gap eccentricity and bearing defects	Acoustic vibration and Current	Hall effect sensor accelerometer and microphone
Analysis of temperature and Motor Current Signature[21]	Stator Insulation Failure	Current and Temperature	Current Sensor and Thermocouple sensor

Table 2 Cost Comparison Of Different Sensors

Method	Complexity of sensor	Method of Signal Analysis	Approximate Sensor cost
Eddy Current analysis[13]	Medium	Fast Fourier Transform	INR 16,600
Sound Analysis[16]	Low	MUSIC	INR 8,300
Analysis of Motor Current Signature[15]	Medium	Wavelet Decomposition	INR 8,300
Analysis of Speed[5]	Medium	Absolute value based Principal Component Analysis	INR 41,500
Wireless Multi-sensor system[28]	Medium	Fast Fourier Transform, HHT	INR 41,500
Analysis of temperature and Motor Current Signature[21]	Low	Short time Fourier transform and Temperature analysis	INR 10,000

5.0 CONCLUSION

This article offers a comprehensive overview of methods for protecting induction motors and monitoring their condition. Included are methods for thermal protection, stator inter-turn fault identification, bearing failure, rotor bar/end ring damage detection, and air gap eccentricity detection. This study examines the available monitoring methods for induction motors, evaluating aspects such as their robustness, accuracy, and implementation complexity to determine their relative merits and shortcomings. Metamaterial Bio-inspired Antennas could be used as part of future research to categorize and anticipate induction motor failure prediction and classification of faults utilizing various deep learning algorithms. The utilization of metamaterials has the potential to shrink the sensor in size without compromising the accuracy and gain. Although the cost of conventional monitoring and protection for induction motor systems is considerable, this does not preclude the possibility of their implementation.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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