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Research Article

The Role of Fault Detection and Diagnosis in Induction Motors

Mohamed Khaleel [1,2]*, Mehmet ŞİMŞİR [1], Zıyodulla Yusupov [1], Nassar Yasser [3]
Hala Elkhozondar [4,5], Abdussalam Ali Ahmed [6]

[1]Department of Electrical-Electronics Engineering, Faculty of Engineering, Karabuk University, Karabuk, Turkey
[2]Research and Development Department, College of Civil Aviation, Misrata, Libya
[3]Mechanical and Renewable Energy Engineering Department, Faculty of Engineering, Wadi Alshatti University, Libya
[4]Electrical Engineering and smart systems Department, Islamic University of Gaza, Gaza, Palestine
[5]Materials and London Centre for Nanotechnology Department, Imperial College London, United Kingdom
[6]Mechanical and Industrial Engineering Department, Bani Waleed University, Bani Walid, Libya

*Corresponding author: lykhaleel@yahoo.co.uk

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Abstract: Induction Motors (I-M) aim to enhance interface technologies for more safety, reliability, productivity, and greener operations. In addition, malfunction monitoring functionalities are embedded into the system to detect impending faults and predict their consequence on the system's future actions using fault diagnosis techniques. This article broadens the scope of their investigation on current trends in fault detection and diagnosis of induction motors (CT-FDD) of I-M. In this direction, Modern applications, in particular, depend heavily on the rapid and accurate diagnosis of machinery malfunctions, which leads to increased productivity and reduced downtimes. It is worth mentioning that Artificial Intelligence (A-I) is a powerful technique for enhancing the capacity of I-M fault diagnosis, notably during the upkeep decision-making process. With this aim in mind, this article highlights the signatures of failure, including analysis of current motor signatures, voltage signatures, and acoustic and vibration analysis. In this direction, Actual stages in the design process of a fully automated CT-FDD system, such as system information processing, data capture, information theory, fault classification, and repair selection actions, are explained by the variation to provide an overview of the current state of CT-FDD.

Keywords: Fault Detection; Fault Diagnosis; Induction Motors; Artificial Intelligence

1. Introduction

Induction motors (I-Ms) are fully incorporated into machinery and used in various manufacturing processes, engineering products, and amenities. It is critical to keep I-Ms healthy to ensure that many industries are running correctly. Nevertheless, numerous faults occur regularly in IMs due to challenging operative situations, regular wear and tear, enduring and excessive loads, and unplanned circumstances [1-4]. Moreover, electrical machines (EM) are sensitive to a wide variety of malfunctions. Stator faults can be caused by open phase, inconsistency due to short circuits, or continuously rising resistance between the terminals. Rotor electrical faults typically occur in the rotor which is prone to undergo, disparity due to short circuits or increasing resistance between parts for wound rotor machines and corroded bar(s) or cracked end ring(s) for squirrel cage induction machines. Rotor magnetic fault can be triggered by ferromagnetic components in synchronous permanent magnet equipment. These challenges must be recognized and resolved as soon as possible to protect the health of EM equipment and prevent expensive maintenance down the line [5-8].

Control systems, autonomous vehicles, monitoring, remote systems, rescue operations, domestic robotic systems, advanced manufacturing, and rail networks are considered safety-critical because any technical fault can result in human protection and infrastructure damage. Previously, fault detection and diagnosis schemes have become essential features of safety-critical application domains. On the other hand, CT-FDD is integrated into several sophisticated and up-to-date mechanisms due to the demands of increased production and reliable operation [12-13].

It is becoming increasingly common to use artificial intelligence (A-I) to diagnose electrical machine faults, especially when deciding what maintenance should be performed. Fuzzy-neural networks, expert systems, neural networks, and fuzzy logic are some of the A-I techniques that can be employed. Furthermore, recent years have seen a rash of contributions to fault diagnosis using deep learning, shallow learning, and transfer learning frameworks based on machine learning and pattern recognition. Here are a few examples of representative works.

One of the earliest studies and current work focuses on deep transfer learning, which combines transfer learning and deep learning components designed to enhance the generalization performance of intelligent fault diagnostics. This work also discusses the recent investigation into deep transfer learning for machinery fault diagnosis. It summarizes, categorizes, and explains numerous publications on the subject while discussing various deep transfer configurations and theoretical underpinnings [14-16]. Recently, the research study aims to analyse condition monitoring (CM) and fault diagnosis (FD) investigations based on sound and acoustic emission (AE) for four various disturbances: stator, bearings, rotor, and compound. The authors also highlights the benefits and drawbacks of using sound and AE analysis in CM and FD. In addition to that, one method employed [17-21] is intelligent fault diagnosis (IFD), which involves using machine learning theory to diagnose machine faults. This is a beneficial method for reducing human labour while automatically recognizing machine health states, and it has garnered significant attention in the last two or three decades. Even though intelligent fault diagnosis (IF-D) has had a series of successes, an evaluation still leaves a blank space to cover the development of IF-D from the cradle to the bloom and rarely provides potential recommendations for future growth [22-25].

This article contributes significantly to the review of the current trends in fault detection and diagnosis (CT-FDD) of induction motors (I-M). Artificial intelligence (A-I) is a powerful technique for enhancing the capacity of I-M fault diagnosis, notably during the upkeep decision-making process. In this direction, Actual stages in the design process of a fully automated CT-FDD, such as system information processing, data capture, information theory, fault classification, and repair selection actions, are explained by the variation to provide an overview of the current state of CT-FDD. Besides that, the article demonstrates failure signatures, including analysis of present motor signatures, voltage signatures, and acoustic and vibration analysis.

In light of these findings, this paper follows this organizational structure: **Section 2** illustrates different induction motor (I-M) faults, including mechanical and electrical faults. **Section 3** highlights the signatures of failure, including analysis of motor current signatures, voltage signatures, and acoustic and vibration analysis. **Section 4** demonstrates the I-M fault diagnosis using artificial intelligence (A-I). Finally, **Section 5** discusses the conclusion of this paper.

2. Different types of I-M faults

In this section, the induction motor (I-M) comprises three main parts: the stator, the rotor, and the bearings. However, damage to any of the IM's features or individual functions causes it to struggle. Faults in IM are broadly classified as either mechanical faults (MF) or electrical faults (EF), as demonstrated in Figure 1. To emphasize; the EF consists of stator faults, electrical supply faults, and rotor faults. On the other hand, MF composes of bearing faults and rotor faults [26-28].

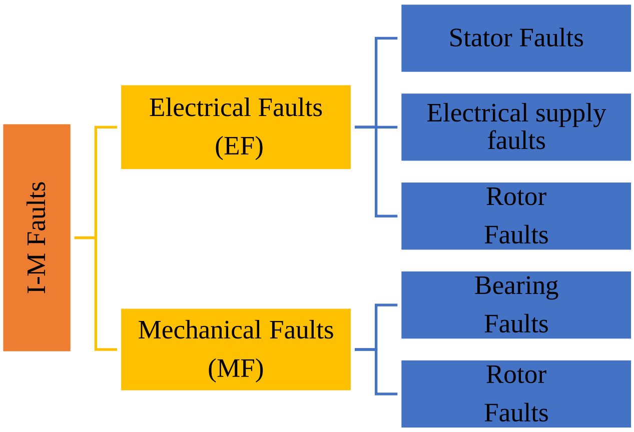


Figure 1. Type of regular I-M faults.

There is a considerable proportion of bearing faults (BF) in IMs that use ball or roller bearings, which combine the rolling element, external ring, an internal ring, and rail (or cage). This causes the following effects of BF: (i) excessive rotational vibration caused by massive output load torque, which eventually causes fatigue, (ii) incorrect installation of bearings, (iii) deterioration of bearing lubrication resulting from high bearing currents caused by shaft voltage, (iv) through the shaft heat is conducted, (v) contamination and friction at the end of the process. An unbalanced magnetic pull is directly impacted by the BF because it causes rotor eccentricity [29-31].

As a result of rotor-related faults and little to no I-M deficiency, rotor and stator air gaps remain identical, and the rotor's rotation axis aligns with the stator's geometrical axis. Even so, when the rotational axis and the geometrical axis of the stator differ, the air gap varies. It is worth mentioning that the most widely accepted rotor fault of I-Ms. Moreover, the abnormalities are classified as static and dynamic, as illustrated in Figure 2. The air gap is classified into rotor motion (RM), typical motor (NM), motor with static eccentricity (MSE), and motor with dynamic eccentricity. When the rotor is rotated, the position of the minimal air gap the minimum is fixed; when the rotor is static, the position changes with the rotor [32-34].

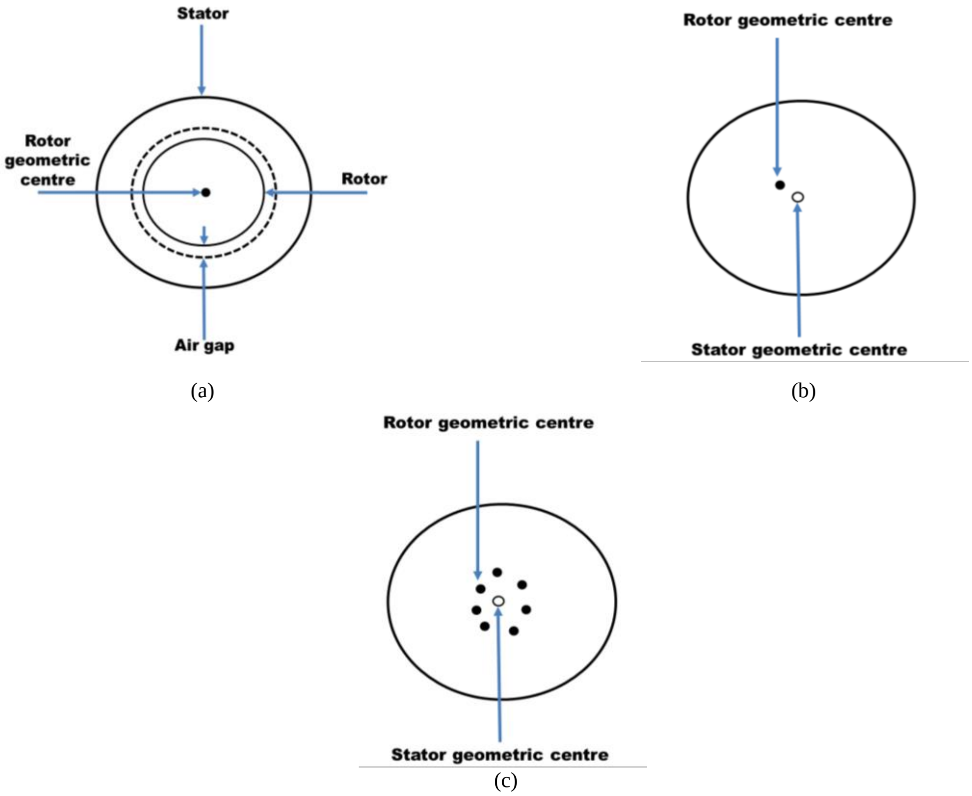
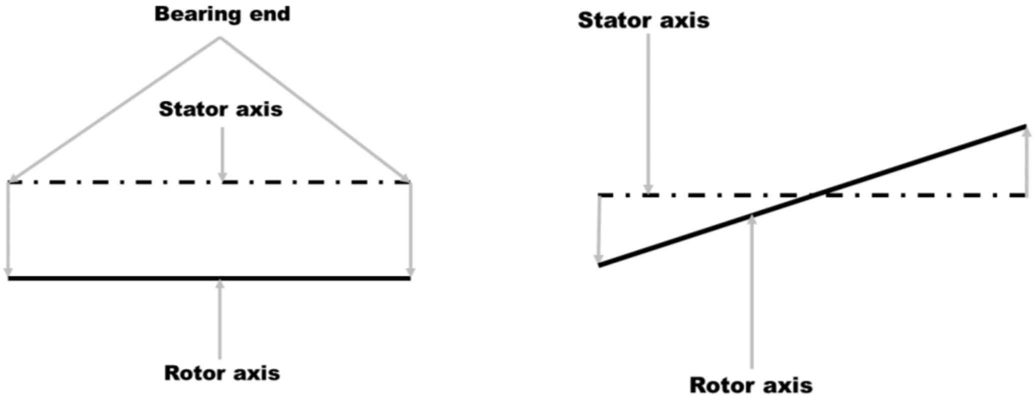


Figure 2. The air gap eccentricity in the I-M during (a) RM, (b) NM, (c) MSE.

Both the bowed rotor (BR) and bent rotor (BR) are essentially the same occurrences; the only disparity is that the bowed rotor deflection is demonstrable within the machine housing (or when the rotor is mounted on bearings). It is ended up caused by the static weight of the rotor, whereas the bent rotor deflection can be noticed from the outside machine (without mounting on the bearing) and is caused by permanent rotor deformation [34-36]. It is responsible for dynamic air-gap eccentricity. Figure 3 indicates the angular and parallel (A&P) rotor misalignment in the I-M: (a) parallel misalignment (PM) and (b) angular misalignment (AM). The BR is affected by external rubbing (which results in permanent metallurgical changes), municipal expansion and generating (which results in permanent bowing and cracking), the weight of the rotor when it is stationary for an extended period (creep), and contact pressure. Figure 4, illustrates the BR in the induction motors (I-M).



(a) (b)

Figure 3. The A&P rotor misalignment in the I-M: (a) PM (b) AM.

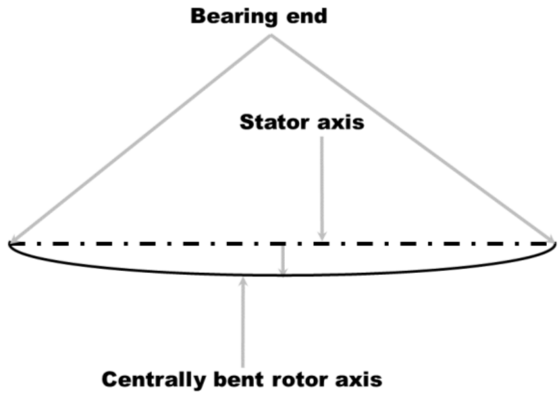


Figure 4. The BR in the induction motors.

Despite that, EF in induction motors is inside the scope of the article. The fault of stator winding (F-SW) can happen due to a turn-to-turn, coil-to-coil, phase-to-phase, or phase-to-ground fault. The majority of winding faults are the consequence of undiagnosed turn-to-turn deficiencies. The principal reason for turn-to-turn defects is long-term thermal ageing, which eventually leads to equipment failure. Moreover, F-SW can take place as a result of overheating (thermal stress), an unstable power feed (electrical stress), a hit by a broken, unsteady, or misaligned rotor bar (mechanical stress), vibration, installation failure, and oil contamination [37-39]. In this regard, the F-SW could cause the opening, shorting, or grounding of one or more winding circuits, extreme heating, and total production malfunction. Figure 5, displays several possible faults in the SW of an I-M.

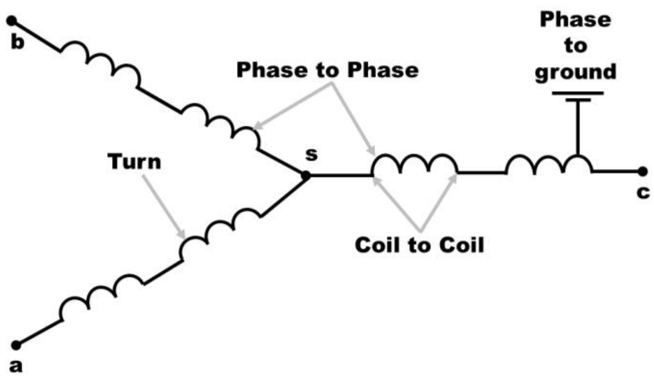


Figure 5. Several feasible faults in the SW of an IM

Due to faults of the broken rotor bar (BRB), the rotor of a squirrel cage I-M is exceptionally challenging, and the BRB is mainly due to rotor bar and end ring malfunction. The most prevalent IM rotor faults are BRB and the principal reason for these faults is fluctuating load and direct online starting. Figure 6, indicates the solid model of the BRB in an I-M.

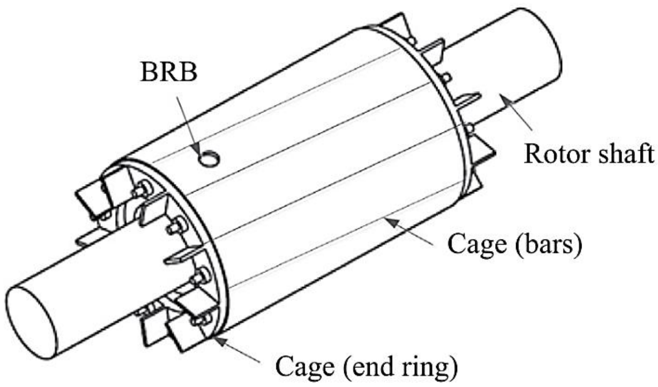


Figure 6. The solid model of the BRB in an I-M

In terms of single phasing and phase unbalance fault (SP&PUF), Whenever the voltages between the three phases are not approximately equivalent (unbalanced), the SP&PUF. A slight voltage variation leads to a sharp rise in current in the motor winding; if allowed to continue for an extended period, the motor could be destroyed by overheating. While one phase of the I-M is eventually open-circuited during operation, a single phasing occurs. Connectivity issues, blown fuses, and partial switch gear malfunction caused this. The single phasing effect is similar to voltage unbalance the worst possible case of voltage distress [36-40]. It is the main reason for overheating, shaft vibration noise, serious insulation harm, and stator winding missteps.

3. Signatures of failure

To detect the BRB fault, different fault signatures can be employed. The motor current is the most widely accepted fault signature due to its non-invasive technique. Furthermore, the voltage is the I-M neutral or the power flow. Lately, acoustic and vibration features have been utilized to diagnose induction motor faults [8]. In addition, many fault signatures, such as flux, motor speed, and torque, do not pique the attention of researchers due to their difficulty and expensive demand. This study explores these signatures for the fault identification process, as illustrated in Figure 7.

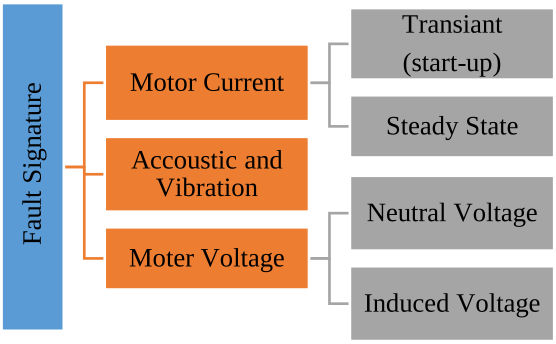


Figure 7. Fault signatures category

3.1 Analysis of motor current signatures

The BRB fault discourages current from flowing thru the broken rotor bar, which tends to result in a poorly balanced rotor flux. The poorly balanced rotor flux can indeed be thought of as a mixture of positive and undesirable sequence elements rotating in different directions at the slip frequency [40-43]. By each fault type, diverse conceptual research revealed a frequency signature element. The broken rotor bar fault in the I-M produces a distinct frequency range as expressed in Eq. (1) and Eq. (2).

$$F_b = (1 + 2\,k\,s)\,F_s \tag{1}$$

$$k = 1\,, 2, \ldots$$

The per-unit slip can indeed be determined as follows:

$$s = \frac{F_{slip}}{F_{syn}} = \frac{2\,f_s\ * I(p - f_r)}{2\,f_s\ * I * p} \tag{2}$$

Where the term p refers to the poles, f_s represents the rotor current frequency, f_r indicates the frequency of the supply.

3.2 Analysis of voltage signatures

In the following points, an evaluation of the detection method in two situations by using the voltage signal as a fault signature is described. Initially, a diagnosis based on determining the neutral voltage is made, accompanied by a diagnostic test based on determining the induced voltage. The categories of induced voltage and unbiased voltage diagnosis methodologies are based on signal processing techniques that are used at the loading level.

3.3 Acoustic and vibration analysis

Undoubtedly, all electrical machines produce significant vibrations, and vibration analysis can be employed to start investigating machine conditions. Magnetic, mechanical, and electrical forces all contribute to the beat. Surface vibration analysis is a commonly used method for identifying bearing and BRB faults [17]. Besides that, the detection process is supplied and especially in comparison to the detection process utilizing the current signature and instant angular speed. In this regard, the involvement of broken bars ended up causing speed oscillations, which also appear as harmonics from around the rotation duty cycle in the vibration spectrum.

4. The I-M fault diagnosis using artificial intelligence

The AI-based diagnostic system involves signal-based techniques and categorization capabilities, including the Bayesian classifier, fuzzy logic (FL), hidden Markov model, support vector machine (SVM) algorithm, genetic algorithm (GA), deep learning (DL), neural network (NN). Moreover, if firmly assessed and utilized effectively, A-I based on fault diagnosis could reduce operational costs by minimizing the number of pointless, scheduled corrective and preventive functions, as presented in Figure 8.

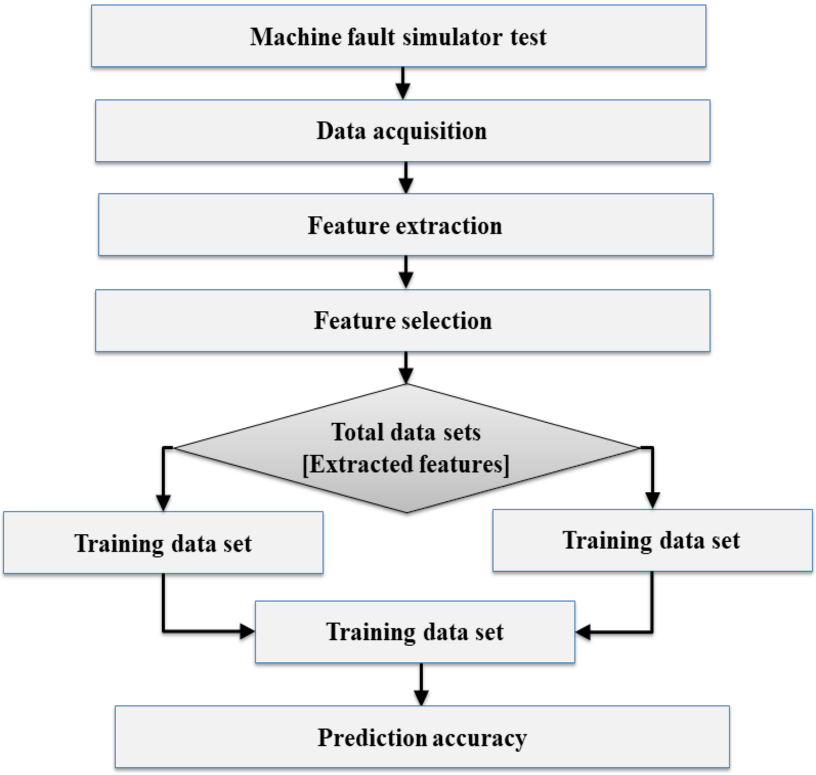


Figure 8. Fault diagnosis using the A-I

Moreover, it involves the following steps: data acquisition, feature extraction, feature selection, fault diagnosis, and system prognosis. Data can include vibration, current, acoustic, temperature, pressure, and oil analysis data, among other things [8]. In this point, the diagnostics' practical predictability relies entirely on extracting relevant features corresponding to I-M health conditions [44-49]. Table 1, indicates the purpose and A-I technique for Fault Detection and Diagnosis of I-M.

Table 1. The purpose and A-I technique for Fault Detection and Diagnosis of I-M.

Ref.	Purpose	Technique
[9]	• This work proposes to describe two feature selection techniques for induction motor acoustic signals SMOFS 32 MULTI-EXPANDED 1&2 GROUPS. • For acoustic signal identification, the k-nearest neighbors classifier (K-NN) backpropagation neural network (B-NN) and reconfigured classification algorithm (RC-A)based on coding were utilized.	K-NN B-NN RC-A
[10]	• This article characterizes different aspects of algorithms rotating machinery fault diagnosis trends utilizing the A-I, including naive Bayes (NB), deep learning (DL), and artificial neural network (ANN).	NB DL ANN
[11]	• Motor current signal-based bearing fault diagnosis methods provide an attractive solution to these drawbacks. As a side effect, this paper proposes a novel motor-current data-driven strategy for bearing fault diagnosis that employs statistical properties, genetic algorithms (GA), and machine learning (ML) models.	GA ML

5. Concluding

An effort has been made to evaluate the existing fault detection and diagnosis strategies of I-Ms for various electrical and mechanical faults. The performance and barriers of these strategies have also been explained clearly. In this context, the I-Ms are any industry's core and essential machines because they sustain and speed up the production process. As a result, enterprises are prepared to invest heavily in measurement, early detection, and diagnostic test of caused and incipient faults in I-Ms, particularly in specific applications, whenever they end up causing unplanned repairs and, in most instances, a complete collapse of I-Ms. Furthermore, the AI-based fault diagnosis strategies for I-Ms have been provided due to their reliability and are ultimately better than classical signal-based strategies. Because there are a lack of studies in this field, AI-based fault monitoring and fault diagnosis strategies for I-Ms, as disclosed in the literature, would further involve more motivation and consideration in the upcoming years. In the end, this article highlights the signatures of failure, including analysis of current motor signature, analysis of voltage signatures, and acoustic and vibration analysis.

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