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Review

Early Detection of Faults in Induction Motors—A Review

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Abstract: There is an increasing interest in improving energy efficiency and reducing operational costs of induction motors in the industry. These costs can be significantly reduced, and the efficiency of the motor can be improved if the condition of the machine is monitored regularly and if monitoring techniques are able to detect failures at an incipient stage. An early fault detection makes the elimination of costly standstills, unscheduled downtime, unplanned breakdowns, and industrial injuries possible. Furthermore, maintaining a proper motor operation by reducing incipient failures can reduce motor losses and extend its operating life. There are many review papers in which analyses of fault detection techniques in induction motors can be found. However, all these reviewed techniques can detect failures only at developed or advanced stages. To our knowledge, no review exists that assesses works able to detect failures at incipient stages. This paper presents a review of techniques and methodologies that can detect faults at early stages. The review presents an analysis of the existing techniques focusing on the following principal motor components: stator, rotor, and rolling bearings. For steady-state and transient operating modes of the motor, the methodologies are discussed and recommendations for future research in this area are also presented.

Keywords: artificial intelligence; condition monitoring; early detection; fault diagnosis; fault severity; frequency analysis; incipient fault; induction motor; machine learning; signal processing

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1. Introduction

Electric motor failures in industrial systems often result in unplanned downtime, loss of production, higher operating costs, and loss of profits [1]. The most common family of electric motors used in homes, businesses, and industry is the induction motor (IM) [2], for which there is a variety to choose from, depending on the power source, load requirements, mechanical interface, operating cost, energy efficiency, and reliability. IMs are often preferred over other kinds of motors since they are significantly less expensive, more robust, and capable of reliable operation in harsh ambient conditions, even in an explosive atmosphere. Induction motors, particularly those of the squirrel cage type, have been for almost a century the principal workhorse in industry [3]. Although IMs are more reliable than other types of motors, these machines are not exempt from developing faults in their structure or components, and these failures could lead to motor malfunction. Therefore, reliable condition monitoring for induction motors is of great value to avoid catastrophic unscheduled downtime [4]. An unexpected failure might lead to the loss of valuable human life or a costly standstill in industry, which needs to be prevented by precisely detecting the fault. The induction motor consists of many mechanical and electrical parts, such as a motor frame, stator windings, rotor cage, rolling bearings, fan, rotor shaft, among others. Despite induction motors are designed to be robust machines, they are exposed to external situations such as unstable supply voltage, unstable supply current sources, overloads, unbalanced loads, and electrical stresses. Due to the above-mentioned situations, damages in operation and natural deterioration of the material parts (or manufacturing defects), the motor will eventually develop a faulty condition.

Different condition states of an IM component can be characterized as healthy or faulty condition. In the healthy condition, the internal components have no degradation, and the induction motor operates with maximum energy efficiency. There are three states that characterize a faulty condition in IM. The first one consists in an incipient fault, known as the early stage, where the degradation begins to develop in one or several of the internal components. Although the motor component has damage (i.e., partially broken rotor bars), the induction motor can continue to operate with no apparent symptoms. In the second faulty state, known as the developed fault, the damage on the motor component is advanced (i.e., one or more broken rotor bars). In this condition, the IM still operates; however, the damaged component severely affects the motor performance. Finally, the third faulty condition, known as catastrophic fault, occurs when the developed failure has propagated to other components, and the IM is no longer operating. Three stages of fault growth can be considered for an IM: the incipient fault with a steady propagation, the advanced fault with an accelerated propagation, and the catastrophic stage with a very accelerated propagation. The first stage is from the healthy state of the component until the very incipient fault state. This stage covers most of the portion of the IM component's useful life. After the incipient fault is present, the degradation propagates slowly until the developed fault state is reached. Once the IM component presents developed fault symptoms, the last stage is the accelerated propagation, where the fault grows rapidly until a breakdown. The early detection of IM faults is carried out before an internal component exhibits a developed fault stage. According to the literature, the tendency in industry and academia is to consider incipient fault of the rotor or bearing when there exists only a partial fracture of an internal component. Whereas for the stator, it considers incipient fault when there exists a short circuit among less than 3% of the total turns winding.

Some surveys [5–7] revealed that the occurrence rate of bearing faults can reach around 40% of the total failures in induction motors, while other studies indicated that this rate can be even higher for small motors. On the other hand, as per the study by the Institute of Electrical and Electronics Engineers (IEEE) and the Electric Power Research Institute (EPRI), faults that occur in the stator of an IM are 36% and 28%, respectively. Finally, it is reported in the literature that rotor faults are responsible for 8–10% of failures in induction motors [8]. Bearing defects usually lead to an increment in the sound and vibration levels as well as high temperatures. A severe damage can even provoke catastrophic failures (i.e., rotor-stator rubbing, insulation damage). Moreover, stator failures during motor operation lead to reduced efficiency of the machines. Once begun, the stator fault provokes progressive degradation of insulating materials, ultimately leading to electrical breakdown. Despite rotor failures have a lower rate of occurrence compared to the above-mentioned ones, these faults are just as important because they can lead to shaft vibrations and winding damages, and thus bearing or stator failures. The existence of damages or anomalies at incipient stage implies additional losses in that part of the machine due to their improper operation. IM faults usually progress from incipient to a very advanced stage in a lapse of time, depending on the type of failure. Unless detected early enough, a motor failure may lead to costly standstill in industry or fatal consequences such as fire, explosion, and even loss of human lives. The constant need for reducing industrial injuries, unscheduled shutdowns, and operational costs has led to developing new techniques for early fault detection before they become prominent to cause machine failures. Some of the advantages of early fault detection in induction motors are as follows:

- Cost savings which are realized by estimating potential failures before they occur [9].
- Facilitate pre-planned preventive machine schedules.
- Better maintenance activities instead of replacing components [10].
- Prevent unexpected stop in the production lines.
- Prevent an extended period of down-time caused by extensive machine failure.
- Improve the induction motor efficiency [11].

In the recent literature, there are some excellent reviews on fault detection techniques and their implementation in induction motors [12–16]; however, these reviews are limited to detecting developed or advanced faults. This paper presents a review of diagnosis techniques and methods for the detection of faults at incipient severity stages, due to its important role in the condition monitoring field, and decision-making in industrial maintenance activities. The existing literature on the subject is categorized into two approaches based on the operational mode of the IM: steady-state and transient regime. In the steady-state regime, the reported techniques apply analysis in the time-domain or frequency-domain to extract fault indicators and evaluate the motor condition. In the transient-state regime, the reported methods obtain fault indicators from time-frequency maps that allow evaluating the present state of fault indicators as well as their evolution over time. The organization of this paper is as follows. Section 2 presents the type of faults that induction motors develop in their main components and briefly describes the causes and consequences for each failure with special focus on early detection. A brief description of different signals used in the monitoring condition field for fault detection is presented in Section 3 including practical considerations for proper signal analysis and remarking advantages and limitations of each monitoring signal. In Section 4, a review of various techniques that are used for early fault detection in induction motors is presented; including those that are based on signal processing and knowledge-based. Section 5 is dedicated to the analysis of the different methodologies, whose strengths and weaknesses are described and discussed. According to the reviewed techniques, the conclusions are shown in Section 6. Lastly, in Section 7, directions and a future perspective are presented.

2. Faults in Induction Motors

Induction motor faults are commonly categorized as mechanical faults and electrical faults. Despite the existence of many fault classifications, this work categorizes motor failures according to the component that develops the fault for the sake of simplicity. The most common failures occur in three principal components of the rotatory machine. Figure 1 shows these main parts: the stator, the rotor, and rolling bearings.

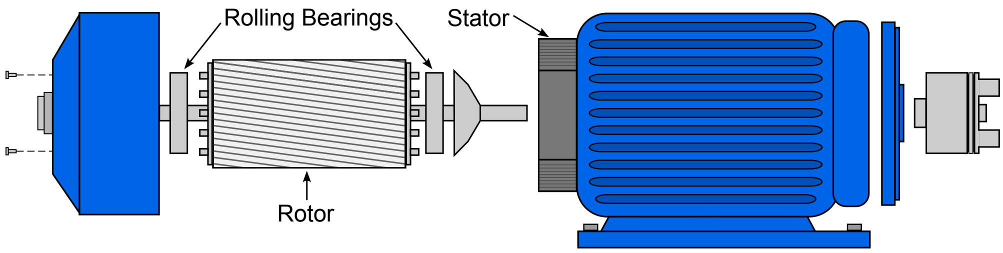

Figure 1. Three fundamental components of an induction motor: stator, rotor, and rolling bearings.

2.1. Stator Faults

The stator consists of a laminated core, an outer frame, and insulated electrical windings. Its components are subjected to electrical and environmental stresses, which severely affect the stator condition leading to faults [17]. Stator faults (SF) can be categorized based on their localization as failure in the stator frame, fault in the stator winding, and failure in the laminations of the stator core. Among these, stator winding failures are the most severe faults and are often caused by failure of insulation of winding, which leads to local heating. If unnoticed, this local heating further damages the insulation of the stator winding until a catastrophic failure may occur. This fault is also known as the short circuit inter-turn fault. The appearance of stator faults depends on the size of the electrical machine [18]. According to [19], low-voltage IM stator faults account for only 9% of total failures. In medium-voltage IM, the percentage increases to 35–40%, whereas for high-voltage IM, it is more than 65%.

2.2. Rotor Faults

The rotor is the main driving shaft in induction motors through which the mechanical energy is transferred to the load. This component is placed inside the stator, and for a squirrel-cage type, it consists of the shaft, the aluminum or copper bars, and the end rings. Approximately 8 to 10% of all failures in IM are at the rotor. These faults can be classified as: broken rotor bars (BRB), cracked end-ring, and rotor eccentricities. Broken bars are caused by a combination of different stresses (mechanical, electrical, and thermal), manufacturing problems, dynamic stress from shaft torque, and fatigued mechanical parts [12]. This type of fault may not show any incipient symptoms, propagating to the next bars and leading to a sudden collapse of the rotor, producing damage in the stator and an abrupt interruption of the motor operation [20]. On the other hand, air-gap irregularities are produced by rotor eccentricities when the rotor axis of rotation does not coincide with stator geometrical axis. Manufacturing and constructive errors that generate a non-uniform air-gap or an incorrect positioning of the stator and rotor at the commissioning stage produce static eccentricity. When the center of the rotor is not at the center of rotation, then dynamic eccentricity is produced. The common causes of dynamic eccentricity are rotor shaft bending and bearing faults.

2.3. Rolling Bearing Faults

Rolling element bearings are the support of the shaft rotor in the induction motor in order to facilitate its rotation by reducing friction. In a rough manner, a bearing has four components: an inner raceway, an outer raceway, balls, and a cage that provides an equidistant arrangement between the balls. Bearing faults (BF) are classified as localized failures and distributed faults (roughness or non-cyclic) [7]. Distributed defects affect a whole region and their mathematical modeling is very difficult. In contrast, localized failures are single-point defects and can be classified according to the affected element: inner raceway defect, outer raceway defect, ball defect, and cage failure. Bearing wear can be caused by a wide variety of reasons, such as excessive or deficient lubrication (due to inadequate viscosity, excess or lack of grease, lubricant contamination, etc.), circulation of bearing currents (in power converter-fed motors), brinelling (due to punctual overloads, severe impacts), etc.

2.4. Early Detection of Faults

Induction motors are symmetric machines and the occurrence of any type of fault is linked to the harmonic content of its monitored signals. The existence of a fault in IM results in the appearance of specific frequency signatures. In general, fault detection techniques are based on the magnitude evaluation of these signatures. When there is an anomaly in the mechanical structure of the rolling bearing, characteristic frequencies emerge in the vibration spectrum as a consequence of the asymmetry. There are two bearing defects that are analyzed in the literature from the severity level point of view, the outer race defect and the inner race defect. The related frequencies are shown below [21].

$$\text{Inner raceway}: \ f_i = \frac{N_b}{2} f_r \left(1 + \frac{D_b}{D_c} cos\,\beta\right), \tag{1}$$

$$\text{Outer raceway}: \ f_o = \frac{N_b}{2} f_r \left(1 - \frac{D_b}{D_c} cos\,\beta\right), \tag{2}$$

where f_r is the rotational frequency, N_b is the number of balls in the bearing, D_c is the pitch or cage diameter, D_b the diameter of the balls, and β is the contact angle between a ball and the raceway. When a stator fault occurs, the current through the shorted winding affects the magnetic field and is reflected in the axial flux as follows [22].

$$\text{Stator fault}: \ f_{ss} = f_s \left[\left(k \pm n\frac{1-s}{p}\right)\right] \tag{3}$$

where k is the order of the time harmonic, n the order of the shorted coil space harmonic, s the machine slip, p the number of pole pairs, and f_s the supply frequency. The damage of broken bars in the rotor produces additional frequencies in the current spectrum. These signatures are characterized by [23]:

$$\text{Broken rotor bars}: \ f_{brb} = f_s(1 \pm 2s) \tag{4}$$

Additionally, any fluctuation in the load torque will produce oscillations in the stator currents at frequencies of

$$\text{Load oscillation}: \ f_{load} = f_s \pm m f_r = f_s \left[1 \pm m\left(\frac{1-s}{p}\right)\right] \tag{5}$$

where m is the order of the harmonic. Since the same fault harmonic is given by BRB, a low-frequency load-oscillation results in stator currents that can overlap those produced by the BRB fault [24].

The magnitude of each of these fault frequencies is directly related to the severity level of the fault. The higher the severity level, the higher the magnitude of the spectral component. Each failure type has a different evolution over time since the degradation of the component depends on its construction and the material from which it is made. Figure 2 illustrates the degradation of the motor components and its severity levels: bearing failure (Figure 2a), stator failure (Figure 2b), and rotor fault (Figure 2c). The tendency in industry and academia is to be able to make an early detection of the motor component degradation. For bearing failure, the early detection is considered when the diameter of the crack (λ) is less than $1/8$ the diameter of the bearing ball (Θ). For broken rotor bars, early detection is considered when one bar is partially broken and the depth of the breakage (ρ) is less than the total length of the bar (l). Whereas for stator faults, it is considered that an early fault occurs when there is a short circuit between less than $1/30$ times the total turns of the winding (Φ). Figure 2d–f illustrates the relationships of the fault with the construction of the motor components. As component degradation is very low at an early stage, the magnitude of fault signatures is also very low. Therefore, a condition diagnosis of the motor component when the degradation is incipient presents a challenge in the detection, identification, and evaluation of failure indicators.

The most important characteristic of any condition monitoring scheme is its quickness of detection. Different types of faults usually progress from incipient to a very advanced stage in a different manner, as is shown in Figure 2. This work only considers fault detection at an early stage. For the detection of early rotor failure, only partially broken rotor bars are taken into account, whereas fully broken rotor bars are considered a developed fault. This is because once a bar is completely fractured, the failure spreads rapidly to adjacent bars and subsequently damages the stator winding causing irreparable damage. In the case of bearing faults, the early fault condition is considered when the diameter of the fracture in the inner or the outer race is less than 12.5% of the diameter of the bearing ball, since from then on, the bearing stroke undergoes great alterations and alters the rotor symmetry, making the failure to be considered as developed or advanced. Finally, the stator failure is considered in an early condition before exceeding 3.33% of the turns in the stator phase. Once the short circuit begins, it propagates rapidly in a very short time. Unless detected early enough, it might lead to catastrophic consequences. Faults detected at advanced stages are far more likely to cause unplanned breakdowns in the line production than those detected while the failure is still at an early stage. Techniques that can detect faults at an early stage are very desirable for the possibility of correcting the faulty condition entirely with low impact to the production line. For early detection to be an effective and practical approach, techniques must satisfy three basic requirements. First, the detection analysis should be able to distinguish faulty IM from healthy IM cases with a high degree of accuracy, showing both low rates of false-positives and false negatives. Second, the detection should be possible before the fault progresses to a developed stage, when the propagation is accelerated, and preventive actions are less effective. Lastly, the diagnosis methodology should allow the assessment of the IM condition when the motor is fed by inverters. It must be noticed that inverters induce several spectral components to the voltage, current, and vibration signals, which overlap with the fault-related spectral signatures; moreover, the magnitude of the fault-related components are very close to the noise floor, making the evaluation of the fault severity difficult.

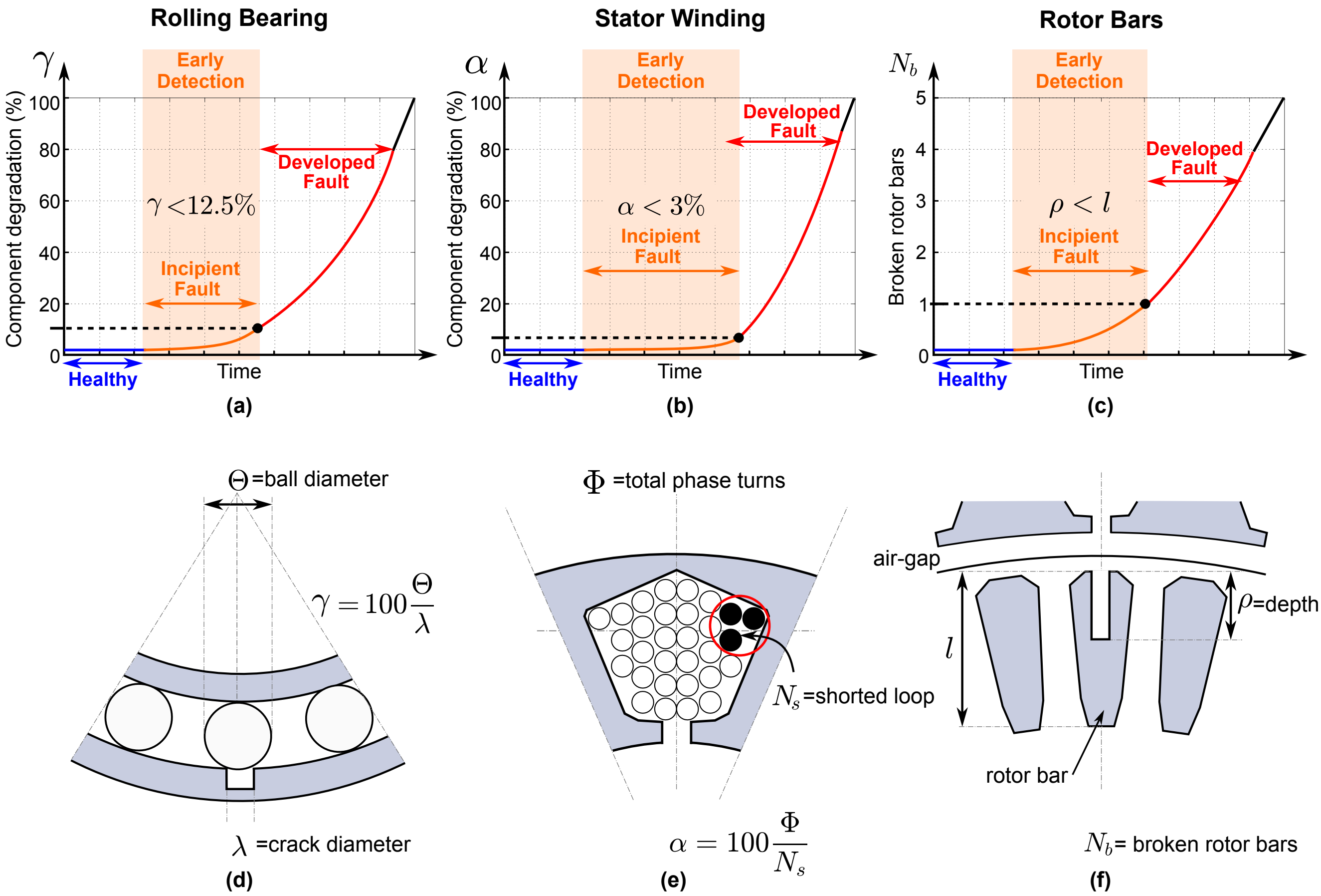

Figure 2. Degradation stages of induction motor components: (**a**) rolling bearing degradation, (**b**) stator winding degradation, (**c**) rotor bar degradation, (**d**) rolling bearing schematic, (**e**) stator winding schematic, and (**f**) rotor bars schematic.

3. Monitoring Signals for Fault Detection

When IMs are running, each type of fault generates characteristic features in the machine's behavior. Fault detection techniques can be based on the analysis of vibrations, stator current, shaft speed, acoustic emissions, voltage, internal air-gap flux, external stray flux, electric power, and temperature (usually trough infrared thermography).

3.1. Vibration Monitoring

Among the many condition monitoring techniques, vibration-based methods are the most widely preferred owing to their reliability, non-intrusiveness, and easy measurability. Vibration monitoring has been used for decades and utilized to detect mechanical faults in IM. In working mode, radial magnetic forces are produced between the rotor and stator surfaces and are proportional to the square of the flux density. These forces result in stator core, winding, and motor frame vibrations. As faults associated with the rotor, stator, and rolling bearings alter the machine symmetry, vibration signals which are a function of the symmetrical air-gap and symmetrical components will also change [25]. Most vibration measurements usually use sensors of vibration-acceleration that work based on the piezoelectric effect, whose output voltage is proportional to the force applied to the sensor [26]. The vibration signals need to be processed in order to extract the fundamental components and to filter out nonlinear effects due to the cover frame and noise from the environment.

3.2. Stator Current Monitoring

Even though vibration signals have been widely utilized, most of the work in the last decade has been directed toward stator current monitoring also known as motor current signature analysis (MCSA) [27]. The stator current monitoring can provide unique fault patterns for the effective detection of mainly electrical faults, i.e., the stator winding fault, broken rotor bars fault, phase unbalance, and single phasing [28]. Motor current monitoring provides a non-intrusive way to continuously monitor the health condition with the aim of using non-invasive sensors and possibly already existing in the drive for motor control.

3.3. Magnetic Flux Monitoring

An alternate approach based on magnetic flux monitoring has received the attention of many researchers and motor manufacturers during the last years. The great improvements and reduction in the costs and dimensions of the required transducers, the development of advanced signal-processing tools that are suitable for magnetic flux analysis, along with other inherent advantages provided by this technology, are important aspects that have permitted the proliferation of flux-based methods [29]. The magnetic flux in IM is broadly classified as internal magnetic flux and external stray magnetic flux. However, using magnetic flux as monitoring signal for fault detection is not new and there are works carried out decades earlier [30].

3.4. Others

Apart from locating specific features in the above-mentioned signals, other physical magnitudes, such as rotor position, rotor speed, torque, acoustic emissions, electric power, and temperature have been investigated in the recent years by researchers in the field. Sometimes, the combination of several monitoring signals is used by fault detection techniques to improve the detection rate. There are also other detection methods being developed on modeling and control techniques, such as state observers [31], state estimators [32], signal injection, and parameter estimators.

Despite the relevant advances obtained with the vast diversity of proposed approaches in the fault detection field, the effectiveness of the techniques usually depends on the induction motor size, loading, state operation (steady or transient), supply type, control mode, type of the fault, and to a great extent, on the type of the monitoring signal. Table 1 summarizes some of the main advantages and drawbacks of the most common monitoring signals.

Table 1. Main advantages and drawbacks of common monitoring physical magnitudes.

Signal	Advantages	Drawbacks	Sensor Cost
Vibration	high sensitivity to mechanical faults	environment noise, reverb effects	low
Stator Current (MCSA)	remote monitoring, clear fault patterns	high amplitude of the supply frequency	very low
Magnetic Flux	easy sensor installation	interference among patterns	very low
Shaft Speed	low noise level	high dependence on load inertia	high
Sound	very easy sensor installation	environment noise, echo effects	low

4. Review of Techniques and Methodologies

In general, early fault detection techniques based on signal analysis relies on: (1) acquiring one or various physical magnitudes of the induction motor, (2) processing the measured magnitudes (signals) with suitable tools to extract fault patterns, and (3) analyzing the patterns to determine the fault severity. According to the reviewed technical literature, two main approaches for early fault detection can be determined based on the IM operation mode: the steady-state analysis and transient-state analysis. The techniques employed in these approaches depend on the stationarity or non-stationarity of the monitored signals.

4.1. Early Fault Detection via Steady-State Analysis

When an induction motor operates at a constant speed, measured magnitudes from the machine can be described by periodic signals. Thus, in the literature, the best-known techniques for processing these signals belong to the frequency-domain analysis.

Although most IMs in the industry are fed directly from the grid, in the recent years, the use of inverters has become more widespread due to their capabilities in speed control and energy efficiency advantages. Nevertheless, their use also affects fault detection in IMs due to the higher noise and rich harmonic content they cause in the measured signals for condition monitoring. For these reasons, it is important to separate the analysis of early fault detection methods according to the motor power supply.

4.1.1. Direct Line-Fed Induction Motors

Condition monitoring methods for the early detection of induction motor faults based on signal spectral analysis are found in the literature. In [33], the authors presented a methodology for incipient broken rotor bar detection based on the spectral analysis of vibration signals with the FFT. The proposed approach is based on sparse signal representations [34] and the use of dictionaries trained with sets of signals with the fault to be detected. The incipient fault is simulated by drilling only 5% of the length of a rotor bar, and high detection accuracy is achieved even in unloaded motor operation but only for a line-fed induction motor.

As the authors of [35] pointed out, online detection of low-severity stator interturn faults is one of the most challenging electrical machine defects to detect. If this fault develops undetected, it can lead to a ground fault and complete motor burning. The authors used a modified induction motor that allows them to simulate very low severity interturn faults: 0.25%, 0.5%, and 0.75%. They proved that conventional monitoring methods, such as MCSA, Park's vector approach and negative sequence current analysis, are unreliable and insensitive to these very low-severity interturn faults. However, they were able to detect these faults by using three different coils placed in different motor locations to collect the motor stray flux. The Park vector of these three signals is calculated, and its modulus is analyzed with the FFT.

Recent condition monitoring approaches have benefited from advances in computational technologies that allow the combination of signal processing methods (time and frequency domain) with knowledge-based techniques (KB) such as machine learning (ML), genetic algorithms (GA), artificial intelligence (AI), surface learning and deep learning (DL). For instance, reference [36] dealt with the detection of partially broken rotor bars. It proposed a hybrid approach combining electrical-synchronous averaging (ETSA), Discrete Wavelet transform (DWT), and fuzzy logic algorithms. The first two techniques are used to identify a frequency band with fault-related components in the stator current, and the third is a classifier to assess the severity of the fault. It is worth noting that this methodology can detect a hole of only 2 mm in a 36 mm bar, even under no-load conditions.

In the paper [37], hybrid DL architectures were explored to solve the problem of classifying interturn faults at an incipient stage. This detection method uses a hybrid architecture based on a one-dimensional Convolutional Neural Network (1DCNN), long short-term memory, and gated recurrent unit. This approach can distinguish this fault from other conditions, such as voltage imbalance and load variations.

Reference [38] also showed very good results in detecting interturn faults at an early stage. The authors compared two different ANN-based approaches: (1) the first one is based on a multi-agent system with a classification behavior; (2) the second one uses a neural estimator. The input data of both methods are the analysis of the stator current in the time domain, which differentiates them from other approaches based on frequency-based signal processing. Their approach has been tested by simulating short circuits covering 1 to 10 percent of the stator winding and with a wide range of motor power ratings and voltage supplies. Reference [39] made another contribution to the same topic as the previous one. Their proposal is based on analyzing the negative sequence of the stator current to detect motor asymmetries produced by this type of fault. The results are based on simulation and corroborated by experimental measurements under varying motor load conditions. Most of these knowledge-based (KB) works achieve good detection accuracy of over 95%. However, it is important to note that these KB approaches require a large amount of data (from both the healthy and faulty induction motors), so they have limitations for generalization and are techniques with low scalability.

The detection of bearing failures has also attracted many researchers, and numerous papers have been published. However, few of them deal with their early detection or the diagnosis of these faults at an early stage before they develop into catastrophic breakdowns. The vast majority of these works is based on signal processing, knowledge-based techniques or a combination of both.

In [40], the processed signal is the stator current, which allows the detection of incipient cage and outer race-bearing faults in a 2.2 kW line-fed induction motor. The authors proposed a spectral frequency subtraction using several wavelet transforms (DWT, stationarity wavelet transform (SWT), and wavelet packet decomposition (WDP)) to suppress the dominant components in the stator current spectrum. This suppression makes it possible to observe fault-related frequency components whose amplitude is very small, especially at an early fault stage. Due to the impossibility of installing vibration sensors in many industrial applications, the authors in [41] also proposed using two stator current signals for early bearing damage detection. Their interesting contribution pre-processes these two signals with fractional B-spline wavelet transforms for denoising them. Next, the overlapping group shrinkage (OGS) algorithm reconstructs two signals that will be used as the input to a convolutional neural network (CNN) and a long short-term memory (LSTM) algorithm for feature extraction. Next, information fusion and fuzzy c-means algorithms perform the fault diagnosis. Remarkably, this methodology is based on unlabeled learning, and it is tested in an actual industrial application with an induction motor driving a centrifugal pump.

4.1.2. Inverter-Fed Induction Motors

Even though much research has been done on incipient fault diagnosis in induction motors, all previous works still deal with line-fed motors under stationary conditions. Recently, in industry, it is more common to see IM fed by power electronic converters (also known as voltage source inverters) [42]. Furthermore, the stationary operation is quite unusual in the industrial environment due to voltage variations, speed oscillations, and load changes [43]. In this context, some techniques have been proposed and showed very good results for early fault detection in inverter-fed IM and some of them under non-stationary conditions. In [44], a combination of two-level hybrid hierarchical CNN with SVM was proposed for incipient interturn fault diagnosis. The authors showed that their proposal is fast and has significant performance improvement in accuracy in comparison with other proposals. The authors of [45] concentrated on the incipient inter-turn short circuit detection and estimation of its severity. Moreover, they studied the effect of load oscillations on the recognition of fault patterns in the stator current. Another combination of SP and KB techniques can be found in [46], the authors described a methodology combining the DWT for multi-resolution analysis, statistical features, and ML to detect incipient short circuits using axial leakage flux signals.

Several authors targeted the detection of one or more BRB in IMs controlled by electronic converters. Besides the fact that many of those works established a successful detection, other works improved the techniques to extract more incipient BRB fault features from the measurements. Interestingly, in [47], the authors presented a novel supervised classification approach for BRB fault diagnosis based on adaptive boosting algorithm with an optimized sampling method that deals with an imbalanced experimental dataset. Experimental results of the proposal provide accurate diagnosis of different intermediate severities before a full BRB. Another work that investigates various severity levels was presented in [48], where a combined approach with the fast Fourier transform (FFT) and the multiple signal classification (MUSIC) algorithm is proposed. This study exposes that incipient rotor faults in a squirrel-cage rotor, prior to the complete breaking of a rotor bar, are better identified when IMs are feed by some inverters than others. In addition, to detect incipient BRB, the authors of [49] proposed to use robust statistical techniques that are commonly applied in quality control applications. In this study, the proposal can detect partial bar breaks of 6.4 mm, 11.7 mm, and 17 mm (a full-broken bar).

Otherwise, different types of diagnosis methodologies have also developed for bearing failures in inverter-fed induction motors. The investigation in [50] presented a technique to attenuate multiple dominant harmonics with the aim to reduce spectral leakage, expose minute fault components, and improve the amplitude estimation of fault-related harmonics. Experimental outcomes of the methodology prove that the algorithm used for the spectral estimation of the vibration signal is adequate for an early determination of inverter-fed IM faults (inner raceway, outer raceway, cage train, rolling element, and in a single bar of the rotor). Another interesting technique for bearing failure recognition was presented in [51]. Its main contribution lies in the proposal of a condition monitoring strategy that is focused on the analysis and identification of five different fault severities of the outer race bearing (drill bits with diameters of 1 to 5 mm). The proposed approach is supported by fusing information from different sensors and the application of ML and AI. Apart from KB methods, reference [52] proposed a new approach based on a dynamic model in $d-q$ coordinate systems and analyzed BRB and turn-to-turn short fault. This approach uses a residual technique between model and measured signals. Experimental analyses show that the designed detection and isolation scheme provides high sensitivity and accurate isolation to incipient winding faults. To suppress the impact of the motor fault, an interesting control method was proposed in [53]. This control method includes a monitoring technique that can detect faults occurring due to stator winding short circuit at an incipient stage by means of a harmonic analysis of the magnetic air-gap flux. Methods based on steady-state analysis such as the above-mentioned are noteworthy in motor fault detection. However, these methods have severe limitations and may lead to false positives or false negatives. Table 2 shows a performance comparison of the above-mentioned applied methodologies.

Table 2. Comparison of early fault detection methodologies applied on IM under steady regime.

Ref.	Monitoring Signal	Power Source	Detected Fault	Applied Algorithm	Fault Severity
[33]	vibrations	line	broken bar	FFT + OMP + SVM	10%
[35]	magnetic flux	line	interturn	FFT + PV + EPV	0.25%
[36]	1-ϕ current	line	broken bar	WT + ETSA + FL	15.5%
[37]	3-ϕ currents + 3-ϕ voltages	line	interturn	1DCNN + LSTM + GRU	0.358%
[38]	3-ϕ currents	line	interturn	ANN	1%
[39]	3-ϕ currents + 3 voltages	line	shorted turn	Phasor Compensation	1.7%
[41]	3-ϕ currents	inverter	bearing	Fuzzy + C-means	10%
[44]	3-ϕ currents	inverter	interturn	HCNN + SVM	0.3%
[45]	1-ϕ current	inverter	interturn	DWT	1%

Table 2. *Cont.*

Ref.	Monitoring Signal	Power Source	Detected Fault	Applied Algorithm	Fault Severity
[46]	axial flux	inverter	interturn	DWT + SF + ML	1.41%
[47]	1-ϕ current	inverter	broken bar	AB + OS	25%
[48]	1-ϕ current	inverter	broken bar	MUSIC + FFT	50%
[49]	1-ϕ current	inverter	broken bar	QCC	33.33%
[50]	1-ϕ current	inverter	bearing	RQS	10%
[51]	1-ϕ current + 2 vibration	inverter	bearing	SF + ANN	11.1%
[52]	3-ϕ voltages + speed	inverter	interturn	Robust Observer	3.83%
[53]	1-ϕ current + 1-ϕ voltage + 1 flux	inverter	interturn	DNN	2.8%

4.2. Early Fault Detection via Transient-State Analysis

On the other hand, the analysis of IM data with non-stationary behavior mostly relies on time-frequency transforms computed from signals that are measured when motors are running under transient regimes. The most common time-frequency decompositions are the short-time Fourier transform (STFT) and the wavelet transforms (WT). The use of a combination of one variant of wavelet transform, the recursive wavelet transform, and a widely used tool in quality control, the statistical process control was presented in [54] to detect incipient stages of rotor fault. The methodology offers high accuracy in broken bar detection, starting from a deep hole of 3 mm in one bar to 2 fully broken bars. The detection was implemented during a steady-state operation mode and for short transient events of the motor. Another methodology using the wavelet transform has been reported in [55]. The fault diagnosis system is based on an empirical neuro-predictor and the application of wavelet analysis to residual signals between the model and the measured physical magnitudes. The method reports effective accuracy in detecting the most widely encountered electrical and mechanical faults. The motor anomalies consist of variations in the balance of the electric power supply and the driven mechanical load level when the IM experiences short transients as the load is varied from 0% up to 120% of the rated load. The investigation carried out in [56] examined the impact of incipient rotor faults on the shaft speed of an inverter-fed induction motor. This work used a tachogenerator to measure the rotor speed and applying a high-resolution spectral analysis (MUSIC algorithm) which detects and quantifies the fault severity in the time-frequency domain. This methodology can identify 5 health condition levels (healthy, $\frac{1}{4}$ BRB, $\frac{1}{2}$ BRB, $\frac{3}{4}$ BRB, and 1 BRB deep hole of 13 mm) during startup transients of 10 s. In [57], the stator current of a DOL-fed motor starting was used to extract statistical features, and using homogeneity as a classification index. This methodology can identify and classify differences between distinct fault severity conditions of the rotor bars (e.g., healthy, $\frac{1}{2}$ BRB, 1 BRB, and 2 BRB). The low computational complexity of the homogeneity index makes the method suitable for hardware implementation. The authors of [58] provided interesting time-frequency results for detecting various motor conditions such as stator winding interturn shorts, and phase to ground faults. In this work, the Stockwell transform (STW) was used to analyze the starting current of a DOL startup transient, the resulting time-frequency matrix was used to extract fault features and fed two different support vector machine (SVM) models. An average classification accuracy of 96% was achieved for both types o faults. Other researchers proposed in [59] a fault diagnosis technique based on the acquisition of signals from multiple sensors in order to assess the occurrence of single, combined, and simultaneous fault conditions in an induction motor. The proposal performs principal component analysis (PCA) to each signal, then joined as input to a decision tree method. The considered early fault stage was a rough hole of 2 mm diameter, at a depth of 14 mm, into the rotor bars of a DOL-fed motor. As another example of the transient analysis, in [60], the tooth-FFT algorithm was introduced to track time-varying frequency components. Half and full broken bars were considered; experimental results obtained a percentage of detection of 97.35% for all motor conditions. In Table 3, a comparison of the applied methodologies is presented.

Table 3. Comparison of early fault detection methodologies applied on IM under transient regime.

Ref.	Monitoring Signal	Power Source	Detected Fault	Applied Algorithm	Fault Severity
[54]	1-ϕ current	line	broken bar	WPD + SPC	75%
[55]	3-ϕ currents 3-ϕ voltages + speed	line	interturn	WPD	0.92%
[56]	speed	inverter	broken bar	short-time Minimum-Norm	25%
[57]	1-ϕ current	line	broken bar	Homogeneity	25%
[58]	3-ϕ currents	line	interturn	Stockwell transform	1.6%
[59]	3-ϕ currents + 3-ϕ voltages + 3-axis vibrations	inverter	bearing	PCA + decision trees	12.5%
[60]	1-ϕ current	line	broken bar	Tooth-FFT	50%

5. Discussion

According to the literature, three monitored signals are principally used for early fault detection in IM: mechanical vibrations, stator current, and magnetic flux. The vibration signal is widely used because it is sensitive to internal asymmetries in the machine during its operation. Despite this advantage, it is difficult to determine specifically the internal fault that produces the asymmetry. Furthermore, used sensors are sensitive to external vibrations also; thus, it is common that vibration analysis suffers from external interference. Important to note that monitoring vibration signals requires a short sampling period at the acquisition stage due to fault patterns appearing in the high-frequency band. On the other hand, the stator current contains specific fault patterns for each type of fault and the measurement is not very sensitive to external interference. Furthermore, most of the spectral patterns related to a fault type are generated in the low-frequency band of the spectral content. Therefore, a short sampling period in the acquisition stage is not necessary. Despite the benefits of current monitoring, when the induction motor is powered by an electronic converter, additional frequency components are induced in the current spectrum, thereby adding many spectral components foreign to the MI behavior that can alter the magnitude of the fault indicators.

Some works use magnetic flux signals. This type of magnitude is spectrally dense, so it has many frequency components interacting with each other, which makes it difficult to evaluate the magnitude of one spectral component without interference from another. One of the advantages presented by the authors when monitoring this signal is that the magnetic flux is not sensitive to external mechanical vibrations and depending on the location of the sensor; the flux signal makes it possible to locate faults in specific places of the motor.

Most of the reviewed works focus on analyzing signals from IM operating at steady state. This analysis has many advantages compared to the transient-state analysis because in the steady-state analysis, several fault indicators can be extracted by classic signal processing techniques. On the contrary, the analysis of non-stationary signals requires more complex tools and advanced signal processing techniques. Despite the complexity of the analysis, the study of IM operating in transients permits locating and tracking the behavior of specific fault indicators for each internal motor component. This allows more accurate fault identification and severity diagnosis compared to the analysis of an IM operating at steady-state.

In the literature, it is possible to find three groups of techniques that are mainly used for early fault detection: classical, modern, and heuristic. In Table 4, a list of the applied methodologies is presented. First, in the classical techniques, statistical tools have been used mainly to extract fault features from the behavior of signals in the time-domain. Meanwhile, frequency-domain tools have also been used to extract fault components from the spectral content of the analyzed signal, the best known is the Fourier transform. Although these classical techniques have worked to detect incipient faults in IM operating at steady-state, this group of techniques is not appropriate for monitoring time-varying systems. Some authors used modern techniques, which allow the analysis of physical magnitudes in a simultaneous time-frequency domain. The tools used for a time-frequency analysis are the STFT, the wavelet transform, the Winner–Ville transform, the Hilbert–Huang transform, and high-resolution decompositions (short-time MUSIC), among others. These modern techniques have positioned as great alternatives in the field to reduce diagnostic errors that classic techniques have. Despite the advantages of this type of techniques, they require a greater computational burden and a higher level of interpretation of results than classical techniques. In most recent works, the application of heuristic methodologies such as GA, pattern recognition, ML and AI techniques can be found. These works report high levels of accuracy in the detection of some faults at incipient stage. Despite the good results reported, these methodologies require a very large and diverse database.

Table 4. List of the different applied techniques.

Technique	Year	Detected Fault	References	Advantages
Adaptive Boosting	2017	BRB	[47]	improves the predictive accuracy of classifiers
Artificial Neural Network	2017	SF	[38]	improves efficiency in process decision
C-means	2021	BF	[41]	improves the performance by suitable changes in regularization, cluster shape, and cost function
Convolutional Neural Network (1D)	2021	SF	[37]	extracts deep features maps
Decision trees	2020	BF	[59]	reduces specific parameters information for diagnosis
Deep neural network	2017	SF	[53]	high accuracy in classification and estimation
Discrete wavelet transform	2021, 2021	SF	[45,46]	multi-scale analysis
Down-sampling	2017	BRB	[47]	reduces data length
Electrical time synchronous averaging (ETSA)	2022	BRB	[36]	improves classification
Extended Park	2021	SF	[35]	improves the relation of harmonics with the severity of the fault
Fourier transform	2001, 2018, 2021	BRB, BRB, SF	[33,35,47]	reduces sensitivity to noise
Fuzzy logic	2022	BRB	[36]	improves classification features
Gated recurrent Unit	2021	SF	[37]	processes extra features
Hierarchical CNN	2021	SF	[44]	improves the severity simultaneously level features/higher classification accuracy with lesser testing time
Homogeneity	2017	BRB	[57]	improves classify differences on distinct operational conditions
Linear discriminant analysis	2021	BF	[51]	reduces the dimensionality of features
Long short-term memory	2021	SF	[37]	improves the classification of long term and nonlinear time data
Multiple signal classification	2017	BRB	[48]	high-resolution frequency analysis
Orthogonal matching pursuit	2018	BRB	[33]	improves the classifier criterion /majority decision classifier
Optimized sampling	2017	BRB	[47]	improves the original imbalanced dataset
Principal component analysis	2020	BF	[59]	reduces the dimension of attributes
Phasor compensation	2022	SF	[39]	improves the calibration of disturbances effect
Quality control charts	2017	BRB	[49]	reduces the problem of classification/improves the robustness
Rayleigh quotient spectrum	2021	BF	[50]	reduces complexity, accuracy in frequency estimation

Table 4. *Cont.*

Technique	Year	Detected Fault	References	Advantages
short-time minimum norm	2021	BRB	[56]	improves the frequency resolution analysis avoiding spurious components
Statistical features	2021	SF	[46]	improves the general accuracy of the prediction system
Statistical process control	2018	BRB	[54]	improves the learning process
SVM	2018, 2020, 2022	SF, BRB, SF	[33,44,58]	better generalization of nonlinear classification
Tooth-FFT	2018	BRB	[60]	higher sensitive of non-stationary signals
Wavelet packet decomposition	2018	BRB	[54]	multi-resolution analysis

6. Conclusions

This paper has reviewed the most recent contributions related to the early fault detection in induction motors. These contributions are classified into two main groups according to the operational mode of the motor: steady-state and transient-state. In this paper, it is shown that most of the research work is focused on the steady-state analysis. Despite the high-level of accuracy reported in the fault severity techniques based on steady-state analysis, these proposals still suffer for diagnostic errors. This work also presents reported algorithms based on different type of monitoring signals used for fault detection, and some characteristics of each measured magnitude. According to the developed review, it can be concluded that the techniques most used for fault detection at incipient stages are heuristic methods (knowledge-based), and sometimes a combination of signal processing methods and KB. The major problems with heuristic methods are the required computational resources and the diverse and large amount of data. Despite the amount of work carried out in detection of incipient faults of IM, just few works analyze transients and just some of them analyze inverter-fed IM transients. Regarding the fault type, most of the research work is focus on the detection of partially broken rotor bars.

7. Future Perspective

Despite constant research activity in the fault detection field, it can be observed that incipient fault detection and severity fault evaluation in IM is still an open challenge. As most of the existing research has been focused on the detection of incipient faults in IM operating under the steady regime, the study of IM operating under non-stationary regime is a natural trend. More importantly, as the use of inverters is increasing in the industry, an approach for future research is the development of new techniques that can diagnose incipient faults in the inverter-fed IM under transient operation. In addition, although some methods to separate load-oscillations from BRB signatures have been proposed [61–66], the effectiveness of early fault detection methods against this kind of external oscillation still needs to be validated. Several techniques have been applied to current and vibration signals; therefore, the reliability of other monitoring signals it could be explored. In order to obtain robust and practical solutions, various corner cases and environmental conditions should also be analyzed, such as the effects of combined multiple faults, realistic degradation, and industrial measurement inference. In in this paper, it is shown how KB techniques have been an increasing activity over recent years, opening new opportunities in which the application of these new techniques and the combination with modern SP can bring interesting advantages. Finally, new indicators are required to know the severity stage of a fault and to extract its features for improving the classification and the remaining useful life of the internal element. This necessity will encourage the development of new techniques able to filter out external interferences and, at the same time, quantify the fault indicator features. In addition, new techniques to be proposed should include the benefits of the existing works in the developed fault detection field, such as reliability, feasibility for implementation (low computational burden), portability, online detection, detection of multiple and combined faults, and so on.

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Nomenclature

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural networks
BRB	Broken Rotor Bar
BF	Bearing Fault
CNN	Convolutional Neural Network
DL	Deep Learning
DOL	Direct on Line
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
ETSA	Electrical-time-Synchronous Averaging
FFT	Fast Fourier Transform
FFNN	Feed-forward Neural Network
FPGA	Field Programmable Array
GA	Genetic Algorithms
IM	Induction Motors
KB	Knowledge-based
LDA	Linear Discrimination Analysis
LSTM	Long Short-Term Memory
MCSA	Motor Current Signature Analysis
MUSIC	Multiple Signal Classification
ML	Machine Learning
PCA	Principal Component Analysis
SF	Stator Faults
SP	Signal Processing
SPC	Statistical Process Control
STFT	Short-time Fourier Transform
SVM	Support Vector Machine
STW	Stationary Wavelet Transform

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