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Review

Inverter-Fed Motor Drive System: A Systematic Analysis of Condition Monitoring and Practical Diagnostic Techniques

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Abstract: Due to their efficiency and control capabilities, induction motors fed with inverters have become prevalent in various industrial applications. However, ensuring the reliable operation of the motor and diagnosing faults on time are crucial for preventing unexpected failures and minimizing downtime. This paper systematically analyzes condition monitoring and practical diagnostic techniques for inverter-fed motor drive systems. This study encompasses a thorough evaluation of different methods used for condition monitoring and diagnostics of induction motors, with the most crucial faults in their stator, rotor, bearings, eccentricity, shaft currents, and partial discharges. It also includes an assessment of their applicability. The presented analysis includes a focus on the challenges associated with inverter-fed systems, such as high-frequency harmonics, common-mode voltages causing the bearing currents, and high voltage gradients (dv/dt) due to fast switching frequency, which can impact the motor operation, as well as its faults analysis. Furthermore, this research explores the usefulness and efficiency of various available diagnostic methods, such as motor current signature analysis and other useful analyses using advanced signal processing techniques. This study aims to present findings that provide valuable insights for developing comprehensive condition monitoring strategies, and practical diagnostic techniques that enable proactive maintenance, enhanced system performance, and improved operational reliability of inverter-fed motor drive systems.

Keywords: condition monitoring; induction motors; pulse width modulation inverters; principal component analysis; spectral analysis; switching circuits

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1. Introduction

Today, industries utilize many electrical machines, particularly induction motors (IM), with wattages ranging from several watts to megawatts to convert electrical power to the required mechanical power. IM has a lower power-by-weight (W/kg) ratio than a synchronous machine of the same rating, has lower costs, is more durable, and requires less maintenance. Hence, they are known as the workhorse of the industry. They are more useful in about 80% of the industry's operations, such as the petrochemical industry, vehicular technology, mining process, propulsion systems, aerospace, nuclear-reactor plants etc. Their healthy and continued operation is required, because motor failure can shut down the whole plant process. This situation will generate significant financial loss and should be avoided to the maximum extent. Hence, early detection of faults with appropriate condition monitoring and diagnostic techniques within the motor is always required in terms of all means of time and money [1–3].

Many publications [4–7] investigated the condition monitoring (CM) and fault diagnostics (FD) of IM faults related to electrical, mechanical, and environmental scenarios when operated with the grid supply. However, inverter-fed machines also undergo faults due to the impacts of the Pulse Width Modulation (PWM) technique, which has a high-frequency transition, and high steepness in the waveform or high voltage gradient (dv/dt) due to switching frequency (f_{sw}) of power electronic wide band-gap drives (WBG). These WBG devices have demonstrated superior material properties that are accepted worldwide, allowing their high-switching and high-voltage operation, as well as capabilities to operate at high-temperature profiles [8–11].

1.1. PWM Inverter-Fed Motor Drive System

These inverters drive the IM while improving the operation's safety and reliability, but increasing harmonic-frequency traces. The PWM modulation technique and switching frequency determine these harmonic amplitudes and wide-band frequencies. PWM-controlled inverters employed with WBG devices such as SiC (Silicon Carbide), GaN (Gallium Nitride), GaAs (Gallium Arsenide), AlN (Aluminum Nitride), etc. have critical switchinits g frequencies ranging from a few kHz to tens of kHz. Other than generating the increased harmonic contents at the output terminal of the inverter, they also generate a high-frequency common-mode voltage (CMV), a major problem in switching power converter fed IM. This happens with the shaft voltage and generates the bearing current through the AC machine's stray capacitive and inductive coupled paths [12]. High modulation frequency attenuates low-order harmonics and increases the inverter's loss. These low-order harmonics are quite unhealthy for motors, because they cause torsional oscillations, pulsating torques in the shaft, and rotor bar-broken damage. Researchers are trying to reduce switching losses and increase the power converter efficiency with different inverter control strategies, and some novel designs such as [13–16] used discontinuous PWM (DPWM), sine triangle PWM-based DPWM, and space vector-based synchronized DRWM types of design techniques. A typical one-line diagram of an alternating current (AC) source with a voltage-source inverter (VSI), a rectifier system, filters with smoothing capacitors, and an IM operated with inverters is shown in Figure 1. It is worth mentioning that the failure rate of inverter-fed IM drives is 12 times faster than line or grid-fed drives, and this is demonstrated in the literature by a questionnaire survey of 3934 grid-fed drives and 286 variable-speed inverter drives [17].

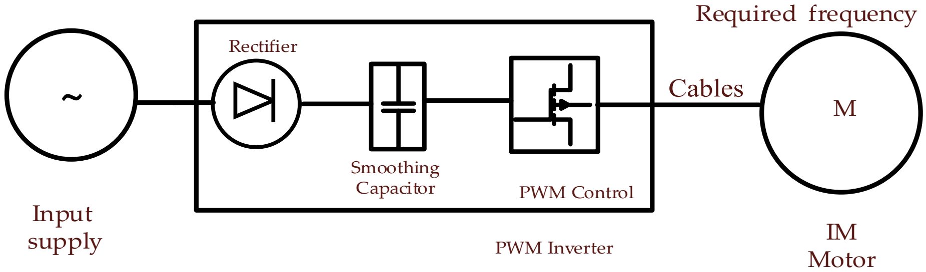


Figure 1. The schematics of a conventional inverter-fed electric motor drive system [17].

Inverter-based supply harmonics have a wide frequency spectrum compared to grid-fed variants, with a simple odd multiple of fundamental components. Since modern inverter-driven motors have high controllability, precision, dependability, and efficiency, they have become an integral component of modern drive systems. With the features described here, the common utilization issues of inverters are increased costs, increased switching losses, iron losses, high torque pulsations, electromagnetic compatibility issues, and acoustics noise. Due to switching frequency and high dv/dt, these high-frequency components are not designed with consideration of the motor's effective response and operation, leading to a high potential research gap in the motor field [7,18]. These random harmonic distributions in the current create an additional frequency spectrum in the wide band. Hence, these drawbacks encourage potential research to develop solutions [19–21].

1.2. Potential Challenges with Inverter-Fed Supply

Since PWM-based inverter-fed induction motors have certain advantages over grid-fed power supply, such as variable speed control, energy efficiency, and flexibility, they also face challenges with regard to condition monitoring and fault diagnostics. Table 1 presents a comparison, based on the available literature, between Pulse Width Modulation (PWM)-based inverter-fed induction motors and those with grid-fed supplies, with regard to the challenges, complexity, and problems they face in their condition monitoring and fault diagnostics.

Table 1. Comparison of challenges posed by supplies to motor drive system.

Sr. No.	Challenges	PWM Inverter-Fed Motors	Grid-Fed Motors	Reference
1.	Noise and distortion	• Harmonics and high-frequency noise. • Lowers the accuracy of methods.	• Lower harmonics and distortion. • Provides stable and reliable signal for fault diagnosis.	[22]
2.	Sensor compatibility	• Complex power electronics require more sensors or interfaces. • Complexity and cost addition.	• Standardized sensors and measurement points. • Simplified CM and FD implementation.	[23,24]
3.	Variable operating conditions	• Feasibility with various load and speed conditions. • Dynamic system behavior and different failure signature complicate the fault diagnosis.	• More stable operation and predictable conditions. • FD is more straightforward.	[25]
4.	Nonlinear-system dynamics	• Nonlinear behavior due to the switching nature. • Greater challenges in FD and assumption with linearity or relying on linear models.	• Linear characteristics. • Simplified in linear-based FD and modeling approaches.	[26,27]
5.	Power quality and transient response	• Adds voltage sags, harmonics, and transients. • Affects power quality and perhaps masks fault signatures.	• Provide stable and high-quality power with minimal transients. • Cleaner environment for FD.	[28,29]
6.	The complexity of fault signatures and analysis	• Power electronics, motor dynamics, and fault conditions create complex and non-traditional scenarios in fault signatures. • Requires advanced signal processing or customized fault detection algorithms.	• Straightforward and conventional in CM and FD. • Simple fault analysis, detection, and interpretation.	[30]

This review article briefly analyzes induction motor faults, condition monitoring, and practical diagnosis and highlights the scientific results of different approaches and their applicability in this field of diagnostics, specifically with motor drive systems. The authors present a thorough detail of induction motor fault classification in Section 2. Then authors include various condition monitoring schemes and diagnostics with various applicability details in Section 3.

A comprehensive analysis of potential induction motor faults, including monitoring and mitigation methods, is covered in Section 4. The authors add the details of most occurring faults like stator, inter-turn short circuits, broken rotor faults known as BRB, mechanical bearing damage, air-gap eccentricity, common-mode voltage development faults, and bearing currents leading towards partial discharges in the induction motor. Additionally, the authors outline the most advanced machine learning and artificial intelligence-based CM and DF techniques of recent times in Section 5. Section 6 of this paper addresses the potential research gaps as a future direction for the research, based on an extensive literature analysis by the authors.

2. Classification of Various Faults in Induction Motor

Based on the available literature, Figure 2 shows various IM fault types, which effectively influence the continuous and reliable operation when operated by an inverter-based power supply [27]. The IM faults are classified into three main categories: mechanical, electrical, or environmental. Electrical faults in particular are initiated at the stator side of IM. Mechanical faults have the most impact on the remaining useful life of the motor, as they are degenerative and tend to increase these faults over time.

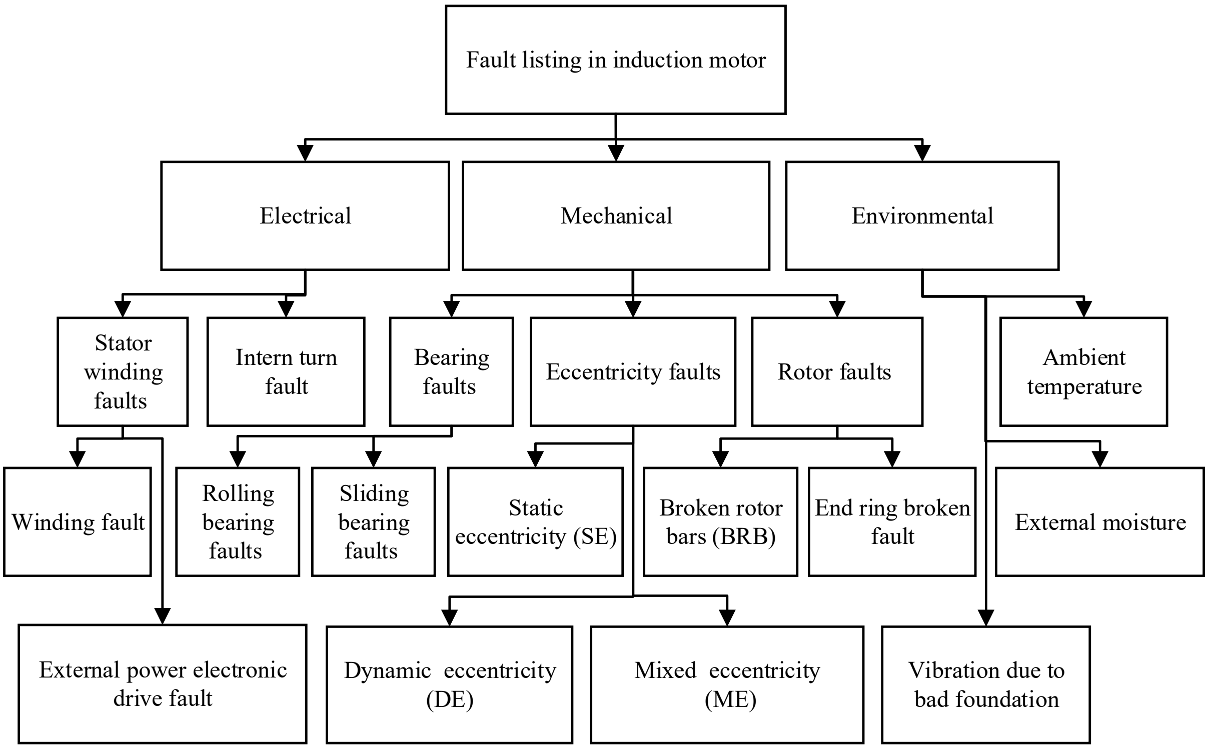


Figure 2. Induction motor various faults classifications [27].

2.1. Fault Type Classification

These faults are likely to be avoided in advance with early detection, and good condition monitoring schemes are required for the motor, before going into catastrophic failure. These faults are more critical and difficult to detect earlier but are equally important to trace. This article highlights the electric motor fault, the diagnosis technique mainly associated with using a power electronic converter [31,32].

Three institutions, named the Institution of Electrical and Electronics Engineers (IEEE), Electric Power Research Institute (EPRI), and Asea Brown Boveri (ABB), have evaluated the IM fault types and their performances. Their surveys, which are depicted in Figure 3, reflect the importance of condition monitoring and diagnostics in different parts of motors, and show the percentage contribution of the faults related to motor's stator, rotor, bearing, and other related considerations [33,34].

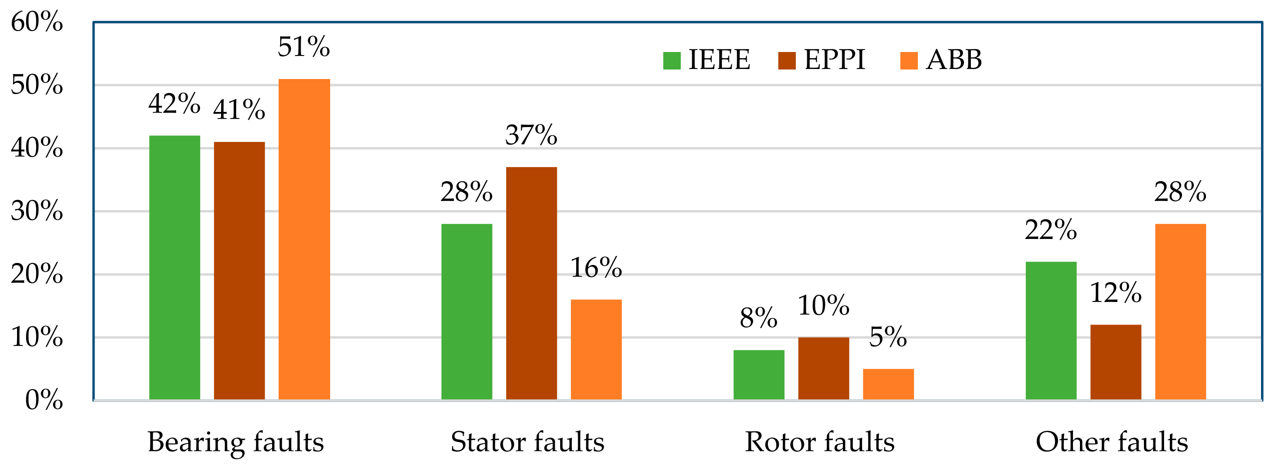


Figure 3. IM percentage fault contribution by the institutions: IEEE study results, EPRI study results and ABB [35].

2.2. Typical Faults with Inverter-Fed Induction Motor

Table 2 illustrates the various faults in an induction motor when supplied with a Pulse Width Modulation (PWM) inverter. It presents a comparative analysis table encompassing various faults and corresponding diagnostic techniques. These CM and FD methods are crucial in facilitating the precise interpretation of fault signatures, offering valuable insights into motor faults' underlying causes and severity. The researchers consistently aimed to improve the dependability and efficiency of inverter-fed induction motors by implementing effective strategies for detecting and diagnosing faults.

Table 2. Fault and companion diagnostics in an inverter-fed induction motor.

Sr. No.	Faults	Diagnostic Techniques	Reference
1.	Stator winding phase(s) faults, inter-tern faults, vibration, and conductor displacements	• Motor current signature analysis (MCSA); ○ Signal spectrum analysis; ○ Wavelet transform; ○ Fast Fourier transform (FFT); ○ Park's vector approach; ○ Artificial intelligence techniques (AI); • Relays and switches.	[36,37]
2.	Rotor faults, mechanical faults	• FEA analysis; • Vibration analysis; • Motor current signature analysis; ○ Fast Fourier transform (FFT); ○ Wavelet transform; ○ Time frequecny analysis, etc.	[11,38,39]
3.	Bearing faults, misalignment of bearings, lubrication loss in bearings, mechanical and thermal imbalance in the rotor	• MCSA; ○ Instantaneous power FFT; • Flux measurement method.	[40–43]
4.	Shaft voltage stress and transient overvoltage	• Parasitic capacitance calculation; • RLC transient modeling; • Shaft current and stray flux analysis; • 2D and 3D analysis.	[29,44]

Table 2. *Cont.*

Sr. No.	Faults	Diagnostic Techniques	Reference
5.	Bearing voltages and leakage currents, corrosion, and failure	• Vibration analysis; • Chemical analysis.	[45,46]
6.	Common-mode voltage (CMV) issues and high dv/dt	• New electrostatic shielded design; • RLC transient modelling.	[47,48]
7.	PWM switching harmonic losses, distortion, and heating	• Infrared thermography; • Infrared recognition; • Thermal monitoring; • Signal spectrum analysis.	[22,49]
8.	Insulation system damages	• Monitoring of winding's temperature, gases composition; • Stray flux analysis; • Partial discharge; • Filtered voltage impulse and partial discharge (PD) spectra; • AI.	[50–52]
9.	Electromagnetic interference (EMI) issues	• High resonance circuit equivalent modeling and analysis.	[53]
10.	Switching harmonic and frequency loss analysis	• Discontinuous Pulse Width Modulation (DPWM) and space vector bases DPWM; • Electromagnetic field monitoring.	[54–56]

3. Condition Monitoring and Diagnostic Techniques

This paper reviews the research on condition monitoring and fault diagnosis and draws attention to the methods proven to be the most reliable and helpful. Fault diagnosis techniques can be categorized based on whether they require invasive or non-invasive methods to assess the condition of the motor drive system. Non-invasive fault diagnosis techniques do not require physical intervention or direct contact with the motor drive system being monitored. These methods rely on external measurements or signals to analyze the system's behavior and detect potential faults. Invasive fault diagnosis techniques involve physical intervention or direct contact with the system to diagnose faults. These methods typically require accessing the internal components or subsystems of the machine [57].

3.1. Common Condition Monitoring Techniques

There are common condition monitoring (CM) techniques based on electrical signature analysis (ESA) through sensor data, which are useful not only for the condition monitoring of induction motors, but also for electrical generators, transformers, and other equipment. The most common type of signature analysis is motor current signature analysis (MCSA), in which the current signal signature is analyzed to trace the faults within the induction motor [38,58]. ESA also includes the motor circuit analysis involving parameters like resistance, phase angle, current response, frequency response, equivalent impedance, inductance, and ground faults. Some of the common condition monitoring techniques used in identifying IM faults are listed below [41,50,59–65]:

- Motor current signature analysis (MCSA) [66];
- Voltage signature analysis (VSA) [67];
- Extended Park vector approach (EPVA) [68];
- Instantaneous power signature analysis (IPSA) [69];

- State monitoring analysis like temperature, noise, speed fluctuation, magnetic flux;
- Condition Monitoring Sensors:
    a. Vibration sensors: accelerometers, proximity probes;
    b. Temperature sensors: thermocouples, resistance temperature detectors;
    c. Current sensors: Hall effect sensors, current transformers;
    d. Acoustic sensors: microphones, ultrasonic sensors;
    e. Emissions-based monitoring;
- Partial discharge and surge testing;
- Motor circuit analysis.

Fault diagnosis methods are mainly divided into categories, i.e., signal processing and model-based techniques. Signal-based techniques for condition monitoring and fault diagnosis of electrical machines involve analyzing various signals acquired from the machines to detect abnormalities, deviations, or fault signatures [31,70,71]. These techniques focus on extracting relevant information from the signals to assess the machine's condition. Some common signal-based techniques are shown in Figure 4.

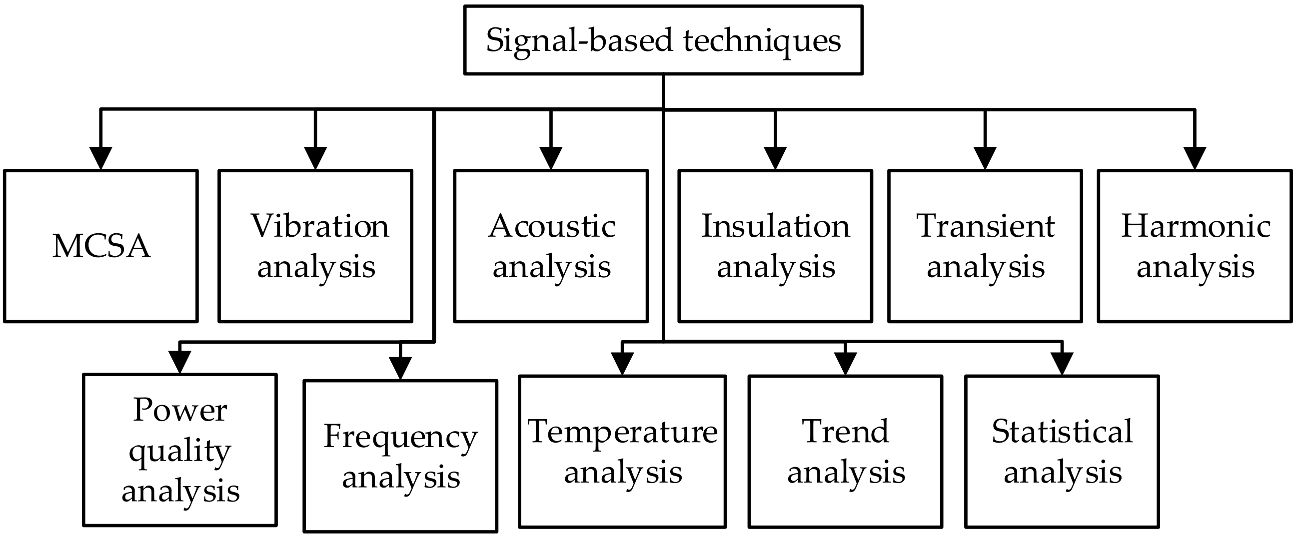


Figure 4. Types of signal-based techniques [71,72].

Model-based techniques for CM and FD of electrical machines are based on mathematical modeling to evaluate the behavior of the motor and detect the relevant faults or deviance from the common operating requirements [73,74]. The most common model-based techniques in FD are analytical models, finite element analysis (FEA), signal processing techniques, Kalman filtering (KF) and state estimation, artificial intelligence (AI), stochastic resonance, and machine learning (ML), as shown in Figure 5. These model-based techniques provide valuable tools for the CM and FD of electrical machines, allowing pre-condition of faults, predictive maintenance, legible reliability, and high performance. The divisions above can also be used in artificial intelligence (AI) based techniques for diagnostics. An artificial intelligence approach to predictive maintenance necessitates both human intelligence and machine learning or training of algorithms for machine fault diagnostics [75–79].

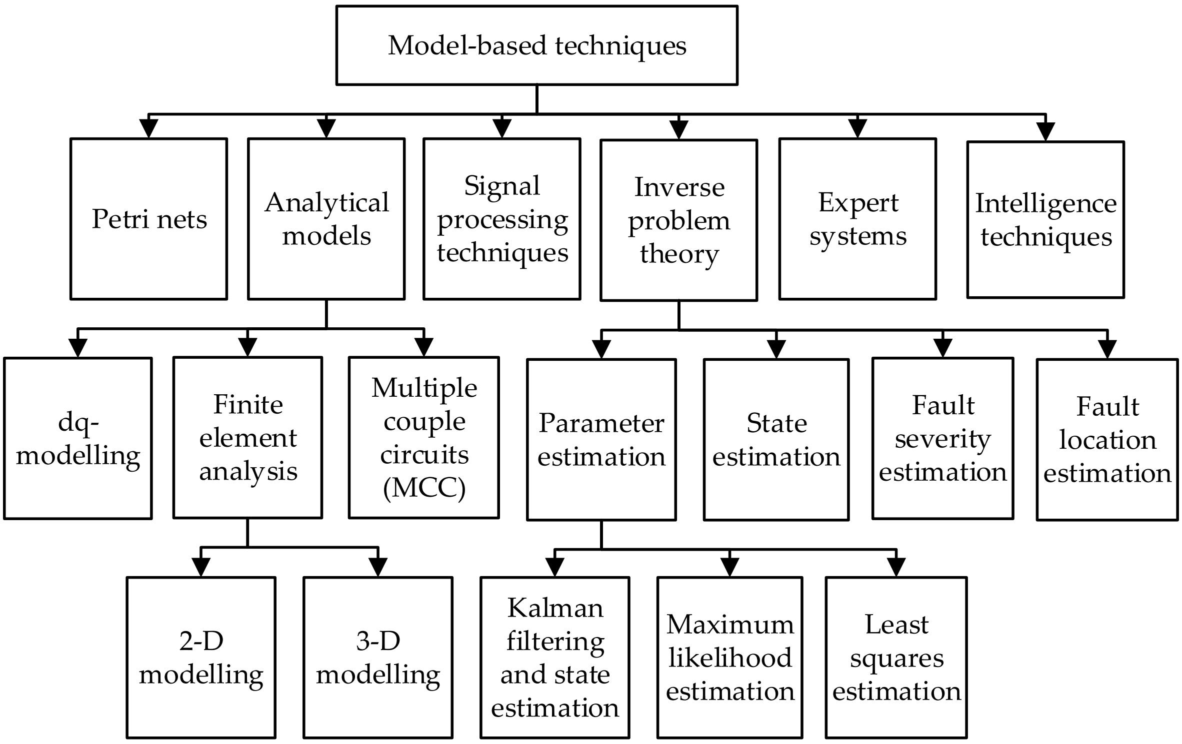


Figure 5. Types of model-based techniques [80].

IM-related faults caused by high-frequency inverter transients and behavior that generate the faults. Academia, and industry are investing heavily in their research and development (R&D) related to condition monitoring and diagnostics [81,82]. Figure 6 shows a tie of an electric machine with an intelligent diagnostics system, which integrates the motor's real-time parameters, for example, electrical, mechanical, flux, optical, acoustic, chemical, partial discharges, and others, to form a diagnostic [83–85].

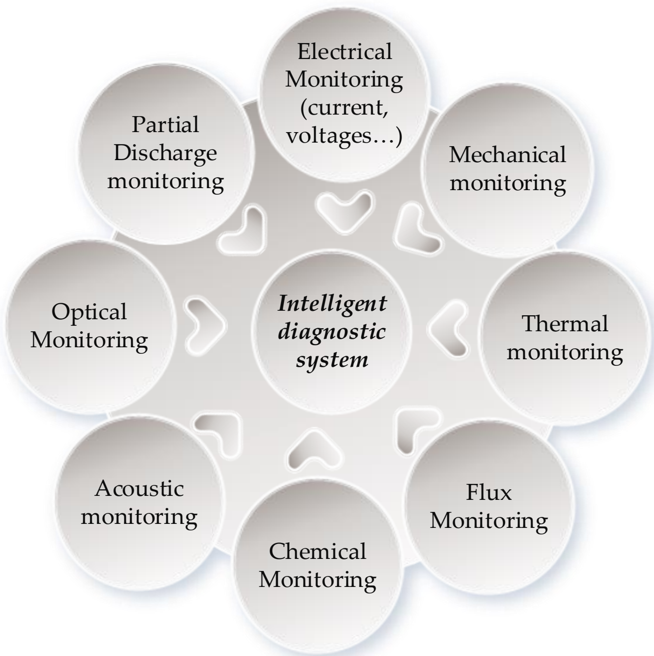


Figure 6. Recent developments in intelligent diagnostics [83–85].

3.2. Latest Trends in Condition Monitoring for IM Faults

Advanced condition monitoring and fault diagnostic methods for induction motor faults have emerged due to advancements in technology and research. The authors present a list of the latest more advanced condition monitoring methods for induction motor (IM) faults, along with their types and further subtypes in Table 3.

Table 3. Condition monitoring and diagnostics with latest trends.

Sr. No.	Latest FD Technique	Feature Application
1.	Advanced signal processing techniques	• Time-domain analysis [86]; ○ Amplitude and RMS analysis [87,88]; ○ Kurtosis analysis; ○ Harmonic order tracking analysis [89]; ○ Time synchronous averaging (TSA) [90–92]; ○ Statistical analysis [93]; ■ Stochastic resonance; ○ Signal decomposition [89]; • Frequency-domain Analysis; ○ Fast Fourier transform (FFT); ○ Wavelet transform [90]; ○ Higher-order spectral analysis [37]; • Time-frequency analysis [70,94]; ○ Spectrogram; ○ Scalogram; ○ Hilbert–Huang transform and its extension; ■ Empirical mode decomposition; ■ Intrinsic mode function; ■ Extracting instantaneous amplitude and frequency; ○ Short-Time Fourier Transform (STFT); ○ Wavelet packet transform [95]; ○ Wigner–Ville distribution [91]; • High-resolution analysis techniques [38,45,92,93]; ○ MUSIC [96].
2.	Intelligent technique	• Artificial intelligence (AI) [97]; • Machine learning (ML) [98]; • Data-driven approach [99–101]; ○ High-dimensional feature reduction [102–104]; • Data mining: date fusion and pattern recognition [105].
3.	Expert Systems	• Rule-based systems [106–108]; ○ Fuzzy logic [109]; ○ Knowledge-based rules [110]; • Case-based reasoning [111]; ○ Experience-based reasoning; • Fault diagnosis from historical cases.
4.	Model-based prognostics and health management (PHM)	• Advanced diagnosis recognition [112]; • Smart classifier-based prognostics [105].
5.	Model-based prognostics and health management (PHM)	• Advanced diagnosis recognition [104,112]; • Smart classifier-based prognostics [105].
6.	Digital twin technology	• Ramanujan digital twin (RDT) [113]; • Model approach [113].
7.	Image processing and computer vision	• Advanced image processing and hyperspectral imaging [110,114]; • Histogram of oriented gradients approach [115]; • Thermal imaging: infrared thermography, temperature mapping [116].

Table 3. *Cont.*

Sr. No.	Latest FD Technique	Feature Application
8.	Hardware-in-the-Loop (HIL) condition monitoring methods	• Virtual HIL; ○ Software-in-the-Loop (SIL); ○ Processor-in-the-Loop (PIL) [117]; • Hardware-in-the-Loop (HIL) with real motors [118]; • Hybrid HIL: a combination of virtual and real components [119,120].
9.	Advanced Fault Detection Methods	• Ensemble methods [121]; ○ Random forest; ○ AdaBoost; ○ Bagging. • Bayesian networks: probabilistic graphical models, fault propagation [122]; • Genetic algorithms: optimization [123], feature selection, parameter tuning [124–126].
10.	Inverse problem theory	• Parameter estimation: Kalman's prediction [127,128]; • State estimation [129]; • Fault location estimation [130]; • Fault severity estimation.

Recent trends include time–frequency analysis (*tf*) methods, such as Short-Time Fourier Transform (STFT), wavelet transform, and Wigner–Ville transform, which provide valuable insights into motor signal transient and frequency-varying components. Applying these techniques makes it possible to detect and diagnose faults that may manifest as changes in frequency content or time-varying patterns. Different methods can identify certain faults in machines, such as the power spectrum graph, phase spectrum graph, cepstrum-graph, autoregressive (AR) spectrum-graph, spectrogram, wavelet scalogram, wavelet phase graph, etc. However, these methods often present several problems in terms of complexity and cost. The conventional signal-based methods are not always reliable, as they depend on the operating conditions of motors [121].

To improve the detection of incipient fault issues, the field of fault feature extraction has also taken advantage of stochastic resonance. Using straightforward techniques, researchers and diagnostic designers can better understand the motor drive system faults. In this approach, the system is represented by a network of interconnected neurons, where each neuron stands for a particular quality or feature of the signals the machinery generates [131]. The optimal signal-to-noise ratio and the misclassification rate are two examples of multi-objective optimization techniques used to determine the ideal coupling strengths between the neurons.

3.3. CM Implementation Strategy

A well-designed implementation strategic plan is important, because it ensures a systematic and organized approach to condition monitoring. It improves the monitoring process's efficacy and efficiency, enables proactive maintenance, reduces downtime, and optimizes resource utilization. Furthermore, a well-defined strategic plan encourages uniformity, standardization, and scalability, allowing organizations to reap the benefits of condition monitoring across various assets and facilities. Figure 7 shows the implementation of a strategic layout of condition monitoring, which refers to the systematic approach and framework for implementing condition monitoring techniques.

Potential future research is always required to precisely analyze the electrical machine's service life expectancy deterioration with improved CM, FD, and prediction methodologies. This predictive maintenance would reduce the cost of the process in its downtime and prevent unexpected motor failures.

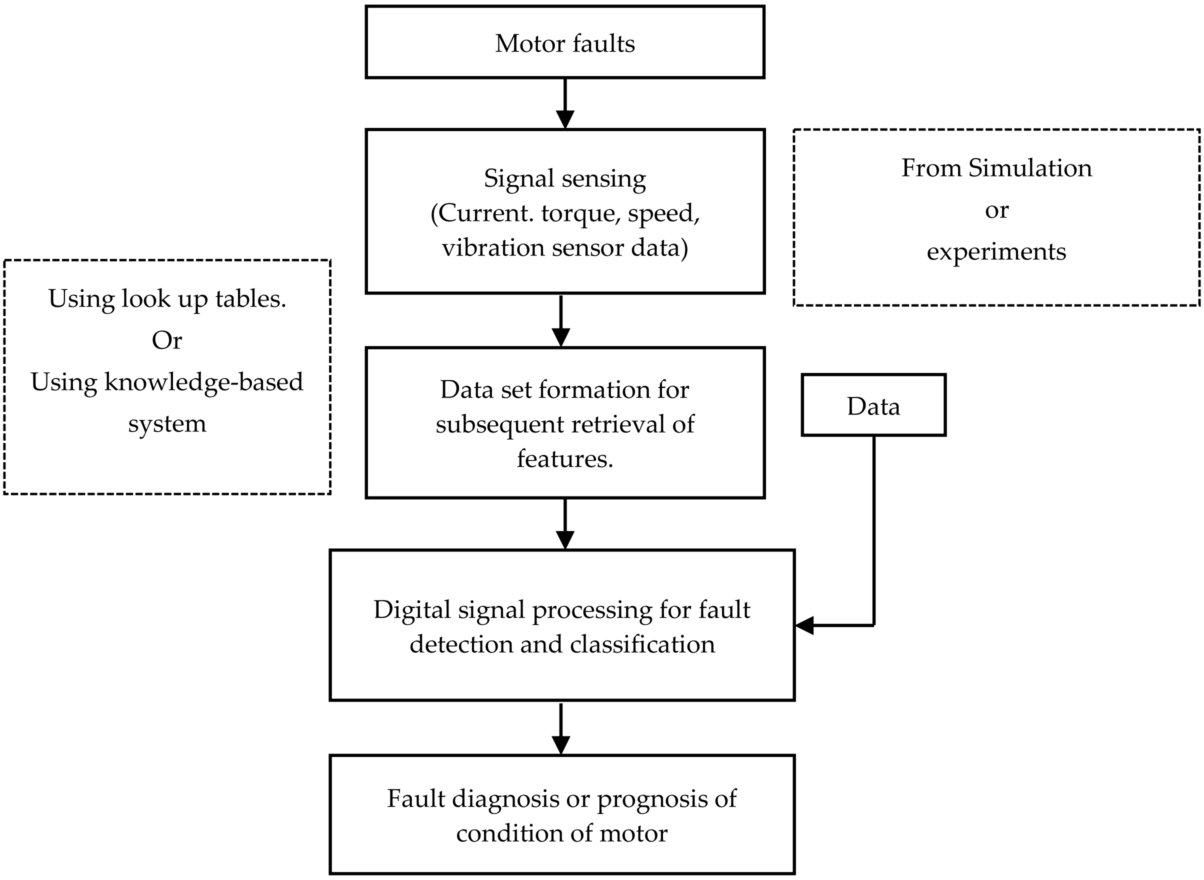


Figure 7. CM implementation strategic layout [75].

4. Fault Monitoring and Diagnosis of Induction Motor

Monitoring and diagnosing fault conditions is crucial to maintaining induction motors' dependable and efficient performance. Utilizing modern sensors and data acquisition systems permits the early identification of fault conditions, such as bearing wear, rotor faults, stator winding faults, and imbalance. Simultaneously, fault diagnostics analyzes the collected data to determine the defect's specific type and severity. Various techniques, such as signal processing, pattern recognition, and machine learning algorithms, identify fault varieties. These techniques extract relevant characteristics from the collected data and classify the fault type [98,132]. The information obtained through fault diagnostics enables maintenance personnel to promptly implement corrective measures, reduce inactivity periods, and prevent further damage to the induction motor. The subsequent subchapters will comprehensively analyze each fault [71,97,133–135], and present condition monitoring and fault diagnosis according to the fault.

4.1. IM Stator's Faults

Stator faults in the induction motor account for approximately 16–37% of the total occurred faults [35]. Induction motor stator faults include winding faults and external drive faults. The stator winding fault (SWF) can be caused by turn-to-turn, coil-to-coil, phase-to-phase, or phase-to-ground faults, as shown in Figure 8. Most stator faults involve broken winding insulation. MCSA can detect broken thread insulation, which can cause phase insulation to break and kill the motor. Insulation is most affected by thermal stress [136]. The combination of different electric stresses generated through the transient voltages is particularly undesirable [137].

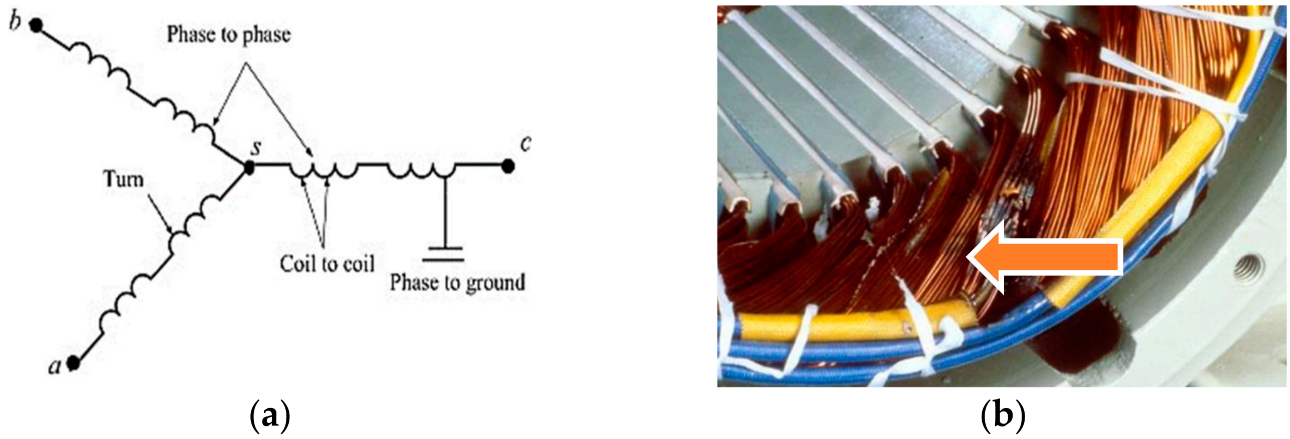


Figure 8. IM stator faults. (**a**) Stator winding multiple fault provision, (**b**) stator winding damage due to coil-coil fault within it [138].

The stator is stressed by thermal, electrical, mechanical, and environmental factors, causing faults [139–141]. Table 4 presents the types of fault diagnostics techniques for induction motor (IM) stator faults.

Table 4. Types of fault diagnostics techniques for induction motor (IM) stator faults.

Sr. No.	FD Technique	Group	Pros	Con	Reference
1.	Motor current signature analysis (MCSA)	Motor current signals (current spectrum)	• Non-invasive. • Specific harmonics specify the fault. • Provides real-time monitoring of motor health. • Diagnose turn-to-turn short circuits, open circuits, and insulation degradation related. • Cost-effective and relatively simple to implement.	• Limited effectiveness for incipient faults. • Expert knowledge is required when analyzing the spectrum. • Difficult in fault segregation in the case of inverter-fed motors. • Influenced by external noise and interferences.	[34]
2.	Motor current Park's vector analysis (MCPVA)	Stator current signal (vector components analysis)	• Provides insights into motor health and faults. • Provides a broad view of motor behavior. • Divides signal into orthogonal components. • Effective in both steady-state and transient conditions. • Early detection of motor faults.	• Requires accurate measurement. • Complex in evaluating vector relationships and deviations from predicted values. • Influenced by noise and measurement uncertainties. • Requires expertise in vector analysis and interpretation. • Limited effectiveness for incipient or small faults.	[68,142]
3.	Neural network techniques	Current or voltage signals	• Capable of handling non-linear and dynamic systems. • Adaptive and self-learning nature. • Can identify fault patterns and diagnose based on their responses. • Robust performance. • Handle multi-variate and high-dimensional data. • fault detection and diagnosis in early stages.	• Require large amounts of training data. • Lack of interpretability and explainability. • Computationally intensive and time-consuming training • Complex in learning to implement in linking between input patterns and fault states. • Limited effectiveness for unknown fault types.	[143–145]

Table 4. *Cont.*

Sr. No.	FD Technique	Group	Pros	Con	Reference
4.	Wavelet transform analysis	Stator current signal	• Effective for time-frequency analysis. • Can handle non-stationary and transient signals. • Ability to detect transitory phenomena, frequency fluctuations, and disruptions. • Offers multi-resolution analysis. • Can diagnose stator faults such as short circuits, broken rotor bars (BRB), and bearing faults.	• Appropriate wavelet basis can be challenging in selection. • Computational complexity • Interpretation of wavelet coefficients requires expertise. • Requires a careful balance between time and frequency resolution. • Compromise in effectiveness for very high or very low frequencies. • Proper selection of wavelet parameters is crucial.	[101–105]

4.1.1. Classification of the Stator Fault

Incipient stator faults fall into the following broad categories.

1. Laminations that create a hotspot in the core and cause slackening in the core.
2. Faults in the frame due to unbalanced vibration, circulating current within it due to shaft voltages, coolant loss, or a potential earth fault.
3. Faults in the end portion, insulation fretting, insulation contamination by moisture, oil, or dirt, damage to connectors, cracking of insulation, discharge erosion of insulation, and the displacement of conductors.
4. Faults in portions from the slot due to the misplacement of conductors.

4.1.2. Inter-Turn Short-Circuit Faults

Industrial drives have a 16–28% stator inter-turn short circuit (ITSC) fault [136]. Inverter-fed induction machines have more harmonics than line-connected motors. The harmonic current heats the stator winding, deteriorating the insulation quickly [37,146]. If undetected, a three-phase IM stator winding short circuit starts with an inter-turn fault and progresses to a phase-phase or phase-ground fault. MCSA detects inter-turn faults in inverter-fed IM. If a PWM inverter feeds the machine, MCSA fails due to high-frequency inverter switching, and the current spectrum is noisy, making fault detection difficult. If undetected, a three-phase IM stator winding short circuit starts with an inter-turn fault, and progresses to a phase–phase or phase–ground fault. MCSA detects inter-turn faults in inverter-fed IM. If a PWM inverter feeds, the machine MCSA fails due to high-frequency inverter switching, and the current spectrum is noisy, making fault detection difficult [147,148]. The details of the current harmonics that the stator intern short circuit has caused and the two-level inverter's currents harmonic are explained below.

4.1.3. Current Harmonics Due to Stator ITSC Fault

In the case of stator inter-turn short circuits (ITSCs), the number of coil turns is reduced, and the remaining coils are used to carry fault current. A short circuit current reduces the faulty phase's MMF, and the air gap's spatial flux distributions are disturbed [149]. The motor's current components at some frequencies are limited to shorted turns. This is described by Equation (1) [150].

$$f_{st} = f_g[\frac{n}{p}(1-s) \pm k] \quad (1)$$

where f_{st} is the component related to shorted turn, f_g is the fundamental electrical frequency, n is $1, 2, 3, \ldots$, p is pole pairs (number), s is slip (per unit), k = 1, 2, 3.

4.1.4. II-Level Inverter's Current Harmonics

The II-level triangular carrier PWM inverter-fed IM has the per phase voltage in Equation (2) [25].

$$\begin{aligned} V(t) &= \tfrac{MV_{dc}}{2}\cos(\omega_f t) \\ &+ \tfrac{2V_{dc}}{\pi}\sum_{m=1}^{\infty} j_0 mM\tfrac{\pi}{2}\sin(m\tfrac{\pi}{2})\cos(m\omega_c t) \\ &+ \tfrac{2V_{dc}}{\pi}\sum_{m=1}^{\infty}\sum_{n=\pm 1}^{\infty}\tfrac{j_n mM}{m}\tfrac{\pi}{2}\sin[(m+n)\tfrac{\pi}{2}]\cos(m\omega + m\omega_f t) \end{aligned} \tag{2}$$

where V_{dc} = DC link voltage, M is Modulation index, ωf is the fundamental frequency, ωc is the carrier frequency, m is the integer, J_0, & J_n are the Bessel functions, and $V(t)$ = fundamental voltage.

Equation (2) shows the modulation index's analytical function (which is defined as M), while the second and third term reflect the carrier frequency band harmonics. By varying the coefficients ωf, ωc stated in Equation (2), the output of the inverter is varied, and the required voltage for the fed induction is achieved. Since the voltages are non-sinusoidal, they are being fed to the motor; they cause the harmonics in the phase current, and most reflecting harmonics are along the side of switching frequency ($\omega c \pm 3\omega f$, $2\omega c$) [151]. ITSC fault generates the current i_f, and the R_f fault resistance is reflected as shorted turns in the phase winding undergone to the fault, as shown in Figure 9.

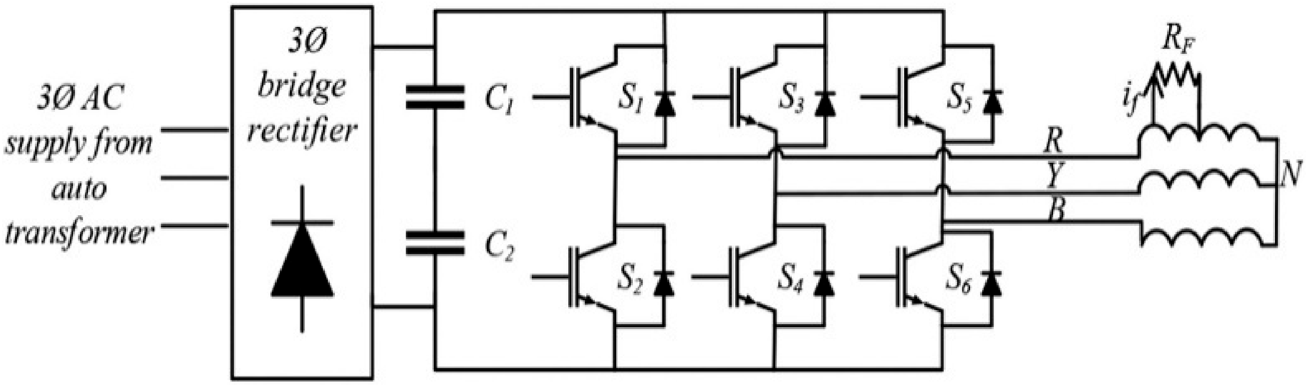


Figure 9. Induction motor ITSC fault [36].

Researchers recently proposed the most efficient and applicable fault diagnostic techniques using the observer coil based FFT analysis and measuring the internal flux methodology [152]. Furthermore, coil based FFT analysis and sensors based on the Hall effect are separately installed inside the motor's geometry, which requires extra labor [63].

Also, it is not influential for implementation because of being sensitivity-dependent due to load variation, current harmonics, and an unbalanced supply voltage.

Table 5 summarizes different motor ratings, implemented schemes, and different parameters in the event of inter-turn short faults.

Table 5. Summary of inter-turn short circuit faults in different motors.

Sr. No.	Motor Specification	FD Technique	Fault Resistance (Ω)	Fault Current I_f (A)	Fault Severity I_f/I_r (%)	References
1.	3.7-kW,41-V, 4-pole, 50-Hz,	Wavelet transform analysis on the Stator current	2	0.7	12.73	[69]
2.	400-V, 11-kW, 50-Hz, 4-pole	Fast Fourier transform and stray-flux	0	3.75	16.66	[70]

Table 5. *Cont.*

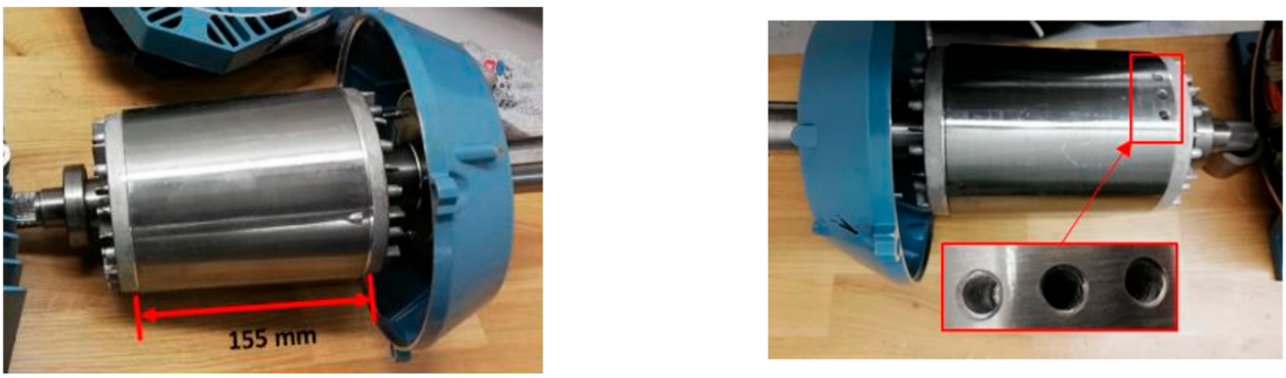
Sr. No.	Motor Specification	FD Technique	Fault Resistance (Ω)	Fault Current I_f (A)	Fault Severity I_f/I_r (%)	References
3.	15-kW, 400-V, 50-Hz, 4-pole	Stator current multi-reference frames	0.012	6	20.33	[71]
4.	400-V, 5.5-kW, 50-Hz, 4-pole	Symmetrical components of the stator-current (input current)	-	2	18.18	[72]
5.	110-V, 1-kW, 50-Hz, 4 pole	IM stator current phase averaging	6	1.3	26.00	[73]
6.	415-V, 3-kW, 50-Hz, 4-pole	Discrete wavelet transform (DWT)	0.5	10	200	[74]
7.	380-V, 3.7-kW, 60-Hz, 4-pole	Discrete Fourier transform (DFT)	0	12	100	[75]
8.	460-V, 3.7-kW, 60-Hz, 6-pole	Waveform envelope construction	1	3.5	71.86	[76]

4.2. Rotor Faults

The induction motor rotor can undergo the following faults, which are stated below as:

1. Broken rotor bars (BRB);
2. Rotor bar displacement;
3. Rotor bar eccentricity;
4. Rotor end ring damage;
5. Rotor core faults and overheating;
6. Rotor skewing issues;
7. Rotor short circuits.

Rotors can be divided into wound types and squirrel cage types. In the case of the squirrel cage rotor, the windings are a cage of conducting bars that meet at the end ring [153]. The wound rotor consists of the winding made on the rotor with different winding topologies. The main faults occur with the motor due to irregular fluctuations and high pulses. Figure 10 shows the rotor bar broken faults within it.



(a) **(b)**

Figure 10. IM rotor images showing broken rotor bars (BRB): (**a**) healthy-rotor, (**b**) three-bars broken [9].

Most MCSA-based methods take advantage of electrical machine faults leaving fault-frequency components in the current spectrum. Poor materials, overloading, or heavy starts can cause these faults. BRB faults can increase resistance or break the electrical circuit. Rotor bar failures mostly affect motor starting and parasitic moments. The missing bar (due to an open circuit within it) current path increases the current in other bars, causing more faults (where one bar is broken). The current components in the stator windings can be identified at the frequencies mentioned in Equation (3), in case of a BRB [154,155].

$$f_{brb} = f_g[\frac{n}{p}(1-s) \pm k] \tag{3}$$

where f_{brb} is a broken rotor bar (BRB) frequency, f_g is the electrical input inverter primary frequency, k is 1, 2, 3, . . ., p is the number of pole pairs, s is slip (per unit).

The typical problem with commercial induction motors is BRB faults. The authors of [156] presented the diagnostic techniques based on the existence of the motor current signature analysis. In [157], a low-complexity fault detection algorithm was implemented based on the analytic current signal's sub-Nyquist sampling. The algorithm was tested for BRB-related faults. The proposed techniques in [94] are based on advanced signal processing tools, such as spectrogram, scalogram, and Hilbert–Huang transform. Results demonstrated the effectiveness of these approaches in simulation and experimental validation. The author of [158] adopted SOGI-ANF, a new time domain signal processing algorithm for stator current envelope extraction in induction motors, suitable for embedded devices, and its adaptive nature allows accurate tracking of envelope variations. Based on the literature, Table 6 compares different diagnostic methods.

Table 6. Induction motor BRB fault diagnosis methods in the MCSA group.

Sr. No.	FD Technique	Group	Pros	Cons	Reference
1.	Active and reactive currents	FFT (MCSA)	• Non-invasive. • Can segregate load vibration effects. • Moderate level of mathematical calculation.	• Medium level of memory required.	[159]
2.	Ant clustering	Park's vector, FFT	• Non-invasive. • No speed estimation is required.	• Difficult to segregate different faults. • Large mathematical calculations and memory required.	[99]
3.	Autoregressive method	DTFT and Notch	• Non-invasive. • No speed estimation is required.	• Operated on steady-state current.	[160]
4.	Information entropy and fuzzy inference	Fuzzy logic	• Non-invasive. • A medium level of mathematical calculation is required.	• Requires steady-state current. • Large memory required.	[107]
5.	Homogeneity estimation	FPGA	• Non-invasive. • Used with transient current. • No speed estimation is required. • A low level of mathematical calculation is required.	• Segregation of faults is difficult.	[161]

Table 6. *Cont.*

Sr. No.	FD Technique	Group	Pros	Cons	Reference
6.	Principle slot harmonics	FFT	• Non-invasive. • Used with an unbalanced power supply.	• Segregation of different faults is difficult. • Large mathematical calculations and memory required.	[162]
7.	Harmonic order tracking	Gabor transform	• Non-invasive. • Capable of segregating faults and non-stationary conditions.	• A medium level of memory is required to use.	[89]
8.	Hilbert Transform (Envelope detection)	Hilbert transform	• Non-invasive. • Steady-state analysis. • A low level of mathematical calculation and memory is required.	• Segregation of different faults is difficult. • Problems with varying load conditions.	[163]
9.	Reduced envelope	Hilbert transform	• Non-invasive. • Suitable for diagnostic on low slip • Suitable to implement on DSP and FPGA kits.	• Segregation of different faults is difficult.	[164]
10.	Notch-filter	Fast Fourier transform	• Non-invasive. • Suitable for diagnostic on low-slip. • Difficult under varying load conditions.	• Segregation of different faults is difficult.	[165]
11.	Parameters estimation	Analytical	• Non-invasive. • It can be more accurate under steady-state conditions. • It can be used to segregate faults.	• The high mathematical calculation is required. • High memory is required.	[166,167]
12.	Pendulous oscillation	Analytical	• Non-invasive. • Suitable for implementing under low slip conditions and steady-state conditions. • It can be used to segregate faults.	• The complex mathematical calculation is required.	[168,169]
13.	Power spectral density	Short-time FT and wavelet	• Non-invasive. • Suitable to implement under low slip conditions. • Cab be applied under varying load conditions. • It can be used to segregate faults.	• An accurate sampling rate is required. • Selection of mother wavelet required.	[170]

Table 6. *Cont.*

Sr. No.	FD Technique	Group	Pros	Cons	Reference
14.	Spectrum synch technique	Local band synch, central kurtosis analysis	• Non-invasive. • It is suitable to implement under low slip conditions and can be used to segregate faults.	• Difficult to implement under varying load conditions.	[168]
15.	Zero-sequence voltages	Analytical	• Non-invasive. • Suitable for constant load conditions.	• Segregation of different faults is complicated.	[171]
16.	Wavelet transform (WT)	t-f analysis	• Non-invasive. • It can be used to segregate faults • It can be used for varying load conditions.	• The sampling rate and selection of the mother wavelet are important.	[172]
17.	Adaptive neuro-fuzzy inference system	Time domain analysis	• Non-invasive. • Used with stator current. • Detectability with a wide speed range. • Can detect BRB and air gap eccentricity. • Reduced complexity and high accuracy.	• High computational burden. • Extensive training of the network.	[173,174]

4.3. Bearing Faults

Bearing mechanical faults contribute to an impact of 40–50% of overall rotating electric machine failures [35]. IMs use ball or roller bearings with the rolling element, outer race, inner race, and train (or cage) defects, as shown in Figure 11, due to mechanical stress and bearing currents, poor installation, assembling, temperature rise, and maintenance cause most bearing failures. Pollution or contamination added from outdoors also cause bearing failures due to adverse impact on the bearing lubricant. Dust and liquid contamination entering the seal cause bearing failures [175]. Most diagnostic methods for machine electrical and mechanical failures use MCSA [43,176,177].

(a) (b) (c)

Figure 11. Depict of bearing structural faults: (**a**) ball bearing, (**b**) outer raceway fault, (**c**) inner raceway [178].

Bearing faults can have the following causes:

1. The rotor vibrates heavily and increases the fatigue stress due to high output load torque;
2. Loss of lubrication brought on by a shaft voltage;
3. A high bearing current result in the heat that the shaft can conduct.

Different sensor data, such as vibration measurements, motor current, input voltage, stray flux, and temperatures at different motor locations, are used in conventional bearing condition monitoring and diagnostics.

Motor vibration analysis gives the frequencies produced by the failures can be expressed in Equations (4)–(7):

$$f_{outer} = \frac{N_b f_r}{2}(1 - \frac{d\cos\phi}{D}) \quad (4)$$

$$f_{inner} = \frac{N_b f_r}{2}(1 + \frac{d\cos\phi}{D}) \quad (5)$$

$$f_{cage} = \frac{f_r}{2}(1 - \frac{d\cos\phi}{D}) \quad (6)$$

$$f_{ball} = \frac{d f_r}{2D}\{1 - (\frac{d\cos\phi}{D})^2\} \quad (7)$$

where f_{cage} is the cage failure frequency, f_{outer} is the outer race frequency, f_{inner} is the inner race f_r quency, f_{ball} is the ball defect frequency, d is the ball diameter, D is the pitch diameter, and f_r is the frequency of the rotor (mechanical).

$$f_{cur-harmonics} = |f_i - nf_c| \quad (8)$$

where $f_{cur\text{-}harmonics}$ is the harmonic current frequency, f_i is the fundamental inverter frequency, f_c is the characteristic vibration frequency, and n is an integer. Figure 12 summarizes different approaches from the spectrum waveform and signals, illustrating faulty or abnormal attributes [42,178,179].

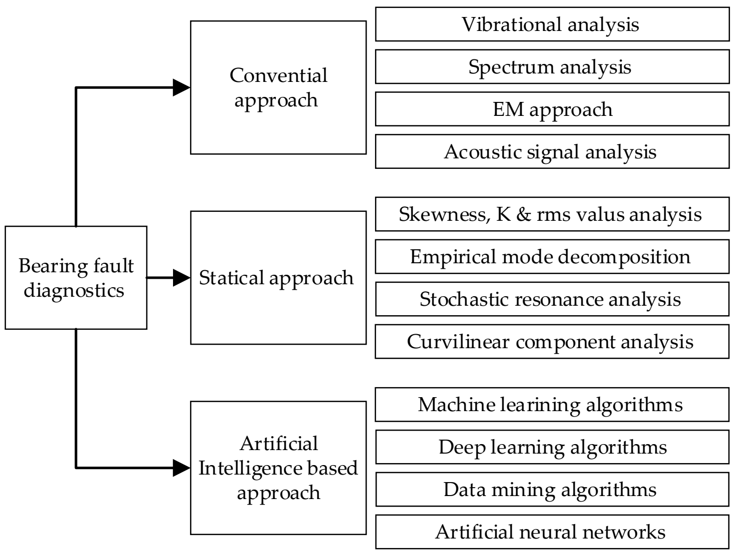


Figure 12. Bearing fault diagnostic approach [178].

The inaccurate and air-gap irregularity in stator–rotor structure and bearing stiffness can cause excessive motor vibration by affecting shaft dynamics. IM break or destroy early due to rotor bar failures caused by bearing failures. Using the homogeneity algorithm (HA), the authors of [180] presented the fault traces in outer race-bearing in IM that use the vibration signals to estimate the change on the normal structural line and initiate the fault detection.

The author of [181] proposed the mechanical fault of bearing using the motor current signature analysis based on the normalized triple co-variance in the IM. The author of [182] proposes a prospective Envelope Harmonic Spectrum (EHS) and adaptive second order cyclo-stationarity blind deconvolution algorithm. This research implementation can estimate the IM bearings. Based on the literature, Table 7 compares different traditional diagnostic methods.

Table 7. Induction motor bearing fault diagnosis methods.

Sr. No.	FD Technique	Pros	Cons	Type of Fault	Reference
1.	Harmonics in motor current signature analysis (MCSA)	• Features are extracted well. • Immune to noisy environments.	• Stationary signals are excluded.	• Ball bearing.	[62,131]
2.	Instantaneous frequency-power spectrum	• Identify the useful information.	• Measurement errors of faulty signals.	• Ball bearings • roller bearings.	[183–185]
3.	FFT and current-voltage information	• Measures value quickly. • Isolates bearing faults.	• Inclusion with data manipulation.	• Ball bearings.	[186,187]
4.	Phase modulation and high-resolution stator current spectral analysis	• Accurate. • Measures faults where segregation is difficult.	• Nonlinear. • Expensive.	• Inner race. • Outer race faults.	[188]

4.4. Air-Gap Eccentricity Faults

Non-uniformity in the airgap in the motor's rotor-stator physical structure creates these eccentricity faults. Three types of these faults as stated below [189,190].

1. Static eccentricity (SE);
2. Dynamic eccentricity (DE);
3. Mixed eccentricity (ME).

SE has a fixed minimal radial air gap, and the rotor center of the axis remains fixed regardless of the center stator diameter. In contrast, in DE, the center of the rotor moves with the stator, while ME includes both SE and DE. The rotor in ME rotates around the third fixed center of rotation other than the center of the stator or the rotor [191]. Figure 13 shows the state of change of the center of rotation in operation and Table 8 shows the induction motor diagnosis methods related to eccentricity fault.

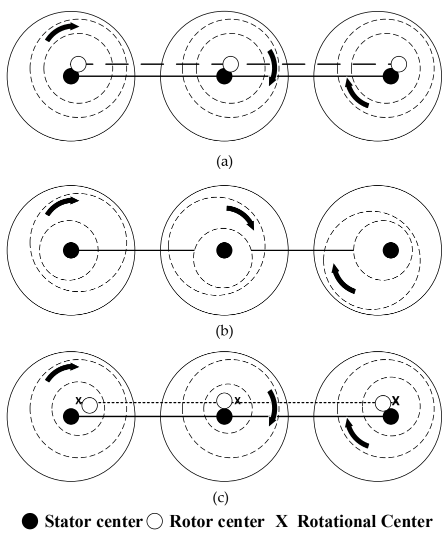


Figure 13. Eccentricity faults: (**a**) static eccentricity, (**b**) dynamic eccentricity, (**c**) mixed eccentricity [192,193].

Table 8. Induction motor eccentricity fault diagnosis methods.

Sr. No.	FD Technique	Pros	Cons	Reference
1.	Air gap eccentricity monitoring using magnetic flux	• High accuracy.	• Various sensors are required. • Complex representation.	[194,195]
2.	Stator current analysis in time and frequency domain	• Non invasive. • FFT measures value quickly. • Isolates bearing faults.	• Difficult in fault segrigation. • Expertise required in implementation. • Inclusion with data manipulation.	[196]
3.	Instantaneous frequency-power spectrum	• Identify the useful information.	• Measurement errors of faulty signals.	[197]
4.	Wavelet transform analysis (WT)	• Only current or voltage signal are required. • t-f analysis. • High resolution analysis. • Can segrigate faults amoung PHS and fault sidebands.	• Can be used to segregate faults. • Can be used for varying load conditions.	[198]
5.	Eddy current testing	• Easy in detection due to variations in magnetic fields.	• Multiple sensors required. • Complex FD technique.	[199]
6.	Neural network technique	• High accuracy in model. • Accounts for turn-to-turn capacitances and 3D end winding.	• Difficulty in training ANNs with historical data.	[200,201]

Equations (9)–(11) below show the eccentricity fault frequency, and f_c shows the central frequency.

$$f_{ec} = f_g\{(R \pm n_d)(\frac{1-s}{p}) \pm n_{ws}\} \tag{9}$$

$$s = \frac{N_s - N_r}{N_s} \tag{10}$$

where, f_{ec} is the eccentricity frequency (also called the irregularity frequency), f_g is the fundamental frequency, R is the number of rotor bars, n_{ws} is $1, 3, 5, 7, \ldots$, N_s is rotor slip, N_r is synchronous speed, s is slip (per unit), and slip is calculated from the equation, n_d is $+1$ or -1. Central frequency f_c on the air gap-static eccentricity spectrum is determined by Equation (11).

$$f_c = Rf_g \tag{11}$$

4.5. Common-Mode Voltage (CMV) and Bearing Current Faults

Each pulse's voltage waveform at the inverter terminals has steep lines at the start and end. Recent studies have shown that PWM inverter's common-mode voltage (CMV) is the primary reason for this, which creates the bearing current (BC) as a serious side effect [48]; the most effective reasons for this are as follows.

1. The voltage at the equipment terminals is doubled because of reflections, putting extra strain on the windings' insulation.
2. In windings, capacitive currents and non-uniform voltage distribution can cause electrical machines to experience a circulating current nominated as a bearing current.
3. Charges stored in the ground capacitors.

The common-mode voltage and bearing current faults are discussed below.

4.5.1. Common-Mode Voltage (CMV)

PWM inverters usually cause motor bearing failures. Bearing currents, also known as shaft voltages, flow from the shaft through the bearings and must be monitored and diagnosed when PWM inverter sources feed an electric machine. This issue is usually caused by bearing material erosion and mechanical failures like rotor eccentricity, homopolar flux effects, and electrostatic discharge in electric devices [48]. Since the phase output voltages alternate between +V_{dc} and $-V_{dc}$. The neutral-to-ground voltage in a star-connected machine is the zero-sequence voltage, expressed in Equation (12). Figure 14 shows that the voltage change rate and CMV frequency is three times more than the switching frequency. The overall CMV activity is done by the parasitic capacitance, starting from the stator winding point to the rotor [24,27].

$$V_{com} = \frac{V_A + V_B + V_C}{3} \tag{12}$$

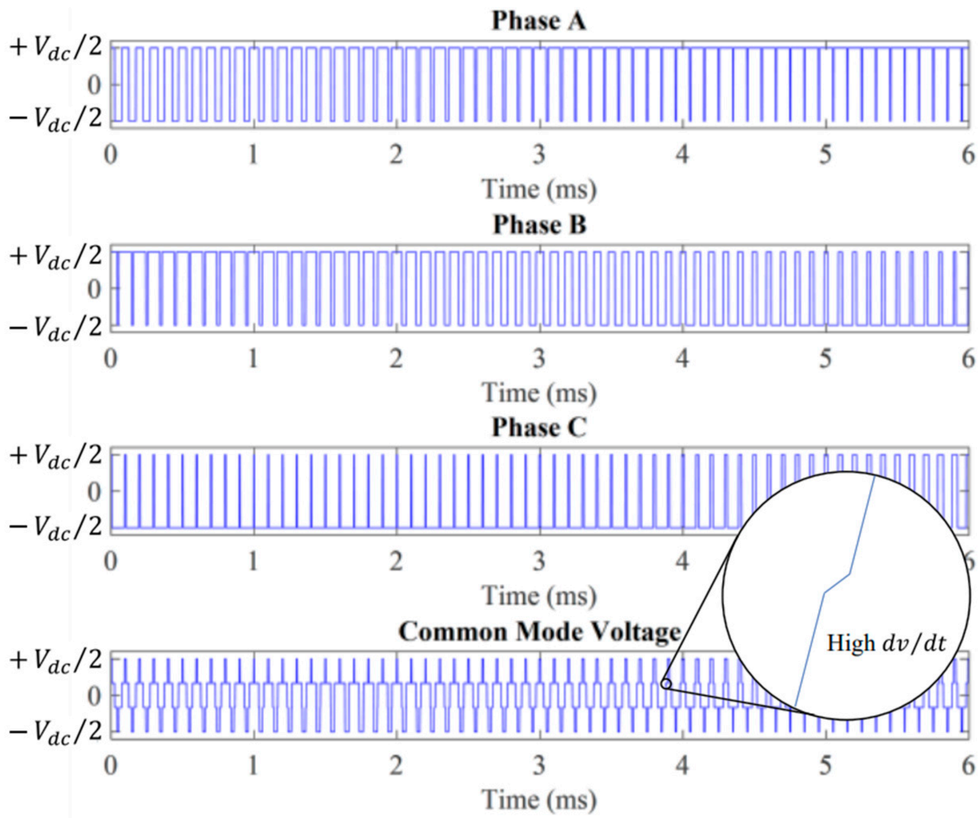


Figure 14. Impact of PWM inverter with CMV [12].

Since each pulse's voltage waveform at the inverter terminals has very steep lines at the start and end, this is the root cause of the negative effects on the motors' service lives and the overall system's vulnerability. Recent studies have shown that PWM inverters' CMV is the primary reason for these side effects [81]:

1. The voltage at the equipment terminals is doubled because of reflections, putting extra strain on the windings' insulation.
2. In windings, capacitive currents and non-uniform voltage distribution can cause electrical machines to experience a circulating current nominated as a bearing current.
3. Charges are stored in the ground capacitors.

Charging current is generated due to the developed common mode capacitive coupling. It flows from the rotor to the end bearing due to the highest switching application of PWM drives for the induction motor with the high *dv/dt*. Bearing currents are classified by their courses inside the machine and origin:

1. Capacitive BC,
2. Non-circulating BC,
3. Circulating BC (electric discharge machining),
4. Current in rotor-ground.

As depicted in Figure 15, the bearing current I_{brg} comes from a simple inverter with one phase (phase a) and an impedance Z_{inv} between the DC-link and the ground. Stator winding and the rotor create capacitance C_{wr}, which starts charging the rotor shaft current when the inverter current flows into the motor's main windings.

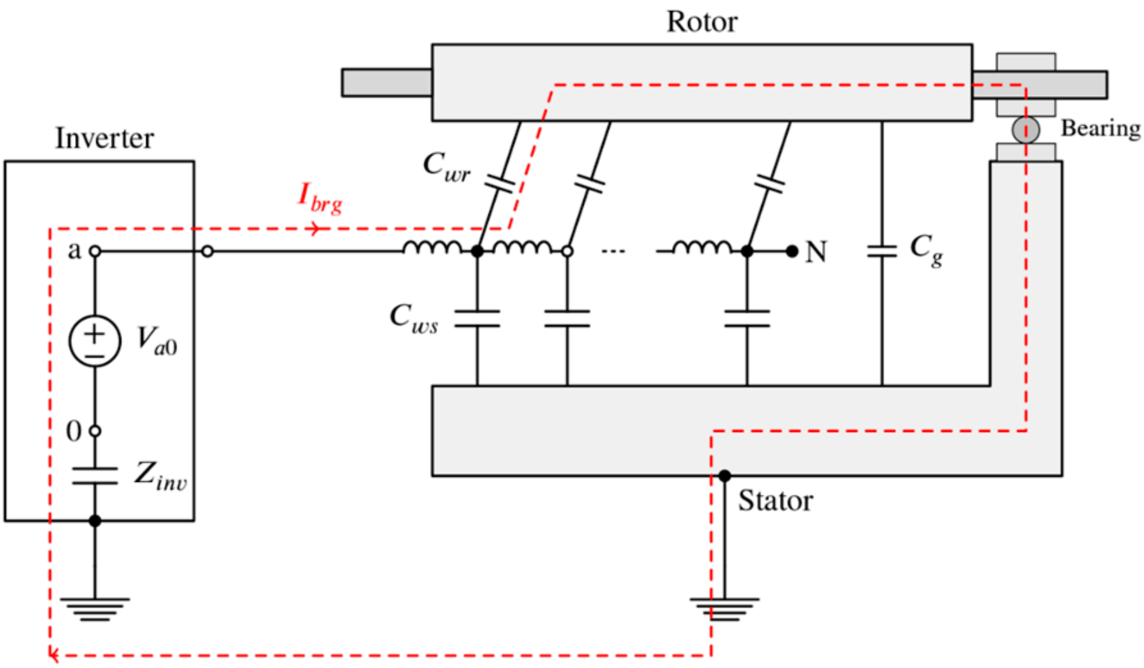


Figure 15. Bearing currents with the ground return [26].

C_g is the capacitance across the bearing C_{ws} and C_{wr} are parasitic capacitance in motor, respectively. Z_{inv} is the inverter-ground capacitive coupling. This is non-circulating because the bearing current returns to the inverter instead of the machine. Stray capacitances in the stator winding cause bearing leakage currents generated by the parasitic capacitive coupling between the rotor and stator alone. the second circulating current arises due to the electromagnetic induction caused by the stray magnetic flux path field within the winding coils, due to uneven current distributions.

High dv/dt generates capacitive currents to the stator iron, causing this uneven current distribution. Terminal-end currents are higher than far-end currents, creating a current unbalance on each coil side, as shown in Figure 16.

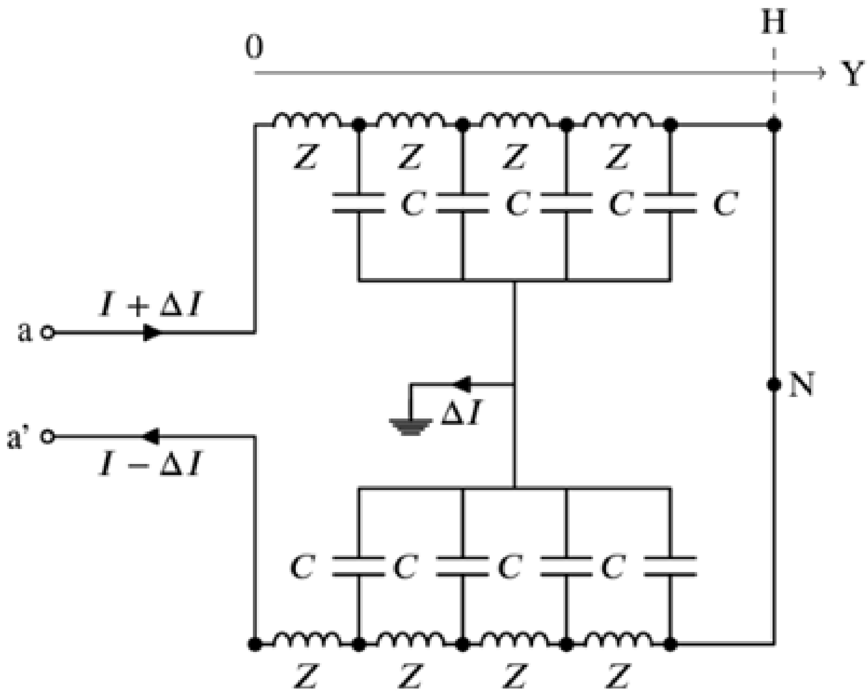


Figure 16. Stray capacitances between winding and stator iron [202].

A fast and accurate method of fault diagnosis using a common-mode voltage and an open switch has been proposed and implemented. An active common-mode voltage injection (ACMVI) is used to improve the algorithm's robustness applicability, reduce the false frequency alarms, and enhance fault diagnosis accuracy [203]. For the modeling of current faults and circuit parameters, it is required to have an in-depth analysis of the reflection of typical electrical machines' complex geometry and their material composition. Different Analytical (DA), Finite Element Analysis (FEA) two-dimensional (2D), and FEA three-dimensional (3D) modeling techniques evaluate the bearing or shaft currents process [12]. A comparative summary of the different parameter identification for the parasitic capacitance for the bearing current estimation and further analysis for the condition monitoring and diagnostics is presented in Table 9.

Table 9. Machine parasitic capacitance calculation methods in fault mitigation.

Sr. No.	FD Technique	Pros	Cons	Reference
1.	Impedance fitting algorithm	• Accurate and validating. • No assumptions; naturally consider all factors.	• Inspection points. • Difficulty in decoupling specific capacitances from adjacent capacitances. • Turn–turn capacitances.	[204]
2.	Geometrically simplified analytical methods	• Have low computational burden. • Featured with the estimation of stray capacitance.	• Inedequete approximations. • Difficult in end-winding modelling to quantify the effect.	[205]

Table 9. *Cont.*

Sr. No.	FD Technique	Pros	Cons	Reference
3.	2D FEM	• Better in estimation of turn to turn capacitance. • End-winding is simplified by the axis-symmetric modelling.	• Non-consideration of turn-to-turn capacitance. • Non-consideration of end-winding.	[206,207]
4.	3D FEM	• High accuracy in model. • Accounts for turn-to-turn capacitances and 3D end winding.	• Calculation difficulty in the material and geometry.	[208–210]

4.5.2. Diagnostic of Bearing Currents Faults

Inverter-fed IM drives have more potential impact on generating more shaft voltages and subsequently cause bearing current, so their diagnostic is a pre-condition for a prognostic of the overall power system [211]. For an effective motor fault diagnostic, authors suggested several mitigation methods based on the motor's physical, analytical modeling, which considers the overall surrounding of the motor containing the whole bearing current path installation [212].

The primary methods for reducing bearing current are depicted in Figure 17 based on the inverter, motor, and connection side. New inverter topologies and modulation strategies have been devised to reduce the CMV amplitude and voltage and impact of high dv/dt, which also feature the bearing-current diagnostic approaches from the input source side [213–215].

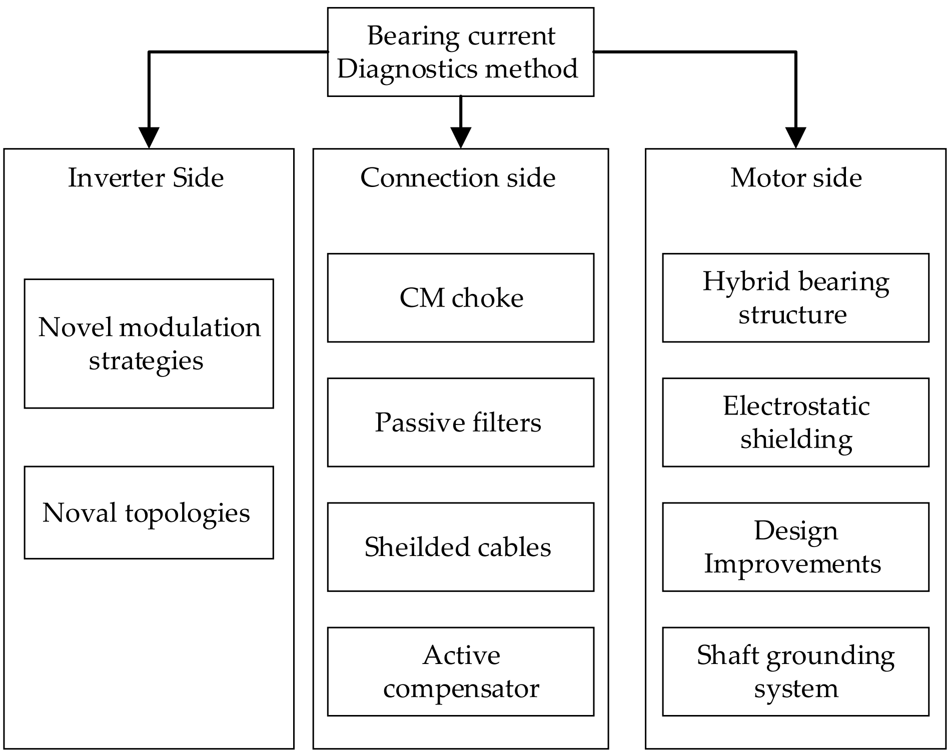


Figure 17. Main bearing current mitigation strategies [12].

Table 10 summarizes the mitigation method's pros and cons. It shows that not all mitigation methods reduce all bearing current types. Understanding the bearing current mechanism is necessary before choosing mitigation methods. Most mitigation methods are costly and require high accuracy bearing current modeling to determine their necessity.

Table 10. Methods of bearing current fault mitigation.

Sr. No.	FD Technique	Pros	Cons	Reference
1.	Filtered-hybrid selective elimination of harmonic with Pulse Width Modulation	• Harmonic elimination. • HF noise mitigation with PWM.	• Feasible for fans or pumps.	[216]
2.	Space vector PWM control design	• PWM rectifiers/inverters' CMV can be greatly reduced.	• Fully controlled rectifier needed.	[217]
3.	1-φ half-bridge, multi-level-inverter system	• A potential reduction of 98.67% of bearing currents.	• Extra hardware.	[218]
4.	An LC-filtered fourth leg	• Eliminates CMV.	• Extra hardware.	[219]
5.	Dual-bridge inverter	• Significant mitigation of leakage-current. • Eliminating the shaft voltage. • Reduction of bearing currents.	• Additional six IGBTs devices. • Additional three-phase machine. • Costly.	[220]
6.	Dual/Paired IV-level inverter with a strategic switching strategy	• CMV is suppressed down.	• System complexity.	[221]
7.	Active common noise canceler	• Reduce shaft voltage, ground current, and EMI.	• Hardware and control complexity.	[222,223]
8.	Shielded cables	• EMI and voltage reflection reduction.	• Increased circulating bearing currents.	[224]
9.	Ceramic-ball hybrid bearings	• Simple design.	• Bearings cost more.	[225]
10.	Multiple conductive microfibers	• Low friction. • Good electrical contact.	• Costly.	[226]
11.	Oblique in slots	• A 98% shaft-to-frame voltage reduction.	• Compromise the electromagnetic performances. • Reduced electromagnetic capabilities.	[227]

4.6. Partial Discharge (PD)

The dielectric of the electric motor insulation system deteriorates with high terminal voltage stresses, transient voltages, and an elevated exchange rate of voltage fed at the output terminal of inverter utilization with the PWM faster wide-bandgap devices (WBG) [228]. There is acceleration aging by stimulating partial discharges. Motor terminal surges most often cause drive failure. To avoid motor partial discharge faults, multiple HF motor models have been developed, analyzed, and presented [26,229,230].

The output terminal of the inverter has high voltage gradient attributes (high dv/dt), and high transient frequency generates the partial discharge (PD). Therefore, its output terminal voltage stresses the IM stator winding, and electrical stress at the insulation with a high impact compared with grid-fed machines leads to a permanent insulation failure [231–233]. Therefore, high-frequency modeling and lumped parameters estimation has been implemented for the condition monitoring and fault diagnostic in IM. This shows the research and development work that has been carried out in critical parameters and overvoltage mitigation to avoid partial discharges. As a result, the PD impacts and accelerated gaining parameters are necessary for effective predictive maintenance through numerical modeling.

Partial discharges lead to the ongoing degradation of the protective enamel, resulting in delamination, erosion, and breakage. These factors caused the conducting surface area in the whole component to register short circuits and signaling through the current relay with autonomous detection, as explained by the authors in [234,235]. There are four types of PDs, as depicted in Figure 18.

A summary of insulation aging analyses according to the available literature is depicted in Figure 19.

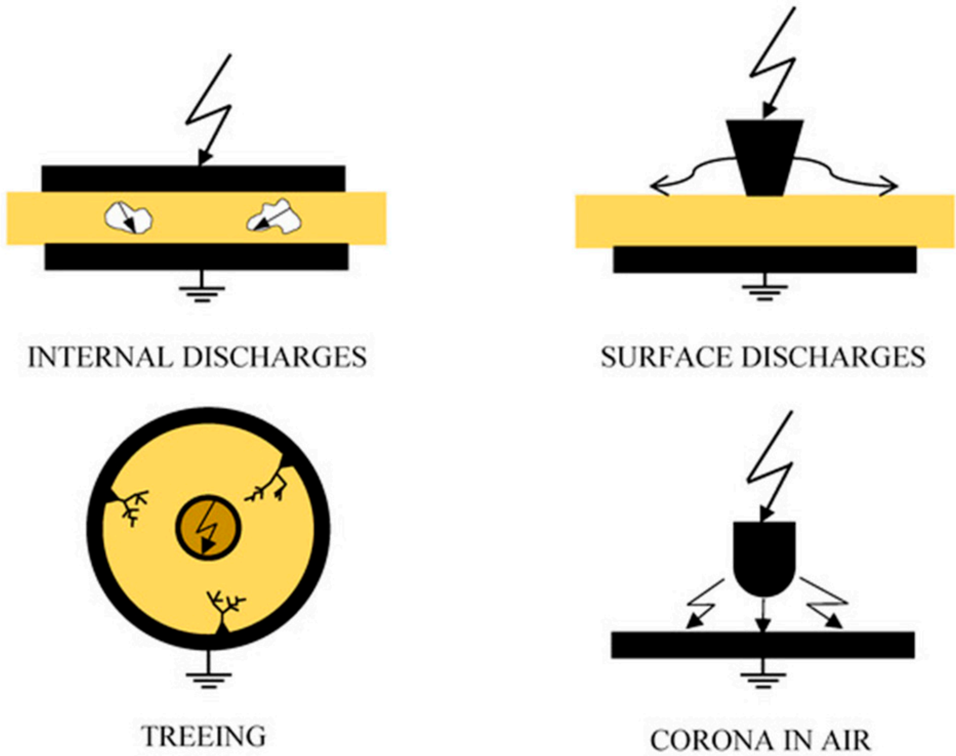


Figure 18. Partial discharge types [236].

The impedance analysis of the motor is used for a response measurement with a wide frequency range, starting from low frequency to several megahertz frequency levels. For this purpose, parameterized motor models are estimated within a motor, connection cables, and inverter, along with the corresponding series and branch impedance and an effective lumped parameter value. The LTspic software tool was used to estimate the building of numerous models, with a motor, cable, and inverter setup, as well as one-phase estimation and in-depth analysis.

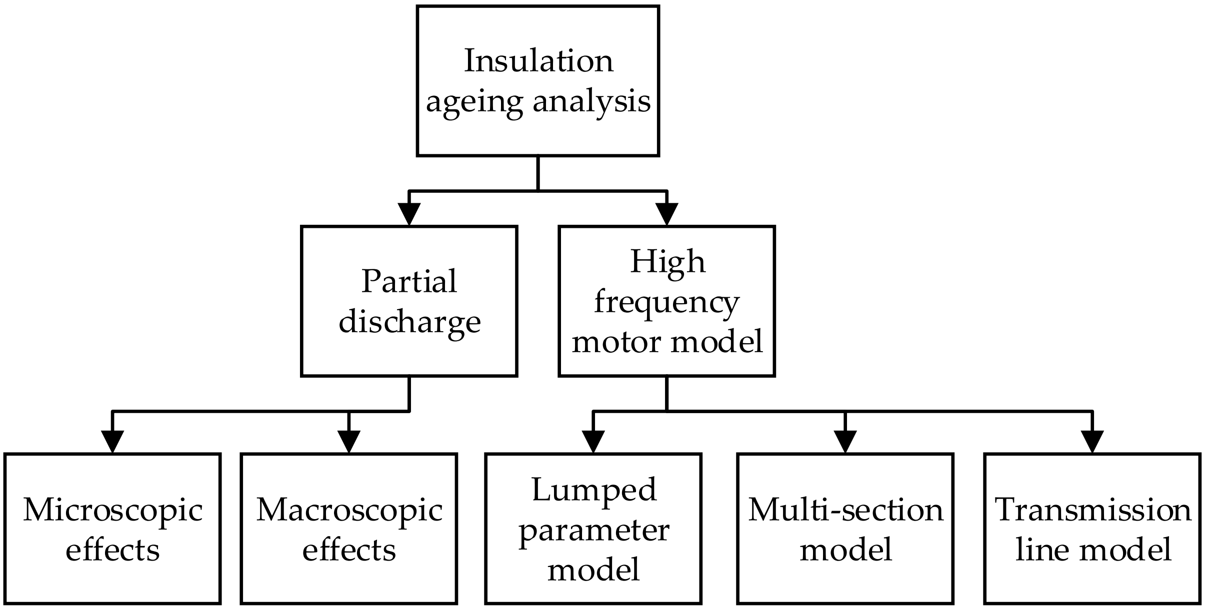


Figure 19. Review of aging insulation [234].

5. Intelligent Diagnostic Techniques

Intelligent diagnostic techniques for induction motor condition monitoring and diagnostics include fuzzy logic (FL), as well as model-free optimization methods like genetic algorithms, a hidden Markov model, a Bayesian classifier, a support vector machine (SVM), deep learning, and artificial neural networks (ANN) [98,237,238]. Figure 20 shows multiple diagnosis types based on artificial intelligence algorithms used in modern computations.

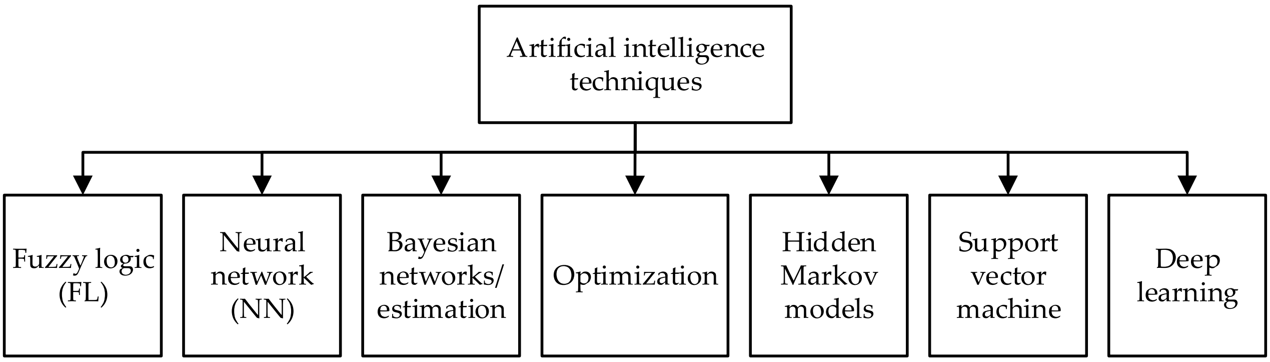


Figure 20. Artificial intelligence-based fault diagnosis of IMs.

Thus, the system should monitor algorithms with input–output mapping, dynamics, and control expressions. An artificial neural network (ANN) is used in a system for prospective detection of bearing faults in IM using MCSA [94]. ANN uses Levenberg–Marquardt-trained three-layered backpropagation.

There is another type of neural network called a Trained Neural Network (T-ANN), which is now confirmed for implementation and validity with the use of the trained data. Residuals are obtained from the output of the ANN. The resultant output data can be monitored for the delivered accuracy and validity in which the residues threshold illustrates the potential fault estimation.

Author study [99] used machine learning and k-means clusters as assessment criteria for condition monitoring and fault diagnostics, among other behaviors. The author of [239] proposed a neural network structure for detecting the induction motor bearing fault. Real-time torque and voltage unbalance monitoring was used to examine faults further. In [102], the author demonstrated the hybrid feature reduction process using the motor vibration signature analysis in a novel way. The following features listed below can help to recognize and show the fault or failure in IM:

- Decomposition methods of the signal,
- Statistical time-based feature prediction,
- Genetic algorithm (GA) optimization based on the feature,
- Component analysis based on integrating principal,
- Selection procedure based on the feature,
- Selection based on the Fisher score,
- Extraction of the feature.

Additionally, fuzzy logic (FL) can be used for the condition monitoring of the IM. The following algorithms concerning the real-time implementation of the artificial intelligence (AI) field for condition monitoring and fault diagnostics are listed below:

- Adaptive neuro-fuzzy inference systems (ANFIS),
- Fuzzy wavelet logic,
- Wavelet packet transform (WPT),
- Support vector machine (SVM).

K-function, also known as Kernel function, and wavelet transform were added to SVM techniques for fault diagnostics goals. Wavelet fusion features and decision analysis can also detect IM faults [240,241].

6. Summary and Future Directions

Modern drives operated by WBG-based power electronic converters are more effective when used in electric traction or propulsion systems because they work better, are more portable, and have fewer moving parts than traditional Si-based drives. The main challenges affecting the reliable operation of electric motors are the sharp pulse steps with large over-voltage transients and high-switching frequency in the operation of inverters observed at motor input terminals. The impact of the inverter on the electric machines must be considered according to the faults, and, hence, its CM and FD increase their service life. In the case of inverter-operated machines, the complexity level of segregating the fault frequency trances and investigation becomes higher.

Limitations such as discontinuities in available data, a lower sampling rate of the sensor signals, and fractional signal data at the start and end lead to enduring spectral leakage when applying some FFT algorithms. Spectrum resolution also has limitations for some of its complexity in the available fault condition monitoring and diagnostics. The application of advanced signal processing techniques makes the process more extensively complex, and places a high computational burden on addressing the abovementioned issues. Therefore, there is good research potential in simple algorithm development to improve the spectrum resolution without the complexity of advanced signal processing techniques. Furthermore, based on the research gap, some recent directions and research ideas for future studies in CM and FD for IM operated by PWM high-frequency inverters are stated below and explained in detail.

1. FD in IM fed with high-frequency PWM inverter: Research into the impact of high-frequency PWM switching on the motor insulation, partial discharge impacts, bearing mechanical faults, common-mode voltage adverse effects, and other components, and to foster techniques to detect and diagnose faults specifically related to the PWM operation.
2. Sensor-less fault detection techniques: Analyze some of the advanced sensorless FD techniques that can be used to supervise the condition and identify the faults in IM, without relying on additional usages of the sensor's entity, without much complexity, and overall cost of FD strategic implementation,
3. FD with machine learning (ML): This area highlights the investigation related to applying machine learning algorithms, such as deep learning or reinforcement learning, with improved models of high accuracy in IM operated by high PWM inverters.

4. FD in multi-level inverters: This is also a potential research area to study the impact of multi-level PWM inverters on motor operation, output performance, transient response caused to load changes, operation in high-speed environments, and flux weaken range, while operating in wide-beyond speed, tailored to the characteristics of multi-level modulation techniques.
5. Condition monitoring in harsh environments: Development of robust fault diagnostic technique suitable for IM operated in harsh environments, such as in the zone of extremely high temperature, high humidity, contaminated environments, and the high duty cycle of operation, which create indigenous faults within IM. The robustness defines the compactness of the algorithm or FD techniques, which shows insensitivity in its output, with some changes in input-sensitive parameters. The probability of robustness can be analyzed through different statical analyses and analytical techniques, especially in the time domain signal analysis that include RMS value, standard deviation, skewness, kurtosis, high statical moments. It can be enhanced with optimization algorithms, such as particle swarm optimization, genetic algorithms, and other naturally inspired algorithms.
6. IoT for remote access: The most feasible and influential process can be implemented by exploring the IoT integration techniques with FD. Real-time remote monitoring of IM operated by a high transient inverter allows continuous time monitoring and early detection from anywhere.
7. Model-based predictive maintenance: For this type of FD, state-of-the-art, physics-based IM models; real-time sensor instrumentation; and measurement capability can be utilized to establish a FD scheme for predictive maintenance strategy. For the high-performance output of FD technique, the maintenance schedule can be optimized to minimize the IM motor's downtime.
8. FD in mechanical faults: Examine methods for fault identification and diagnosis in bearing, e.g., outer, inner race, and roller fault. Examples of rotor faults include broken rotor (BRB) faults and eccentricity. It is necessary to consider the one-of-a-kind difficulties and negative impact that high-PWM inverters present.
9. Online-parameter estimation: Developing the online-parameter estimation methods to accurately access the motor parameters, which can detect the fault and generate a potentially viable solution for FD. These parameters are resistance, inductances, load torque, and speed response, which vary with IM operation and employ monitoring criteria and algorithms for the FD.
10. Hybrid FD techniques: A good combination of numerous techniques, such as advanced signal processing techniques, artificial intelligence, machine learning, and model-based techniques, can be used to create a hybrid FD approach that can improve overall performance and reliability by taking advantage of the strengths inherent in each diagnostic procedure.

The above-described directions can provide an area for new research in the field of CM and FD.

7. Conclusions

In conclusion, this research paper comprehensively analyzes condition monitoring and practical diagnostic techniques for induction motors fed by inverters. With a systematic approach, this paper reviewed the impact and challenges associated with an inverter-fed system on the induction motor, different fault scenarios, and concern approach of condition monitoring and diagnostics. This study emphasized the practicality and applicability of diagnostics schemes with its pros and cons, starting from conventional methods such as MCSA, monitoring analysis, and acoustics emission. The authors also highlighted the most advanced techniques, such as data-driven prognostics, artificial intelligence (AI) and machine learning (ML), model-based fault detection and diagnosis, fault signature analysis using advanced signal processing techniques, and condition-based maintenance optimization. The fault condition monitoring and diagnostics schemes discussed in this study utilize state-of-the-art technologies to enhance the precision, productivity, and efficacy of fault detection and diagnosis across diverse systems and industries.

The presented case studies of the literature demonstrate the effectiveness of these techniques in detecting and diagnosing different induction motor faults in its stator, rotor, bearing, shaft voltages development, and partial discharge. The insights gained from this research contribute to advancing condition monitoring strategies and practical diagnostic techniques, thereby benefiting industries that rely on inverter-fed motor drive systems and researchers in the field of diagnostics.

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