Comprehensive Survey on Fault Detection and Classification in Three-Phase Induction Motors

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ABSTRACT

Electric motors have revolutionized the way of human living and resulted in the modern lifestyle. These motors are exposed to a variety of undesirable conditions and often operate in corrosive environments, dusty places, and situations that result in the failure of the motor. The most common among these motors is Induction Motors (IM). Hence, the faults occurring in Induction Motors need to be detected at a proper time for avoiding losses and further consequences. A well-designed fault detection scheme not only reduces motor failure but also increases productivity and even sometimes avoids accidents. This paper presents a critical review of fault detection and classification techniques in three-phase induction motors (TPIM). The main theme of this paper is to revisit the conventional methods for fault detection in TPIM and compare them with recently published methods based on parameters to be sensed, and the type of fault to be detected, with advantages and drawbacks. More than a hundred papers are critically reviewed from old and new regimes. Each major fault like inter-turn, rotor, bearing, and joint fault is considered for review purposes. Attention is also given to fault detection methods based on artificial intelligence (AI) and machine learning (ML). After an exhaustive review, future scope and challenges for fault detection and classification are elaborated in a separate section. Lastly, the paper concludes with brief remarks which will be very useful for new researchers who are willing to do the research in the domain of fault detection and classification of IM.

Keywords: Classification, Detection, Fault, Induction Motor.

1. INTRODUCTION

Whenever a fault occurs in the motor, the parameters such as air-gap voltages, line currents, torque, losses, and the efficiency of the motor are affected as well as excessive heat is generated in the winding. One or more of these parameters are used as a symptom to identify the type and nature of the fault in an induction motor (IM). The study of the maintenance of a three-phase induction motor (TPIM) and its failure analysis is a vast area of research for researchers for many years. Traditionally, the fault detection of the IM was dependent on current and vibration. The methods which were used include over-current, overvoltage, and earth-fault. The exhaustive literature survey of the existing condition monitoring and a protection method of medium voltage motors has been reported in [1]. Benbouzid [2] elaborated on the various types of faults in IM and the signatures generated by them for detection. The motor current signature analysis (MCSA) method is discussed in detail for the detection of various faults. However, it is observed that the use of MCSA for analyzing a signal having transitory characteristics such as drifts, abrupt changes, and frequency trends is not satisfactory as this method is load dependent. Attention is also given to the automatic fault detection algorithms based on neural networks, and fuzzy logic expert systems. Liu and Bazzi [3] submitted a detailed survey of old and recent methods for detecting the major faults in IM. The paper presents a comprehensive discussion of recent research advances, trends as well as difficulties and possibilities for fault diagnosis and detection of IM. The methods focused on artificial intelligence (AI) techniques namely, expert systems, fuzzy logic, artificial neural networks (ANNs), and integrated systems with advantages and limitations of the AI techniques. The focus is given to fault detection in induction machines, multi-phase machines, permanent magnet synchronous machines, and power converters [5]. Kazzaz and Singh [6] suggested the wavelet transform (WT) technique for analyzing non-stationary signals and getting time-frequency information. It is also shown that WT is more sensitive to small variations in a signal than Fast Fourier Transform (FFT); thereby it allows the detection of a fault in an early stage. Gundewar and Kane presented an exhaustive survey on fault detection and condition monitoring of electrical machines [7]. Peng and Chu [8] reviewed WT for fault diagnosis and condition monitoring of electrical machines which cover the various features of time-frequency analysis such as feature extraction, singularity detection, and extraction and de-noising of weak signals.

This paper presents a comprehensive review of fault detection and classification techniques in a three-phase induction motor (TPIM. The main contribution of this paper is to compare old methods with recently published

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methods on the common platform. The paper has been divided into different sections. Section 2 enumerates the faults and their causes in the TPIM. Section 3 includes the survey of fault diagnosis techniques for various faults in TPIM, which is further divided into four subsections. Section 4 presents the discussion, limitations, and future scopes of the relevant topic. Finally, Section 5 ends the paper with concluding remarks about the work.

2. TPIM FAULTS AND THEIR CAUSES

TPIM often works in hostile environments such as corrosive and dusty places. Moreover, these motors are also subjected to mechanical, electrical, and thermal stresses during running conditions [9]. If the stresses become severe then various faults may initiate in the TPIM. It is essential to detect the fault at an incipient stage; otherwise, it will result in the total failure of the motor and further result in costly downtime of the plant. More importantly, these failures may even result in the loss of lives, which cannot be tolerated. Accordingly, it is essential to provide some arrangements to protect the motors from failure and to enhance the life of the motor. The motor is protected normally under the following conditions, i) over-current, ii) over-voltage, and iii) earth-fault. However, as the tasks performed by these motors grew increasingly complex and the existing protection schemes are not enough, it has become essential to develop a scheme to protect these motors against unavoidable conditions or detect faults at an inception stage. Various surveys on IM failure have found the most common failure mechanisms [10]. These have been categorized according to the main components of a machine – stator-related faults, rotor-related faults, bearing-related faults, and other faults. Several surveys of faults of large IMs, conducted by IEEE, EPRI, and Allianz are compared in Figure 1. The survey conducted by IEEE and EPRI focuses on medium-sized IMs, while the Allianz survey focuses more on medium-to high-voltage large IMs.

In the following subsection, various faults and their causes are discussed briefly.

2.1 Stator Faults and Their Causes

According to [9], 35-40 % of IM failures are related to the stator winding insulation. Moreover, it is observed that a large portion of stator winding faults is initiated by insulation failures in several turns of a stator coil within one phase. These faults are mostly due to the slow and constant aging of the insulating material of winding. Such aged winding may get damaged due to excessive stresses produced by an inter-turn short circuit fault and the fault current will circulate through the damaged turns. Due to thermal runaway, the fault current progressively reduces the insulation strength of the affected and neighbouring turns. The fault further extends to the adjoining turns and the fault current rises. At last, the slot insulation or insulation of the neighbouring phase can be affected, reaching

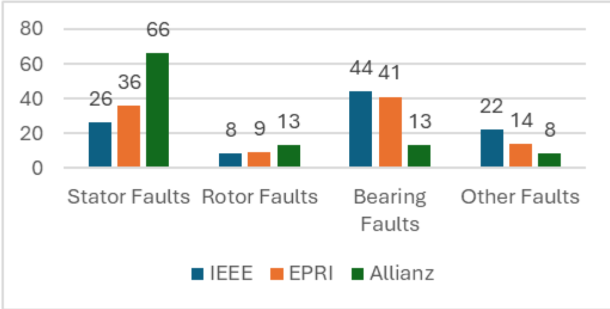

***Fig. 1**: Percentage of Fault Distribution.*

to a catastrophic failure of the motor. Although the IM can still run when some of the turns are shorted, they can consequently lead to damage to adjacent coils and a stator core, so that a ground fault can occur. Among the possible causes, the following stresses are the main reasons for the degradation of the stator winding insulation.

- Thermal Stresses: Thermal aging is a result of the operating temperature. As well known, the insulation life gets half for every 10^{o}C increase in temperature. To cope with the thermal aging due to the temperature rise in the windings, reducing the operating temperature or increasing the class of insulation materials is employed. Thermal overloading can be caused by applied voltage variations, unbalanced phase voltage, cycling overloading, obstructed ventilation, higher ambient temperature, etc. All of these can increase the temperature and can initiate thermal stress in the machine.
- Electrical Stresses: The voltage stress in the windings can be caused by having a void in the insulation, which can cause partial discharge. In addition, the surge in the electrical supply system can initiate the voltage stresses in the windings.
- Mechanical Stresses: These stresses might be due to coil movement, which is a result of the force inside the machine, and rotor striking the stator, which is caused by many reasons, such as bearing failures, shaft deflection, rotor-to-stator misalignment, etc.
- Environmental Stresses: The winding insulation can be deteriorated by chemicals, such as oil, moisture or dirt, etc.

2.2 Rotor Faults and Their Causes

According to the failure survey [9], it is stated that about 10% of total failure cases are related to rotor failures. Broken rotor bars do not initially cause an IM to fail but there can be serious secondary effects of broken rotor bars. The broken parts of the rotor bar hit the end winding or stator core of a high-voltage motor at a high velocity. This can cause serious mechanical damage to the insulation and a consequential winding failure may follow, resulting in high repair costs and outage time. Broken rotor bars or end rings can be caused by one of the following reasons:

- Thermal Stresses: These stresses may be due to thermal overload unbalance in voltages, hot spots, or excessive losses and sparking (mainly fabricated rotor type).
- Magnetic Stresses: These stresses are caused by electromagnetic forces, unbalanced magnetic pull, electromagnetic noise, and vibration.
- Residual Stresses: These stresses occur due to manufacturing problems in the motor. These can be present in any plane and are normally not harmful to the rotor as long as they do not cause any significant change in the rotor geometry. Some of the more common residual stresses are the result of casting, brazing, welding, stacking, and machining operations.
- Dynamic Stresses: These are arising from shaft torque, centrifugal forces, and cyclic stresses.
- Environmental Stresses: The stresses caused by contamination and abrasion of rotor material due to chemicals or moisture.
- Mechanical Stresses: The stresses may be due to losing laminations, fatigued parts, bearing failures, etc.

2.3 Bearing Faults and Their Causes

Bearing is a very important part of the machine. The bearing is used to hold the rotor shaft of IM. About 40% of faults are bearing-related [9]. Faults on the bearing may result in increased vibration and noise levels. Bearing faults can also cause some damage to mechanical couplings that connect to a rotor shaft. Bearing faults can also cause rotor eccentricity. The bearing damages can result from the different reasons given below.

- High vibration due to foundations, mechanical couplings, or loads.
- Inherent eccentricities cause unbalanced magnetic force.
- Bearing current which causes an electrical discharge or sparking in bearings.
- Contamination and corrosion which is caused by the pitting and sanding action of hard and abrasive minute particles or the corrosive action of water, acid, dirt, etc.
- Improper lubrication including both over and under-lubrication causes heating and abrasion.
- Improper installation of the bearing, by improperly forcing bearings onto a shaft or in housing (due to misalignment) indentations formed in the raceways.

2.4 Load and Other Faults

In some applications such as aircraft, the reliability of gears may be critical in safeguarding human lives. For this reason, the detection of load faults (especially related to gears) has been an important research area in mechanical engineering for some time. Motors are often coupled to mechanical loads and gears. Several faults can occur in this mechanical arrangement. Examples of such faults are coupling misalignments and faulty gear systems that couple a load to the motor. The other faults include eccentricity and gear-related faults. Eccentricity fault occurs when the rotor is not centered within the stator, producing a non-uniform air gap between them. In an ideal machine, the rotor is center-aligned with the stator bore, and the rotor's center of rotation is the same as the geometric center of the stator bore. Air gap eccentricity is a common fault of IMs. There are three types of air gap eccentricity: a) Static eccentricity; b) Dynamic eccentricity and c) Mixed eccentricity. Static eccentricity is characterized by a displacement of the axis of rotation, which can be caused by a certain misalignment of the mounted bearing or the bearing plates or stator ovality. Since the rotor is not centered within the stator bore, the field distribution in the air-gap is no longer symmetrical. The non-uniform air gap gives rise to a radial force of electromagnetic origin, which acts in the direction of the minimum air gap. Therefore, it is called unbalanced magnetic pull (UMP). Moreover, static eccentricity may cause dynamic eccentricity, too. Dynamic eccentricity means that the rotor is rotating on the stator bore axis but not on its own axis. The off-center axis of rotation spins along a circular path with the same speed as the rotor does (first-order dynamic eccentricity). Mixed eccentricity is a combination of both eccentricities. Therefore, the non-uniform air-gap of a certain spatial position is sinusoidally modulated and results in an asymmetric magnetic field. This accordingly gives rise to revolving UMP. This can be caused by defective bearings or manufacturing faults. The variation in air gap disturbs the magnetic field distribution within the motor which produces a net magnetic force on the rotor in the direction of the smallest air gap. This so-called unbalanced magnetic pull can cause mechanical vibration. There may be a bent shaft which can result in a rub between the rotor and stator, causing serious damage to the stator core and windings [10-11].

3. LITERATURE REVIEW

More than a hundred research papers are studied exhaustively in the area of fault detection and classification in TPIM. The survey is carried out separately for each major fault such as stator fault, rotor fault, and bearing fault. Attention is also given to combined fault detection. Accordingly, the proposed section is divided into four subsections depending on the nature of the fault.

3.1 Review of Stator Inter-Turn Fault Detection

Siddique *et al.* [12] presented a comprehensive review of various stator faults, their causes, detection techniques, and the latest trends in condition monitoring technology. Futuristic trends in stator fault diagnosis have also been discussed. The recently available techniques for online stator inter-turn fault detection and diagnosis in electrical machines are presented. Special attention is given to short-circuit-fault diagnosis in permanent magnet machines, which are fast replacing traditional machines in a wide variety of applications. This technique utilizes the results of spectral analysis of the stator current for detecting the various faults in an induction motor. These faults are mostly due to the slow and constant aging of the insulating material of winding. Such aged winding may get damaged due to excessive stresses produced by an inter-turn short circuit fault and the fault current will circulate through the damaged turns.

The methods that are non-invasive and non-intrusive are mostly considered for fault diagnosis of induction motors which monitor the motor's condition using only electrical parameters. MCSA is a traditional non-invasive technique that utilizes the spectral analysis of stator current for fault detection [13]. But the limitation of MCSA is that the magnitudes of characteristic frequency components depend on the load variation making it difficult for fault detection in the motor. It is also observed that the magnitude of the characteristic frequency component is very small compared to a fundamental component which is very difficult to extract from the frequency spectrum. The accuracy of MCSA is enhanced by combining the conventional MCSA method with the wavelet transform, short-time Fourier transform, and expert system. Further, the variation in transfer impedance obtained from symmetrical components of the motor is suggested for fault analysis in closed-loop multiple-motor drive [14]. The symmetrical components are derived from the stator phase current from which the magnitudes of negative and homo-polar components are used as stator fault indicators [15].

Park's Vector Approach (PVA) is used in [16] for fault identification in which three currents are transformed into two currents using Park's Transformation. The pattern obtained from two-phase quantities is observed to be circular for healthy motors and elliptical for stator faults [16-18]. The FFT analysis of Park's Vector Modulus (PVM) of currents is also proposed for inter-turn fault detection in which fault is quantified by observing the magnitude of the frequency component at double the fundamental frequency. The recent development in fault diagnosis by PVA is being discussed and the performance evaluation of four algorithms i.e. normalized currents average values (NVAV), errors of normalized current average absolute values, current Park's Vector phase and currents polarity, and normalized reference current errors (NRCE) are being analyzed in [19]. Modified PVA is proposed based on the higher harmonic index of the d and q components of Park's vector to detect stator faults in induction motors [20]. The authors propose to detect and classify simultaneous effects of demagnetization and inter-turn short circuit fault in the case of permanent magnet synchronous machines by analyzing the current angle in the synchronous frame [21].

Patel and Chandorkar [22] developed a dynamic model of an induction motor for detecting and locating the inter-turn faults in the stator winding. The mapping of positive and negative sequence stator current information on the polar plot is proposed for the identification and location of the fault.

Many methods are applicable only under steady-state conditions. Further, due to the non-stationary behaviour of the PVM, the time-frequency decomposition tool is more desirable than FFT analysis. The best tool for analyzing the non-stationary signal and getting time-frequency information is WT and widely used in fault diagnostics. WT is more sensitive to small variations in a signal than FFT; thereby it allows the detection of a fault in an early stage. The review of WT for fault diagnosis and condition monitoring of electrical machines is presented in [23] which covers the various features of time-frequency analysis such as feature extraction, singularity detection, extraction, and de-noising of weak signals. Siddiqui *et al.*[24] addressed the inter-turn fault detection in inverter-fed induction motor drives based on discrete wavelet transform (DWT). In this work, the transient currents are used for analysis. The low-frequency approximation and high-frequency detailed signals have been used to differentiate healthy and stator inter—turn winding motor conditions.

Spyropoulos and Mitronikas [25] suggested a method based on the combination of PVM and continuous wavelet transform (CWT) for the detection of inter-turn faults. The inter-turn fault and its severity can be detected by examining the frequency component in the PVM signal. The existence of the frequency component at twice the supply frequency is the characteristic component for inter-turn fault detection. Das *et al.* [26] demonstrated the use of cross-wavelet transform (XWT) for inter-turn fault detection. The XWT has been used to extract unique features from the PVM signal and classify various operating conditions using Rough Set Theory (RST). The CWT has been applied to the AC components of non-stationary PVM signal to extract unique features for discriminating the inter-turn faults and incipient insulation failure [27]. The various peaks in the CWT spectrum have been used to discriminate these conditions. In the continuation of research, a simplified Fuzzy Art-Map (SFAM) based classifier is shown to be more suitable for classifying the severity levels of direct inter-turn short circuit faults and equivalent incipient insulation faults [28]. Das *et al.*[29] addressed the time domain, frequency domain, and time-frequency domain features of the PVM signal for classifying the inter-turn faults. Support Vector Machine (SVM) based Recursive Feature Elimination (RFE) algorithm is used to select, rank, and optimize the number of effective features. A Support Vector Regression (SVR) classifier is proposed to classify different stator winding fault conditions based on selected features. It is noticed that the algorithm gives better results for known load conditions. To make the fault classification algorithm immune to varying load levels, additional two features of the PVM based on detrended fluctuation analysis are extracted. Bessam*et al.* [30—31] suggested the method for the detection and location of the inter-turn short circuit fault in the stator windings using DWT and neural networks. The energy in the seventh decomposition level is used as an input to the feed-forward multilayer-perceptron neural network trained by back-propagation. The proposed technique is efficient and accurate to detect and locate automatically an inter-turn short circuit fault in the stator windings of the IM. Seshadrinath *et al.* [32–33] developed the minor inter-turn fault detection technique in the stator winding using complex wavelet transform. A genetic algorithm is used for feature optimization and SVM is adopted for classification purposes in which four conditions: healthy, turn fault, balanced supply conditions, voltage imbalance, and the inter-turn fault with voltage imbalance, both occurring at the same time are considered for classification.

In recent years, artificial intelligence-based techniques are used for monitoring and fault detection. Filippetti *et al.* [34] proposed the applications of AI techniques (expert systems, neural networks, and fuzzy logic) for rotor fault detection. Nejjari and Benbouzid suggested and classified healthy, stator fault and voltage unbalance cases in induction motors using the Parks vector approach and ANN [35]. LF-organizing Kohonen neural networks are used for detecting stator and bearing faults [36].

Rama Devi *et al.* [37] presented the three modular neural networks, in which wavelet features are extracted from three-phase currents to classify various disturbances. The first network is used for classifying single phasing, supply unbalance, under voltage, stator inter-turn faults, sudden load change, and phase faults whereas the second network is used for classifying the stator winding phase faults, and the third one is used for identifying the faulty phase and severity level of stator inter-turn faults. The stator faults are detected using DWT of transient current in the case of an inverter-fed induction motor drive [38]. The author claims that the proposed method provides notable results, reduces the computational burden, and simplifies the estimation process remarkably.

Bouzid *et al.* [39] proposed a method for inter-turn fault detection based on three-phase shifts between the line current and the phase voltage. It is achieved by a feed-forward multi-layer perceptron neural network (NN) trained by back-propagation. Rodrguez and Arkkio [40] used the fuzzy logic system for detecting the inter-turn faults in the stator winding. The layout has been implemented with both data from a Finite Element Method (FEM) motor simulation data and real-time data.

The inter-turn short-circuit fault and winding resistive asymmetrical fault are discriminated for the simulation model using the rotor-reference-voltage signals inside the rotor-side-converter control system. DWT is used to determine the energy of the signal and to propose the fault severity index [41]. Diagnosis and classification of the stator winding insulation faults on a three-phase induction motor are detected using DWT and classified various practical conditions such as fault, voltage unbalance, and sudden load changes using a multilayer neural network in [42]. Yi-Hang Wu et al. detected the minor inter-turn short circuit fault at the incipient stage using a metal-coated fiber Bragg grating sensor in which temperature and magnetic field around the end winding are acquired and analysis is carried out in the time-frequency domain and claiming very good results [43]. Inter turn faults in the SCIM are detected using the harmonic analysis of stator winding current, external magnetic field, and electromagnetic torque. Authors are able to detect the stator faults with voltage unbalance conditions and the variable loading environment. Authors claim that stray flux monitoring is more effective as compared to stator current and electromagnetic monitoring [44]. A short circuit fault in the stator winding is detected using Kalman Filter [45]. The residual signals of voltage and current are used for the analysis purpose. The proposed method is tested with different power quality issues and claims very good accuracy with robustness. The authors detected the inter-turn short circuit fault in VSI fed IM drive by applying the DWT to the stator current and estimated the L2 norm statistical feature to classify the fault using SVM [46]. Authors invented the inter-turn fault detection based on features extracted from the voltage and current signal i.e. phase shift between these two signals and used as inputs to train the SVM. The obtained results showed that the SVM performance is better than the neural network under the light load condition of the motor [47].

3.2 Review of Rotor Fault Detection

Rotor faults are of significant importance as they cause secondary failures which lead to serious motor malfunction. Mehrjou *et al.* [48] presented the critical review, summary, and developments of recent research performed in the area of rotor fault diagnosis. Rotor faults can be categorized into rotor eccentricity, breakage of rotor cage bars, breakage of end-rings, and rotor bow. The rotor is subjected to various stresses that severely influence the rotor condition and cause subsequent failures. Bonnett and Soukup [49] studied the various stresses and their causes in IM. Kliman *et al.* [50] developed an instrument for detecting broken or cracked rotor bars using the MCSA method. The FFT spectrum of the square of the current is considered and more relevant information about the rotor fault is obtained compared to MCSA [51]. Cardoso *et al.* also suggested the PVA method for rotor fault detection in which the relative thickness of the Lissajous pattern is utilized for deciding the severity of the rotor faults in an induction motor. The spectral analysis of PVM was obtained from three-phase currents used for detecting rotor cage faults in three-phase induction motors [52-54]. Talhaoui *et al.* [55] detected rotor fault in the case of sensor-less vector control induction motor using speed, and current signals. To prove the effectiveness analysis of DWT for transient and non-stationary signals, FFT and DWT are applied to the motor signals. In this, it is observed that the performance of DWT is quite better as compared to FFT analysis. Daviu*et al.*[56] suggested a method for the diagnosis of rotor bar failures in induction machines, based on the analysis of starting currents using the

DWT. The faults are detected under practical operating conditions and compared with the classical FFT method. The authors also proposed rotor fault detection using the Hilbert-Huang-based method and studied the advantages and disadvantages of both methods. Kia *et al.* [57] proposed rotor fault detection based on DWT for varying load conditions. It is shown that applying the proposed algorithm to the squared instantaneous magnitude and the squared stator current space vector magnitude of the stator current can detect the rotor fault without knowing the value of the slip. However, the single current sensor technique is preferred since it induces a lower cost than the space-vector current involving three current sensors with the problem of balancing them. Tsoumas *et al.* [58] suggested a method for rotor fault detection under low-loading conditions. The stator current is filtered through a complex wavelet to remove the fundamental supply frequency component so that faulty components can be easily highlighted. Moreover, the mean absolute deviation (MAD) of the wavelet transform is extracted and used as an input to a support vector machine and Multi-layer Perceptron (MLP) classifier to detect rotor fault at very low values of slip. Ayhan *et al.* [59] investigated a different approach for rotor fault detection in which multiple signature processing is suggested to overcome or reduce the effect of any misinterpretation of the signatures that are obscured by factors such as measurement noises and different load conditions in the conventional methods. Two different multiple signature processing techniques are demonstrated and shown that the proposed approaches are more efficient and accurate than a single signature processing.

R. Senthil Kumaret al. presented a method for the detection of broken rotor bar fault by combining Artificial Neural Network (ANN) and Hilbert Transform (HT) for three-phase InductionMotor Drives (IMD) operated under Direct Torque Control (DTC) topology under steady state [60]. The combination of both Park's vector approach and the extended Park's vector approach (EPVA) for broken rotor bars (BRBs) fault detection and identification is presented in [61]. In the case of a gearbox-based Induction machine, frequencies induced in the stator current are always overlapped due to Low-frequency torque (LFT) oscillations and rotor asymmetry (RA). The authors separated these two frequency components using the single-phase current in the stator winding. The method benefits from a novel pre-processing stage based on several sign functions. The proposed method maps the static reference frame obtained through a single stator current and its associated Hilbert transform to the proposed rotating reference frame, which can separate the effects of LTOs from RA effectively [62].

3.3 Review of Bearing Fault Detection

The bearing-related faults cause a percentage of motor failures in the range of almost 41-50 % [63]. Consequently, it is essential to detect such incipient faults to avoid loss of revenue and to enhance the life of the machines. The faults related to bearing originate from distributed types, such as raceway roughness and waviness, and then develop into local types, such as cracks, pits, and spalls. Based on the locality of the fault, these can be sub-alienated into inner-race, outer-race, ball broken faults. Most of the traditional methods developed for fault detection are based on vibration analysis. These are based on the monitoring of exact characteristic frequencies for specific bearing faults in the frequency spectrum of the signal. Tandon *et al.* [63] and Patidar *et al.* [64] reviewed the methods for bearing fault detection based on vibration and acoustic analysis using different signal processing techniques. However, the vibration sensors required for these techniques are very costly, and access to the motor is also required. Schoen *et al.* [65] addressed the detection of bearing faults using stator current monitoring by correlating the relationship between vibration and current frequencies. The obtained signatures fall at locations that are different from the supply and slot harmonics of the motor with a relatively small magnitude. With spectral resolution techniques, current monitoring will be an effective way for bearing fault detection. Consequently, stator current-based bearing fault detection has received more and more attention in research.

A common review of stator current analysis for bearing fault detection with different signal processing techniques is presented in [66]. The bearing faults are mainly classified into single-point defects and generalized roughness.

Singh *et al.* [67] presented the detection of outer race faults using current monitoring. The technique is based on the application of CWT to the current signal and compared the results with the FFT technique. Saeidi *et al.*[68] used Park's vector approach for bearing fault detection in which four-time domain features are extracted from the PVM signal and classified healthy and inner race faults using an adaptive neuro-fuzzy inference system. The results obtained by this method give better performance compared to the results obtained from a single-phase current. Zarei and Poshtan [69] implemented an FFT analysis of the PVM signal of currents for bearing fault detection. The obtained results compared with the MCSA and concluded that the proposed method is reliable for detecting bearing faults in the induction motor. The Concordia approach along with fuzzy logic is applied to the detection of stator faults in variable load applications [70]. Delgado *et al.* [71] identified the bearing faults using the statistical time features of vibration signal and curvilinear component analysis. The hierarchical neural network is used for classifying the various bearing faults under operating conditions.

The localized bearing faults such as inner race and outer race faults are detected using stator current and vibration envelope analysis based on squared envelope spectrum analysis in the induction motor. The authors claim that the method based on the analysis of squared envelope spectrum current is superior in comparison with any existing stator current or vibration monitoring techniques [72]. Picot *et al.* addressed bearing fault detection with a statistical parameter of particular frequency bins in high-speed permanent magnet synchronous machines. The method is also compared with the vibration method and obtained satisfactory results [73]. The bearing faults are detected using the non-Gaussian model in which a combination of kurtogram and alpha-stable model is proposed [74]. Frosini *et al.* [75] calculated the statistical parameters of the stray flux signals. These signals are acquired using a special flux probe and placed at multiple locations around the motor for detecting localized bearing faults in the induction motor. Zhu *et al.* [76] proposed the hybrid of null space pursuit and S transform for detecting various bearing faults in an induction motor. Maruthi and Hegde investigated the multiple bearing faults using vibration analysis using micro-electro-mechanical-systems (MEMS) accelerometers under various operating conditions [77]. Zarei *et al.* designed removing non-bearing fault component (RNFC) filter for detecting bearing faults using a neural network. It is shown that satisfactory results are achieved when the filtered component of the vibration signal is used for fault classification instead of the use of the original vibration signal [78].

Soft computing approaches have also been employed to enhance the accuracy of bearing fault detection. Li *et al.* [79] proposed bearing fault detection and classification based on the mixed features of the vibration signal and the neural network. Four different faults include; looseness, inner race, outer race, and defect in the rolling element are considered for fault analysis. Zarei [80] suggested that only time domain features are sufficient for bearing fault classification which not only leads to a lower computational burden but also results in more accurate fault diagnosis. Samanta *et al.* presented pre-processing techniques like high-pass, band-pass filtration, envelope detection (demodulation), and wavelet transform of the vibration signals, before feature extraction [81].

Many methods are proposed using support vector machines and neural-based techniques for bearing fault detection. Soualhi *et al.*[82] combined the Hilbert Huang transform (HHT), the SVM, and the SVR to detect faults in ball bearings. The SVR is used to estimate the remaining life of the bearings. Samanta *et al.* [83] presented a comparative performance of ANN and SVM for bearing fault detection. The dominant features of the vibration signal are extracted using a genetic algorithm. The performance of SVM is better than ANN with the entire feature set. Patel and Giri [84] explore the development of a random forest (RF) algorithm for bearing fault detection. The statistical features of the vibration signal are extracted and fed to RF and ANN classifiers. The performance of the RF classifier is observed to be superior to ANN. Kimothi *et al.*[85] studied the effectiveness of a random forest classifier for detecting faults in the helical gearbox. The genetic algorithm is used to extract the features from the vibration signal and the J48 decision tree is used for proper feature selection. An extensive investigation is done on an RF classifier that produces better performance for fault detection than any other classifier. An intelligent passive thermography-based technique is proposed for detecting bearing faults using Convolutional Neural Network (CNN) with Transfer Learning (TL) under varying working conditions. The proposed method enables and speeds up the training process of CNN towards accurate adaptation for fault diagnosis approach in the escalated time frame [86]. The work presented in [87] is about the detection of faults in the outer bearing's raceway with three different fault severities using motor dynamic strain signals collected from sensors based on Fiber Bragg grating. The tests were carried out on the motor operating under no-load conditions, with 47 different power supply frequencies. The occurrence of fault judged is by two features namely the four highest peaks in the frequency spectrum and the principal component analysis method whereas severity is evaluated using SVM. Thermal imaging-based fault detection is used to detect the various faults in bearing under different loading conditions [88].

3.4 Review of Mixed or Joint Fault Detection

It has been observed that most of the research work carried out by the researchers is to detect an individual fault in the motor. However, the simultaneous presence of two or more faults is a very common scenario in an industrial environment. Thomson and Fenger [89] developed an instrument based on the MCSA method for detecting stator and rotor faults. Antonino–Daviu *et al.* suggested the application of the DWT to the starting current of the induction motor for detecting rotor, eccentricity, and stator faults. The various combinations of mixed faults are also detected using currents in parallel branches of the stator winding [90]. The rotor and stator faults are detected using short-time Fourier transform (STFT)and WT [91]. A comparison between STFT and WT is carried out and features extracted from WT are used for further analysis. The energy in the detail coefficient is used to detect and distinguish the type of fault in the variable and constant load applications. Martins *et al.* [92] implemented a pattern recognition-based system for the continuous monitoring of induction motors. The method is based on the image identification of the three-dimensional current state space patterns that allow the identification of distinct types of faults as well as their fault severity. The analysis of instantaneous active power, reactive power, power factor, and phase angle have been suggested for detecting and discriminating broken rotor bars and air-gap eccentricity conditions from mechanical load oscillation effects in operating three-phase squirrel cage induction motors [93]. Toliyat and Lipo [94] developed a generalized mathematical model for multi−phase cage induction motors with various faults. The modeling is based on winding functions and makes no assumptions; therefore the derived model includes all the space harmonics in the machine. The equations describing the performance of multi−phase induction machines during the transient as well as steady-state behavior including the effects of stator asymmetry, broken rotor bars, and broken end rings have been derived. Ghate and Dadul [95] have developed the radial basis function multilayer perceptron cascade connection NN-based fault-detection scheme for the small and medium sizes of three-phase induction motors. Simple statistical features of stator current are extracted and optimized using principal component analysis. The algorithm is tested with uniform and Gaussian noises for detecting stator fault, rotor eccentricity fault, and combined fault. The generalized feed−forward network and support vector machine-based classifier is developed for detecting various faults in the induction machine [96−97]. Cunha Palacios *et al.* [98] evaluated the performance of classification methods for fault identification in IM. The classifiers namely: Naive Bayes, k-Nearest-neighbor, SVM, ANN, and C4.5 Decision Tree are discussed for stator, rotor, and bearing fault detection under various operating conditions. The adaptive neural fuzzy inference system (ANFIS) is proposed for the detection of stator and bearing faults [99]. The positive features of neural networks and fuzzy logic are combined for detection. The algorithm is tested with two and five measurable parameters of the motor and shows that five inputs predict more accurate results than two parameters. Vilhekar *et al.* [100] proposed the detection of multiple faults using multiple Park's vector approach. In this technique, the characteristic fault frequency component of stator winding faults, the rotor winding faults, unbalanced voltage, and bearing faults are extracted from three-phase stator currents. By monitoring the variation in multiple Park vector patterns, the type of fault and its severity level is identified. Sonje *et al.* proposed to detect and classify different faults in IM under practical operating conditions and claimed that the random forest classifier is providing satisfactory results compared to any other classifiers [101-102].

Several authors investigated and distinguished the different faults in three-phase induction motors at the incipient level. Motor speed and load current spectra are used as features to classify bearing faults, broken rotor bar faults, and short-circuit insulation faults. In [103], the author claims that the minor fault of one turn short can be judged at the very initial stage. Different faults in the SCIM are investigated by the authors in [104]. The analysis is based on statistical data in which signal homogeneity and Kurtosis is estimated using starting transient current. Fault classification is performed using ANN. A comparison is also shown with the earlier publications and it is claimed that the proposed method is far better. The authors proposed a fault detection technique for multiple fault detection using the dilated convolutional neural network-based model. In this research work, real-time vibration data is transformed into image form and processed using a convolutional neural network to detect and classify rotor and bearing faults with different severities and claimed very good accuracy [105]. Inter turn short circuit faults and broken rotor bars are investigated in [106] using a modified FFT method in which motor current normalized residual harmonic signal is used for analysis. Authors are claiming that not necessary to conduct a wide spectral sweep to search each time for different faults like motor current signature analysis that have variable characteristic frequencies depending on the type of fault. The authors suggested the use of DWT analysis of current for the detection of various faults in SCIM. The stator current is decomposed into various levels, extracted statistical features, and classified various fault cases using ANN. The authors obtained very good accuracy with the proposed method with the tanh function [107].

4. DISCUSSION, LIMITATION, AND FUTURE SCOPE

It is observed that a large number of techniques are suggested to detect and classify the various faults in TPIM. Moreover, the decision of choosing the proper method is a very difficult task for detecting and classifying the fault due to uncertain conditions that occurred in the motor during its operation. Conventionally, frequency analysis, time-domain analysis, and their combination are used for analyzing raw data. In time domain analysis, statistical measures like mean, standard deviation (SD), kurtosis factor and skewness, etc. are estimated. In frequency domain analysis, the time domain signal is converted into the frequency domain and features are extracted for analysis. To extract more information from the raw data, other methods like WT, CWT, DWT, WPT, STFT, HHT, etc. are used.

A detailed comparison of techniques discussed throughout the study is carried out in Table 1. The comparison covering the number of sensors required, signal to be acquired, and type of fault with advantages and drawbacks of the respective method is elaborated in Table 1. DWT-based fault detection is more effective to detect all types of faults under any abnormal operating condition. This method is very sensitive to small variations in the magnitude of current and is also applicable in abrupt conditions, transient situations of currents, and sudden load variation scenarios. The only disadvantage of this method is that it requires expertise to judge the type of fault and fault severity. PVA is a very simple graphical technique to identify the various faults under the balanced condition of the supply system. In PVA, it is essential to know the geometry of the stator winding, and also three phase supply should be balanced to get accurate results. In the industrial scenario, MCSA is a very powerful and low-cost solution to detect and identify all types of faults only under constant loading applications. The advantage of the MCSA technique is that no additional sensors are required to acquire the data. This is because the basic electrical quantities associated with electromechanical plants such as currents and voltages are readily measured by tapping into the existing voltage and current transformers that are always installed as part of the protection system. As a result, current monitoring is non-intrusive and may even be implemented in the motor control center remotely from the motors being monitored. But this method is not giving satisfactory results in the variable load applications, abnormal conditions of supply, and abrupt load variations because in all these conditions, the speed of the motor changes which directly affects the slip of the motor. In another approach, TPIM faults can be detected successfully with the statistical parameter obtained from the current and vibration signals. These techniques are very costly due to costlier vibration sensors. Another disadvantage of vibration monitoring is that it requires access to the machine to place the vibration sensor on the motor. For accurate measurements, sensors should be mounted tightly on the electric machines, and expertise is required in the mounting. However, high product costs can be incurred just by employing the necessary vibration sensors for a sensitive electric machine. The current monitoring technique is also attractive due to one more reason there is no physical contact between the current sensor and motor-driven equipment with the operator which enhances the safety of human beings. Further, with the availability of modern tools and advancement in signal processing techniques, the combination of traditional and modern approaches provides an efficient technique for fault detection in the TPIM in the near future.

Nowadays, artificial intelligence and machine learning are becoming mature in every field. The application of a machine learning algorithm for condition monitoring of TPIMs requires signal processing of raw data. The implementation of AI techniques in the real world requires feature extraction and selection using some feature extraction algorithms. The main parts of fault detection have four components, namely: (a) Identifying fault location; (b) Determining faulty parts; (c) learning incipient failure and their causes; (d) predicting the pattern of faults. Fault detection can be treated as a classification problem and pattern recognition problem too. Fault detection in IMs is divided into multiple stages data acquisition, data processing, feature extraction, and implementation of machine learning (ML) algorithms for fault recognition. Most AI-based fault detection system requires features for developing the input vector for the ML algorithms. The data can be pre-processed by various feature extraction algorithms like Genetic algorithm (GA), WT, Particle swarm optimization (PSO), etc. to extract input features. Sometimes, principal component analysis (PCA), and linear discriminant analysis are used to reduce the high dimensional vector to a low dimensional vector for easier analysis and to reduce the computational burden. Features can also be estimated using simple statistical learning methods. These feature vectors are used as input vectors for developing an AI-enabled fault identification system. For developing AI-based systems, ML algorithms like k-Nearest Neighbor (k-NN), Artificial Neural Networks, Support Vector Machines (SVM), Decision trees, Bayesian Classifier, random forests, and deep learning techniques have been efficiently used. A decision tree represents a tree-like structure. Decision trees are often used for fault classification properties. A higher version of decision trees, i.e. random forests can be used as it is immune to external noises and easier to interpret. It is observed that the random forest provides very good accuracy in classifying the various faults in TPIM as compared to any other algorithm.

Future Scope and Challenges

Some of the future scope and possibilities are enlisted below:

- Feature Extraction: Extracting relevant and informative features from motor signals is crucial for fault detection and classification. Developing efficient feature extraction techniques that capture the distinctive characteristics of different faults is a challenge.
- Noise and Interference: Motor signals are often contaminated with noise and interference, which can affect the accuracy of fault detection algorithms. Finding robust methods to mitigate the impact of noise and interference is a research challenge.

Fault Severity Assessment: Determining the severity of a detected fault is important for timely maintenance and decision-making. Developing accurate fault severity assessment methods that provide reliable information about the extent of the fault is a challenge.

Multiple Faults: In real-world scenarios, motors may experience multiple simultaneous or sequential faults. Developing techniques that can effectively detect and classify multiple faults is a challenge, as the presence of one fault can obscure the detection of other faults.

Unbalanced Operating Conditions: Induction motors often operate under unbalanced conditions due to unequal loads or supply voltages. Fault detection algorithms should be robust to handle such unbalanced operating conditions and accurately identify faults.

Generalization and Adaptation: Fault detection and classification algorithms should be capable of generalizing to different motor types, sizes, and operating conditions. Developing algorithms that can adapt to varying motor characteristics and different fault patterns is a challenge.

Labeling and Training Data: Obtaining labeled training data for fault detection and classification can be challenging and time-consuming. Creating accurate and representative datasets that cover a wide range of fault scenarios is crucial for developing robust algorithms.

Real-Time Implementation: Implementing fault detection and classification algorithms in real-time systems with limited computational resources is a challenge. Developing efficient algorithms that can provide accurate

***Table 1**: Comparison of techniques applied for the detection of motor faults.*

Technique	Parameters to be measured	Faults Detected	Advantages	Drawbacks
MCSA	Only one stator phase current	Stator inter-turn fault	Low-cost solution	Not possible to detect the fault in variable load applications.
			Effective under constant speed And constant load applications	
		Broken rotor bar fault		Not suitable for non-stationary signals.
PVA	All three phase currents	Stator inter-turn fault	Low-cost solution	Not effective for under Unbalanced supply condition
			Effective under balanced supply conditions	
		Broken rotor bar fault		Cannot be used in load Varying applications
		Mixed faults	Useful at a constant speed and constant load applications.	
DWT	All three phase currents	All types of faults	Effective under balanced and unbalanced supply conditions.	Require expertise
			Can be used in sudden change load applications	
			Can be used in variable load applications	
Statistical Method	Three phase currents	Stator inter-turn fault	Can be used to detect the fault in practical operating conditions	More sensors are required
		Rotor broken bar fault		
	Vibration signals	Mixed fault		
		Multiple bearing fault		

results in real time is an ongoing research focus.

Fault Diagnosis Interpretability: Interpreting the results of fault detection and classification algorithms is important for maintenance personnel to understand the underlying issues. Developing interpretable models and visualization techniques to aid in fault diagnosis is a research challenge.

Online Monitoring and Fault Prediction: Developing techniques for online monitoring and predicting impending faults in induction motors can enable proactive maintenance and reduce downtime. Designing predictive models that can anticipate faults before they occur is an area of active research.

Addressing these research challenges can lead to the development of more accurate, reliable, and efficient fault detection and classification methods for three-phase induction motors, improving their overall reliability and performance.

5. CONCLUSION

This paper has presented a detailed review of fault detection in TPIM. Indeed, the scope of this area is not limited to some important publications from the old around the year 1995 to till date are considered for the study. In the initial part of the paper, different types of faults such as stator faults, rotor faults, bearing faults, and joint or mixed faults with their causes are discussed in detail. The review and comments for each paper on stator fault, rotor fault, bearing fault, and joint fault are separately presented in the subsection. In each subsection, due attention is given to AI techniques for fault detection and identified some algorithms such as Random Forest, and Convolution Neural Network (CNN) as effective and accurate tools for fault and fault severity classification. These sections will be very informative and useful for beginners who wish to start research in the fault detection and classification of TPIM. As every technique is having its pros and cons, an attempt has been made to compare a few popular methods such as DWT-based, MCSA, PVA, and statistical-based methods on the common platform with their advantages and drawbacks. The paper concluded with some brief remarks and also suggested some areas for further studies. It is sure that this review will be fruitful for the new researcher and will get some specific direction for further research in the domain of fault detection and classification for TPIM.

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