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An Assessment on the Non-Invasive Methods for Condition Monitoring of Induction Motors

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Additional information is available at the end of the chapter

Abstract

The ability to forecast motor mechanical faults at incipient stages is vital to reducing maintenance costs, operation downtime and safety hazards. This paper synthesized the progress in the research and development in condition monitoring and fault diagnosis of induction motors. The motor condition monitoring techniques are mainly classified into two categories that are invasive and non-invasive techniques. The invasive techniques are very basic, but they have some implementation difficulties and high cost. The non-invasive methods, namely MCSA, PVA and IPA, overcome the disadvantages associated to invasive methods. This book chapter reviews the various non-invasive condition monitoring methods for diagnosis of mechanical faults in induction motor and concludes that the instantaneous power analysis (IPA) and Park vector analysis (PVA) methods are best suitable for the diagnosis of small fault signatures associated to mechanical faults. Recommendations for the future research in these areas are also presented.

Keywords: condition monitoring, fault diagnosis, mechanical faults, bearing distributed faults, gear faults

1. Introduction

Induction motors are the industry workhorse due to the fact that they are rugged, reliable and economical. Induction motors are used in industry for conversion of electrical energy into mechanical energy [1]. As shown in **Figure 1**, induction motors are being used in various applications, such as in the nuclear power plants, aviation industry, transportation industry, mining industry, chemical processing plants, paper mills and the petroleum industry [1].
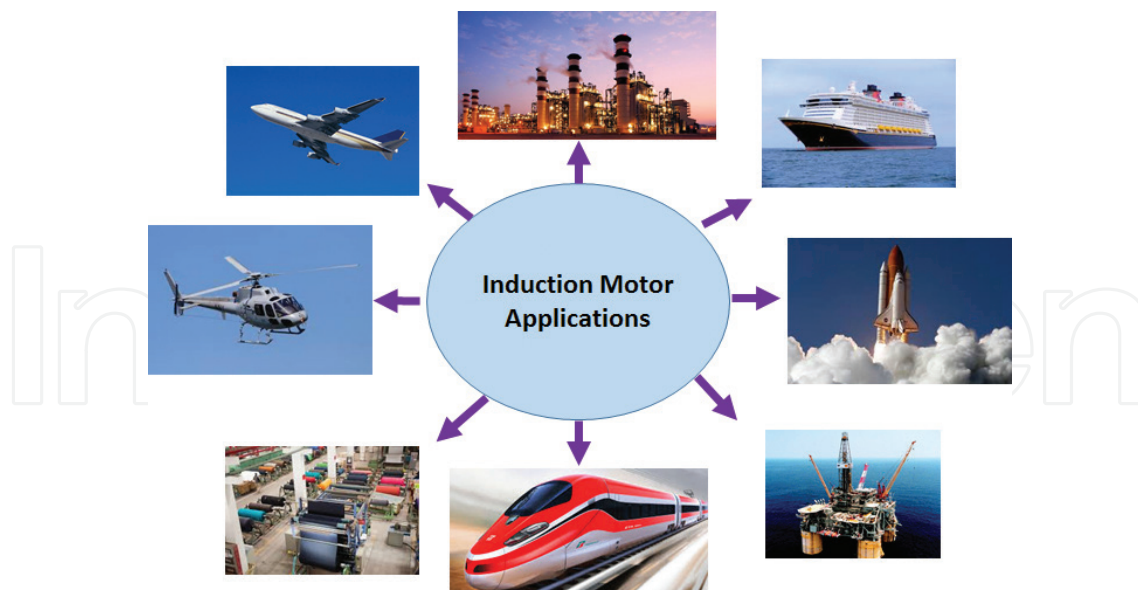
Figure 1. Applications of induction motors.

The operation of induction motor in harsh industrial environment affects its reliability and has been a critical issue. The unexpected breakdown of induction motor might result in the disturbance of critical services such as medical applications, transportation military operations and aviation. An unexpected breakdown of a motor might result in costly maintenance or loss of life in applications where continuous process is needed and where down-time is not tolerable. The induction motors require only basic maintenance and have a very low failure rate. However, the burning of the motors causes a great deal of unacceptable production loss. Consequently, diagnosing incipient faults will prevent the problems of unexpected breakdowns of the machines and it helps in reducing the maintenance costs. As reported in [2], 50% of operating cost of manufacturing and processing plants is related to maintenance. Therefore, this is a major area of concern in industries. The researchers are constantly looking for new techniques to minimize the unexpected machine failures and maintenance cost.

The scheduled replacement, scheduled maintenance and condition-based maintenance are the basic methods used in the industry for reliable operations of the machines. The scheduled replacement is a simple but expensive method as the replacement of machine parts is conducted on a regular basis. In the scheduled maintenance method, the checking and/or overhauling of the equipment has to be done on a regular basis and this method is widely used in industry as it is less expensive as compared to the scheduled replacement. The condition-based maintenance method determines the machine condition by taking measurements using sensors. By this method, the time periods between maintenance can be increased and machines can be monitored continuously so that maintenance can be scheduled on a needed basis. Condition monitoring (CM) is a method used in condition-based maintenance (CBM). It is an effective type of predictive maintenance (PM). The main steps involved in PM are shown in **Figure 2**.

Normally, the condition monitoring maintenance process would be monitoring the specific parameters like vibration, overheating, over current of equipment for early sign of coming
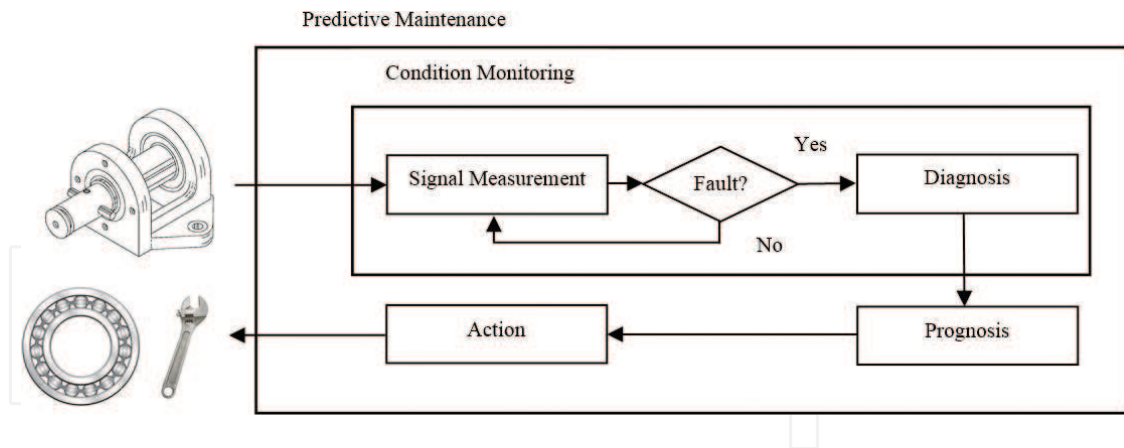
Figure 2. Activities in predictive maintenance.

failures and to predict the need of maintenance before rigorous failures. CM could be performed through visual inspection or through sophisticated fault diagnosis system. CM is suitable for continuous process plants where machine breakdowns can be very costly.

The methods of condition monitoring are categorized into two primary classifications, namely the offline tests and the online tests. The offline tests are performed by isolating the machine from main AC power supply. Although this is a comprehensive approach, sometimes causes unnecessary shutdowns on machines. Alternatively, the sensors which are installed on the machine are used to detect faults for online condition monitoring and fault diagnosis in an induction motors during the operation of the machine. The online tests cause fewer disturbances than offline tests but the results produced from online testing are more complicated and their interpretation is difficult than the offline tests. Over the past two decades, there has been an abundance of research work done in the online condition monitoring techniques for diagnosing problems in induction motors. For the detection of various faults usually affecting machines, several different techniques have been not only proposed but also used successfully. However, a good understanding of the mechanical and electrical properties of the machine in healthy and faulty conditions dramatically influences the accuracy and reliability of the online condition monitoring methods [3, 4]. Online condition monitoring techniques can be classified into two categories: firstly the classical method and secondly the digital method [4]. In classical method, electromechanical devices are used to protect the motors. The electromechanical devices are expensive, less efficient, having very slow response and not reliable as some of the devices have even shorter life than the motor itself. The digital method is the latest method for the condition monitoring and involves integrated circuits, micro-controllers, micro-processors and programmable logic controllers.

2. Overview of induction motors

An induction motor is normally composed of the following parts: frame, stator, winding, rotor and bearings. The structure of induction motor is shown in **Figure 3**. Induction motors are
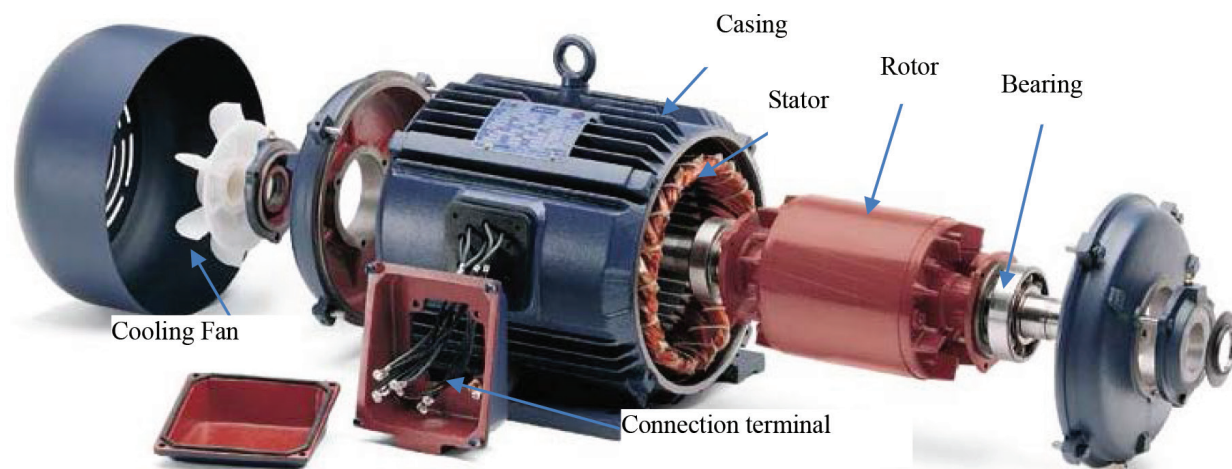
Figure 3. The structure of induction motor [5].

used in almost all types of industries. Induction motor is an asynchronous machine made up of a magnetic circuit that is joined to two electrical circuits; these circuits rotate with respect to each other. Electromagnetic induction is used to pass power from one circuit to the other. These electric motors are used to convert electrical energy into mechanical energy [5]. The conversion of energy is dependent upon the natural presence of the phenomena connecting magnetic and electrical fields in one side while motion and mechanical force are connected into the other side. On the basis of types of rotor winding, induction motors can be placed into two categories. They are the wound-rotor induction motors and squirrel-cage motors [6].

The squirrel cage induction motor is made up of conducting bars that are placed in slots of the rotor body. These conducting bars are short circuited through end rings. Magnesium, copper, or aluminium alloys are the materials usually used in manufacturing of the rotor bars. Another kind of rotor is known as a form-wound rotor since it possesses a poly-phase winding much like that of the winding of the stator. There are three slip rings which are joined to the winding of the rotor shaft. In a form-wound rotor, the slip rings are joined to a variable resistance and can restrict the current as well as the heating of the rotor [6].

The squirrel-cage induction motor is economical and robust than the wound-rotor induction motor. At constant supply of voltages and frequency, squirrel-cage induction motor runs at a constant speed. In this motor, if there is an increase in the load torque, the speed will decrease slightly. Therefore, it is appropriate to be used in drive systems that run at a constant speed [5, 6]. However, a variety of applications used in industrial areas need adjustable speeds drives. Traditionally, it is a direct current (DC) motor that is utilized in adjustable drive system. However, DC motors are expensive and possess carbon brushes that must be frequently maintained. As squirrel cage induction motors have no brushes so they are cheap and are preferred for high speed applications. Furthermore, due to the availability of solid state controllers, mostly high speed drive systems use squirrel cage induction motors. This type of induction motor is extensively utilized in drive applications of both low and high performance due to its versatility and ruggedness. Induction motors are suitable for almost all commercial and industrial applications due to their construction being so simple and they

have only a few parts, which reduce the cost of maintenance. Applications in both adjustable-speed drive (ASD) and constant-speed drive are the main uses of induction motors.

Induction motors are often exposed to operating environments that may not be ideal and in some cases are even harsh. These situations could be due to insufficient cooling, inadequate lubrication, structure vibration, overload, frequent motor starts and stops, etc. In such situations, induction motors are put under detrimental stresses which can lead to failure [7, 8]. Because of the significant role that motors play in various applications, improvement in the reliability of motors is required. The reasons why electric motors fail in industry have been commonly reported as follows [9–11]

- Wrong-rated power, voltage and current

- Mistakes during repairs

- Unstable supply voltage or current source

- Post the standard lifetime

- Overload or unbalanced load

- Electrical stress from fast switching inverters or unstable ground

- Residual stress from manufacturing

- Harsh application environment

3. Faults in induction motor

As induction motor is most often symmetrical, so faults in the motor normally disturb the symmetry of the motor. Burning of motors in the industry could be due to following reasons: thermal overloading, overloading due to undesirable stresses, air-gap eccentricity, speed oscillations, stator winding failure, broken rotor bars, bearing failure, coupled gear failures and unbalanced voltages. A concise discussion is made regarding these defects based on how important they are with regard to the condition monitoring of induction motors. According to a survey conducted in 2005 by the Electric Power Research Institute, more than 40% burning of AC motors is due to the failure of bearings (more than 50% burning of the motor is due to mechanical defects, i.e. bearing defects, gear defects, belt and pulley defects). The summary of the survey report is shown in **Figure 4** [2, 3, 12].

As stated in Peter Vas [13] and P.J. Tavner and J. Penman [14], the defects of the motor are categorized into two groups.

- Mechanical defects

- Electrical defects

Air gap eccentricities, bearing defects, shaft misalignment and abnormalities at the mechanical transmission system are included in the list of mechanical defects. Broken rotor bar and
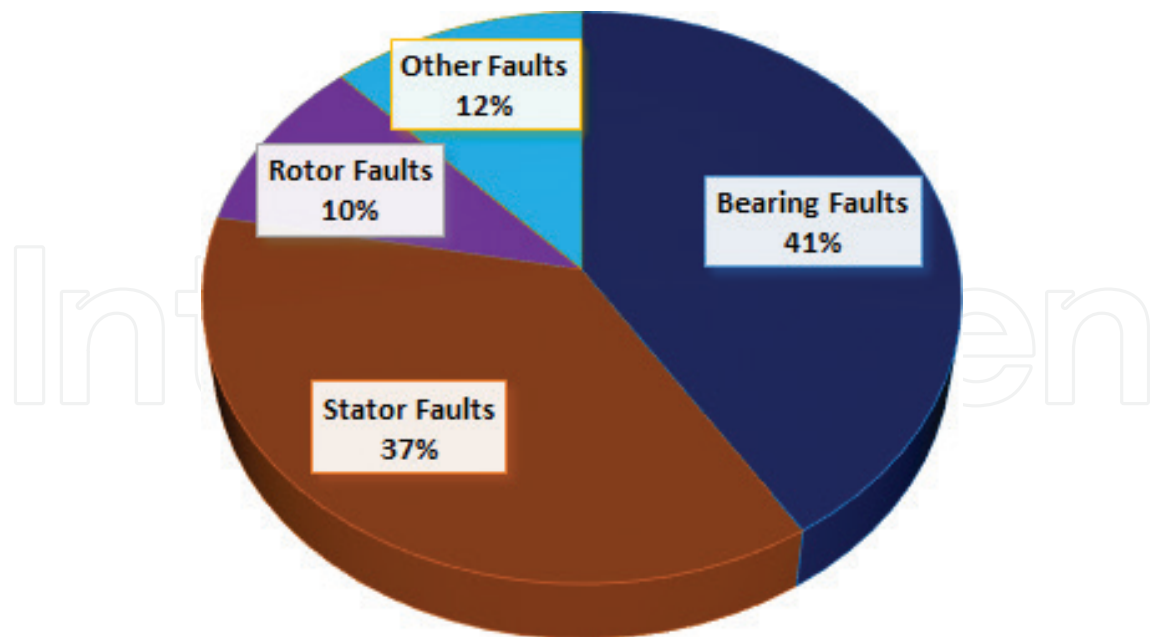
Figure 4. EPRI survey report 2005 [2, 3, 12].

stator winding defects are included in the list of electrical defects. The detail of these defects is discussed in following subsections.

3.1. Mechanical defects

The typical examples of mechanical defects that usually occur in an induction motor are presented as below.

3.1.1. Bearing defects

Bearings are widely used in rotating machinery across various industries that include paper, textile, aerospace, nuclear power plants, oil refineries, offshore pumping stations, steel, railways, construction, mining and renewable energy. The defects in the bearings cause breakdown of rotating machinery, which results in significant economic losses and in certain situations loss of human lives; for example, when a train derails or an aircraft engine fails due to a bearing defect. Bearings are typical components found in the motors that are used to allow for the shaft rotation. Majority of the motor failure is due to the bearing malfunctions. Bearings as shown in **Figure 5** are made up of inner and outer races. Several rolling elements (balls) are placed in between these two races. Cage is used to keep the balls moving at equal distance from each other. Normally, stresses developed in the motor causes fatigue in the bearing races. This fatigue causes localized defects (single-point defects like spalling or pitting or dents or holes) and distributed defects (generalized surface roughness) in the bearings of the motor [15–17].
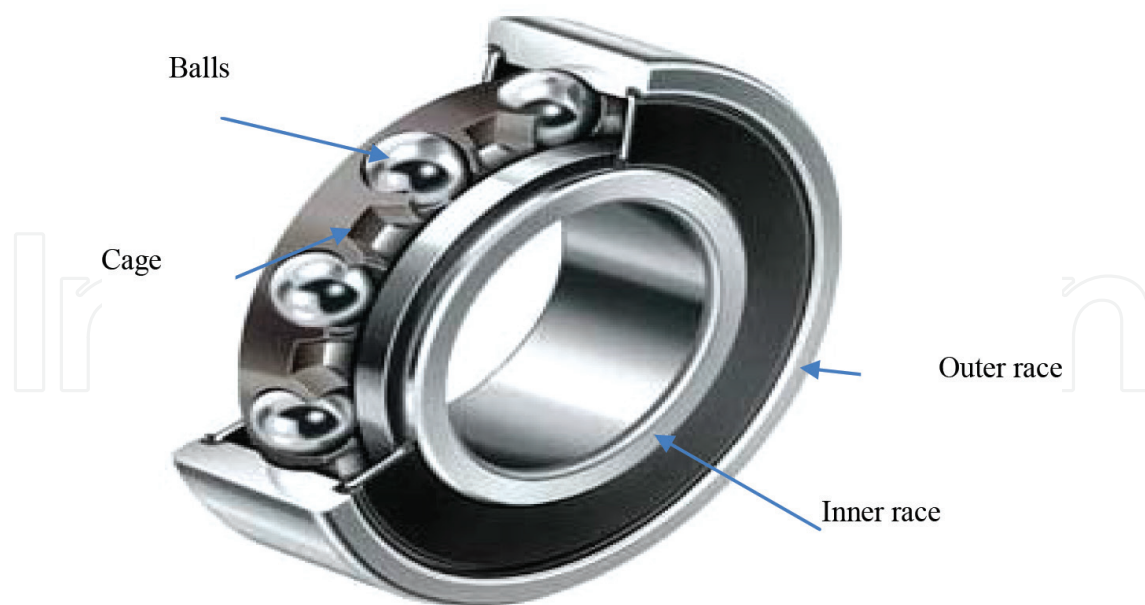
Figure 5. The structure of ball bearing.

The localized defects are induced mainly due to the operational wear (contact fatigue) of bearings. If the bearings are properly installed, kept free of contamination and well lubricated during operation then bearing failure will occur only after the pre-determined life (millions of cycles) of the bearing. This type of failure initially starts in a subsurface at micro-scale level at a single-point and then due to continuous stress cycles, they eventually cause material to break. These single-point defects are characterized as spalling or pitting or localized defect [15–21]. Littman [22, 23] characterized as micro-scale subsurface defects as spalls and macro-scale surface originated defects as pitting. These types of faults produce impulsive type of vibration and serve as indication of incipient failure and due to this reason many fault diagnosis techniques have been developed to diagnose these types of faults.

The distributed defects are induced due to the manufacturing errors or due to contamination, improper lubrication, corrosion, electrical fluting and misalignment during running operation of the bearing. In these types of faults, the magnitude of the contact force between race and ball varies continuously during shaft rotation. Distributed faults create continuous type of vibration and cause premature failure of the motor bearings and thus it is important to develop a suitable condition monitoring scheme to diagnose these types of faults. **Figure 6** shows the example of typical localized and distributed defects in bearings of induction motor.

Vibration and noise are generated in the motor due to these defects [24]. The failure of bearings can also occur due to high bearing temperature. The temperature of the bearings should not increase beyond specific degrees at rated conditions. An example of this would be in the petroleum and chemical industries where the IEEE 841 standard specifies that the rise in temperature of the bearings under a rated load should not go above 45°C. Rise in the winding temperature, improper lubrication, the distribution of the temperature within the motor and
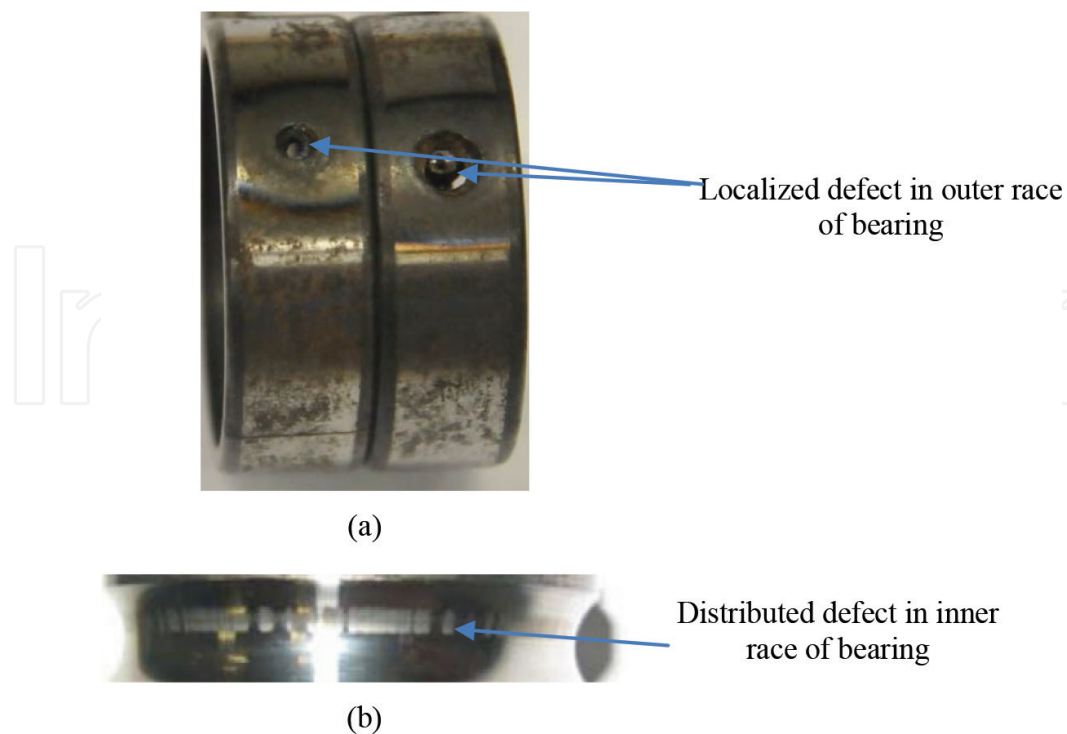
Localized defect in outer race of bearing

(a)

Distributed defect in inner race of bearing

(b)

Figure 6. Example of bearing (a) localized defects and (b) distributed defects.

the operating speed of the motor are the main factors for the rise of the bearing temperature. Consequently, the bearing temperature measurements can give helpful data to estimate the health of the bearings as well as health of the motor [25, 26].

3.1.2. Air-gap eccentricity

Air-gap eccentricity is a typical defect found in the rotor of the motor. Noise and vibration in the motor structure are usually produced due to eccentricity. For the healthy motors, the centre of the rotor and stator bore is perfectly aligned. Moreover, the centre of rotation for the rotor is the same as the stator bore centre. If the rotor is not aligned centrally, radial forces or magnetic pull will be developed, which causes the rotor-stator rub resulting in the damage of rotor and stator [27]. As demonstrated in Ref. [28] air-gap eccentricities are of three kinds

- Dynamic eccentricity

- Static eccentricity

- Mixed eccentricity

A dynamic eccentricity as shown in **Figure 7** results in an unbalanced magnetic pull (UMP) that acts on the rotor. The rotation of the UMP is similar to the rotation of the motor. The UMP can be easily monitored via current or vibration analysis. On the other hand, eccentricity that is static possesses a constant pull in only one direction, which also causes a UMP. However, it is not easy to detect this type of UMP [29].

Sometimes, dynamic and static eccentricities often exist together. Moreover, one can never assume that ideal centric conditions exist. Therefore, a certain amount of eccentricity is always
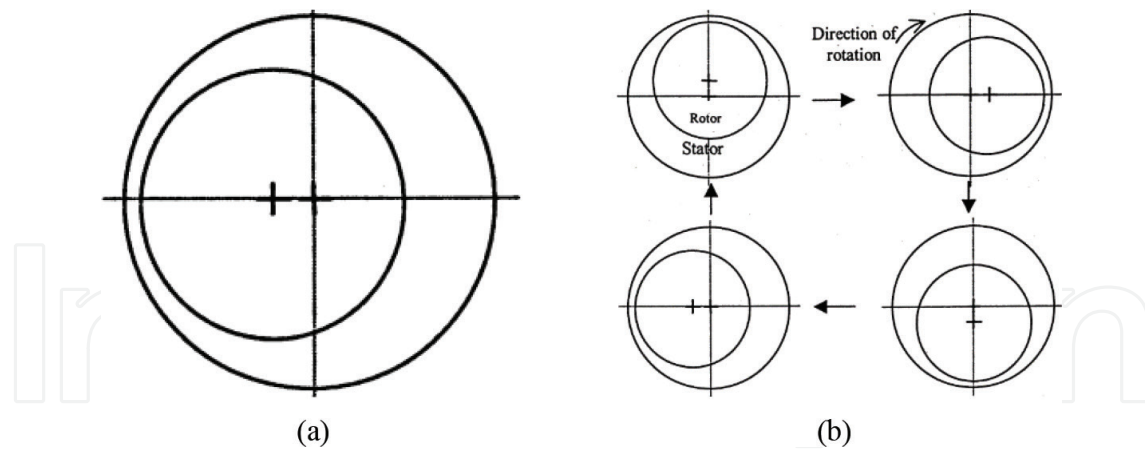
Figure 7. Example of (a) static eccentricity and (b) dynamic eccentricity [29].

expected in any real motor. This combination of eccentricities such as dynamic and static is known as mixed eccentricity.

3.1.3. Abnormalities in mechanical transmission system

Detecting abnormalities at the mechanical transmission system has been a vital area of study for quite a long time. Mechanical loads and gears are frequently connected to motors and a variety of faults such as defected gearing system, belt-pulley system and coupling misalignment are possible in these mechanical arrangements. An example of the gear fault is shown in **Figure 8**. In some applications like in aircraft, the condition monitoring of gears coupled with drive system is very much important to enhance the reliability of the gear [30]. Gear failures tend to occur when a gear is working under high stress conditions. The common gear faults are related to gear tooth irregularities namely chipped tooth, root crack, spalling, wear, pitting, tooth surface damage and broken tooth. Gear faults usually have significant effects on power transmission. They create disablement of the drives, which often causes damage to
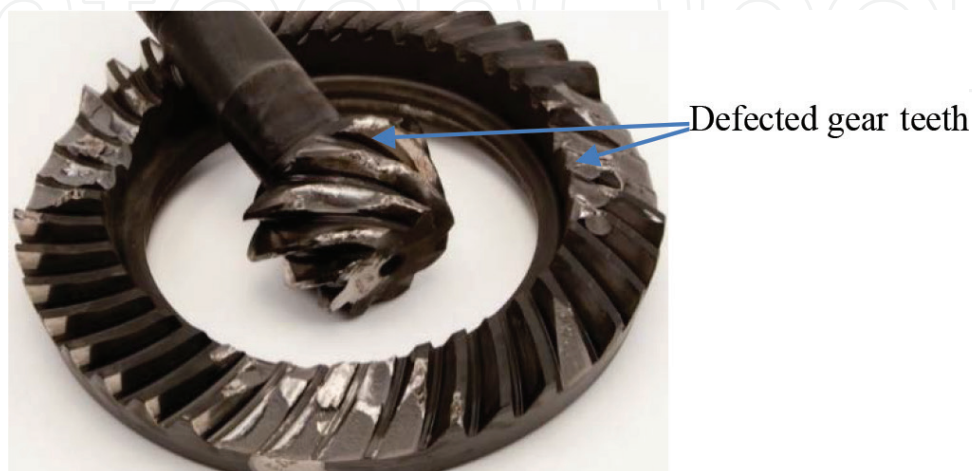

Figure 8. Example of the gear defects [30].

other gearbox components such as the shaft, bearing, etc., by pieces of the broken tooth. The tooth breakage can be due to overload or impact and damage.

3.2. Electrical defects

The following subsections give some of the typical examples of electrical defects in induction motors.

3.2.1. Stator winding defects

The general belief is that damage in the insulation of the winding turns contributes majority of the defects related to stator. This kind of defect is known as a 'stator turn defect' [31]. In a symmetrical induction motor, a stator turn fault produces a huge amount of current to flow through turns which creates too much heat in the shorted turns. The motor will burn if this heat, which is in direct proportion to the square of the current, is more than the threshold value [32]. An example of the stator related fault is shown in **Figure 9**.

In induction motors, the insulation used in stator winding is subjected to degradation due to contamination, transient voltage stresses on the insulating material, mechanical stresses and thermal overloading. Notably, thermal stresses are the primary cause for the deterioration of the insulation in the winding of the stator. Insulation even of the best quality could experience a rapid failure if the motor is run at a temperature greater than its threshold value. Generally, the life time of the insulation is decreased by 50% for every 10°C increase over the threshold value of the temperature of stator winding [33]. Therefore, monitoring the temperature of the winding of the stator is vital so that the motor will not run at a level greater than its thermal capacity. To accomplish this, several methods have been introduced. However, these methods could not identify the exact heating-point at the earliest stage [34, 35].

Some factors that speed up the deterioration of the insulation include the defected bearings, broken rotor bars, vibrations of the rotor, movement of a coil and misalignment of the rotor and air-gap eccentricity [36]. Consequently, these mechanical failures should be identified before they cause the failure of the insulation in the stator winding [37, 38]. Another problem
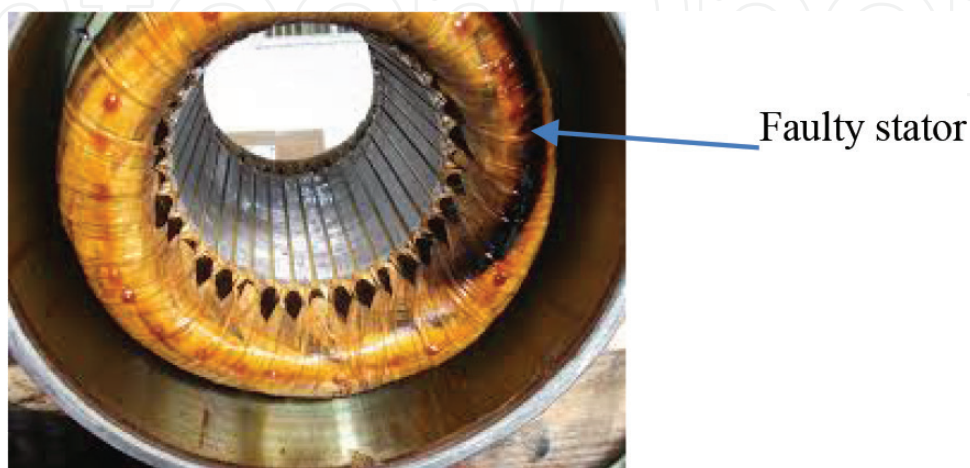

Figure 9. The stator fault in induction motor [31].

for the insulation is foreign materials such as dust and bearing grease which can cause contaminations over the insulation of the stator. This contamination could possibly cause the reduction in dissipation of heat from the stator winding [39]. Due to this reason it is recommended that all the motors should be kept clean and dry.

3.2.2. Rotor fault

Most often, the rotor bars in lower rated motors are produced by methods of die casting. However, the rotor bars of high rating motors are manufactured using copper. Producing rotor bars using methods of die casting has been found to cause a variety of technologically problems. Asymmetries in the rotor of the induction motors have been found which were caused by either technological problems, or because of the melting of end rings or bars. On the other hand, there is abundance of other factors causing the failure of rotors. Some of these are listed below [12, 13]

- Metallurgical stresses that are non-uniform could possibly be created in the assembly of the cage during manufacturing process and these stresses could result in a failure while the motor is operating later on.

- When thermal stresses are put on the rotor bar at the start-up of the motor, the rotor might not be capable of moving longitudinally in its slot.

- Some stresses could be developed on the rotor bars due to heavy end rings.

The reasons mentioned above could cause damage to the bars of the rotor and at the same time cause the rotor to become unbalanced. Furthermore, asymmetrical rotor currents are produced due to asymmetry on the cage of the rotor. Because of this, damage to just one rotor bar could result in damage to the surrounding bars. This damage could then spread, resulting in fractures in several rotor bars. Cracks in bars cause overheating of the bar due to which the bar may break. Consequently, the bars in the surrounding area will begin to carry higher currents subjecting them to even greater mechanical and thermal stresses. These stresses can start cracking in rotor bars and rotor lamination will be damaged as well [13]. The distribution of the temperature throughout the lamination of the rotor is also altered because of the asymmetry of the rotor. Bar fractures can take place at different areas on the rotor. During frequent starts of the motor, the chances of fracture in the rotor end rings increase [28]. Typical example of rotor faults is shown in **Figure 10**.
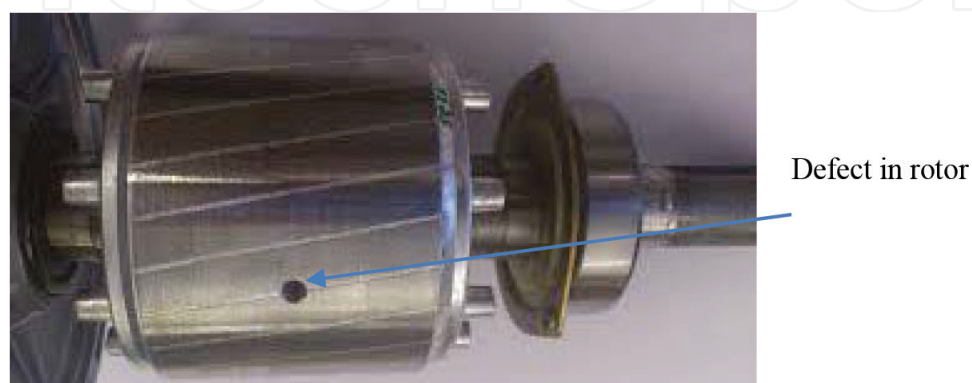

Defect in rotor

Figure 10. Example of rotor fault in induction motor [13].

4. Condition monitoring techniques

Continuously evaluating the health status of an industrial plant and its machinery throughout the entirety of its service is known as condition monitoring. Incipient failure detection is a vital process by which detection of defects in the early stages of their development is possible [13]. Fault diagnosis of the induction motor with some comprehensive condition monitoring system is becoming even more vital. An early alert about forthcoming failure is possible through the use of condition monitoring system. Furthermore, scheduling of preventive maintenance of the machines is also possible. Optimal preventive maintenance schedules are the result of this and also lead to the least amount of down-time on the machines [14]. Moreover, condition monitoring system gives indication to maintenance staff to arrange the required spare parts before serious breakdown occur on the machine, thus reduces overall down-time. Consequently, to improve productivity, reliability and safety of electric machines, a suitable condition monitoring system is essential. A tremendous significance has been put on by condition monitoring system in the environment of business because of several reasons that are listed below [13, 14]:

- To decrease the maintenance cost

- To determine the failure of machinery

- To enhance the reliability of both the machines and their parts

- To optimally use manpower and machine spare parts

- To maximize the performance of the machinery

- To enhance the failure prediction accuracy

The usage of condition monitoring for both mechanical and electrical machinery is not new. While there have been a variety of techniques developed and improved over time, invasive techniques such as acoustic emission analysis, noise analysis, thermal analysis, chemical analysis and vibration analysis, and non-invasive techniques such as motor current signature analysis (MCSA), stator current Park vector analysis and instantaneous power analysis (IPA) are considered as the most prominent methods in steady state operation conditions. The structure representing various motor faults and fault diagnosis techniques is shown in **Figure 11**.

It has been observed that even though invasive condition monitoring and fault diagnosis techniques are optimal for the diagnosis of bearing localized and distributed defects, however, costly sensors and their associated wiring is the major disadvantage of these methods [40–45]. For example, vibration sensors (accelerometers, velocity transducers) which are integral part of this technique are too much expensive. As a result, the use of invasive fault diagnosis methods is restricted in a variety of applications. This is particularly so with
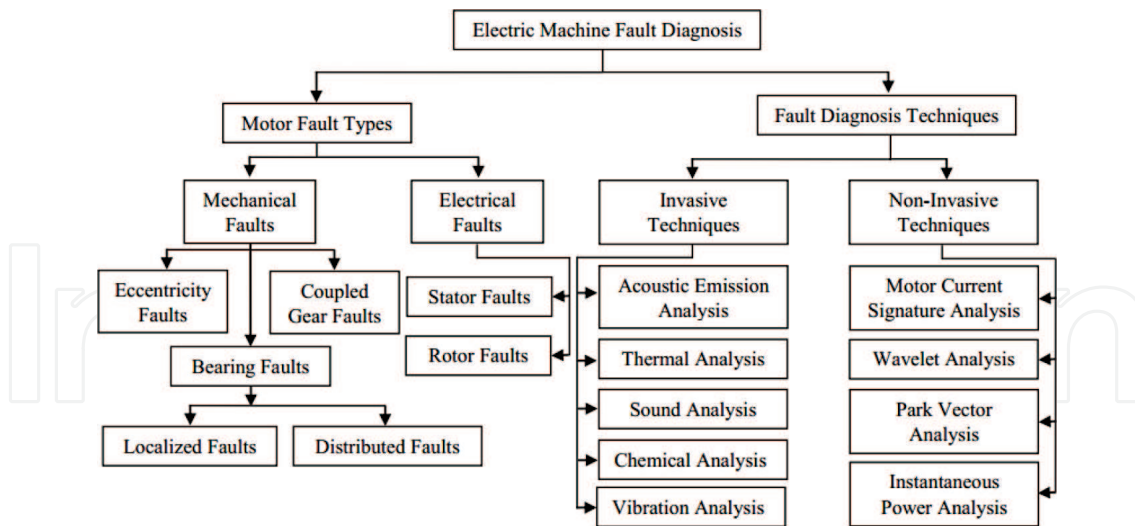
Figure 11. The structure representing various motor faults and fault diagnosis techniques.

applications using small sized motors as cost has an important role to play when making the decision as to which technique of condition monitoring is to be used. Another disadvantage of these techniques is that sensors need to be installed on the machine, and so it needs access to machine which is not possible in every application. Sensor needs to be mounted on the machine rightly for accurate results. As sensors also have some life period after which they fail, in this aspect, bearing life period is more significant than sensor life period [46–51].

Thus, the focus of this chapter is on the development of non-invasive condition monitoring and fault diagnosis method for induction motors.

5. Overview on non-invasive fault estimation parameters

Induction motor defects can be diagnosed via its terminal quantities, such as voltage, current, discharge and power, measurable outside the motor to give an indication of its condition. A fault in motor (i.e. in bearings or gears) produces a distortion of the electromagnetic field in the radial and circumferential plane due to which harmonic frequencies appear in the stator current and in instantaneous power. The stator current or instantaneous power of the healthy motor would have a single component of supply frequency (fundamental component). Motor faults will modulate the air-gap flux distribution which causes forward and backward rotating magnetic field and as a result sideband harmonic frequencies appear around fundamental component. Faults in the motor will generate one-side band below the supply frequency which is called lower-side band (LSB) and one side band above the supply frequency which is called upper-side band (USB).

Even though thermal and vibration monitoring have been utilized for decades, most of the recent researches have been directed towards electrical monitoring of the motor with emphasis on inspecting the stator current of the motor.

5.1. MCSA for bearing localized defects

The MCSA method was utilized for diagnosis of the motor and inverter defects using information from the motor stator current. In majority of applications, the stator current of an induction motor is easily obtainable because it is utilized in the protection of the motors from over-currents, ground currents. Thus, for the condition monitoring and fault diagnosis via MCSA, no extra sensors are required. It is a non-invasive method as it does not require direct access to the motor for its implementation [25, 52–58]. Thus, MCSA for the condition monitoring of the induction motors finds its application majorly in nuclear power plants, offshore pumping stations and defence industry where access to the motor is not possible.

Due to its non-invasive feature, MCSA has received the attention of many researchers and intensive research has been conducted on the MCSA. Initial efforts in MCSA can be credited to Schoen et al. [25, 53, 54]. They present a method to diagnose the motor faults based on the spectral analysis of stator current signal. Artificial neural networks were trained to learn the characteristic defect frequencies in current spectrum for the online fault diagnosis. The detection algorithm was implemented on a custom-designed test rig and its performance was verified on various fault types. Benbouzid et al. [55–57] addressed the application of MCSA for the diagnosis and localization of electrical and mechanical faults of induction motors. The initial steps taken to investigate the efficiency of MCSA for the purpose of motor fault diagnostic were discussed. Experimental results clearly illustrate the stator current spectral analysis sensitivity to induction motor faults. Later, Duque et al. [58] validated the bearing fault detection capability of MCSA on inverter-fed induction motor. In the current spectrum analysis of the motor, running values are compared with baseline values. In real time applications, baseline values are dependent on the operating conditions. To tackle this issue, Stack et al. [59] proposed new method which keeps track on baseline data at various operating conditions of the motor. They used different load conditions and for each case they compare the baseline values with running values to estimate the health condition of the motor. Along with the FFT method for the analysis of the spectrum, they used some advance signal processing and pattern recognition techniques for defecting analysis of the motor. An assessment of monitoring methods used for detection of bearing localized faults of induction motors was presented by Refs. [38, 60–62]. They proposed stator current monitoring as a very applicable technique in an industrial environment. Their research presented the current spectrum analyses along with noise cancellation method to detect mechanical faults of a variety of motors. They also propose a new method to damage the bearings via shaft current. The interpretation of the spectrum of the motor current indicates that this technique can successfully diagnose the bearing localized defects.

An improved stator current-based monitoring scheme was reported in Ref. [63], which perfectly blends Fourier transform, self-adaptive filter and rotor slot harmonics-based slip estimation techniques together. The experimental results on the bearing outer race localized

defects demonstrate that the presented scheme is effective. In order to diagnose the incipient faults in rotor bars, a bilinear time-frequency analysis of stator current along with adaptive filter technology was performed by Boqiang et al. [64]. The results indicate that the proposed method has the capability to diagnose broken rotor bar faults at their incipient stages. Application of MCSA for the detection of artificially damaged rolling bearings in asynchronous machine was confirmed by Trajin et al. [65]. Blodt et al. [66] and Terra et al. [67] utilized the stator current analysis and vibration analysis techniques to detect bearing localized defects. They also proposed a new model for the investigation of the effect of load torque variations on the stator current spectrum. The experimental results indicated that oscillations of the torque produce the varying frequency contents which can be observed in the stator current spectrum. Bayindir et al. [68] and Ioannides et al. [69] presented an automated fault detection system for the induction motors based on programmable logic controllers. They used the speed sensor, temperature sensor and current sensor to measure the motor speed, motor temperature and running current. The system was developed to automatic turn-off the motor if any one of the measured variable exceeds the preset values. However, the proposed condition monitoring system proves to be very expensive due to involvement of the sensors.

A novel method for the use of the stator current and efficiency of the motors as pointer of rolling-bearing defects was proposed by Frosini et al. [70, 71]. Their work describes the experimental results of bearing localized faults in outer and inner race of bearings. The analysis of the reduction in the efficiency of the motor due to defected bearings was also reported. Ebrahimi et al. [72] investigated the efficiency of the MCSA for the detection of stator faults in permanent-magnet synchronous motors. Experimental results indicate that the introduced method can detect the short-circuit fault incisively. Mehala [73] used the MCSA scheme to identify the bearing localized defects. FFT spectrum of the motor stator current was obtained and analysed. Experiments were conducted on the two defect levels (hole sizes 2 and 4 mm) in outer and inner race of the bearing under no-load and full-load conditions. The results obtained through the experiments indicate that under no-load condition, the change in amplitude values at characteristic defect frequencies is very small (<5 dB) however for full-load conditions, the change in amplitude is detectable (>5 dB to <8 dB). Along with FFT analysis of stator current, the researcher also performs wavelet and Park vector analysis of stator current for diagnosis of various motor faults.

A novel method was proposed by Romero et al. [74] which merged information entropy analysis with fuzzy logic inference to diagnose and classify faults like broken rotor bars, bearing malfunctions, stator unbalance and combinations of faults by analysing stator current signal. The proposed method shows satisfactory results that prove its suitability for online detection of single and multiple faults in an automatic way through its hardware implementation. Seera et al. [75] presented a novel approach to detect and classify comprehensive fault conditions of induction motors using a hybrid fuzzy min–max (FMM) neural network and classification and regression tree (CART). MCSA method was applied to form a database comprising stator current signatures under different motor operating conditions. Comparison of stator current analysis via FFT and wavelet transform was shown in Ref. [76]. Experimental results indicates that stator current analysis via

FFT can diagnose bearing localized defects only under steady state conditions, while, it is unable to diagnose the faults when motor is operating in transient condition. However, stator current analysis via wavelet transform has the capability to diagnose the faults under steady state and transient operating conditions of the motor. Recently, a stand-alone multi-sensor wireless system for continuous condition monitoring of induction motors has been proposed by Ref. [77]. The proposed wireless system provides a low-cost alternative to an expensive condition monitoring technology available through data acquisition equipment.

In a recent study, the fault frequencies inside the stator current spectrum were analysed through iterative method which provides an efficient fault diagnosis in the non-linear motor operations [78]. The winding function approach was used by Ref. [79] to diagnose rotor faults. The theoretical derivations were validated with experimental results. To enhance the reliability of the fault diagnosis system, Choi et al. [80] proposed a condition monitoring scheme which is based on speed feedback error management. In Ref. [81] a cross-correlation-based condition monitoring system was used to diagnose the induction motor eccentricity faults. The validity of the proposed method was confirmed through real time experiments performed on digital signal processing (DSP)-based motor drive. In a recent paper, Aydin et al. [82] proposed a hybrid approach based on multiple wireless sensor systems for fault diagnosis of induction motors. The proposed method was shown to be useful for analysing and monitoring signals from multiple induction motors. A novel analytical model based on stator current monitoring was developed by Blodt et al. [83] for the analysis of bearing defects. The results obtained through spectral analysis of the measured quantities validate the proposed theoretical approach. Stack et al. [84] presented various techniques to simulate artificial defects in the bearings of induction motor. Motor asymmetrical fault signatures were identified by Benbouzid et al. [85] through spectral analysis of motor current signal. An envelope analysis of the vibration signal was used to diagnose bearings localized defects [86]. The results achieved with proposed technique are shown to be strong function of selection signal bandwidth [86]. A wavelet-based condition monitoring system using analysis of the acoustic emission signal was proposed by Kang et al. [87]. A generalized fault analysis system in multi-phase machines was proposed by Choi et al. [88].The fault diagnosing capability of the proposed scheme has been verified mathematically through simulations. Wang et al. [89] has used an improved combination of the Hilbert and wavelet transforms to analyse the incipient bearing localized defects. Experimental results indicate that the extraction capability of bearing localized fault frequencies is greatly enhanced by the proposed method. An intelligent fault diagnosis scheme based on an independent component analysis was presented by Widodo et al. [90]. An integrated system for motor bearing fault identification is presented in Ref. [91]. Hwang et al. [91] proposed an integrated fault diagnosis system based on cepstrum coefficient method for feature extraction from motor vibration signals. The experimental results indicate the effectiveness of cepstrum in diagnosing the bearing health. Neural networks models with a decision structure are presented in Ref. [92] to analyse the bearing localized defects. The results show good performance of the implemented model and its ability to identify the bearing localized faults.

5.2. MCSA for gear defects

Gears are the main part of an electromechanical power transmission system in majority of industrial applications [93]. Unexpected failures can be prevented through detection of incipient gear faults. This will also help to reduce machine down-time and minimize financial consequences of gear damages. This cannot be realized without using an efficient fault diagnosis and condition monitoring system [94]. Although vibration analysis has been shown to be the reliable method for gear fault detection but the sensitivity to the installation position and the background noise due to external mechanical excitations are main drawbacks of the vibration measurement for gear and researchers are constantly looking to have non-invasive method for gear fault diagnosis [95, 96]. The gear fault detection using non-invasive method offers great advantages over invasive techniques principally due to its effective cost and the need of minimum changes in the system installation. In this context, an extensive research has been performed during recent years for the gear fault diagnosis using non-invasive techniques, example, using current and voltage measurements in the vicinity of motor drive systems [97–101].

As related to this, Blodt et al. [102] examined the detection of mechanical fault-related load torque oscillations in induction motors using a stator current monitoring. They developed a theoretical model to show the link between torque oscillation and modulation of a stator current component. However, they neglect the impact of the gear stiffness on the stator current. The effect of gearbox characteristic frequencies in the stator current of induction machine was studied by Ref. [95]. It was shown that the input shaft, layer shaft and output shaft frequencies in a multi-stage gearbox appear in the electromagnetic torque spectrum. Also, these harmonics appear as the sideband frequencies around the electric supply frequency of the stator current. The mesh frequencies were also well identified in the measured stator current. Their experimental investigation indicates that magnitudes of some rotation and mesh related frequencies are sensitive to the gear tooth fault [95, 103, 104]. A more rigorous attempt was carried out by Kia et al. [105, 106] to analyse the impact of motor coupled gear on the stator current spectrum. Their theoretical and experimental investigations indicate that harmonics appeared in motor current spectrum at mesh frequencies and mesh-related frequencies for healthy gears. For defected gear, additional harmonics related to fault-induced mechanical impacts are produced at the rotational frequency. The experimental results indicate that mesh and mesh-related frequencies have very weak signatures and are suppressed in the noise. The diagnosis of damaged tooth of the gear through MCSA at motor full-load conditions was reported in Refs. [107–109]. They also presented the comparison of diagnosis capabilities of vibration, acoustics and stator current analysis techniques. Stator current has been shown to be the suitable non-invasive method to diagnose gear faults. A simplified dynamic model considering a realistic behaviour of gear with minimum number of gear mechanical parameters was used to study the effect of gear torsional vibrations on motor current spectrum [110–112]. The impact of transmission error in gear was shown to be related to pinion and wheel eccentricities and tooth profile abnormalities which produces pinion and wheel rotation sidebands around the fundamental and mesh frequencies.

An attempt has been performed by Ottewill et al. [113] to diagnose the tooth pitting fault in a multi-stage gear. They have used a low-degree of freedom model for gear dynamic model. It was verified by Girsang et al. [114] that the gear teeth faults may generate mechanical impacts which can be observed in the torque and hence in machine electrical signatures. In Ref. [115], Huh et al. focused on extracting operating point independent fault signatures by using a kinematic error observer, spatial domain sampling methods and spatial domain signal filtering methods for gear fault diagnostics of electromechanical actuators. Bogiatzidis et al. [116] reported the identification of mechanical vibrations due to backlash phenomena appearing between the pinion gear and the girth gear rim of the kiln is realized using the MCSA. The proposed diagnostic method was tested on under-scale laboratory test rig. It was shown that due to fault in pinion gear, the pinion rotation frequencies appear around fundamental supply frequency.

An online gear fault diagnosis system was reported in Refs. [108, 117] using a non-invasive stator current space vector analysis. The proposed algorithm is based on the computation of the fault index by using fault-related frequencies in the current space vector instantaneous frequency spectrum. Tests performed with different load levels demonstrate a possible online condition monitoring and fault diagnosis of gear tooth surface damage fault detection. It has been demonstrated that incipient faults in gears produce small fault signatures that are sometimes buried in environment noise and thus could not be reliably detected through MCSA. Recently, a statistical tool called spectral kurtosis with reference has been proposed to define the electromechanical system healthy state reference. This technique proves its effectiveness in case of load torque oscillation fault only [118].

Although MCSA has the capability to diagnose gear defects and bearing localized defects, however, very small change in amplitude occurs at characteristic defect frequencies under no-load condition. Also in an arbitrary noise condition, the small fault signatures are buried in noise and it is difficult to discriminate between change in amplitude value due to fault and random noise [38, 53–72]. Another disadvantage of the MCSA is that sometimes two side band components (LSB and USB) lie near to the fundamental component and amplitude of the side band components is suppressed by the highest peak at fundamental component. This can create misdetection in an online fault diagnosis system [107–118].

6. IPA for motor electrical defects

Since bearings are used to support the rotor during rotation, hence any defect in bearing will affect the radial movement of rotor. Due to this radial movement, air-gap between rotor and stator will change to cause magnetic flux variations. These flux variations create modulations (oscillations) in the instantaneous power which could be observed as two sideband components, at $(2f_e - f_v)$, $(2f_e + f_v)$, and one fault component appears directly at the vibration frequency (f_v). The location of these harmonic frequencies allows the identification of abnormalities in the bearing.

The instantaneous power analysis (IPA) method has been used by several researchers to detect rotor and eccentricity defects. Ahmad [119] uses the motor current, voltage, flux and IPA methods to investigate the broken rotor bars and eccentricity defects of the motor. His

study shows that although the rotor bars and eccentricity defect of the motor can be detected through current, voltage and flux analysis, however, these techniques are not effective under no-load conditions of the motor. On the other hand, the instantaneous power analysis scheme diagnosis the rotor and eccentricity defects effectively even under no-load condition of the
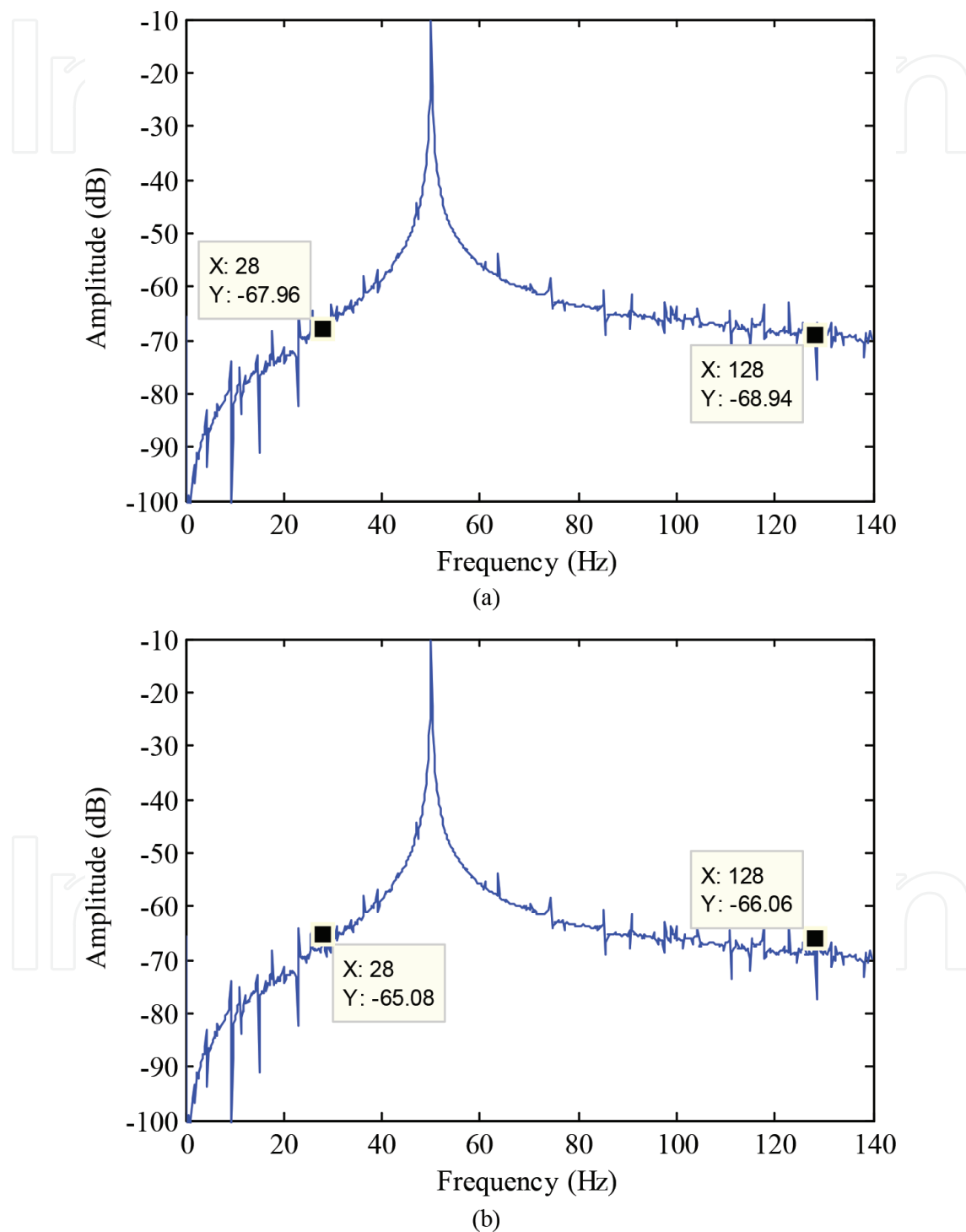

Figure 12. The stator current spectrum under no-load conditions of the motor (a) healthy motor and (b) defected bearing with 2 mm outer race defect.

motor. This is due to the reason that the motor power is the product of the supply voltage and current so it contains more information than the current and voltage only. In later work, the superiority of the IPA method over MCSA was confirmed in [120–123] for the diagnosis of faults in rotor, stator and eccentricity.

The comparison of the MCSA and IPA for 2 mm bearing outer race defect is shown in **Figures 12** and **13**, respectively. It has been observed from **Figures 12** and **13** that the MCSA is not
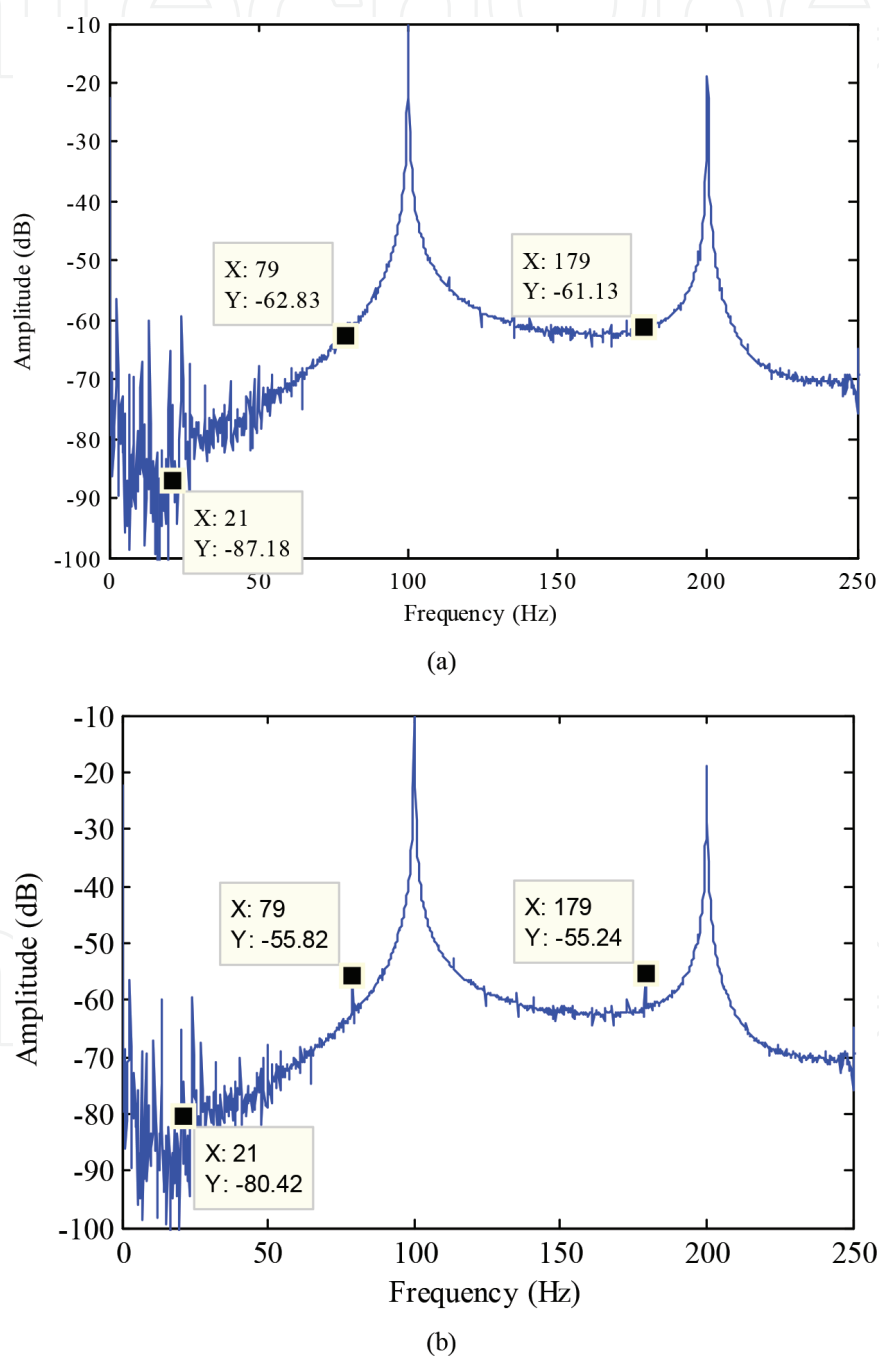

(a)

(b)

Figure 13. Instantaneous power spectrum under no-load conditions of the motor (a) healthy motor and (b) defected bearing with 2 mm outer race defect.

suitable for detection of defects at lower load levels because very small change in the amplitude value (2 dB) appears at characteristic defect frequencies of 28 and 128 Hz in stator current spectrum. However, comparatively large change in amplitude value (7 dB) appears at characteristic defect frequencies of 21, 79 and 179 Hz in instantaneous power spectrum. Also, it has been observed that the IPA carries an additional characteristic frequency component that provides an extra piece of information that can be utilized in a reliable intelligent condition monitoring system. Thus, IPA has more capability to detect bearing defects at low-load conditions as compared to MCSA.

7. Impact of environmental noise on decision making of existence of fault signatures

Incipient defects are defined as slowly developing defects or small unpredictable variations in the system. They are characterized by small amplitude compared to the useful signal. Considering the definition of incipient defects, as a slowly developing defect, it is important to address the issue of detecting these defects at the earliest possible stage meaning smallest amplitude (smallest severity). It has been observed that the low energy harmonics are produced due to incipient bearing localized faults and stator current analysis technique proves to be less efficient to detect low energy fault signatures especially under noisy environment. The IPA method has the ability to detect low energy fault signatures but in an online testing system it is difficult to discriminate the amplitude changes due to environment noise and due to existence of the fault. Therefore, it is unlikely to make decisions without considering the noise variations. As related to this, in an online fault diagnosis system the environmental noise modelling has been a practical issue and many studies have been performed to deal with it.

The averaging of multiple spectrums of stator current was used to eliminate the noise disturbances [124]. Recently, in Ref. [125], Wiener filter is used to eliminate all signatures that are irrelevant to the motor fault signatures. To achieve the high performance of the condition monitoring system, a statistical process control (SPC) is used [63]. Golafshan et al. [126, 127] presented the Singular Value Decomposition (SVD) and Hankel matrix-based de-noising process for the elimination of the background noise and the improvement in the reliability of the fault detection process. However, the proposed method is proven to be computationally intensive. A classical multiple signal classification method has been proposed by Kia et al. [128] to suppress the noise during the fault diagnosis of the motor. However, the proposed method takes long computation time to find fault signatures and is affected by the low signal-to-noise ratio. To solve this problem, an algorithm that is based on zooming in a specific frequency range of the FFT spectrum was proposed in [129]. Kim et al. [130] proposed the idea for separating rotor faults and load oscillations to reduce the false alarm rates in an online fault diagnosis system. It was reported in Ref. [131] that Wigner–Ville spectrum analysis based on cyclic spectral density (CSWVS) was able to separate the bearing fault patterns from random noise in the vibration signal. As compared with the envelope analysis for rolling element bearing diagnosis, the strongest element of CSWVS may be its diagnostic ability for bearing with

distributed faults. In the experimental study, the results of envelope analysis, no matter what filtering techniques are used, fail to extract bearing fault features and might be misinterpreted as a gear fault. However, CSWVS utilizes the second order cyclo-stationary property of the vibration signals produced by bearing distributed fault, and clearly extracts its fault features reducing the masking effect of additive stationary noise. Wang et al. [132] addressed challenging issues on de-noising and identification of the incipient fault deterioration grade from the noisy vibration signal for aircraft engine rotor prognostics. The enhanced robust methods include an adaptive wavelet de-noising technique for weak signature enhancement and correlation dimension for performance degradation assessment. The experimental results verified that the weak vibration signal features of rotor are successfully revealed and enhanced using adaptive wavelet de-noising method, and correlation well identify the rotor rub-impact fault deterioration grade.

Eccentricity faults in induction motor were analysed by Refs. [133, 134] using a cross-correlation method. The pre-determined threshold levels that have been used are as follows: amplitude less than –60 dB healthy motor, amplitude –60 dB to –40 dB tolerable defects and amplitude higher than –40 dB severe defects. A statistically derived adaptive threshold definition was proposed by Toliyat et al. [135]. The experimental results confirm the validity of the proposed approach to diagnose eccentricity and rotor fault at 70% loading condition of the motor. Although, the proposed approach considers the noise variations in real time applications; however, the performance of the proposed approach was not tested under variable operating points of the motor. In a similar work, Rajagopalan et al. [136] use an adaptive threshold scheme based on percentage of the fundamental current signal. The advanced signal processing algorithms are used to diagnose fault signatures [137]. In this study, the threshold is pre-determined based on prior tests before the diagnostic procedure starts. Although, the statistical performances of the instantaneous noise and bias with respect to motor operating points are not provided in that study but the suggested solutions present an intuitive way to design a performance oriented adaptive threshold scheme for an online fault diagnosis system. An analytical model to detect the incipient faults in the plant process in presence of an arbitrary noise was recently presented in Refs. [138–141]. Their modelled threshold scheme that is based on the probability distribution function has shown higher efficiency for incipient fault detection in noisy environment.

Notably, the pre-determined threshold schemes for reliable diagnosis of electrical faults in induction motor faults using MCSA presented in Refs. [133–137] could be used to estimate the fault severity, but these threshold schemes tend to detect sufficiently strong fault signatures to avoid noise interference. Thus the scheme could not be used to diagnose small fault signatures associated to motor mechanical faults under no-load conditions.

Fournier et al. [142] defined the threshold references in healthy condition of the motor based on the statistical spectral kurtosis measurements. The threshold scheme produces efficient results at specific speed and load levels of the motor. However, this threshold scheme does not consider instantaneous noise variations with respect to motor operating point (load, speed), so errors in the detection occur when operating point of the motor changes. Picot et al. [143] proposed a threshold scheme for the detection of small fault signatures related to bearing cage defects in permanent magnet synchronous motor (PMSM). The noise variance of

the measured motor current spectrum was minimized by integration process and threshold was designed by calculating mean and standard deviation of the frequency bins. Although, the proposed method was shown to produce good performance at various speeds (variable supply frequency) of the PMSM, however, it has some limitations. Firstly, the performance of their designed threshold was not measured at various load conditions. Secondly, the designed threshold scheme is dependent on the sampling size and window size. The large window size may attenuate the amplitude of bearing fault signatures. The impact of noise variations with respect to load variations on the reliable decision making of the existence of small fault signatures needs to be investigated. Notably, this work provides intuitive way towards the design of performance-based decision making system independent of environment impacts and motor operating points.

Limitations of the existing non-invasive fault diagnosis techniques considering environment impacts are described in **Table 1**.

Reference	Fault type	Threshold design technique	Limitations
[133, 134] 2008, 2011	Eccentricity	Pre-determined threshold	• Does not count non-linear noise variations with respect to motor speed and load • Detection with two sideband fault signatures have ambiguities
[135] 2012	Eccentricity, Rotor	Statistically derived threshold	• Does not count non-linear noise variations with respect to motor speed • Detection with two sideband fault signatures have ambiguities
[136] 2006	Eccentricity	Pre-determined threshold	• Does not count non-linear noise variations with respect to motor speed and load • Detection with two sideband fault signatures have ambiguities
[137] 2006	Bearing, Rotor	Zero input test-based statistical analysis	• Does not count non-linear noise variations with respect to motor speed and load • Detection with two sideband fault signatures have ambiguities
[142] 2013	Unbalance	Reference-based statistical analysis (spectral kurtosis)	• Does not count non-linear noise variations with respect to motor load • Detection with two sideband fault signatures have ambiguities
[143] 2014	Bearing cage Defect	Reference-based statistical analysis (mean and standard deviation)	• Does not count non-linear noise variations with respect to motor load • Detection with two sideband fault signatures have ambiguities

Table 1. Limitations of previously used MCSA-based fault diagnosis techniques considering environment impacts.

8. Park vector analysis for bearing localized defects

Park vector analysis (PVA) of motor current which is mainly used for field oriented control of induction motor has received a growing attention in the recent years in condition monitoring applications. Few researchers have used PVA with emphasis on the bearing localized faults, rotor faults, eccentricity faults and stator faults [144–147]. In Park's transformation process, the three balanced AC quantities (I_a, I_b, I_c) are reduced to two DC quantities (I_d, I_q). In analysis of three-phase synchronous machines, Park's transformation transfers three-phase stator and rotor quantities into a single rotating reference frame to eliminate the effect of time varying inductances [144, 145].

The Park vectors under ideal conditions of the motor represent a circular pattern centred at the origin. However, the shape of the circle changes in presence of the faults inside the motor and the various types of faults generate various types of shapes. Thus by detection of various patterns, one can analyse the type of fault inside the motor. The Park's transform is a graphical method to analyse the status of motor and does not require analytical expressions to calculate any specific defect frequency.

Zarie et al. [144] performed experiments on induction motor to diagnose bearing localized and extended defects (multiple holes in inner or outer race). Classification of the various faults was achieved through utilization of neural networks. It was concluded in their study that the proposed method provides a powerful and general approach to incipient fault detection. Spyropoulos et al. [145], Laughman et al. [146] and Parra et al. [148] reported that impact of the motor stator related faults could be examined through the Park vector transformation approach. It was claimed that by using this approach, effects of stator faults can be differentiated from time-varying loads. Salem et al. [147] measure the thickness of Park vector curve using curve splitting factor. The experimental results on bearing outer race defect indicate that thickness of the Park vector curve increases due to fault. Rezig et al. [149] and Salem et al. [150, 151] conducted experimental study to diagnose the bearing localized defects and eccentricity faults through Park vector transform of motor stator current. Experimental results indicate that Park vector transform method can detect the occurrence of faults but unable to identify the fault locations. In a recent study, Kuruppu et al. 152] demonstrated that Park vector analysis method has capability to diagnose stator inter-turn faults in inverter-fed field-oriented control motors. Proof of accurate fault detection capability for a wide speed range is presented through simulation and experimental results.

The example of Park vector analysis of stator current for bearing localized defects is shown in **Figure 14**. It can be observed from Figure 14 that bearing localized defects cause an increase in thickness of the I_d, I_q curves. The increase in curve thickness is due to the harmonics induced by the localized defects inside the bearing of the motor. Therefore the analysis of the I_d, I_q curves can be a useful means for the fault diagnosis of induction motors.
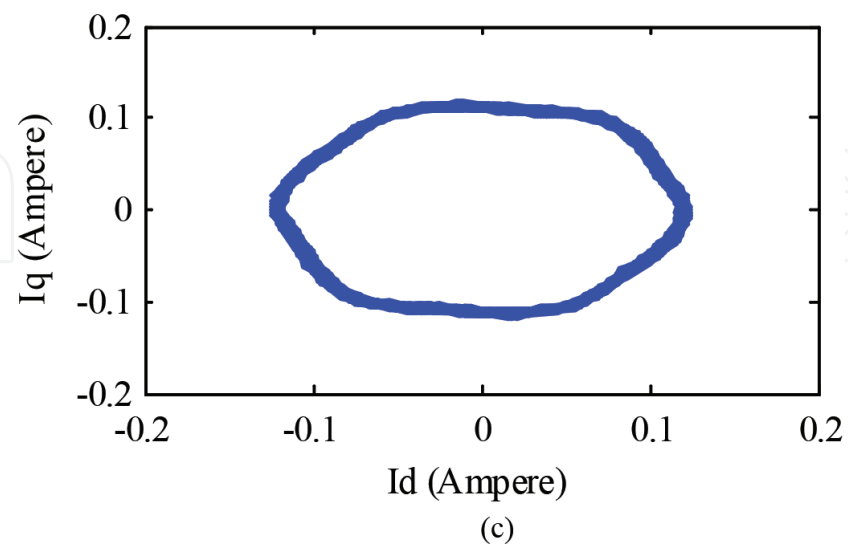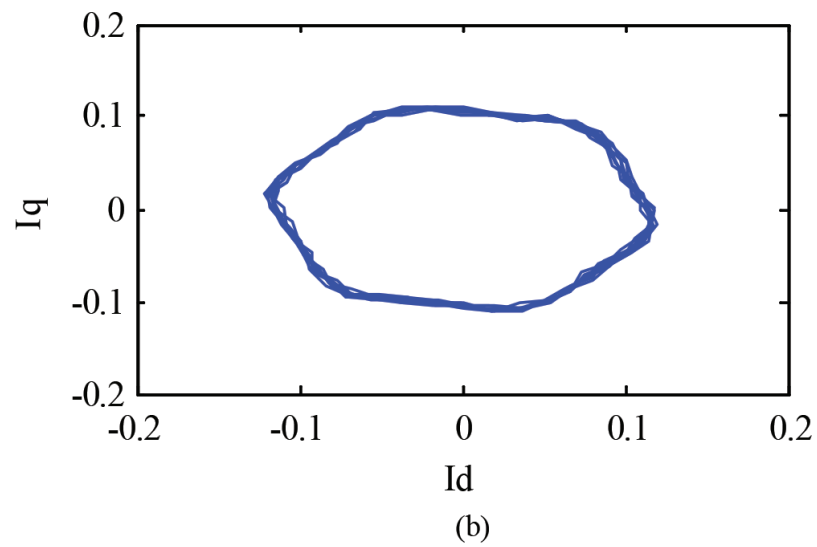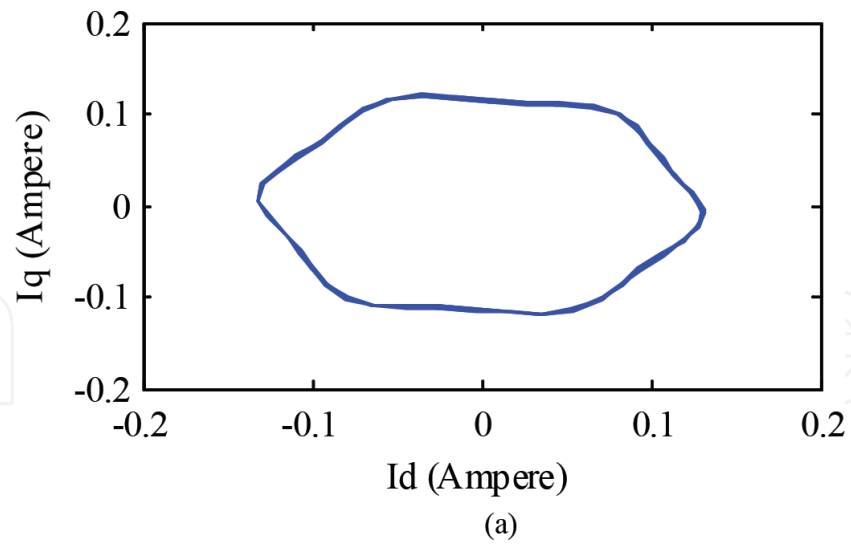
Figure 14. Example of Park vector analysis of stator current for (a) healthy bearing, (b) outer race localized defect and (c) inner race localized defect.

9. Non-invasive method for diagnosis of bearing distributed defects

Most of the published work on the bearing condition monitoring via non-invasive techniques as discussed in focused on diagnosis of bearing localized defects. It is based on some characteristic fault frequencies that appear in spectrum of the stator current or instantaneous power. However, the absence of clear characteristic fault frequencies should not be interpreted as a completely healthy condition of the bearing. On the other hand, the bearing distributed faults produce unpredictable broadband effects which are not necessarily related with specific fault frequencies. These faults are common in industry, while they are often neglected in the research literature.

Time-domain analysis is a useful feature extraction tool for condition monitoring and fault diagnosis of electrical motors. Time domain averaging (TDA) is a traditional and typical method to detect fault signals in electrical motors. It extracts a periodic component of interest from a noisy compound signal. Data-clustering techniques are used to extract an average pattern that serves as the mechanical imbalance indicator. Zhang et al. [153] proposed the idea of creating artificial distributed defects in bearings of induction motor via externally applied shaft current. This idea was important as the defects would be sorted according to the kind of signatures generated by defects instead of where the defects were located physically. Most of the condition monitoring approaches concerning fault detection found in the literature have been mainly focused on identifying single-point defects. Indeed this class of defects is quite important, however, an approach that is comprehensive and robust must have the capability of detecting not only single-point defect but also distributed defects in the bearing. The data obtained from 10 bearings failed by their proposed method, was analysed in time domain. It was shown that drastic variations in machine vibration and stator current occur in case of defected bearings. A method to segregate the bearing localized and distributed defects based on the time domain analysis of vibration, stator current and acoustic emission signals was presented by Navarro et al. [154]. The RMS values of the multi-sensory signal for healthy bearing, bearing localized and distributed defects were collected and faults were classified based on fuzzy inference analysis. In Refs. [155, 156], it was reported that generalized roughness in bearings of the motor produces a frequency spreading of the characteristic fault frequencies, thus making it difficult to detect with MCSA method. In the papers, it was proposed to use a statistical analysis of typical bearing faults in order to identify the spreading bandwidth related to bearing surface roughness faults, relying on current and vibration measurements only. A diagnostic index based on computation of energy in the previously defined bandwidth was used to diagnose bearing surface roughness faults. The proposed method was validated experimentally with vibration and current signals, with robust and reliable results. However, implementation of their proposed method needs computational efforts and implementation of this method for inner and outer race surface roughness was not given. In a recent study, Dalvand et al. [157] analyse bearing distributed defects in inner and outer race of bearing simultaneously. They use statistical analysis of the instantaneous frequency of motor voltage space vector (MVSV) and vibration signal. The statistical indices like mean value (M), RMS value, standard deviation (SD), global kurtosis (GK), skew factor (SF) and crest factor (CF) were utilized to analyse the measured signal. It was shown that mean value and RMS are not proper indices to analyse the distributed

defects in bearings because the values of these indices for healthy and defected bearings are not significantly different. However, the GK, SF and CF are proper indices to diagnose bearing distributed faults. Experimental results indicate that although the statistical time domain analysis of MVSV and vibration signals have capability to diagnose the bearing distributed defects; however the reliability of MVSV is better than vibration monitoring. The analysis of individual defect in bearing elements was not presented in their study.

10. Condition monitoring issues

The literature review has shown that the invasive methods like vibration analysis, acoustic emission, noise analysis, chemical analysis and temperature measurements were applied to protect motors from various faults. However, sensors used in these methods are very expensive. Another disadvantage of these methods is that they require access to machine for sensor installation which is not possible in every application. Also it requires special expertise for the proper installation of sensors on the machine for accurate results. Therefore sensor-based condition monitoring methods are not reliable.

Review papers presented in Refs. [158–163] on the condition monitoring techniques for the induction motors demonstrate that extensive research has been carried out in the last decade on the development of a non-invasive condition monitoring system for diagnosis of gear defects and bearing localized faults. It has been found that the mechanical vibration produce characteristic frequencies in stator current spectrum. The magnitude of the specific characteristic frequencies increases with the increase of vibration. Every type of the motor defect has its own unique characteristic defect frequencies. The MCSA has been extensively used to find out these frequency modulations.

The implementation of MCSA for motor condition monitoring is not so complex. However, low amplitude fault signatures are induced due to incipient faults under no-load condition and thus could not be reliably diagnosed through MCSA. Recent developments in non-invasive condition monitoring scheme demonstrate that PVA of motor stator current has the capability to diagnose the motor faults at incipient stages. It was shown that the proposed method would give good analysis of machine faults even if accurate fault frequency information is unavailable. In recent years, IPA method to diagnose rotor, stator and eccentricity faults at incipient stages conditions was proposed by few researchers. However, applicability of the IPA for mechanical fault diagnosis in induction motor has not been reported in literature [164–170].

The incipient defect diagnosis in the machinery with unknown distribution of measured signals and unknown changed parameters is an important issue. However, most of the fault diagnosis techniques need a priori knowledge on the signal distribution, changed parameters and the changed amplitude. Fault detection plays a key role in enhancing today's technological system's high demands for performance, productivity and security. The sensitivity of the condition monitoring and fault diagnosis methods depends on the application of main goals. When productivity is the main goal then the sensitivity requirement of condition monitoring and fault diagnosis system is weak and only large defects should be detected. However, when

security is the main goal, undetected defects even with very small severity assessment may result in catastrophic growing failures. For online fault diagnosis, when safety is the main priority, it is crucial to be able to diagnose incipient faults in presence of environment noise. Although IPA has some implementation advantages over MCSA for incipient fault detection but the signatures of IPA are affected by industrial noise perturbations. There is much scope for research to improve the capabilities of IPA in reliable online fault diagnosis in an arbitrary environment noise.

Notably, the substantial number of research studies has been found focusing into detection of bearing localized faults via non-invasive condition monitoring methods. Nonetheless, bearing distributed defects does not produce localized defect frequencies and thus could not be analysed via these methods. Recently, few studies have been found focusing on time domain analysis of stator current signal and extracting the features like RMS and kurtosis values. However, complexity involved in time domain analysis of stator current signal is the major drawback. As PVA performs the graphical analysis of stator current and does not require frequency information for fault detection thus its capability to diagnose bearing distributed defects should be further researched.

The advantages and drawbacks of the existing non-invasive condition monitoring methods are presented in **Table 2**.

No	CM technique	Advantages	Drawbacks	Reference
1.	MCSA	• Inexpensive • Non-invasive	• Unable to detect defects at incipient stages • Fault detection affected by environment noise	[25, 38, 52–73]
2.	PVA	• Inexpensive • Non-invasive	• Further investigation required to test its capability for bearing distributed defects	[144–152, 171]
3.	IPA	• Inexpensive • Non-invasive • Can detect rotor and eccentricity defects at incipient stages	• Fault detection affected by environment noise • Capability to diagnose mechanical faults needs to be tested	[119–123]

Table 2. Advantages and drawbacks of non-invasive condition monitoring methods.

11. Future directions

Based on the findings, there are further problems to be considered both in the development of the technique and in the experimental design. These include

• Development of non-invasive condition monitoring scheme to diagnose faults in an arbitrary environment noise conditions

The non-invasive IPA has shown some implementation advantages over MCSA to reliably diagnose mechanical faults. However, small fault signatures under low load conditions are buried in noise and it is difficult to discriminate amplitude changes due to fault and due to noise. Thus, there is a need to develop a robust non-invasive condition monitoring scheme to make reliable decisions on the existence of fault signatures.

- Development of non-invasive condition monitoring scheme to diagnose bearing distributed faults

  Most of the published work on the bearing condition monitoring via non-invasive techniques is focused on diagnosis of bearing localized defects. It is based on the some characteristic fault frequencies that appear in spectrum of the stator current or instantaneous power. Nonetheless, bearing distributed defects does not produce characteristic defect frequencies and thus could not been analysed via MCSA or IPA. These faults are common in industry, while they are often neglected in the research literature. As PVA performs the graphical analysis of stator current and does not require characteristic defect frequencies information for fault detection thus its capability to diagnose bearing distributed defects should be further researched.

- Development of hand-held instrument for on-site machine condition monitoring

  The IPA and PVA algorithms could be embedded to develop a hand-held instrument for on-site condition monitoring of induction motors. This will help to reduce the installation cost of the data acquisition system especially for small and medium scale industrial use.

- Reliability tests for mainstream industries

  The developed IPA and PVA algorithms should be expanded and utilized to analyse faults in turbines and generators. For consideration to be acceptable by the main stream industries, a reliability test of the developed algorithms should be conducted on large size motors (more than 40 HP).

- Multiple bearing faults analysis

  Even though the two techniques as proposed i.e. the instantaneous power analysis and Park vector analysis can monitor the conditions of induction motors from various scenarios, however these are not sufficient for most applications because outcomes of the analysis are based on the assumptions that each fault occurs independently. The extension of the approach as proposed in this work, to understand how each approach reacts to a combination of several faults (e.g. stator, rotor, eccentricity, bearings, etc.), would be useful.

12. Conclusion

The ability to forecast motor faults at incipient stages is vital to reducing maintenance costs, operation down-time and safety hazards. This paper synthesized the progress in the research

and development in condition monitoring and fault diagnosis of induction motors. The review presented in this paper has contributed to an improved understanding of the development of practical non-invasive condition monitoring and diagnostic tool for induction motors. The non-invasive methods, namely MCSA, PVA and IPA overcome the disadvantages associated to invasive methods. The MCSA, PVA and IPA can successfully diagnose the gear and bearing localized defects. However, further research is required to analyse bearing distributed faults via non-invasive condition monitoring methods. It has been observed that IPA has some implementation advantages over MCSA for incipient fault detection but IPA can be affected by environment noise perturbations. There is much scope for research to improve the capabilities of IPA in reliable online fault diagnosis system operating in an arbitrary environment noise. Furthermore, to realize the greatest economic and implementation benefits of IPA and PVA, it is important to design a hand-held condition monitoring system based on IPA and PVA techniques by considering the asset management perspective.

Acknowledgements

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