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ORIGINAL PAPER

Condition Monitoring and Fault Diagnosis of Induction Motors: A Review

Anurag Choudhary[1] · Deepam Goyal[2] · Sudha Letha Shimi[1] · Aparna Akula[3]

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Abstract

There is a constant call for reduction of operational and maintenance costs of induction motors (IMs). These costs can be significantly reduced if the health of the system is monitored regularly. This allows for early detection of the degeneration of the motor health, alleviating a proactive response, minimizing unscheduled downtime, and unexpected breakdowns. The condition based monitoring has become an important task for engineers and researchers mainly in industrial applications such as railways, oil extracting mills, industrial drives, agriculture, mining industry etc. Owing to the demand and influence of condition monitoring and fault diagnosis in IMs and keeping in mind the prerequisite for future research, this paper presents the state of the art review describing different type of IM faults and their diagnostic schemes. Several monitoring techniques available for fault diagnosis of IM have been identified and represented. The utilization of non-invasive techniques for data acquisition in automatic timely scheduling of the maintenance and predicting failure aspects of dynamic machines holds a great scope in future.

1 Introduction

Condition Monitoring (CM) of induction motor is the process of continuously monitoring or observing the health of the system. This aims at improving productivity, efficiency, cost reduction and increases the machine availability [1, 2]. IM, a critical component in industrial processes, are most significant prime movers in industrial applications due to their simplicity and reliability of construction [3]. IMs are widely used in different sectors of industries, such as, railways, mining, wood working machines, automotive, chemical, paper mills, etc. Single phase IMs are used widely in domestic applications i.e. fans, centrifugal pumps, blowers and industrial machines, due to their high efficiency and reliability. A study has been done on variety of faults, such as unbalanced stator winding, broken rotor, eccentricity, bearing and misalignment faults in induction motor [4–6].

Conventionally, maintenance of IM occurs at a fixed interval of time. However, due to environmental and operating conditions, performance of IM may deteriorate at irregular interval. Therefore, online monitoring of the IM is necessary to achieve higher efficiency. The key element of new developing approaches is predictive maintenance through CM, which aims at predicting the maintenance schedule depending upon the plant or process condition [7, 8]. The condition based monitoring is used for increasing the performance and efficiency of IM, enhancing life and productivity, reducing internal and external damages [9]. The CM and fault detection of IMs has become necessary to stop the unexpected breakdowns and minimize unscheduled downtime. Several techniques *viz.* Acoustic Emission (AE) monitoring, vibration signature analysis, Motor Current Signature Analysis (MCSA) are

✉ Deepam Goyal
bkdeepamgoyal@outlook.com

Anurag Choudhary
anurag.choudhary087@gmail.com

Sudha Letha Shimi
shimi.reji@gmail.com

Aparna Akula
aparna.akula@csio.res.in

[1] Department of Electrical Engineering, National Institute of Technical Teachers Training and Research, Chandigarh 160019, India

[2] Department of Mechanical Engineering, National Institute of Technical Teachers Training and Research, Chandigarh 160019, India

[3] Department of Computational Instrumentation, CSIR-Central Scientific Instruments Organization, Chandigarh 160030, India

used for condition monitoring of IM, but these monitoring techniques are complex and require expensive sensors [10]. An efficient CM scheme is capable of providing warning and predicting the faults at early stages. The CM system collects primitive data information from the motor using signal processing or data analysis techniques. However, the major drawback of the system is human interpretation [11]. The automation of the fault detection and diagnostic process is a logical progression of the CM technologies [12]. The automatic fault diagnostic system requires an intelligent system such as artificial intelligence techniques, Genetic Algorithm (GA), Fuzzy Logic (FL), Artificial Neural Network (ANN) and expert systems [13–19]. An industry based comprehensive survey on high voltage IM failures has been carried out using different type of categorization, including protection scheme, machine size, age, number of poles, maintenance regime and running hours [20]. The cause of both stator and bearing faults which together constitutes 75% of all failures has been investigated in induction machines [21].

This report focuses on surveying and summarizing the recent developments in the field of condition monitoring and diagnosis of faults for determining the health of IM. This review is useful for orienting new research in the area of condition monitoring of rotating machines and its components. An attempt has been made to consolidate the work of various scholars and researchers on condition monitoring related to induction motors. This study endeavors to provide an in-depth analysis to researchers for future reference which may help in paving a way for advanced research in this field.

2 Foregoing Research

Condition monitoring of electrical rotating equipments has attracted the attention of researchers for more than three decades. The art of CM should be moderate enough to take the minimum measurements. The first modern book on the CM of electrical machine was published in 1987 [22] followed by many revised versions by various researchers [23, 24]. An efficient sequence impedance as a predictor of incipient failure has been suggested. The results of IM fault detection using vibration, stator current and AE methods have been compared [25]. The stator current method has been found to be more sensitive to rotor fault, while the vibration monitoring technique is sensitive to bearing defects identification. AE monitoring has been considered as very appealing to contain less noise and interference within the analyzing frequency band of generated signal. Several researchers have reported the CM and fault diagnosis for electrical rotating components [26], large motors and generators [27]. The comprehensive analysis of CM signals must take into account the inter-relationship between mechanical and electrical signals. The study focuses not only on identifying the most common causes for majority of motor problems but also on preventive actions to be taken to avoid these problems [28]. The facts about CM and diagnostic measures have been collected by conducting a survey on IM drives for industrial applications [29]. The study concentrates on the existing and upcoming issues in the development of automatic diagnostic processes. Advance tools for online CM of induction motors have been developed in LabVIEW environment [30]. The use of stator current analysis based demodulation techniques has been considered most appropriate for diagnosis of bearing fault [31]. The various non-contact CM techniques have been discussed for diagnosis of inductor motor faults [32]. It was found that the Park vector analysis and instantaneous power analysis techniques are best suited for identifying the motor fault signatures. The author proposed Support Vector Machine (SVM) based techniques and demonstrated that it gives better results for CM and fault diagnosis of a three-phase IM [33]. The Bearing Damage Index (BDI) based on wavelet packet node energy coefficient analysis method has been proposed not only to detect the faults in bearing but also to detect the severity level of the fault [34]. The most recent reviews have been presented on automation of condition monitoring of IM [35, 36]. The ratio of CM cost to equipment cost has been proposed as one of the impeding factor for guiding maintenance for majority of the electrical machines.

3 Induction Motor Faults

In today's world, IM is contemplated as a fault tolerant motor and is a more pleasing choice for industrial applications [36, 37]. Installation, manufacturing defects and tolerance, working environment and schedule of maintenance are the major factors responsible for failures in electrical rotating machines [38]. The protection of IM is a challenging task for engineers and technicians [39]. In the conventional method, protective relays were used to monitor these faults and to disconnect the motor if any faults occurs [40]. IM can be categorized into internal and external faults that are further classified into mechanical, electrical and environmental faults. Faults may be classified into the rotor, stator, bearing and other mechanical faults based on its location in the equipment as shown in Fig. 1. These faults and their causes are summarized in Table 1. Induction motor is reliable in operation, but it has different types of undesirable faults which leads to unexpected machine breakdowns. The statistical studies of IM failure by Institution of Electrical and Electronics

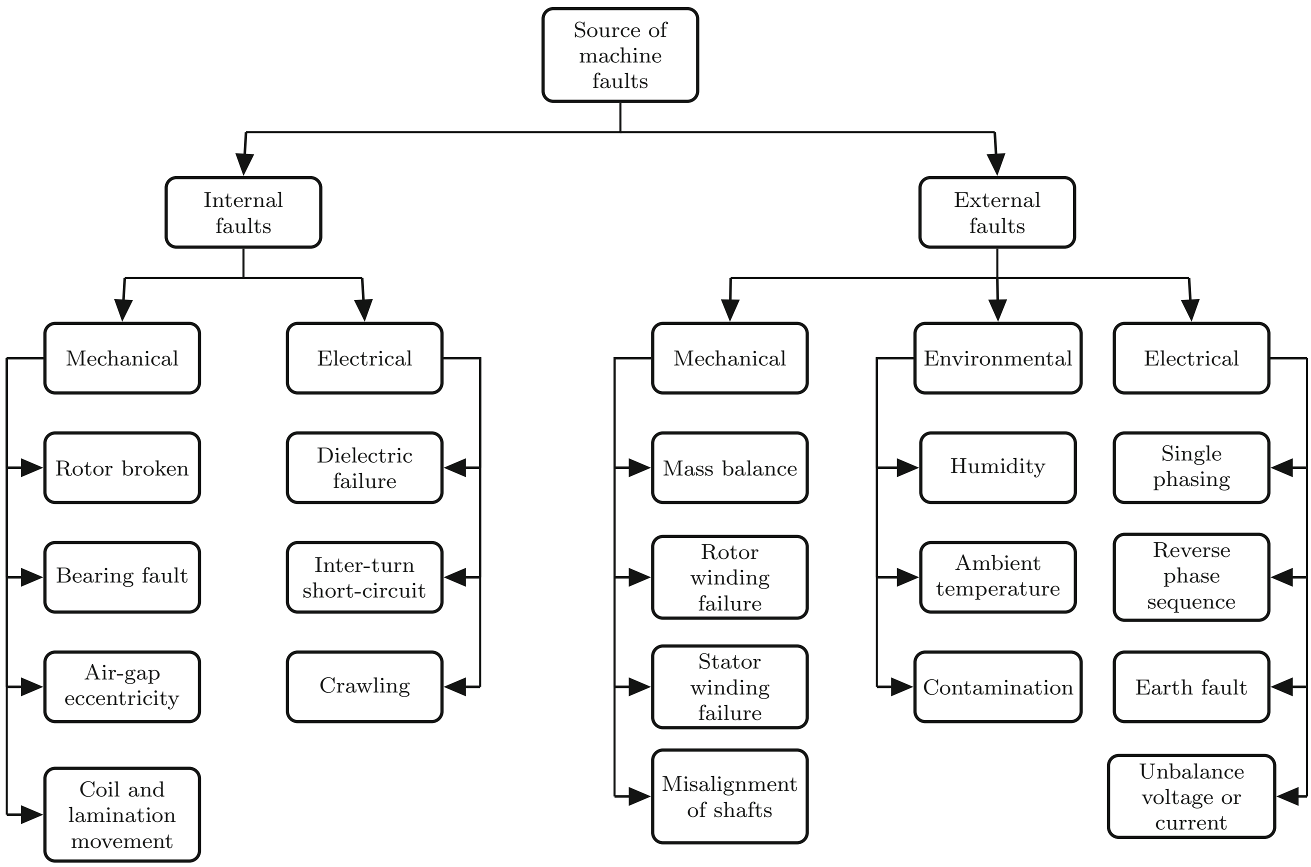

Fig. 1 Classification of faults in induction motor

Engineers (IEEE), ASEA Brown Boveri (ABB) and Electric Power Research Institute (EPRI) are shown in Fig. 2. IMs are symmetrical electric rotating machines because of rotating magnetic field, so any kind of defect can change its symmetrical properties. The reliability of IM has been reported in several surveys [41–43]. According to these surveys, commonly encountered failures in IMs are bearings and stator winding defects [44, 45]. Several conventional methods have been used in industries to prevent severe defects in IM. The scheduled maintenance has been developed to investigate the integrity of IM bearing defects, broken rotor and stator winding related integrity. Redundancy, as a conventional method, has been used to prevent unexpected shutdowns, but not motor failure. This solution has many limitations such as high maintenance cost and physical space required for motor due to implantation of preventive measures [46].

3.1 Bearing Faults

Bearings are considered as essential components of electrical rotating machine, having a wide range of industrial applications such as rope conveyors, bicycles, electric motors, turbines, rolling mills etc. [67]. The bearing of IM provides support to the rotating shaft placed at both the ends of the rotor [68]. The most common fault in IM is bearing failure. Bearing defects can be classified into localized and distributed faults. The most dominant mode of the rolling element bearing failure is spalling on raceway surface, improper mounting, manufacturing errors and corrosion. Although they are subjected to diverse influences that affect their service life. The bearing fault occuring in IM during operation, according to IEEE and EPRI, are 41% and 42% respectively as shown in Fig. 2b, c. Different category of bearing defects i.e. cage, ball, outer race, inner race and the healthy bearing are depicted in Fig. 3. Bearings defects can lead to failures, inefficient operation and downtime. Acoustic emission and vibration monitoring techniques are well-known techniques for CM of bearing in IM [69, 70]. The survey story of fault detection in IM has been presented with different bearing faults using vibration and acoustic signals [71]. Fig. 3 depicts various parts of the bearings.

During bearing failures, there is an increase in shaft friction increases which causes further increase in temperature of the bearings of concerned IM and hence this change provides useful information regarding the health of

Table 1 Popular induction motor faults and their causes

Name of fault	Classification	Part/region	Causes	Description	References
Mechanical faults					
Bearing failure	Internal	Bearing	Manufacturing defects, overstress, improper lubrication, wear debris	Common source of vibration (range of frequency, 2–60 kHz), better detection by thermal imaging technique	[4, 36, 40, 47]
Broken rotor bars	Internal	Rotor	Unbalance magnetic pull, large transient, negative sequence in supply, thermal stress, manufacturing defects	Difficult to detect because of small amplitude but from current signal better detection level	[4, 39, 40, 47, 48]
Misalignment	External	Rotor	Incorrect coupling, defective installation, bearing failure, over loading	Better detection using IRT and vibration signature	[49–52]
Rotor mass unbalance	External	Rotor	Internal misalignment of rotor, manufacturing defect, end ring movement	Centrifugal force produces excessive vibration in rotor as well as stator	[9, 53]
Air gap eccentricity	Internal	Between rotor and stator	Unbalance magnetic pull, rotor misalignment, bearing defects	Early detection of air-gap eccentricity fault on the basis of spectral analysis of complex apparent power modulus	[54–58]
Coil and lamination defects	Internal	Rotor or stator	Damage during installation or service, frequent starting, high and low temperature and humidity, thermal aging	It is required to reduce the eddy current losses	[32, 59]
Stator winding failure	External	Stator	Failure in installation, Surge in supply, slacking of coil	Problem can be identified as electrical signal like current, thermal imaging technique can be used for this problem	[60–62]
Electrical faults					
Crawling	Internal	Between rotor and stator	Abnormal magneto motive force, 7th harmonic presence of higher order harmonics in power supply to the motor	Significant different changes of harmonic distortion are observed in two axes of larke plane	[63]
Unbalance supply voltage or current	External	Power supply	Unbalanced supply voltage, short circuit in supply cable	Detection of abnormal condition of unbalanced voltage supply through dynamics symbolic state machines (DSSM)	[39]
Single Phasing	External	Connection	Slack joints, excessive vibration, blown fuse of the utility system, short circuit in one phase	Infrared inspections of these motors enabled to detect this kind of fault	[59]
Earth fault	External	Connection	Slack core lamination, abrasion of insulation connection, failure or short-circuit	Converting to high resistance grounding will control and reduce the ground fault current	[59, 64]
Environmental faults					
Ambient temperature	External	-	Reflective errors	It carries the risk of inaccuracy	[7, 59, 65, 66]
Contamination	External	–	Oil lubrication, oil debris	Particulate in metallic construction is 200% larger than the measured in the final packing	[59, 66]
Humidity	External	–	Moisture in foundation	Negligible effects on object temperature measurement	[59, 66]

the bearing using acoustic signals [4]. An experimental comparison of bearing fault diagnostics with a new AE based approach begins with a heterodyne approach that allows AE signals to be sampled at a rate comparable to vibration signal based approaches. The report consists of a detailed survey of rolling element bearing and their

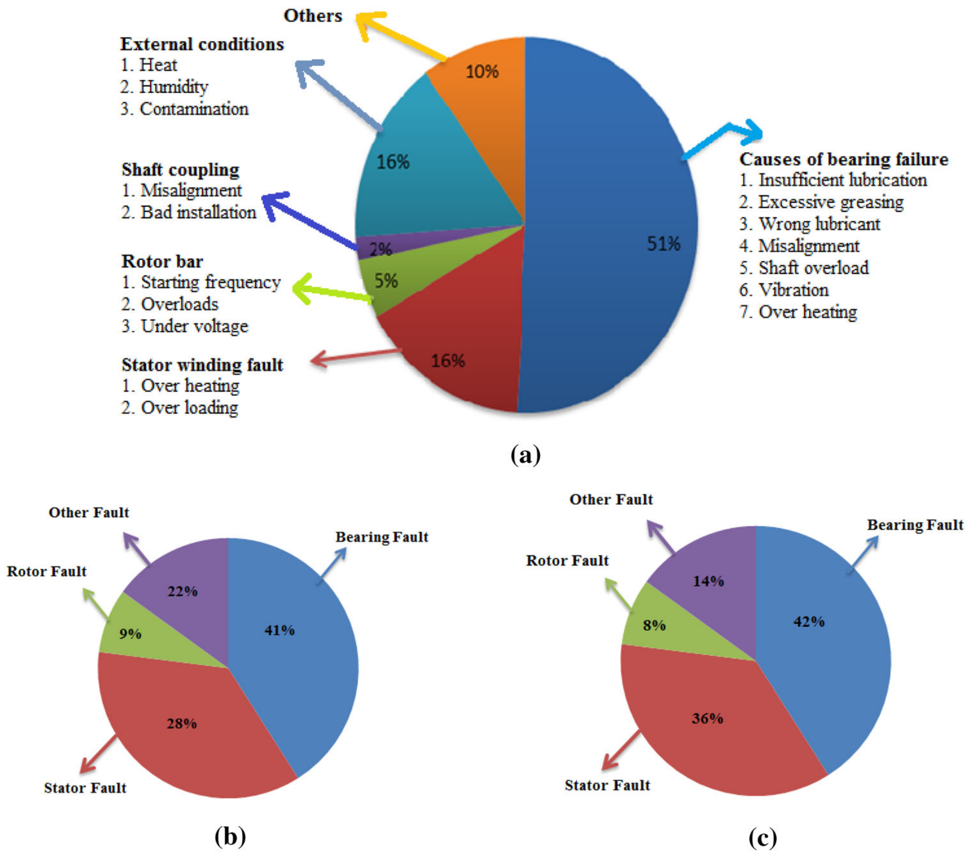

Fig. 2 Study on induction motor faults. **a** ABB, **b** IEEE, **c** EPRI

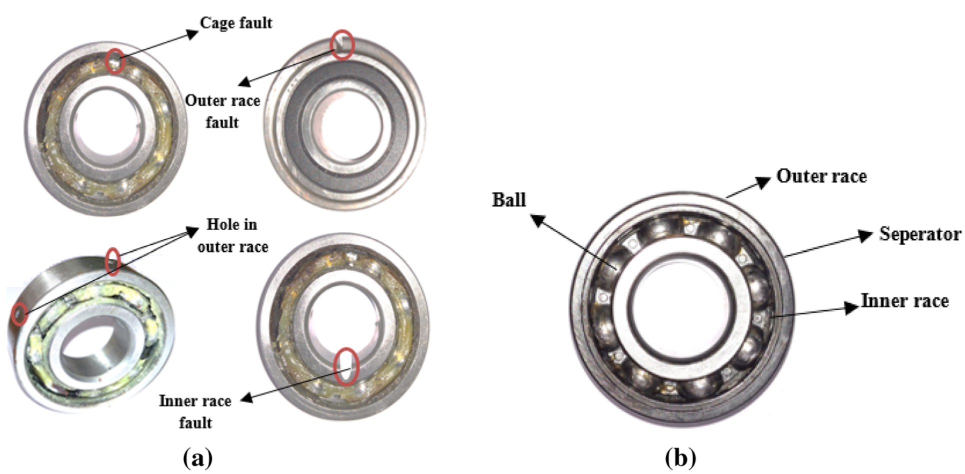

Fig. 3 Structure of ball bearing. **a** bearing defects and **b** healthy

diagnostic schemes [72–74]. A new technique has been developed for CM of rolling element bearings using vibration analysis [75]. This technique has the ability to identify the bearing faults of IM at an early stage. The stator current monitoring technique based on wavelet analysis of the starting current transient has been proposed to detect bearing defects in IM [76].

3.2 Stator Fault

The most common faults in IM are stator inter-turn fault due to heavy current flow in the short-circuited coils and insulation downgrading [60–62]. The stator faults can be classified as faults in stator winding, winding laminations, and the frame of the stator. Out of these, the first one is the most commonly occuring fault in stator. The different types of faults in stator winding such as turn to turn, coil to

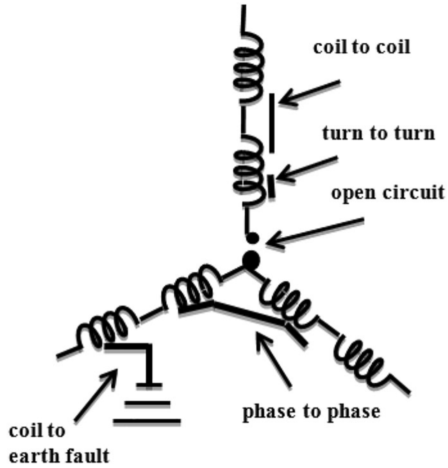

Fig. 4 Types of stator winding faults

ground faults, coil to coil, phase to phase are shown in Fig. 4.

Many researchers have presented the techniques based on negative sequence current that is sensitive to different phenomena beyond stator asymmetry [77]. Positive, negative and zero sequence are used in order to transform a generic set of phasors into balanced vectors. Three balanced vector can be expressed as:

$$\begin{bmatrix} \bar{I}_n \\ \bar{I}_p \\ \bar{I}_o \end{bmatrix} = \begin{bmatrix} 1 & \alpha & \alpha^2 \\ 1 & \alpha^2 & \alpha \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \bar{I}_u \\ \bar{I}_v \\ \bar{I}_w \end{bmatrix} \quad (1)$$

where, $\alpha = e^{ja}$, $a = \frac{2\pi}{3}$, $\bar{I}_u$, $\bar{I}_v$ and $\bar{I}_w$ are line currents, $\bar{I}_p$, $\bar{I}_n$ and $\bar{I}_o$ are positive, negative and zero sequence currents respectively.

A novel indicator of inter-turn fault in stator winding has been developed in IM with pseudo-coloring of grayscale using hottest region segmentation of thermal images [60]. It has been found that the proposed technique is not suitable for different environmental conditions. The original method of area selection of image has been discussed for diagnosis of stator fault with different classifiers [78]. All the known possible harmonic fields were first tabulated for stator related problems in quiet IM [79]. As per the study by EPRI and IEEE, faults occur in the stator winding of IM are 36% and 28% respectively. A novel technique for fast detection of stator winding faults in three phase IM has been presented using autoregressive model [80]. The fault diagnosis method applied on IM, is based on higher-order spectrum [81].

3.3 Rotor Fault

The rotor is the inner part of an IM which is made by bars of solid copper or aluminum that spans the rotor length and is connected through a ring at each end [82]. The rotor broken fault (with single rotor broken bar) is shown in Fig. 5. The synchronous speed can be expressed as

$$N_s = \frac{120f}{p} \;\&\; N_r = N_s(1 - s) \quad (2)$$

where, p = number of pole, f is supply frequency, N_r is rotor speed, N_s is synchronous speed and s is slip. The slip can be expressed as

$$s = \frac{N_s - N_r}{N_r} \times 100\% \quad (3)$$

for the locked rotor $N_r = 0$, therefore $s = 1$. The slip will decrease as the rotor speed increases [83].

The thermal image segmentation using IRT has been applied to identify the rotor broken faults and faulty end rings [84]. IRT technique has been proved to be more efficient as compared to other CM methods. Such faults do not initiate the failure of IM, but have some skew to reduce noise and harmonics. The rotor fault which occur in IM during operation, according to EPRI and IEEE, are 8% and 9% respectively. A transformative based technique has been proposed for rotor broken bar fault detection in IM using stator current signal [85]. A novel technique based on Singular Value Decomposition (SVD) and information entropy has been suggested for broken-rotor-bar and bearing faults detection in IM [83].

3.4 Eccentricity Fault

The common cause of eccentricity is bearing fault, which contributes approximately 42% of IM faults [86]. The eccentricity faults create a non-uniform air gap between rotor and stator [87]. There are three types of eccentricity faults i.e. static, dynamic and mixed eccentricity (both static and dynamic coexisted in the motor). R_s is the stator radius and R_r is the rotor radius as shown in Fig. 6.

In the case of static eccentricity, the sideband components for frequencies can be determined as:

$$f_{ec} = f_g\left[(R \pm n_d)\left(\frac{1-s}{p}\right) \pm n_{ws}\right] \quad (4)$$

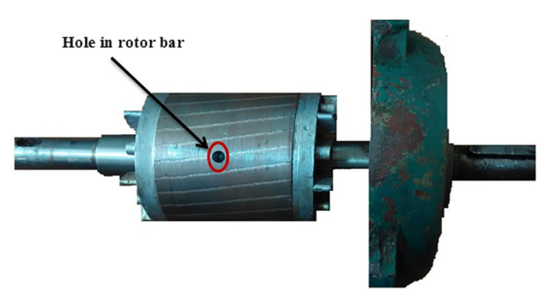

Fig. 5 Single broken rotor bar of induction motors

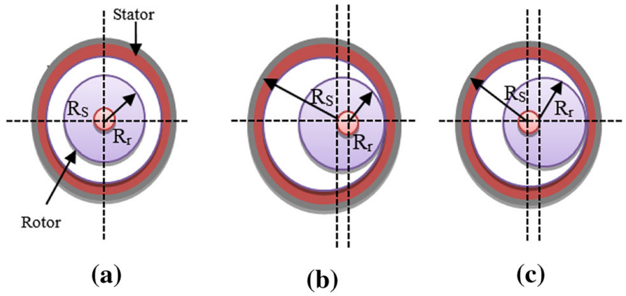

Fig. 6 Cross-section of induction motor **a** normal (concentric), **b** static eccentricity and **c** dynamic eccentricity

where, R is number of rotor bars, s is slip, f_{ec} is eccentricity frequency, f_e is electrical supply frequency, $n_d = \pm 1$, $n_{ws} = 1, 3, 5, 7, \ldots$, p is pole-pairs.

Therefore, either mechanical (vibration or torque) or electrical (current or instantaneous power) quantities can be analyzed to identify the eccentricity related problems [88]. A new transformative based approach for early detection of air-gap eccentricity fault in three phase IM has been suggested for healthy as well as faulty motor conditions [89]. A review has been carried out to detect the eccentricity fault in large IM [90]. Fast Fourier transform, wavelet and Hilbert method are most suitable methods to extract the signal for identifying the eccentricity faults in IM.

4 Condition Monitoring Techniques

One of the most important elements of Condition Based Maintenance (CBM), condition monitoring, has become an efficient strategy for carrying out the predictive maintenance of IM for industrial applications. Induction motor is considered inherently reliable due to its robust and relatively simple design. About 50% of total energy generated in the whole world is utilized by IM for industrial and domestic applications [89]. The different CM indicators have been explored for fault analysis of dynamic machines [91]. The times of action in maintenance process through CM is summarized in Table 2, which aims at predicting the maintenance schedule depending upon the motor condition.

Traditionally, the techniques used for maintenance procedures in industries are electromagnetic torque analysis, acoustic noise measurements, vibration monitoring and partial discharge [29]. Recently, artificial intelligent techniques such as IRT, MCSA, ANN, GA, FL, Adaptive Neuro Fuzzy Inference System (ANFIS), expert systems etc. have been employed to assist the CM and fault diagnostic systems [13]. A review of the utilization of soft computing techniques has been introduced in CBM [92]. There is a huge extension for ideal usage of non-invasive instruments for measuring vibration in assessing the maintenance and failure aspects of machines that are progressive in nature [93]. Figure 7 shows the different maintenance strategies through condition monitoring to maintenance actions.

Table 2 Timing of action for maintenance

Times of action	Maintenance
Operating failure	Breakdown or shutdown
Fixed time based	Preventive
Condition based	Diagnostic or predictive

4.1 Vibration Monitoring

Vibration analysis has been developed as the most effective method for CM of induction motor [94]. Over the past decade, new signal processing techniques and their application to induction motor has increased [95, 96]. Several effective signal analysis techniques i.e. wavelets analysis, FFT, Short Time Fourier Transform (STFT), and auto diagnostic expert system using artificial intelligence to extract the vibration signature that embedded in the raw vibration signals have been introduced [13–19, 97].

Induction motors without vibration in the operating environment are something non-existent [97]. During operations, motors generate vibrations which are directly linked to the problems in systems having rotating components such as rotor shaft, bearing etc. These vibrations in IM are the effects of electromagnetic forcing on the motor parts i.e. stator and rotor [99]. The first research in vibration monitoring was reported way back in 1930s [79].

The mathematical expression of electromagnetic vibration has been described as a force-wave expression:

$$P(\alpha, t) = P(r, w)cos(r\alpha - wt - \psi_p) \tag{5}$$

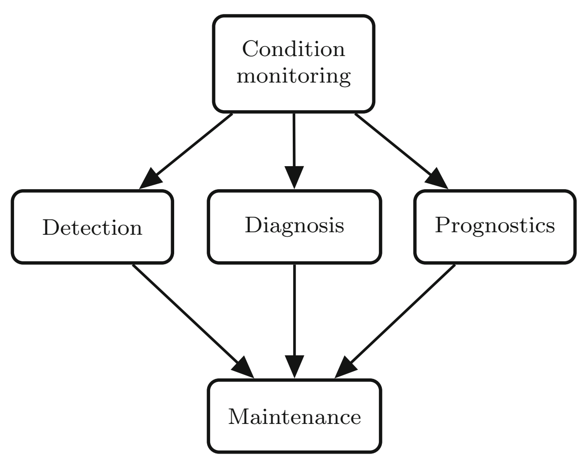

Fig. 7 Condition monitoring and prognostics and health management

where $P(r, w)$ is amplitude of force wave, r is order of force-wave (mode), ψ_p is phase angle, w is wave angular frequency, α is angular coordinate, t is time period.

In healthy conditions, IM produces a weak vibration signal which is very useful to identify the fault in IM using vibration spectrum. When a fault occurs in internal part of IM it generates large vibration signals. Vibration signals can be detected in the term of velocity or acceleration or displacement in relative or absolute value [58]. An online CM system has been developed to record the frame, temperature, line voltages, vibrations and speed from a three-phase IM for different operating conditions [97]. The combined method of vibration spectrum analyses and current signature has fast detection reliability, which plays a vital role in vibration based signal classification [100]. The detection of different types of faults occurred in IM, using vibration analysis technique, are summarized in Table 3.

4.2 Acoustic Emission Monitoring

AE is frequently encountered technique to detect defects and flaws in equipment and electrical rotating machine, which provide early warnings to find preventive solutions for maintenance or diagnostic actions [82, 104, 105]. AE signals generate complexity as the wave travels through the medium. It requires knowledge of the wave characteristics, starting with the properties of the medium through which the wave travels [106]. AE monitoring system essentially involves two integral elements: a material deformation that becomes the machine, and transducers that receive the stress signals generated from the machine [68]. AE monitoring works with ultrasonic and audible frequencies monitoring techniques [107]. This monitoring technique can be exploited for detecting bearing and rotor related problems. The ultrasonic waves have the ability to monitor the stator related fault [4]. However, in all CM techniques, various actuators and sensors are used to acquire data from the models. On the other hand, the application of high frequency acoustic signal can be utilized for CM of bearing defects in electrical rotating machinery [98]. It has been observed that the AE monitoring method is less efficient for diagnosing the faults in IM as compared to recently developed monitoring methods [101–103, 108]. Hence, there is a need for a comprehensive study of AE techniques for CM and fault detection in IM with the combination of acoustic and vibration signals. The application of AE monitoring has been suggested to measure the condition of low speed anti-friction bearings of slewing cranes [109]. The different types of faults occurred in IM detected using AE analysis technique have been summarized in Table 4.

4.3 Air-Gap Torque Monitoring

The production of air gap torque is dependent on current and flux linkages [56]. The air-gap torque can be measured, when the IM is in running condition. The instantaneous input power of a three phase IM can be expressed as [57]:

$$P = v_a i_a + v_b i_b + v_c i_c \tag{6}$$

The power distribution in the term of voltage can be written as:

Table 3 Summary of condition monitoring of different faults in induction motor using vibration monitoring

Fault	Year	Data processing/feature extraction	Input signal	Description	References
Bearing	1999	Time and frequency domains along with signal processing techniques	Vibration	Computed individual signal processing techniques using theoretical and experimental data	[98]
Phase imbalance	2012	STFT	Vibration	Developed vibration monitoring procedure for phase imbalance of IM	[88]
Inter-turn short circuit	2012	Vibration specified harmonic amplitude	Vibration	Accomplished a series of time- domain analysis and frequency- domain analysis for inter-turn short circuit	[61]
Broken rotor	2013	Vibration signal analysis using FFT	Steady-state vibration	Developed a load independent fault diagnosis method	[47]
Fan gearboxes	2000	FFT analyser	Current	Investigated the ability of spectrum analysis for diagnosing the defective elements in gearbox	[99]
Bearing	2017	Vibration spectrum analysis using FFT	Current	Diagnose the slight misalignment between the bearings, overall vibration and the spectra gives much quicker and precise results	[89]

Table 4 Summary of condition monitoring of different faults in induction motor using AE monitoring

Fault	Year	Data processing/feature extraction	Input signal	Description	References
Bearing	2000	Method of ringdown counts	AE	Ring down counts based on acoustic signal has ability to detect faults in both rolling ball and inner race of the bearings	[73]
Bearing defect	2006	Data acquisition and FFT	Vibration and AE	Effective to detect bearing defects	[101]
Bearing and seal rubbing	2011	Discrete wavelet transforms	Vibration and AE	Improves air-gap torque profile for both healthy and faulty conditions of IM (with one broken). bar	[102]
Bearing	2013	Data acquisition card using LabVIEW software	AE	Data acquisition approach for monitoring the bearing defects	[103]

$$v_a = \frac{d\psi_a}{dt} + ri_a \tag{7}$$

$$v_b = \frac{d\psi_b}{dt} + ri_b \tag{8}$$

$$v_c = \frac{d\psi_c}{dt} + ri_c \tag{9}$$

Substituting Eqs. (7), (8) and (9) in (6) to get instantaneous input power:

$$P = \left[i_a \left(\frac{d\psi_a}{dt} + ri_a \right) + i_b \left(\frac{d\psi_b}{dt} + ri_b \right) + i_c \left(\frac{d\psi_c}{dt} + ri_c \right) \right] \tag{10}$$

where, P is power, v_a, v_b and v_c are instantaneous phase voltages, i_a, i_b and i_c are instantaneous phase currents, ψ_a, ψ_b and ψ_c are flux linkage of windings, and r is phase resistance.

It is laborious to directly measure the air-gap torque in electrical rotating machine. A finite element analysis has been proposed for estimating the air-gap torque in IM under standard supply systems at different frequencies [98, 110–112, 114]. The investigation have discussed the different states of the motor in either healthy or faulty condition at different loading conditions i.e. no load, half load and full load using air-gap torque monitoring [114]. This MCSA technique can give early indication of the presence of one or more broken bar in three phase IM. The comparison and experimental validation using FFT technique has also been provided to validate the proposed technique for fault detection of broken rotor bar [113]. An efficient diagnosis system has been developed by combining MCSA and neural network techniques which may exhibit high performance in industrial applications [48]. The detection of different faults occurred in IM using air-gap torque analysis are summarized in Table 5.

4.4 Motor Current Signature Analysis

MCSA has been considered as one of the most popular fault diagnostic technique to detect the common faults in electrical rotating machines [115]. MCSA techniques have been suggested for reliable performance and for improving the efficiency of large IM drives [95, 116, 117]. Many researchers have successfully implemented MCSA technique to diagnose the IM related problems [116–121]. MCSA technique works by acquiring current and voltage signals from the stator which are considered for signature analysis of IM. IRT technique based on thermal image segmentation, feature extraction and statistical analysis under the region of interest can be used as a complement for MCSA in fault detection of IM. The detection of different types of faults occurred in IM using MCSA are summarized in Table 6.

The measured stator current signal is extracted from motor and processed further to produce its power spectrum profile for determining the cause of IM failure [123–125]. Figure 8 shows the general procedure for MCSA technique which is used as an advance tool for CM of induction motor [115].

The power spectrum profiles are helpful in the identification of different faults in IM [81, 107]. Such current and voltage signals are measured through current and voltage sensors, and then apply the advance tool such as artificial neural network, fuzzy logic, digital signal processing tools, etc. [77, 121, 126, 127]. The major faults of IM that can be detected with MCSA technique are

- Stator faults
- Bearing faults
- Broken rotor bar
- Misalignment
- Abnormal stator winding connections
- irregularities in static or dynamic air-gap

Table 5 Summary of condition monitoring of different faults in induction motor using air-gap torque monitoring

Fault	Year	Data processing/feature extraction	Input signal	Description	References
Broken rotor bar or stator	1995	Data acquisition	Stator currents and voltage	The technique has ability to identify bearing defects in different operating condition for both constant and variable speed	[110]
Rotor	2001	FFT	Stator currents and voltage	A rotor fault diagnosis system based on model analysis of squirrel-cage rotor	[111]
Rotor	2003	Air-gap, torque spectra	Stator and rotor currents	A rotor fault diagnosis system based on model behavioral study for three phase IM	[112]
Broken rotor bar	2013	Gaussian mixture models (GMMs) and time-stepping finite-element	Current signal	Optimize the broken rotor bar fault identification using GMMs	[113]
Torque and thermal condition	2017	Finite element analysis	Temperature	An electromagnetic-thermal model of IM using FEM with COMSOL multiphysics	[114]

Table 6 Summary of condition monitoring of different faults in induction motor using MCSA monitoring

Fault	Year	Data processing/feature extraction	Input signal	Description	References
Broken rotor bar or stator	2001	FFT	Stator current	To improve MCSA monitoring technique for broken rotor bar	[122]
Stator broken rotor bars, bearing	2007	FFT	Stator current	To develop start-up current procedure on basis of MCSA. Four case studies of IM fault diagnosis have also been presented	[119]
Broken bar	2011	Neural Network	Stator current	High performance MCSA technique with NN has been proposed. Mixed eccentricity harmonic inherent can be detected efficiently	[48]
Bearing, mass unbalanced misalignment	2014	FFT	Stator current	Complementary technique for incipient bearing fault detection using IRT and MCSA	[53]
Bearings, broken rotor bars, air-gap eccentricity	2015	FFT, wavelet analysis, Park's vector approach, fuzzy logic	Stator current	An early fault detection system with intelligent approach	[85]

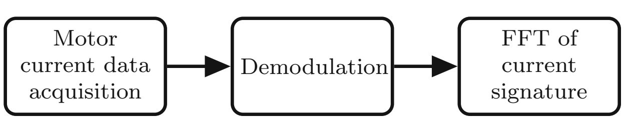

Fig. 8 General procedure for MCSA

MCSA technique analyses the stator current spectrum to investigate any failure in the IM [51, 52]. It can detect these faults at an early stage and avoid failure of IM [96, 99]. Expert system and machine learning techniques such as ANN, FL, ANFIS and SVM are more effective in fault classification and fault diagnosis of IM. SVM can be applied to complement of MCSA [128].

4.5 Infrared Thermography

Infrared thermography, a non-invasive analysis technique, is utilized as a fault detection tool for non-contact CM of induction motor. One of the main advantages of IRT is that it requires minimal instrumentation. It is widely used in various disciplines and sectors *viz.* electrical and mechanical maintenance [11], agriculture [129], defence [130], aviation, geological survey [131], automotive [132], medical [133, 134], electronics [135, 136] etc. for fault detection. It is also used in industries to detect serious faults in equipment, quality control and process control.

IRT has become a widely accepted and matured CM tool for temperature measurement. The measurement of electrical rotating machine using IRT can be done in continuous operation without any physical contact [62, 137, 140–144]. An original method of area selection of image differences with three classifiers i.e. Nearest Neighbour (NN), k-means, Back Propagation Neural Network (BPNN) has been suggested for fault classification. Shaft misalignment diagnosis using thermogram analysis of thermal images has been presented for healthy and faulty conditions of IM [50]. A review of different faults and some cases of temperature measurement using thermal camera has been studied for IM healthy and faulty conditions [145]. The thermal profile study of a induction motor has been considered under different loading and environmental conditions [65]. Cooling failure detection technique using RGB model have been presented for three phase IM with load and no-load conditions [138]. The thermal images were captured in both healthy and faulty environments and analyzed using FLIR tools (open source software for thermal image analysis) to develop a knowledge based technique for IM [140]. Fault diagnosis of IM using IRT techniques has been presented by reviewing different case studies. FLIR Model Fluke Ti-100 thermal camera is used to capture the thermal images and analyzed using thermogram. Losses estimation in IM using IRT has been presented with comparative analysis of natural convection, forced convection, thermal image processing and statical treatment [137]. A HSI model based technique has been demonstrated to improve the IRT for fault identification in IM and the results were compared with physical i.e. electrical and mechanical measurements [146]. Thermal diagnostics in electrical machines has been performed with different faults such as winding connections test, short-circuit detection, cooling-ducts test, heating of bearings and overheating connections [147]. Table 7 shows the summary of popular research using IRT for monitoring and fault detection of different fault in IM. A novel method for diagnosing the stator winding inter-turn fault in IM has been presented with pseudo-coloring of grayscale using hottest region segmentation of thermal images [107]. A new technique has been proposed for early fault detection and to study its impact on kinematic chain using IRT analysis. It was shown that the proposed technique has ability to improve overall diagnosis. Furthermore, it was highlighted that criterion can also be applied on any IM at the thermal steady state [49]. IRT technique is also widely used in civil structures [148], water leakage [149], corrosion damages and welding processes [150], electrical installations [151], nuclear plant [152] and plastic industries [153].

5 Condition Monitoring Using Computational Techniques

A smart approach for predictive maintenance in electrical rotating machine and electrical equipments needs human intelligence along with machine learning, which can acclimatize maintenance needs to different operating environments [13]. With knowledge of limiting parameters of IM, CM analyses each measurement separately [14]. To enhance the performance of the CM and predictive maintenance, a few most common techniques including FL, ANN, SVM, ANFIS approaches are discussed in this section.

5.1 Artificial Neural Network

ANN appears to be a recent development in condition monitoring of IM . However, ANN is a powerful tool to estimate and predict the remaining useful life prediction of electrical rotating machine and equipments more accurately [15]. The machine learning techniques are more suitable for big data gathering around the large induction machines and electrical equipments to draw conclusions about its operating state of health. The computational intelligence methods, including ANN [16] and SVM [17] have been developed as effective methods for automatic diagnosis and identification of bearing faults in electrical rotating machines. An ANN based online diagnosis method has been suggested for CM and fault diagnosis of IM [18]. The researcher presents few techniques for expert system such as qualitative simulation, qualitative reasoning and the requirements of an expert system for CM of electrical machines. Foregoing development of ANN based fault diagnosis techniques are reported in literature [19, 154–158].

5.2 Fuzzy Logic

The main aim of introducing FL is to optimize the preventive maintenance prioritization under the main constraints. Basically, FL is a multivalued logic that can be defined between traditional evaluations like true or false and yes or no. The application of computational intelligence methods for CM and fault diagnosis for machinery have been discussed. The researchers are focused on recently developed computational intelligence methods for CM and fault diagnosis [13]. More published literature has been successfully utilized for condition monitoring and fault classification of electrical rotation machine [159–165]. The typical fault detection and diagnosis technique has been discussed for turbo-generator with a rule based expert system [166]. The approach used by

Table 7 Summary of condition monitoring of different faults in induction motor using IRT monitoring

Fault	Year	Camera used	Detector (spectral range in µm)	Description	References
Inter-turn	2013	FLIR-i60 TIR	Uncooled microbolometer (7.513 µm)	Infrared images of IM are considered for feature extraction using image processing i.e. Histogram mean value, Hullindex, and Hotarea	[60]
Broken rotor bar, bearing, mass unbalance	2014	FLIR A310	Uncooled microbolometer (7.513 µm)	Diagnosis can be performed with weak signal	[49]
Losses estimation	2014	FLIR InfraCam SD	Uncoiled FPA microbolometer (8–14 µm)	An image processing technique divides a thermal image in several isotherms to calculate the natural convection in each image	[137]
Cooling	2015	–	Uncoiled FPA microbolometer (8–14 µm)	Prevented the IM components before any catastrophe failures	[138]
Misalignment	2015	FLIR 440	Uncooled microbolometer (7.513 µm)	Developed an on-line temperature measurement system to detect abnormal conditions	[50]
Thermal error	2015	FLIR ThermaCAMS65	Uncooled microbolometer (7.513 µm)	Generated an ANFIS based thermal error model of machine tools using fuzzy c-means clustering	[139]
Cooling	2016	FLIR-E60	Uncooled microbolometer	Ability to extract the features from weak signals and to early detect the faults in IM	[140]
Bearing	2016	FLIR Lepton	Uncooled VOx microbolometer (8–14 µm)	An economical thermographic analysis based bearing fault detection in IM	[36]
Bearing	2016	FLIR A310	Uncooled microbolometer (7.513 µm)	Determine the level of affectation on IM monitoring using thermal analysis	[10]
Bearing, cooling	2017	model Fluke Ti-100	Uncooled microbolometer (7.5–14 µm)	Cover better analysis under various operating conditions of IM in petrochemical plant	[59]
Broken bars, bearing	2017	FLIR E4	Uncooled microbolometer (7.513 µm)	Proposed a novel method of area selection of image differences using three classifiers i.e. nearest neighbour (NN), k-means, back propagation neural network (BPNN)	[84]

researchers is adopted for knowledge acquisition and uncertainty management.

5.3 Adaptive Neuro Fuzzy Inference System

The knowledge based intelligent predictive maintenance technique mainly composed of an algebraic neurofuzzy network is termed as adaptive neuro fuzzy inference system (ANFIS). ANFIS with decision tree is used for identification and auto diagnosis of faults in IM. The author concluded that ANFIS has the capability of effective fault diagnosis [167]. ANFIS is applied for the identification of stator winding insulation and bearing wear faults using five measurable input parameters [168, 169]. ANFIS and its combination with other techniques was also employed for classification and diagnosis of faults in electrical rotating machine. Few researchers have discussed the hybrid algorithms for fault diagnosis and CM. ANFIS with genetic algorithms and wavelet transform have been applied for detecting bearing defects [170, 171]. Hence, the application of ANFIS and multiscale entropy has been developed for an early and fast detection of bearing defects in industrial applications of IM [172].

5.4 Support Vector Machines

SVM is a supervised machine learning algorithm which can be used for both classification and regression challenges [173]. However, it is mostly used in classification problems for CM and automatic fault diagnosis. SVM is more efficient and accurate than ANN techniques due to risk depreciation. The SVM technique has been presented in fault detection of bearing defects [174]. CM and fault identification using analytical, signal processing and based on features extraction of input signal are more active areas of research. The comparative study has been presented on various techniques for bearing fault identification based on case western reserve university data [175]. For identification and diagnosis of faults in IM, the frequency spectrum of torque, speed and stator currents, Parks transformation, and continuous wavelet transform (CWT) can be applied to train a SVM [176–180]. A Least Squares SVM (LSSVM) has been used to obtaining ideal prediction results under a small sample size. The researchers proposed to estimate the degradation trend of slewing bearings with particle swan optimization (PSO) technique [181].

6 Conclusion

In this study, a review on different types of induction motor faults and their diagnostic schemes has been presented. This review is useful for orienting new research in the domain of condition monitoring and fault diagnosis of rotating machines and its components. The condition monitoring of IM has evolved with motor diagnostics, information management and data analytics platforms. By in-depth study of literature it has become clear that non-invasive MCSA is the most useful technique to identify faults. However, theoretical and modeling analysis of machine faults are indeed necessary to distinguish the relevant component of higher frequency spectrum that may be present due to machine saturation and harmonics distortion etc.

The usage of non-invasive type instruments will overcome the drawbacks of conventional sensors and monitoring schemes which will eliminate the need for mounting the sensor on the machine and results in quick measurement, non intrusiveness and high accuracy. As compared to other non-invasive techniques, the thermal imaging technique is considered as an efficacious tool for online monitoring of IM without human intervention. The consolidation of infrared thermal imaging techniques using artificial intelligence based techniques can further expedite the decision making process for pragmatic applications. After going through the above review, it can be concluded that fault detection methods and condition monitoring result in improved enhanced arrangement compared to conventional procedures for improvement and prioritization of maintenance assets. A qualitative comparison is made for condition monitoring and fault detection in induction motor.

7 Research Trends

Notwithstanding of all, researchers have presented a few condition monitoring techniques for induction motor. Condition monitoring is going to underpin most success stories over the next few years. At its best it will reduce costs, increase production rate, and provide an opportunity to provide more evidence-based decision making.

The development of portable handheld devices is expected to grow manifolds by miniaturization of the machine monitoring systems. The condition of the machine could be assessed in a better way without any contact using such devices. It will make condition monitoring possible even without visiting the actual site and enable us to collect data from remote locations. The comprehensive analysis of condition monitoring techniques must take into account the interrelation between signals. The low-cost and large scale development are key elements of future condition monitoring of electrical rotating machine. Expert system based on artificial intelligence, such as ANN, fuzzy logic and machine learning can be developed for timely maintenance, better detection and auto diagnosis.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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