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A Review on Condition Monitoring and Diagnostic Techniques of Rotating Electrical Machines

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Authors' contributions

Author SAM wrote the first draft of the paper and author SMGM read and approved the final manuscript.

Review Article

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ABSTRACT

Electrical machines are critical components in industrial processes. A motor failure may yield an unexpected interruption at the industrial plant, with consequences in costs, product quality, and safety. To determine the conditions of each part of motor, various testing and monitoring methods have been developed. In this paper, a review on effective fault indicators and condition monitoring methods of rotating electrical machines has been accomplished. Fault detection methods divided to four groups: electrical, mechanical, chemical and thermal indicators. Some fault detection methods based on electrical symptoms like stator current, voltage, their combination or spectrum discussed in electrical group. In second branch, mechanical symptoms like torque, vibration and so on used for condition monitoring. Third group, chemical indicators, assigned to some chemical parameters of materials like oil characteristic or wear and debris in oil analysis. In last group, thermal symptoms in rotating electrical machines will be spoken. Between all methods, some of them are more known like vibration and some of them are recently added like motor current signature analysis (MCSA). Nowadays, combined methods and methods used artificial intelligence (AI) in condition monitoring are more popular. In every group, the fault detection method and the faults that can be detected have been mentioned. Mathematical equations of some new signal processing method have been discussed in literature presented in appendix.

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1. INTRODUCTION

Fault diagnosis and condition monitoring have been studied in the recent decade to prevent costly interruptions due to motor faults and recognize faulty conditions as soon as possible [1–7]. Electrical motors are subjected to faults which may redound to secondary faults. The sources of motor faults may be internal, external or due to environmental conditions. Internal faults can be classified with reference to their origin.

Internal faults can be classified with their outbreak location: stator or rotor. Common machine faults in rotor according to [8] are:

1) Bearing failure;
2) Rotor broken bars;
3) Rotor body failure;
4) Bearing misalignment;
5) Rotor misalignment;
6) Bearing loss of lubrication;
7) Rotor mechanical or thermal unbalanced;

And common faults become apparent in stator as categorized in [8] are:

1) Frame vibration;
2) Stator earth faults;
3) Damage of insulation;
4) Stator turn-to-turn faults;
5) Stator phase- to- phase faults;
6) Displacement of conductors;
7) Failure of electrical connections;

These failures can be detected with several procedures. In this paper, they are discussed by their detection method and parameters will be measured to four groups.

2. FAULT DETECTION METHODS

There are several indicators for faulty conditions of rotating electrical machines help us to distinguish machine conditions. In this paper, fault detection methods persuaded by their fault indicators. So condition monitoring method can be analyzed in four groups as presented in Fig. 1.

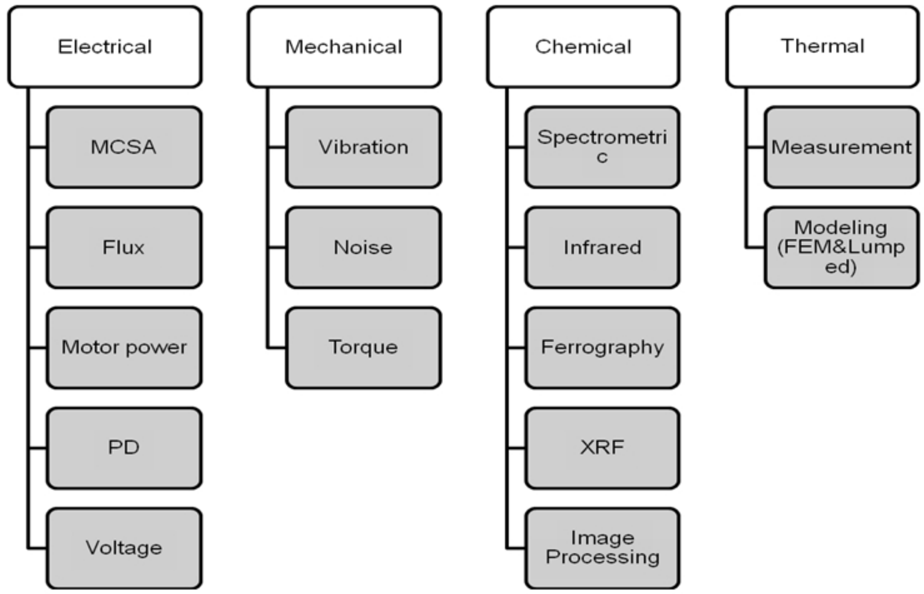


Fig. 1. Fault diagnosis methods

2.1 Electrical Analysis

Some of the electrical faulty condition symptoms are motor current signature, voltage, flux, power and so on. Probable faults can be detected by comparison between electrical signals in healthy and unknown conditions.

Some of the electrical methods are based on signal injection and response analysis. For instance, a method based on signal injection with high-frequency proposed in [9] for fault detection in closed-loop drives, but it’s difficult to implement for many applications due to invasiveness and hardware limitations.

Akin et al. in [10] reported that the reference frame theory directly added into the main motor control subroutine in DSP program can successfully be applied to real-time fault diagnosis of electric machinery systems to find the magnitude and phase quantities of fault signatures even though in nonideal conditions such as offset, unbalance, etc.

In the rated rotor flux test by applying an ac voltage source across each side of the shaft, high shaft current and yoke flux have been utilized. This induces circulating current between the rotor bars and shaft, and the current or flux of each bar is indirectly monitored using iron filings/magnetic viewer or a thermal imaging camera. The influence of a cracked or broken bar or shorted rotor laminations can be observed by this test [11]. These methods are being done under standstill condition and don’t seem efficient for online condition monitoring.

An automated technique for monitoring of rotor condition of voltage source inverter-fed induction machines at standstill has been proposed in [11]. In this algorithm, the motor is excited with a set of pulsating fields at a number of angular positions for observing the change in the impedance pattern for broken bar detection. This technique can be performed without any extra hardware but it’s still an offline test.

2.1.1 Motor current signature analysis (MCSA)

MCSA is one of the most popular approaches since it provides sensor less diagnosis of rotor and bearing problems [11,12,13]. MCSA requires the measurement and manipulation of lengthy steady-state data and an accurate measurement/estimate of the rotor speed for obtaining a reliable and high-resolution assessment but MCSA is not so effective for applications where the load constantly changes.

The prior MCSA techniques assume stationary and high SNR for signal. The nonstationary of stator current is accommodated by the commonly used windowing techniques [14]. The highly transient and dynamic nature of the induction motor stator current during fault conditions demand analysis through algorithms and techniques fit to analyze nonstationary and nonlocalized signals, such as wavelet transform or other time-frequency techniques. The availability of the advanced signal processing tools, such as higher order spectrum analysis [15], high-resolution or subspace methods [16] and wavelet analysis [17,18] have revolutionized the signal processing for fault detection in electrical motors.

MCSA usually has been attempted looking at $(1-2s)f$ and $(1+2s)f$ frequencies, lower sideband (LSB), and upper sideband (USB), which s is slip and f is main frequency [19]. The sideband amplitudes are affected by load level and power rating, constructive details, and by manufacturing asymmetries [20].

Because of the vicinity of signal main frequency to produced components and sidebands, broken bar detection may be difficult by this method [21]. Also, this problem exists under low slip operation. MCSA-based online rotor fault detection is not very effective since the current regulator masks the fault signatures in the current [22-24]. In addition, online monitoring techniques can fail if the operating frequency constantly changes due to adjustable speed operation. In [23,24], spectrum analysis of variable speed controller was proposed for rotor fault detection in field-oriented drives, but the methods can only be applied for a specific control scheme and are strongly influenced by controller parameters [25].

In [19] some new fault indicators for bar-breakage detection are exposed based on the sidebands of phase-current upper harmonics; the ratios $I_{(7-2s)f}/I_{5f}$ and $I_{(5+2s)f}/I_{7f}$ are examples of such indicators, and they are independent on load torque and drive inertia. This method has low independence with respect to machine parameters and has linear dependence on fault gravity.

Jung et al. in [26] conducted an advanced online diagnosis system using MCSA and made up of the optimal slip-estimation algorithm, the proper sample selection algorithm, and the frequency auto search algorithm for more productivity.

In [27] have been compared different fault diagnosis methods like three phase current vector, the instantaneous torque, and the outer magnetic field. Finally, it's declared that MCSA can be the best method for diagnosis the rotor faults.

As a basic tool, various reference-frame-theory-based applications are reported in the recent studies, like finding deviation in an actual Concordia pattern used to determine the types and magnitude of faults in drive systems and stator, respectively [28,29], obtaining negative-sequence stator-fault-related indices from the line current [30], and detecting negativefrequency rotor asymmetry signatures at standstill based on complex fault signature vectors [31].

Time-frequency analysis has been investigated vastly in recent years but its complexity and heavy hardware requirements are limitations for simple low-cost drive systems [22].

There are several ways for data comparison in signal processing like Kolmogorov–Smirnov (KS) technique, Plateau algorithm, Holf–Winters (HW) technique and Mark–Burgess (MB) technique. If two time data series or distributions are at a significant variance the KS technique [32,33], a nonparametric and distribution-free technique [34] is best choice. They are being used for comparison motor current signal with reference signal. The reference signal is motor current signal in healthy condition. The KS parameter is evaluated by taking the vertical difference between the two data distributions under test into consideration. The Plateau algorithm is apposite for handling long-term deviations and seems not suitable for condition monitoring. Holf–Winters (HW) algorithm is a forecasting technique needs a spontaneously event detection procedure, and Mark–Burgess (MB) technique is intended for detecting real-time changes. The KS technique is the best known of several distribution-free techniques that test general differences between data distributions. It is more valuable for applications, which are responsive to data distributions [14].

2.1.1.1 Order tracking method

Similar to vibration analysis in nonstationary condition or in variable speed motors instead of tracking absolute frequency, frequencies can be explained by multiple of a base frequency that is usually power source frequency. For instance this method in [35] used for detection inter-turn in Permanent Magnet Synchronous Motor (PMSM). In [35] by applying a Vold-Kalman Filter (VKF) [36] tried to use order tracking method for selected voltage and current harmonics and detect inter-turn in PMSM. Vold-Kalman Filter Order tracking (VKF-OT) beneficiary is that allows extracting both the amplitude and phase of the analyzed orders at each time instant directly from the original data. Furthermore, its tracking performance does not depend on the slew rate (rotational speed rate of change) [35] and make order tracking on noisy signal easy.

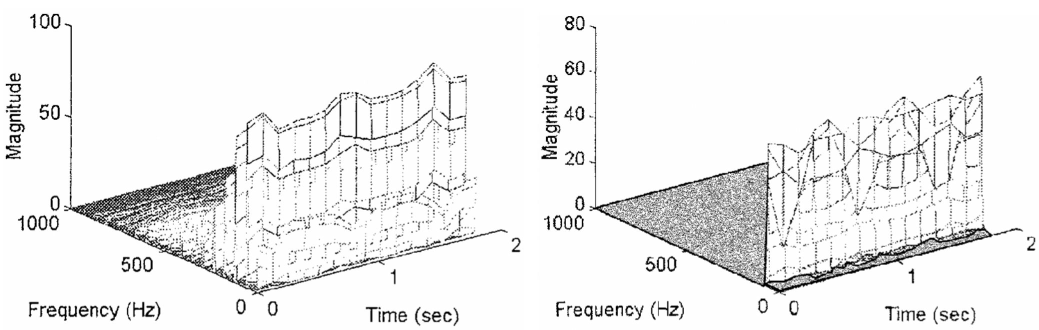
2.1.1.2 Time and frequency domain analysis

There are some restrictions of the Fourier transform, for example it cannot be used for non periodic or nonstationary signals; otherwise, the resulting FFT spectrum will make little physical sense [17,37,38].

However, for machinery operating under unsteady conditions, because of variation in the rotating speed and operating load, even if the machine is in the normal state, the spectrum of the vibration signal is always altering in sampling time. When a nonstationary signal is transformed into the frequency domain, most of the information about the transient components of the signal will be lost [39], hence, a hybrid method has been proposed in [40].

Time-frequency analysis [41] methods can simultaneously generate both time and frequency information from a signal. Therefore, in later studies, time-frequency analysis methods are widely used to detect faults since they can determine not only the time of occurrence but also the frequency ranges of the location [42]. Time-frequency methods mostly use in vibration analysis and MCSA. There are several time-frequency analysis methods, such as the Short-Time Fourier Transform (STFT), Wavelet Analysis (WA), and the Wigner-Ville Distribution (WVD), which may be used for condition monitoring of rotating machinery in transient and unsteady operating conditions. Those time-frequency techniques have been applied to fault diagnosis and condition monitoring in practical plant machinery [18,43,44]. Also Hilbert transform and Zhao–Atlas–Marks distribution in [45] applied to fault diagnosis of motors in nonstationary conditions but this method is not as common as prior methods.

Misalignment detection using STFT and WA signal processing techniques is shown in Fig. 2 [25].



(a) **(b)**

Fig. 2. Misalignment detection using STFT and the wavelet technique: (a) STFT (b) STFT and wavelet technique [3]

In the field of machinery fault monitoring, Wavelet Analysis (WA) has been used widely in the diagnosis of rolling bearings, gearbox and compressors. This technique also has been used for feature extraction and noise cancellation of the various signals [18,43-46].

In [18,43,47], a fault diagnostic technique for rotating machinery is investigated based on discrete wavelet transform. In Reference [48] a time-averaged WA according to Morlet continues wavelet used for fault diagnosis of a gear set. Also, reference [49] presents a combination of Continuous Wavelet Transform (CWT) and Kolmogorov-Smirnov test for fault detection of the bearings and gear box in transient conditions. In [46,50] CWT is used for extract the features of roller bearing fault signals. Reference [51] used CWT for fault signal diagnosis in an internal combustion engine.

In [52], the application of the Wigner-Ville distribution is reported to detect a broken tooth in a spur gear. Reference [53] shows that the WVD can be applied to the description of machine conditions and it is an effective method in machinery fault diagnosis. Reference [44] applies a PWVD to identifying the influence of the fluctuating load conditions for gearbox. A Digital Signal Processing (DSP) implementation is presented in [54] to detect mechanical load faults in induction motors during speed transients based on WVD and stator current analysis.

2.1.2 Flux monitoring

Magnetic flux can be a fault indicator and monitored both inside the machine (search coils) or outside (axial coils). Coil installation and noisy spectra are the main difficulties [19]. One of the most applications of this algorithm is fault detection in rotor cage. The estimated rotor flux in [24] suggested for the diagnosis of rotor faults in vector-controlled drives. In [84]

Dorell et al. showed a relation between air gap eccentricity and air gap flux and vibration signals.

Cruz et al. in [55] presented an algorithm for diagnosis of rotor faults which starts with the measurement of the amplitude of the rotor flux oscillations. It's showed that the ratio between Δi_{ds} and the average value of Δi_{qs}, current changes in d and q axis respectively, gives the degree of asymmetry of the motor or the number of adjacent broken bars, if the total number of rotor bars is known. But this algorithm needs some additional modules for calculating the current average values and tracks the amplitude of currents.

2.1.3 Motor power monitoring

Motor power signature analysis is focused on the detection of double-slip frequencies present in the electric input power spectrum [56] similar to MCSA. These harmonics are evaluated with respect to the average power (dc component), thus obtaining some fault severity factors. In addition, this method needs to acquire both currents and voltages. Also the dependence on the drive inertia is another limitation of this fault indicator [57]. Bellini et al. in [57] tried to detect rotor broken bar by this approach.

2.1.4 Partial discharge (PD) monitoring

This test mainly used in high voltage motors and generator stator windings. By using Partial Discharge Analyzer (PDA) sensors placed within the winding or at the winding terminals, stator winding PD pulses will separate from electrical interference (usually harmless) based on pulse arrival time or pulse shape and easily can be detected [58]. PD is a symptom of many stator winding insulation failure mechanisms. IEEE 1434-2000 reviews all types of PD measurement methods used in rotating machines [59].

There are several discharge monitoring techniques. Among these methods RF coupling method, capacitive coupling method and broad-band RF method [60] are more known. A Radio Frequency Current Transformer (RFCT) installed on neutral point of winding can detect Radio Interference Frequency Intensity (RIFI) caused by PD. Arcs occurred at any location cause RF current flow into the neutral point because of its low potential. The RIFI meter had a narrow bandwidth of about 10 kHz centered at 1MHz [60]. By using a frequency-based method with low power hardware, it is possible to take advantage of the RF technique without the need for wideband signal capture and its associated overheads [61].

Second method use specialized pulse height analyzer with bandwidth 80 MHz. In this approach connection to the winding is made through coupling capacitors at the machine line terminals [60]. Initially, the capacitors were connected to the machine during an outage, but latterly described how the capacitors could be permanently built into the phase rings of the machine and the measurements can be made without service interruption. In [62] showed that the pulse has a rise time (defined as 10%–90% of peak) of 4 ns and the frequency content of this pulse extends to over 100 MHz, thus, an 80-pF capacitor installed on high-voltage machine terminals can be used as the coupling device.

It has been shown that serious PD, sparking or arcing, has faster rise-times than the background corona and PD activity, and therefore produce a much higher bandwidth of electromagnetic energy, up to 350 MHz. If this energy is detected, at as high a frequency as possible, the ratio of damaging discharge signal to background noise is increased.

Frequencies above 0.4 MHz do not propagate from the discharge place along the winding, as with the lower frequency techniques, but by radiation from the winding [60]. This radiation can be detected by an RF aerial located inside the enclosure of the machine or outside, close to an aperture in it and it is basic concepts of broad-band RF monitoring method.

2.1.5 Voltage spectrum analysis

The Growler test and rated rotor flux test with high current ac excitation are another commonly used offline tests for rotor testing [63-67]. A Growler is an electrical device used for testing insulation of a motor for shorted coils with an iron core and excited by AC current for detection insulation problem.

The method consists of inserting an auxiliary small winding which is a coil "sneak'' that forms an angle θ_0 with the A stator phase as shown in Fig. 3 [68]. This coil has no conductive contact with the other phases but it is mutually coupled with all the other circuits on both the stator and rotor sides [69].

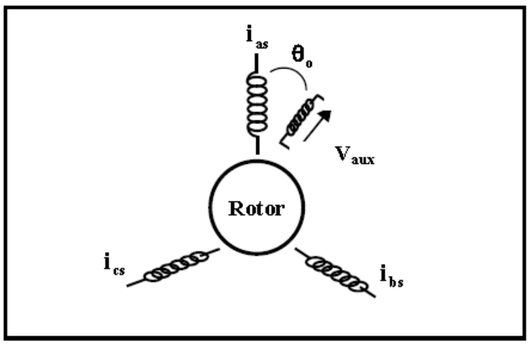


Fig. 3. Auxiliary winding emplacement [69]

Mirimani et al. in [70] investigated the effect of static eccentricity on the back EMF of an Axial Flux Permanent magnet (AFPM) through 3D-FEM (Finite Element Method) as shown in Fig. 4 [68]. The back EMF of the four coils of one phase is obtained to propose a suitable criterion for precise eccentricity fault detection.

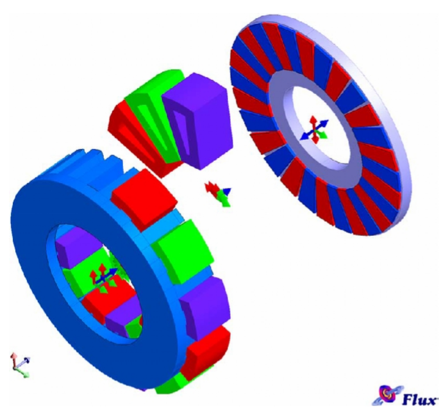


Fig. 4. 3D-FEM model of the axial flux permanent magnet motor [68]

In the case of a healthy motor the auxiliary winding voltage Park components spectra contain one peak at the motor main supply frequency. The Lissajous curve is an ellipse as shown in Fig. 5 [71]. In the different cases of voltage unbalances, the Lissajous curves are also ellipses that have different angles as shown in Fig. 6 [71]. In comparison with damaged and non defected motor, the value of their superior and inferior radiuses will increase [68].

It is also well known that the effects of stator winding inter-turn faults may be detected by monitoring the Zero-Sequence Voltage Component (ZSVC) [72,73]. This method benefit is that it's separate from motor drive against some other methods like MCSA, but it needs to access to stator winding neural point. In [35] attempted to detect inter-turn fault in PMSM by first harmonic amplitude of ZSVC and stator currents third harmonic. Briz et al. [74] used voltage and current zero-sequence components for recognition of faults in induction machine.

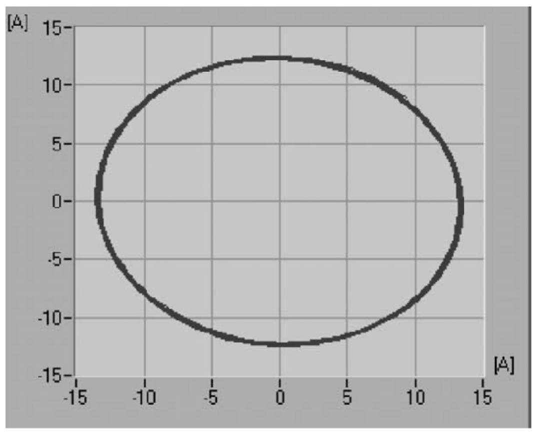


Fig. 5. Park's Currents Vector of a healthy motor [71]

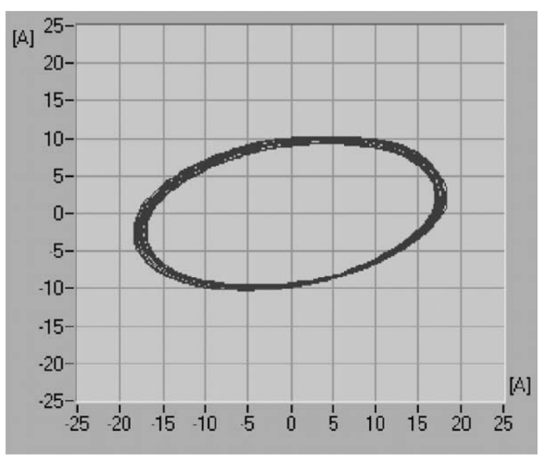


Fig. 6. Park's currents vector for a motor with coils in shortcut [71]

2.2 Mechanical Analysis

There are several mechanical symptoms for faulty condition of electrical machine, such as: vibration, noise, torque and so on.

2.2.1 Vibration monitoring

As almost 80 percent of common rotating equipments problems are related to misalignment and unbalance, vibration analysis is an important tool that can be used to eliminate recurring problems [75,76]. In many cases, the overall vibration level of the machine is sufficient to diagnose mechanical failures [77,78], but in [2] showed that this is not an efficient method for all faults. In [79] showed that the electromagnetic force is the most sensitive indicator of air gap eccentricity. Therefore identifiable signatures should be found in the vibration pattern of rotating electrical machines. The only drawback of this indicator is its low accessibility. Nevertheless, since vibrations are the consequences of the forces on the machine structure, identifiable signatures should be found in the vibration pattern. The measured vibration and associated current harmonics are closely correlated [14].

Literature survey [80-83] shows that most of the bearing fault diagnoses are based on vibration analyses like wavelet transform and Hilbert–Huang transforms or current-based analysis.

In [84] illustrated how eccentricity faults can be identified from vibration analysis using condition monitoring techniques.

The overall RMS of vibration can be calculated by different definition based on the spectrum in frequency domain across all of the effective frequency range, i.e., from DC to maximum analysis frequency range. One of the suggested formulas is [85]:

$$overallRMS = \sqrt{\frac{\sum_{0}^{0.45\times f_s} power(f)}{BW}} \tag{1}$$

In above equation, *BW is* noise power bandwidth of window, f *is* analysis frequency band and f_s *is* sampling frequency band.

Another special frequency analysis is Cepstrum that defined:

$$C(\tau) = \left| F^{-1}\{\log(\left|F\{f(t)\}\right|^2)\}\right|^2 \tag{2}$$

This can be used for examining behavior of gearboxes [21].

2.2.1.1 Frequency-domain analysis

The most common tools of vibration monitoring in industrial plants is frequency analysis. Finley et al. [86] compiled a resume table with a comprehensive list of electrically and mechanically induced components in the vibration pattern. Their analysis is based on analytical formulas.

In [87], a strategy presented based on monitoring slot passing frequencies in high frequency vibration components. Their presented analysis was based on rotating wave approach whereby the magnetic flux waves in the air gap are taken as the product of permeance and Magneto Motive Force (MMF).

Vibration pattern for the healthy motor and with dynamic eccentricity has been compared in [88] as shown in Fig. 7. In paper [88] has been showed that the low frequency components of vibration (measured by accelerometers fixed on the outer casing of motor) can be used as signatures for the detection of eccentricity in induction motors.

2.2.1.2 Order tracking methods

The advantages of order tracking over the other vibration techniques mainly lie in analyzing non stationery noise and vibrations which will vary in frequency and amplitude with the rotation of a reference shaft. The analysis of non stationery conditions needs additional information, as compared to steady state conditions, for an accurate result to be obtained. Order domain analysis relates the vibration signal to the rotating speed of the shaft, instead of an absolute frequency base [21].

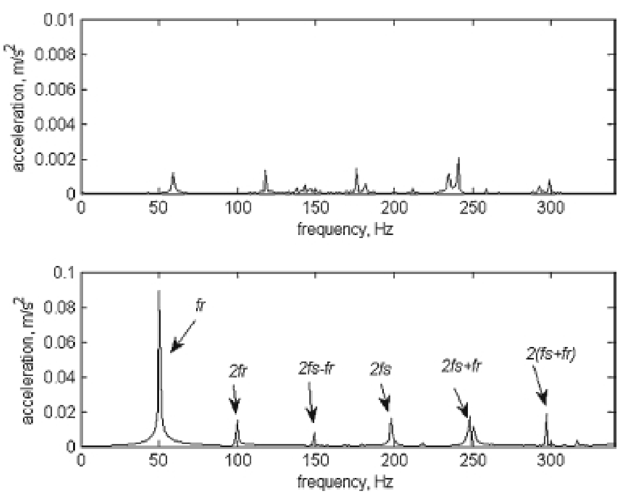


Fig. 7. Vibration pattern for healthy motor (top) and with 37% dynamic eccentricity (bottom), 1.9% and motor fed at 100Hz in both cases [89]

2.2.2 Noise monitoring

Measuring and analyzing the acoustic noise spectrum [90] is another method of condition monitoring in rotating electrical machinery which require special consideration. Acoustic noise emitted from air gap can be an indicator of probably eccentricity in induction motor. But, the application of noise measurement in a noisy environment like a plant is not so efficient. In [89] an approach for air gap eccentricity detection presented and a test carried out in an anechoic chamber. Slot harmonics in the acoustic noise spectra were introduced as an indicator of static eccentricity. Li and He [1] used Hilbert-Huang Transform (HHT) for analyzing nonstationary noise signals incorporates a threshold-based denoising technique to increase the SNR for health monitoring in electrical machines.

Reference [91] examines whether acoustic signal can be used effectively to detect the various local faults in gearboxes using the smoothed Pseudo Winger-Ville Distribution (PWVD).

Scanlon et al. [92] showed that by extraction hide information of acoustic noise signal can predict machinery resident life time.

Defects in the roller element bearings cause particular frequencies to be excited. These frequencies can be detected in acoustic noise spectrum. In [93], an automated approach to degradation analysis is proposed that uses the acoustic noise signal from a rotating machine to determine the remaining useful life of the machines.

2.2.3 Torque monitoring

By comparison between the estimated torque from the model and measured torque can detect some faults in electrical motors, so it's necessary to have a good model and an algorithm to be aware of air gap real torque. The electromagnetic torque estimation has been commonly used in electrical drives to control the torque and the rotor speed of AC electrical machines. So, it is needed to compute stator flux or rotor flux exactly in which the accuracy and the robustness are directly related to electrical machine parameters [94]. In addition, the flux estimation needs to have knowledge about only two parameters of these three parameters: stator phase voltages, currents, and the rotor speed by using an appropriate model [95].

In reference [96] torque estimation beside torsional vibration analysis used for gearbox fault detection in traction system and by measuring the torque their work has been validated.

Guzinski et al. in [97] for identification problems related to transmission system in High Speed Train (HST) used the load torque observer without adding any additional sensors. The presented observer system was able to detect the meshing frequency of the test bench which has very small amplitude in the tested healthy gear.

From the input terminals, the instantaneous power includes the charging and discharging energy in the windings. Therefore, the instantaneous power cannot represent the instantaneous torque. From the output terminals, the rotor, shaft and the mechanical load of a rotating machine constitute a torsional spring system. This torsional spring system has its own natural frequency [98]. The attenuation of the components of the air gap torque transmitted through the torsional spring system is different for different harmonic orders of torque components [99,100].

The locked-rotor torque and breakdown torque will decrease in unbalanced voltage situation. If the unbalanced voltage was extremely severe, the torque might not be adequate for the application although the full-load speed is reduced slightly when the motor operates with unbalanced voltages [101] and it can be an indicator of unbalance voltage condition.

2.3 Chemical Indicators

Insulation degradation can be monitored chemically by the presence of special matter in the coolant gas or by detection some particular gases such as ozone, carbon monoxide or even more complex hydrocarbons, like acetylene and ethylene [60]. Electrical discharge activity, heat and some other electrical and mechanical faults may lead to insulation degradation. The product materials can be gas, liquid or solid. Each of them needs a particular detection method.

An ion chamber was designed in [102] to detect the products of heated insulation and it was applied to a large turbo generator.

The metal wear debris in oil can be classified ferromagnetic wear debris and unferromagnetic wear debris. When wear debris is in the coil of inductive wear debris sensor, the magnetic field distribution of the coil is changed, and then the equivalent inductance of the coil was changed. This technique for metal wear debris in oil is a noncontacting and quick method and can be off-line and on-line [103].

In addition oil particle can be detected for fault diagnosis. With modern diagnostic tools, oil analysis is used to monitor the condition of equipment as well as condition of a lubricant. Various faults such as misalignment, unbalance, overload or accelerated heating condition may lead to wearing in electrical machinery. The different types of wear are: abrasive wear, adhesive wear, cavitations, corrosive wear, cutting wear, fatigue wear and sliding wear [75]. Some types of oil analyses are: viscosity, solids content, water content, total acid number, total base number and flash point [75].

As mentioned, wear particles are the prime indicators of the machine’s health. There are many techniques to evaluate the type and concentration of such particles. The techniques include: spectrometric analysis, infrared analysis, X-ray fluorescence (XRF) spectroscopy, particle counting, direct reading ferrography and analytical ferrography [75].

2.3.1 Spectrometric analysis

This is one of the main techniques that typically reported in PPM (Parts Per Million). This technique generally monitors the smaller particles and large wear metal particles present in the oil will not be detected.

For larger wear particles, there are available techniques such as: acid digestion method, microwave digestion method, direct read (DR) ferrography and Rotrode filter spectroscopy (RFS).

2.3.2 Infrared analysis

Specific groups of atoms called functional groups by this method can be detected. An appropriate wavelength is directed at the sample being analyzed, and the amount of energy absorbed by the sample is measured. The amount of absorbed energy is an indication of the extent of presence for that particular functional group in the sample. It is hence possible to quantify the results. This analysis was first introduced in 1979. After several years a new method extracted from this analysis named Fourier Transform-Infrared Analysis (FT-IR). By this technique, a beam of light is focused through a film of used oil and the wavelengths are then compared to light transmitted through new oil of the same type. The differences in readings provide information with respect to the degradation of the used oil [75].

2.3.3 Wear particle analysis (WPA) or ferrography

Ferrography or WPA utilizes microscopic analysis to evaluate the particles type, shape, size and quantity. The components specifications allow a process of elimination in which the abnormal wear can be identified. This analysis is used in two ways: A routine monitoring and trending of the solid contents, Observing and analyzing the type of wears [75,104].

2.3.4 XRF (X-ray fluorescence) spectroscopy

The XRF spectroscopy entails the excitation of electrons from their orbits. This leads to emission of UV rays with characteristic frequencies, which can be analyzed. During Rotrode atomic emission spectroscopy, an electrical discharge produces plasma, causing thermal emission. When the atoms return to the normal state, the excess energy is emitted as light. Each element emits light at different frequencies on the electromagnetic spectrum. The amount of light emitted at a given frequency corresponds to the concentration of the element present in the sample. Also atoms can be excited by bombardment of X-rays [75].

2.3.5 Image processing

The image processing and computer vision system reveals more information in the form of quantitative data not revealed by the human eye. This technique is used to collect quantitative information from wear particle images. Image analysis system is developed to process and store the information of particle shape and edge detail features. In [105] particles have been defined as regular, irregular, circular and elongated. So, an image processing technique is applied for analyzing wear debris.

2.4 Thermal Monitoring

Due to thermal limitation of various parts of rotating electrical machines such as insulations, coil and so on, it’s necessary to have a good idea about machine parts temperature. Thermal monitoring for electrical machines has two aspects, measuring the temperature and thermal modeling, which each one of them has been illustrated shortly.

Also recently a new wireless sensor for bearing temperature monitoring presented [106]. This sensor is a combination of a ring-shaped permanent magnet and a Hall Effect sensor that detect variation in magnetic field because of growing in temperature.

2.4.1 Temperature measurement

There are three main approaches for temperature measurement in electrical machines: 1) Measuring local point temperatures by embedded temperature detectors (ETD) or resistance temperature detectors (RTD); 2) Using thermal images, fed with suitable variables, to monitor the temperature of the perceived hottest spot in the machine; 3) Measuring distributed temperatures of the machine or bulk temperatures of the coolant fluid [60].

These demonstrate the fundamental difficulty of temperature monitoring; the conflict between easily made point measurements, which give only local information, and bulk measurements that are more difficult and run the risk of overlooking local hot-spots. Choosing location of settling detectors requires careful consideration during specification. Bulk measurement can be found from the measurement of the internal and external coolant temperature rises, obtained from thermocouples located.

Milic and Srechovic in [107] presented a new non-contact measurement system for hotspot and bearing fault detection in railway traction system (RTS).

Of course, due to rotating parts in electrical motors, these methods are not efficient and thermal modeling is inevitable.

2.4.2 Thermal modeling

Generally, thermal models of electric machines are classified into two categories [98,108]:

1) Finite Element Analysis (FEA) based model
2) Lumped Parameter (LP) thermal model

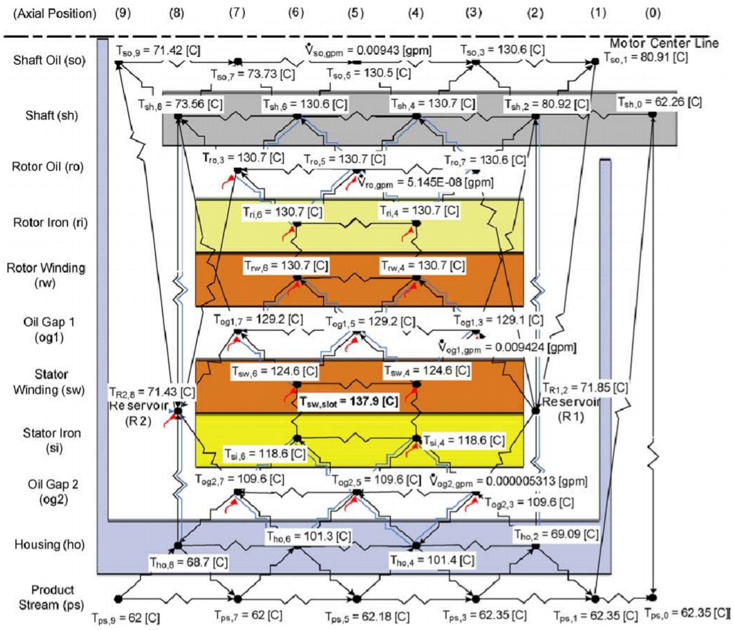
Finite Element Method (FEM) or Finite Difference Method (FDM) tools have traditionally been used to model the thermal performance of electric machines. Their applications have been limited only to small sectors of the stator and rotor and have not shown full-scale simulation for motors with complicated geometry. The accuracy of model is generally dependent on the number of thermally homogenous bodies used in model [109,110]. By this work, researcher may simplify the complicated geometry and shorten computational time for constructing elements and calculating large system matrices.

On the other hand lumped parameter equivalent thermal circuit is easy to solve and gives a good overall view of the temperature rise in different parts of the machine without much computational time [111]. Chowdhury claimed that the lumped parameter thermal equivalent circuit proposed in [112] is easy to visualize as all the parameters are directly derived from the machine geometry. Boglietti et al. [108] compared the LP and FEA for thermal modeling of electrical machines.

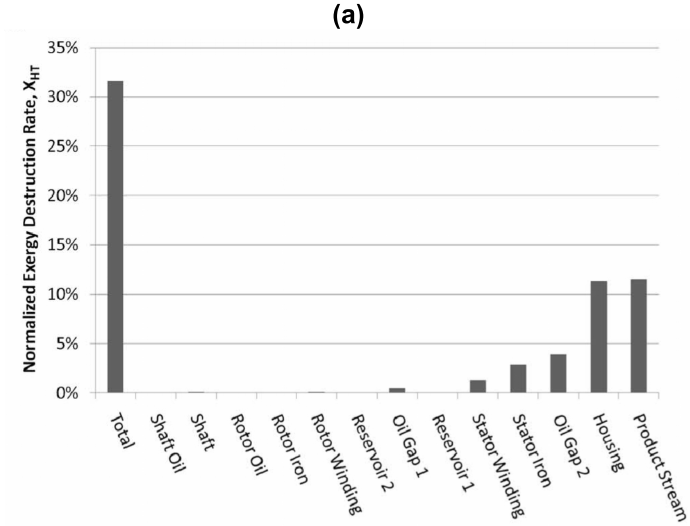
There are two ways for extraction parameters of lumped parameter model. The first one is by using comprehensive knowledge of the motors, physical dimensions and construction materials. The second one is to identify the parameters from extensive temperature measurement at different locations in the motor explained in previous session. Even though an electric machine is made up of various materials that have different characteristics, the machine can be assumed to consist of several thermally homogenous lumped bodies [98]. For example, a simplified model of an induction model and a PMSM consisting of two lumped thermal bodies are presented in [113,114]. Likewise in [115], Milanfar and Lang developed a thermal model of electric machine to estimate the temperature of the motor and to identify faults like turn-to-turn faults and bearing faults.

A time-domain lumped thermal model of an induction motor obtained in [116]. The temperature distribution and the energy destruction are shown in Fig. 8.

Nategh et al. in [117] presented a lumped parameter thermal model for a permanent-magnet assisted synchronous reluctance machine (PMaSRM) developed for propulsion in a hybrid electric vehicle. They divided the stator slot into a number of elliptical copper and impregnation layers and modeled stator winding by some approximation.



(a)



(b)

Fig. 8. Thermal model of an induction motor in the flow loop 3 h after startup. The temperature distribution is shown in (a), and the energy destruction is shown in (b) [116]

Jankowski et al. [116] described the development of a time-dependent lumped-parameter thermal model of an induction motor, and showed that how this thermal model can be used to minimize the internal temperature during operation.

Kolondzovski et al. in [118] discussed about thermal issues of different types of electric motors and different rotor types. Similarly, EL-Refaie et al. in [119] presented multibarrier interior permanent magnet machines lumped parameter model.

Idoughy et al. [120] proved that the analytical techniques may risk underestimating the hotspot winding temperature, especially when the fill factor is below 0.3. In addition, the temperature variation in the axial direction is not considered and hotspot temperatures often arise in the end windings.

In [121,122] it's claimed that they can calculate rotor and stator respectively under the steady state and transient steady by off-line experiment and their model can respond to changes in the cooling conditions. However, their models are generally sensitive to unknown machine parameters and their variation. Also, by DC signal injection thermal parameter of electrical machines components can be achieved [123,124]. This method applied for induction motors fed by closed-loop inverter drives in [125].

3. MODEL BASED & AI-BASED METHODS

A model-based fault monitoring method presented in [126] for variable speed drives without frequency analysis. Nowadays, AI-based which use fuzzy logic, neural network, particle swarm optimization [127] and so on are so popular for researchers. Some of them are explained in this paper.

3.1 Artificial Neural Network

Nejjari et al. in [128] used learning Park's vector pattern based on artificial neural network to discern healthy and faulty patterns. Also, Wang et al. in [129] used combination of these two algorithms for condition monitoring of rolling bearings.

Tag Eldin et al. [130] used Artificial Neural Network and applied result of the RMS measurement of stator voltages, currents and motor speed to train a neural network to monitor and diagnosis external motor faults.

Asiri [131] decided to detect six different types of PD using neural networks and classify different types of PD according to the location of PD activity.

3.2 Fuzzy Logic

The fuzzy logic tool provides a technique to deal with imprecision and recently attracted researchers attention for different applications like fault diagnosis. The utility of fuzzy sets lies in their ability to model uncertain and vague data. Fuzziness in a fuzzy set is characterized by its membership functions [132].

An extraction method based on the Relative Crossing Information (RCI) in [133] proposed for condition monitoring of a machine under the variable rotating speed, by which the instantaneous feature spectrum can be automatically extracted from the time-frequency distribution of the fault signal. The performance of this approach is evaluated using three time-frequency techniques, namely STFT, WA, PWVD and finally using a sequential fuzzy diagnosis method.

Reference [134] claimed that using fuzzy sets and uncertainty phenomena with possibility theory may help in fault diagnosis of satellite applications. A combination of neural network and fuzzy logic used in [129] for condition monitoring of rolling bearings. Also, [135] propounds an intelligent condition diagnosis method for rotating machinery developed using least squares mapping (LSM) and a fuzzy neural network. In [133], possibility theory is also applied to combine with PWVD technique for fault diagnosis.

4. CONCLUSIONS

Condition monitoring methods for rotating electrical machines have been surveyed in four groups. These groups consisted of: electrical analysis, mechanical analysis, chemical analysis and thermal analysis. In each group, there are several symptoms that faulty condition in machines can be detected by them.

Methods based on signal injection seem profit for fault detection in closed-loop drives, but it's difficult to implement for many applications due to invasiveness and hardware limitations. MCSA, the most popular technique, provides sensor less diagnosis of some motor problems but it's not so effective for applications where the load constantly changes. Time-frequency analysis has been investigated vastly in recent years but its complexity and heavy hardware requirements are limitations for simple low-cost drive systems.

Motor power analysis because of need to both currents and voltages simultaneously and dependence on the drive inertia has some limitation. PD monitoring mainly used in high voltage motors and generator stator windings. Most of recurring problems in rotating machinery like misalignments can be detected by vibration analysis. The measured vibration and associated current harmonics are closely correlated. By detection ozone, carbon monoxide and others in the coolant gas or oil analysis, some faults like insulation degradation can be detected easily. Also thermal measurement and thermal modeling are introduced as efficient tools for motors condition monitoring. Finally, AI- based algorithms combined of one or more explained methods were studied.

Besides these methods and algorithms, nowadays web-based monitoring approaches are interesting. They are using one or more of these mentioned procedures in softwares like LabVIEW, as you see in [136] and shown in Fig. 9.

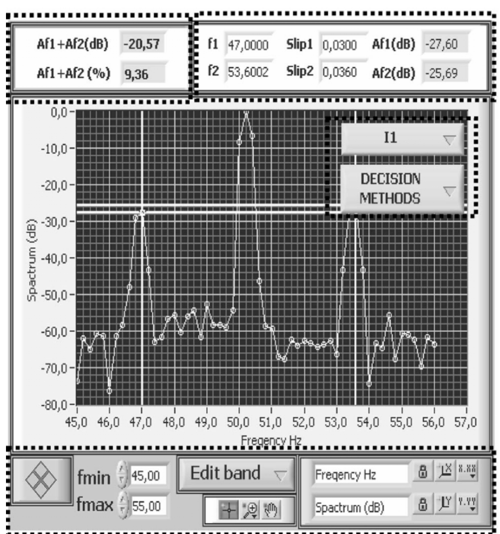


Fig. 9. Diagnosis session panel with decision method menu presented in [136]

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Ruoyu Li, David He. Rotational Machine Health Monitoring and Fault Detection Using EMD-Based Acoustic Emission Feature Quantification. Instrumentation and Measurement IEEE Transactions. 2012;61(4):990-1001.
2. Mortazavizadeh SA, Vahedi A, Zohouri AA. Detection of Stator Winding Inter-turn Short Circuit In Induction Motor Using Vibration Specified Harmonic Amplitude , 2nd International Conf. on Acoustics & Vibration, Sharif Univ. of Technology, Tehran, Iran. Dec. 2012.
3. Hachemi Benbouzid El, Mohamed. A review of induction motors signature analysis as a medium for faults detection. Industrial Electronics, IEEE Transactions. 2000;47(5):984-993.
4. Subhasis N, Raj Mohan Bharadwaj, Hamid A. Toliyat. Performance analysis of a three-phase induction motor under mixed eccentricity condition. Energy Conversion, IEEE Transactions. 2002;17(3):392-399.
5. Dorrell, David G, William T. Thomson, and Steven Roach. Analysis of airgap flux, current, and vibration signals as a function of the combination of static and dynamic airgap eccentricity in 3-phase induction motors. Industry Applications, IEEE Transactions. 1997;33(1):24-34.
6. Devaney, Michael J, Levent Eren. Detecting motor bearing faults. Instrumentation & Measurement Magazine. IEEE. 2004;7(4):30-50.
7. Riley, Caryn M., et al. Stator current harmonics and their causal vibrations: a preliminary investigation of sensorless vibration monitoring applications. Industry Applications, IEEE Transactions. 1999;35(1):94-99.
8. Singh GK, Ahmed Saleh Al Kazzaz. Induction machine drive condition monitoring and diagnostic research—a survey. Electric Power Systems Research. 2003;64(2):145-158.
9. Briz, Fernando, et al. Online diagnostics in inverter-fed induction machines using high-frequency signal injection. Industry Applications. IEEE Transactions. (2004);40(4):1153-1161.
10. Akin, Bilal, et al. A simple real-time fault signature monitoring tool for motor-drive-embedded fault diagnosis systems. Industrial Electronics, IEEE Transactions. 2011;58(5):1990-2001.
11. Kim, Byunghwan, et al. Automated detection of rotor faults for inverter-fed induction machines under standstill conditions. Industry Applications, IEEE Transactions. 2011;47(1):55-64.
12. Bouchikhi E El, Choqueuse V, Benbouzid ME. Current frequency spectral subtraction and its contribution to induction machines' bearings condition monitoring. IEEE Trans. on Energy Conversion. 2013;28(1):135-144.
13. Filippetti F, Bellini A, Capolino G. Condition monitoring and diagnosis of rotor faults in induction machines: state of art and future perspectives. Electrical Machines Design Control and Diagnosis (WEMDCD), IEEE Workshop; 2013.

14. Gupta RA, Wadhwani AK, Kapoor SR. Early estimation of faults in induction motors using symbolic dynamic-based analysis of stator current samples. Energy Conversion, IEEE Transactions. 2011;26(1):102-114.
15. Arthur, Neil, Jim Penman. Induction machine condition monitoring with higher order spectra. Industrial Electronics, IEEE Transactions. 2000;47(5):1031-1041.
16. Bellini, Alberto, Giovanni Franceschini, Carla Tassoni. Monitoring of induction machines by maximum covariance method for frequency tracking. Industry Applications, IEEE Transactions. 2006;42(1):69-78.
17. Peng ZK, Peter W, Tse, Chu FL. A comparison study of improved Hilbert–Huang transform and wavelet transform: application to fault diagnosis for rolling bearing. Mechanical systems and signal processing. 2005;19(5):974-988.
18. Purushotham V, Narayanan S, Suryanarayana AN Prasad. Multi-fault diagnosis of rolling bearing elements using wavelet analysis and hidden Markov model based fault recognition. NDT & E International. 2005;38(8):654-664.
19. Bruzzese, Claudio. Analysis and application of particular current signatures (symptoms) for cage monitoring in nonsinusoidally fed motors with high rejection to drive load, inertia, and frequency variations. Industrial Electronics, IEEE Transactions. 2008;55(12):4137-4155.
20. Bellini, Alberto, et al. On-field experience with online diagnosis of large induction motors cage failures using MCSA. Industry Applications, IEEE Transactions. 2002;38(4):1045-1053.
21. Wang, Ke Sheng. Vibration monitoring on electrical machine using Vold-Kalman filter order tracking. Diss. University of Pretoria; 2008.
22. Bellini, Alberto, et al. Advances in diagnostic techniques for induction machines. Industrial Electronics, IEEE Transactions. 2008;55(12):4109-4126.
23. Bellini, Alberto, et al. Closed-loop control impact on the diagnosis of induction motors faults. Industry Applications, IEEE Transactions. 2000;36(5):1318-1329.
24. Cruz SMA, Cardoso AJM. Diagnosis of rotor faults in closed-loop induction motor drives. Industry Applications Conference, 2006. 41st IAS Annual Meeting. Conference Record of the 2006 IEEE. Vol. 5. IEEE; 2006.
25. Cruz, Sérgio MA, et al. A new model-based technique for the diagnosis of rotor faults in RFOC induction motor drives. Industrial Electronics, IEEE Transactions. 2008;55(12):4218-4228.
26. Jung, Jee-Hoon, Jong-Jae Lee, Bong-Hwan Kwon. Online diagnosis of induction motors using MCSA. Industrial Electronics, IEEE Transactions. 2006;53(6):1842-1852.
27. Szabo L, et al. An Overview on Induction Machine's Diagnosis Methods. Journal of Computer Science and Control Systems; 2008.
28. Gilreath, Phil, Brij N Singh. A new centroid based fault detection method for 3-phase inverter-fed induction motors. Power Electronics Specialists Conference, 2005. PESC'05. IEEE 36th. IEEE; 2005.
29. Xiaoping Tu, et al. Modeling and real-time simulation of internal faults in synchronous generators with parallel-connected windings. Industrial Electronics, IEEE Transactions. 2007;54(3):1400-1409.
30. Cruz, Sergio MA, Marques Cardoso AJ. Multiple reference frames theory: A new method for the diagnosis of stator faults in three-phase induction motors. Energy Conversion, IEEE Transactions. 2005;20(3):611-619.
31. Akin, Bilal, et al. DSP-based sensorless electric motor fault-diagnosis tools for electric and hybrid electric vehicle powertrain applications. Vehicular Technology, IEEE Transactions. 2009;58(6):2679-2688.

32. Tewari, Diwakar. Symbolic dynamic models for highly varying power system loads. Diss. Arizona State University; 2002.
33. Les Cottrell R, et al. Evaluation of techniques to detect significant network performance problems using End-to-End active network measurements. Network Operations and Management Symposium, 2006. NOMS 2006. 10th IEEE/IFIP. IEEE; 2006.
34. Kirman TW. Kolmogorov-Smirnov test at available: http:/www.physics.csbsju.edu/stats/ks-test.html (Tutorial); 1996.
35. Urresty J, Riba J, Luis Romeral. Diagnosis of Inter-Turn Faults in PMSMs Operating under Non-Stationary Conditions by applying Order Tracking Filtering. Power Electronics, IEEE Transactions. 2013;28(1):507-515.
36. Vold, Hsvard. High Resolution Order Tracking at Extreme Slew Rates, Using Kalman Tracking Filters. Shock Vib. 1995;2(6):507-515.
37. Peng ZK, Chu FL. Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography. Mechanical systems and signal processing. 2004;18(2):199-221.
38. Mitoma, Tetsuro, Huaqing Wang, Peng Chen. Fault diagnosis and condition surveillance for plant rotating machinery using partially-linearized neural network. Computers & Industrial Engineering. 2008;55(4):783-794.
39. Douglas, H., Pragasen Pillay, and A. K. Ziarani. Broken rotor bar detection in induction machines with transient operating speeds. Energy Conversion, IEEE Transactions. 2005;20(1):135-141.
40. Lebaroud, Abdesselam, Guy Clerc. Classification of induction machine faults by optimal time–frequency representations. Industrial Electronics, IEEE Transactions. 2008;55(12):4290-4298.
41. Cohen L. Time-Frequency Analysis. Englewood Cliffs, NJ: Prentice- Hall; 1995.
42. Wang, Huaqing, Peng Chen. Fuzzy diagnosis method for rotating machinery in variable rotating speed. Sensors Journal. IEEE. 2011;11(1):23-34.
43. Jian-Da Wu, Chiu-Hong Liu. Investigation of engine fault diagnosis using discrete wavelet transform and neural network. Expert Systems with Applications. 2008;35(3):1200-1213.
44. Stander CJ, Heyns PS, Schoombie W. Using vibration monitoring for local fault detection on gears operating under fluctuating load conditions. Mechanical Systems and Signal Processing. 2002;16(6):1005-1024.
45. Rajagopalan S, et al. Non-stationary motor fault detection using recent quadratic time-frequency representations. Industry Applications Conference, 2006. 41st IAS Annual Meeting. Conference Record of the 2006 IEEE. Vol. 5. IEEE; 2006.
46. Junsheng, Cheng, Yu Dejie, Yang Yu. Application of an impulse response wavelet to fault diagnosis of rolling bearings. Mechanical Systems and Signal Processing. 2007; 21(2):920-929.
47. Jian-Da Wu, Chuang-Chin Hsu. Fault gear identification using vibration signal with discrete wavelet transform technique and fuzzy–logic inference. Expert systems with applications. 2009;36(2):3785-3794.
48. Zheng H, Li Z, Chen X. Gear fault diagnosis based on continuous wavelet transform. Mechanical systems and signal processing. 2002;16(2):447-457.
49. Zhu ZK, et al. Detection of signal transients based on wavelet and statistics for machine fault diagnosis. Mechanical Systems and Signal Processing. 2009;23(4):1076-1097.

50. Tse Peter W, Peng YH, Richard Yam. Wavelet analysis and envelope detection for rolling element bearing fault diagnosis-their effectiveness and flexibilities. Journal of Vibration and Acoustics. 2001;123(3):303-310.
51. Jian-Da Wu, Jien-Chen Chen. Continuous wavelet transform technique for fault signal diagnosis of internal combustion engines. NDT & E International. 2006;39(4):304-311.
52. Staszewski WJ, Worden K, Tomlinson GR. Time–frequency analysis in gearbox fault detection using the Wigner–Ville distribution and pattern recognition. Mechanical systems and signal processing. 1997;11(5):673-692.
53. Meng, Qingfeng, Liangsheng Qu. Rotating machinery fault diagnosis using Wigner distribution. Mechanical Systems and Signal Processing. 1991;5(3):155-166.
54. Blodt, Martin, et al. On-line monitoring of mechanical faults in variable-speed induction motor drives using the Wigner distribution. Industrial Electronics, IEEE Transactions. 2008;55(2):522-533.
55. Cruz SMA, et al. Diagnosis of rotor faults in traction drives for railway applications. Electrical Machines, 2008. ICEM 2008. 18th International Conference. IEEE; 2008.
56. Legowski, Stanislaw F, Sadrul Ula AHM, Andrzej M, Trzynadlowski. Instantaneous power as a medium for the signature analysis of induction motors. Industry Applications, IEEE Transactions. 1996;32(4):904-909.
57. Bellini, Alberto, et al. Quantitative evaluation of induction motor broken bars by means of electrical signature analysis. Industry Applications, IEEE Transactions. (2001;37(5):1248-1255.
58. Stone GC, et al. Development of automatic, continuous partial discharge monitoring systems to detect motor and generator partial discharges. Electric Machines and Drives Conference Record, 1997. IEEE International. IEEE; 1997.
59. IEEE Trial Use Guide to the Measurement of Partial Discharges in Rotating Machinery. IEEE; 1434-2000.
60. Tavner PJ. Review of condition monitoring of rotating electrical machines. Electric Power Applications, IET. 2008;2(4):215-247.
61. Baker PC, et al. Development of an integrated low-power RF partial discharge detector. Electrical Insulation Conference 2009. EIC 2009, IEEE; 2009.
62. Tetrault, Serge M, Greg C Stone, Howard G, Sedding. Monitoring partial discharges on 4-kV motor windings. Industry Applications, IEEE Transactions. 1999;35(3):682-688.
63. Stone, Greg, et al. Electrical insulation for rotating machines: design, evaluation, aging, testing, and repair. Vol. 21. Wiley-IEEE Press; 2004.
64. Toliyat, Hamid A, Gerald B. Kliman, eds. Handbook of electric motors. Vol. 120. CRC Press; 2010.
65. Bishop, Tom. Squirrel cage rotor testing. EASA Convention; 2003.
66. Testing of Squirrel Cage Rotors, Elect. App. Serv. Assoc., Inc., St. Louis, MO, EASA Tech. Note 23, 2003.
67. McKinnon, David L. Using a six fault zone approach for predictive maintenance on motors. Electrical Insulation Conference and Electrical Manufacturing Expo. IEEE; 2007.
68. El Menzhi L, Saad A. Induction motor fault diagnosis using voltage Park components of an auxiliary winding-voltage unbalance. Electrical Machines and Systems, 2009. ICEMS 2009. International Conference. IEEE; 2009.
69. El Menzhi, Lamiaa, Abdallah Saad. Induction motor fault diagnosis using voltage spectrum of an auxiliary winding. Electrical Machines and Systems, 2007. ICEMS. International Conference on. IEEE; 2007.

70. Mirimani, Seyyed Mehdi, et al. Static Eccentricity Fault Detection in Single Stator-Single Rotor Axial Flux Permanent Magnet Machines. Industrial Application, IEEE Transaction. 2011;48(6):1-8.
71. Acosta GG, Verucchi CJ, Gelso ER, A current monitoring system for diagnosing electrical failures in induction motors, Mechanical Systems and Signal Processing. 2006;20:953–965.
72. Urresty J, et al. Detection of demagnetization faults in surface-mounted permanent magnet synchronous motors by means of the zero-sequence voltage component. Energy Conversion, IEEE Transactions. 2012;27(1):42-51.
73. Urresty J-C, et al. Detection of inter-turns short circuits in permanent magnet synchronous motors operating under transient conditions by means of the zero sequence voltage. Power Electronics and Applications (EPE 2011), Proceedings of the 2011-14th European Conference. IEEE; 2011.
74. Briz, Fernando, et al. Induction machine diagnostics using zero sequence component. Industry Applications Conference, 2005. Fourtieth IAS Annual Meeting. Conference Record of the 2005. Vol. 1. IEEE; 2005.
75. Scheffer, Cornelius, Paresh Girdhar. Practical machinery vibration analysis and predictive maintenance. Newnes; 2004.
76. Han Y, Song YH. Condition monitoring techniques for electrical equipment-a literature survey. Power Delivery, IEEE Transactions. 2003;18(1):4-13.
77. Rao JS. Vibratory condition monitoring of machines. CRC PressI Llc; 2000.
78. Tavner, Peter J, James Penman. Condition monitoring of electrical machines. Letchworth: Research Studies Press; 1987.
79. Pöyhönen, S., et al. Numerical magnetic field analysis and signal processing for fault diagnostics of electrical machines. COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering. 2003;22(4): 969-981.
80. Choi, Seungdeog, et al. Performance-oriented electric motors diagnostics in modern energy conversion systems. Industrial Electronics, IEEE Transactions. 2012;59(2): 1266-1277.
81. Pineda-Sanchez M, et al. Diagnosis of induction motor faults in time-varying conditions using the polynomial-phase transform of the current. Industrial Electronics, IEEE Transactions. 2011;58(4):1428-1439.
82. Yang Yu, Cheng Junsheng. A roller bearing fault diagnosis method based on EMD energy entropy and ANN. Journal of sound and vibration. 2006;294(1):269-277.
83. Lin J, Zuo MJ, Fyfe KR. Mechanical fault detection based on the wavelet denoising technique. Journal of Vibration and Acoustic. 2004;126(1):9–16.
84. Dorrell, David G, William T. Thomson, and Steven Roach. Analysis of airgap flux, current, and vibration signals as a function of the combination of static and dynamic airgap eccentricity in 3-phase induction motors. Industry Applications, IEEE Transactions. 1997;33(1):24-34.
85. Zhuge J. Vibration Data Collector Signal Analysis, Part of VDC User's Manual, CRYSTAL instrument; 2009.
86. Finley, William R, Mark M. Hodowanec, and Warren G. Holter. An analytical approach to solving motor vibration problems. Petroleum and Chemical Industry Conference, 1999. Industry Applications Society 46th Annual. IEEE; 1999.
87. Cameron JR, Thomson WT, Dow AB. Vibration and current monitoring for detecting airgap eccentricity in large induction motors. IEE Proceedings B (Electric Power Applications). Vol. 133. No. 3. IET Digital Library; 1986.

88. Rodríguez, Pedro Vicente Jover, et al. Air-gap force distribution and vibration pattern of induction motors under dynamic eccentricity. Electrical Engineering. 2008;90(3):209-218.
89. Ellison AJ, Yang SJ. Effects of rotor eccentricity on acoustic noise from induction machines. Proceedings of the Institution of Electrical Engineers. Vol. 118. No. 1. IET Digital Library; 1971.
90. Sameh M, Metwalley, Shawki A. Abouel-seoud. Condition based maintenance optimization for faulty gearbox under continuous noise monitoring. British Journal of Applied Science & Technology. 2013;3(2):320-339.
91. Baydar, Naim, Andrew Ball. A comparative study of acoustic and vibration signals in detection of gear failures using Wigner–Ville distribution. Mechanical systems and signal processing. 2001;15(6):1091-1107.
92. Scanlon, Patricia, Darren F, Kavanagh, Francis M. Boland. Residual Life Prediction of Rotating Machines Using Acoustic Noise Signals. 2013;1-14.
93. Scanlon, Patricia, Alan M, Lyons, Alan O'Loughlin. Acoustic signal processing for degradation analysis of rotating machinery to determine the remaining useful life. Applications of Signal Processing to Audio and Acoustics, 2007 IEEE Workshop. IEEE; 2007.
94. Shahin Hedayati Kia, Humberto Henao, Capolino G-A. Mechanical transmission and torsional vibration effects on induction machine stator current and torque in railway traction systems. Energy Conversion Congress and Exposition, 2009. ECCE 2009. IEEE. IEEE; 2009.
95. Holtz, Joachim. Sensorless control of induction motor drives. Proceedings of the IEEE. 2002;90(8):1359-1394.
96. Henao, Humberto, Shahin Hedayati Kia, Capolino G. Torsional-vibration assessment and gear-fault diagnosis in railway traction system. Industrial Electronics, IEEE Transactions. 2011;58(5):1707-1717.
97. Guzinski, Jaroslaw, et al. Application of speed and load torque observers in high-speed train drive for diagnostic purposes. Industrial Electronics, IEEE Transactions. 2009;56(1):248-256.
98. Mehala NEELAM. Condition monitoring and fault diagnosis of induction motor using motor current signature analysis. Doctor of philosophy, Electrical Engineering, National Institute of Technology Kurukshetra, India October 2010.
99. Hsu, John S. Monitoring of defects in induction motors through air-gap torque observation. Industry Applications, IEEE Transactions. 1995;31(5):1016-1021.
100. R. Maier. Protection of squirrel-cage induction motors using instantaneous power and phase application. Industry Application s, IEEE Transaction. 1992;28(2):376–380.
101. Motor and Generators, NEMA Standard Publication No.MG 1- 1998 (Revision 2-2001).
102. Carson CC, Barton SC, Echeverria FS. Immediate Warning of Local Overheating in Electric Machines by the Detection of Pyrolysis Products. Power Apparatus and Systems, IEEE Transactions. 1973;2:533-542.
103. Hongbo, Fan, et al. Study on oil detection technology based on inductive wear debris sensor. Electronic Measurement & Instruments, 2009. ICEMI'09. 9th International Conference. IEEE; 2009.
104. Xufeng, Jiang, et al. Study on Aero-engine Wear Fault Diagnosis by Direct Reading Ferrograph. Measuring Technology and Mechatronics Automation (ICMTMA), 2011. Third International Conference. Vol. 3. IEEE; 2011.

105. Laghari MS, Ahmed F, Aziz J. Wear particle shape and edge detail analysis. Computer and Automation Engineering (ICCAE), 2010 The 2nd International Conference. Vol. 1. IEEE; 2010.
106. Lokesh A, Gupta, Dimitrios Peroulis. Wireless temperature sensor for condition monitoring of bearings operating through thick metal plates. IEEE Sensor Journal. 2013;13(6):2292-2298.
107. Milic, Saša D, Milesa Z. Sreckovic. A stationary system of noncontact temperature measurement and hotbox detecting. Vehicular Technology, IEEE Transactions. 2008;57(5):2684-2694.
108. Boglietti, Aldo, et al. Evolution and modern approaches for thermal analysis of electrical machines. Industrial Electronics, IEEE Transactions. 2009;56(3):871-882.
109. Mellor PH, Roberts D, Turner DR. Lumped parameter thermal model for electrical machines of TEFC design. IEE Proceedings B (Electric Power Applications). Vol. 138. No. 5. IET Digital Library; 1991.
110. Okoro, Ogbonnaya I. Steady and transient states thermal analysis of a 7.5-kW squirrel-cage induction machine at rated-load operation. Energy Conversion, IEEE Transactions. 2005;20(4):730-736.
111. Nerg, Janne, Marko Rilla, Juha Pyrhonen. Thermal analysis of radial-flux electrical machines with a high power density. Industrial Electronics, IEEE Transactions. 2008;55(10):3543-3554.
112. Chowdhury SK, Baski PK. A simple lumped parameter thermal model for electrical machine of TEFC design. Power Electronics, Drives and Energy Systems (PEDES) & 2010 Power India, 2010 Joint International Conference. IEEE; 2010.
113. Gao Zhi, Thomas G. Habetler, Ronald G, Harley. An online adaptive stator winding temperature estimator based on a hybrid thermal model for induction machines. Electric Machines and Drives, 2005 IEEE International Conference. IEEE; 2005.
114. Moreno J, Fernández F, Pérez Hidalgo, Martinez MD. Realisation of tests to determine the parameters of the thermal model of an induction machine. Electric Power Applications, IEE Proceedings. Vol. 148. No. 5. IET; 2001.
115. Milanfar, Peyman, Jeffrey H, Lang. Monitoring the thermal condition of permanent-magnet synchronous motors. Aerospace and Electronic Systems, IEEE Transactions. 1996;32(4):1421-1429.
116. Jankowski, Todd A, et al. Development and validation of a thermal model for electric induction motors. Industrial Electronics, IEEE Transactions. 2010;57(12):4043-4054.
117. Nategh, Shafigh, et al. Thermal analysis of a PMaSRM using partial FEA and lumped parameter modeling. Energy Conversion, IEEE Transactions. 2012;27(2):477-488.
118. Kolondzovski Z, Belahcen A, Arkkio A. Comparative thermal analysis of different rotor types for a high-speed permanent-magnet electrical machine. Electric Power Applications, IET. 2009;3(4):279-288.
119. El-Refaie, Ayman M, et al. Thermal analysis of multibarrier interior PM synchronous machine using lumped parameter model. Energy Conversion, IEEE Transactions. 2004;19(2):303-309.
120. Idoughi, Laïd, et al. Thermal model with winding homogenization and FIT discretization for stator slot. Magnetics, IEEE Transactions. 2011;47(12):4822-4826.
121. Lipo, Thomas A. Vector control and dynamics of AC drives. Vol. 41. Oxford University Press, USA; 1996.
122. Sang-Bin Lee, et al. A stator and rotor resistance estimation technique for conductor temperature monitoring. Industry Applications Conference, 2000. Conference Record of the 2000 IEEE. Vol. 1. IEEE; 2000.

123. Zhang, Pinjia, et al. A DC signal injection-based thermal protection scheme for soft-starter-connected induction motors. Industry Applications, IEEE Transactions. 2009;45(4):1351-1358.
124. Zhang, Pinjia, Bin Lu, Thomas G, Habetler. A remote and sensorless stator winding resistance estimation method for thermal protection of soft-starter-connected induction machines. Industrial Electronics, IEEE Transactions. 2008;55(10):3611-3618.
125. Cheng, Siwei, et al. A nonintrusive thermal monitoring method for closed-loop drive-fed induction machines. Energy Conversion Congress and Exposition (ECCE), 2011 IEEE. IEEE; 2011.
126. Samanta B, Nataraj C. Use of particle swarm optimization for machinery fault detection. Engineering Applications of Artificial Intelligence. 2009;22(2):308-316.
127. Nejjari, Hamid, Mohamed El Hachemi Benbouzid. Monitoring and diagnosis of induction motors electrical faults using a current Park's vector pattern learning approach. Industry Applications, IEEE Transactions. 2000:36(3):730-735.
128. Wang, Huaqing, Peng Chen. Sequential fuzzy diagnosis for condition monitoring of rolling bearing based on neural network. Advances in Neural Networks-ISNN 2008. Springer Berlin Heidelberg. 2008;284-293.
129. Tag Eldin EM, et al. Monitoring and diagnosis of external faults in three phase induction motors using artificial neural network. Power Engineering Society General Meeting, 2007. IEEE. IEEE; 2007.
130. Asiri, Yahya, et al. Neural network based classification of partial discharge in HV motors. Electrical Insulation Conference (EIC), 2011. IEEE, 2011.
131. Raj, Santhana, Murali N. Early classification of bearing faults using morphological operators and fuzzy inference. Industrial Electronics, IEEE Transaction. 2013;60(2): 567-574.
132. Chandra Sekhar S, Sreenivas TV. Adaptive spectrogram vs. adaptive pseudo-Wigner–Ville distribution for instantaneous frequency estimation. Signal Processing. 2003;83(7):1529-1543.
133. Cayrac, Didier, Didier Dubois, Henri Prade. Handling uncertainty with possibility theory and fuzzy sets in a satellite fault diagnosis application. Fuzzy Systems, IEEE Transactions. 1996;4(3):251-269.
134. Li Ke, Peng Chen, Shiming Wang. An Intelligent diagnosis method for rotating machinery using least squares mapping and a fuzzy neural network. Sensors. 2012;12(5):5919-5939.
135. Yazidi, Amine, et al. A web-based remote laboratory for monitoring and diagnosis of ac electrical machines. Industrial Electronics, IEEE Transactions. 2011;58(10):4950-4959.
136. Yazici, Birsen, Gerald B, Kliman. An adaptive statistical time-frequency method for detection of broken bars and bearing faults in motors using stator current. Industry Applications, IEEE Transactions. 1999;35(2):442-452.
137. Ocak, Hasan. Fault detection, diagnosis and prognosis of rolling element bearings: Frequency domain methods and hidden markov modeling. Diss. Case Western Reserve University; 2004.
138. Blodt M, Bonacci D, Regnier J, Chabret M, Faucher J. On-line monitoring of mechanical faults in variable-speed induction motor drives using the Winger distribution. Industrial Electronics. IEEE Transaction. 2008;55(2):522-533.

APPENDIX

Time-Frequency Analysis method equations which discussed at this paper are explained in this session.

1) Short-Time Fourier Transform (STFT):

The short-time Fourier transform (STFT) [41] by breaking signal into short blocks and applying an FFT to each part can determine the sinusoidal frequency and phase component of the its local time domain.

Mathematically, the STFT of a signal $x(t)$ is explained as follows [42]:

$$STFT_x(t,\omega)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{+\infty}x(t)h(\tau-t)\exp(-j\omega t)d\tau \tag{3}$$

In the above equation ω is an angular frequency, and $h(\tau)$ is the window function. With the technique of windowing (such as Gaussian, Hamming, Hanning …), the STFT can provide information about both time and frequency of the signal, since the time-varying concentration information is required for real-time applications. STFT analysis may lose the transient and temporal information and it is not good, but the STFT is simpler than the other methods. The STFT spectrum can be defined as follows [40]:

$$P_x(t,\omega)=\left|STFT_x(t,\omega)\right|^2=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{+\infty}x(\tau)h(\tau-t)\exp(-j\omega\tau)d\tau \tag{4}$$

Of course other studies [137,138] showed that the techniques such as short-time Fourier transform, where a nonstationary signal is divided into short pseudo-stationary segments, are not suitable for the analysis of signals with complex time–frequency characteristics.

2) Wavelet Analysis (WA)

WA is another time-frequency signal analysis method that has been widely used and developed recent decade. It has the local characteristic of the time domain as well as the frequency domain, and its time-frequency window is changeable. The Continuous Wavelet Transform (CWT) of $x(t)$ is a timescale method of signal processing that can be defined mathematically as the sum over all time of the signal multiplied by scaled and shifted versions of the wavelet function $\psi(t)$ [42]:

$$CWT_x(a,b)=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty}x(t)\psi^*(\frac{t-b}{a})dt \quad a,b\in R \tag{5}$$

Where $\psi^*(t)$ is the complex conjugate of which denotes the mother wavelet or basic wavelet. a & b are parameters related to scale and time respectively. If a is small, higher-frequency components can be analyzed, and when it is large, lower-frequency components can be analyzed. When b is given a value, the fundamental function can be shifted by a distance in the direction in which time advances. The CWT spectrum is considered as follows. Wavelet transform has the isometric characteristic.

3) Winger-Ville Distribution (WVD):

The Wigner-Ville Distribution (WVD) [41] is a very important quadratic-form time-frequency distribution with optimized resolution in both the time and frequency domains. The WVD is matched to linear chirps and can represent it effectively. The instantaneous frequency of such signals can be estimated easily by picking the peak in the time-frequency plane 40. However, the WVD does not yield a localized distribution for frequency variations that are not linear [44,133].

The instantaneous frequency within the window can be considered to be nearly linear because the VWD variants need windowing.

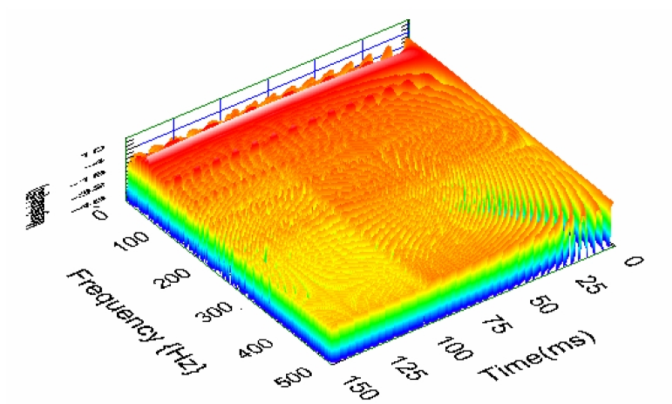
The Pseudo-Wigner-Ville distribution (PWVD) has better resolution and provides a more accurate estimate of the instantaneous frequency. Therefore, it has been used extensively in various applications to display time-frequency spectral information [17]. The PWVD equation defined as follows [98,132]:

$$PWVD_x(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} x^*(t-\frac{1}{2}\tau)x(t+\frac{1}{2}\tau)h(\tau)e^{-j\omega\tau}d\tau \tag{6}$$

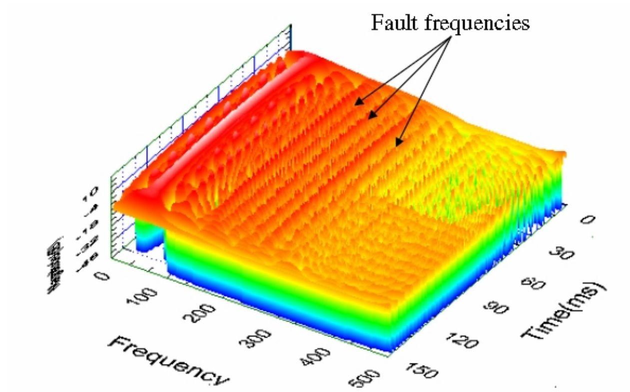
In this equation ω is an angular frequency and $h(\tau)$ is the windows function.

$$W(t,\omega) = \frac{1}{2\pi}\int s^*(t-\frac{1}{2}\tau)s(t+\frac{1}{2}\tau)e^{-j\omega\tau}d\tau = \frac{1}{2\pi}\int S^*(\omega-\frac{1}{2}\theta)s(\omega+\frac{1}{2}\theta)e^{-js\theta}d\theta \tag{7}$$

Winger-Ville distribution of a motor in healthy condition and with faulty bearing is shown at Fig. 10 [98].



(a)



(b)

Fig. 10. Winger-Ville distribution of motor (a) in healthy condition (b) Winger-Ville distribution of motor with faulty bearing [98]

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