A Review of Fault Diagnosis for Traction Induction Motor

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Abstract: With the rapid development of traction motor, the mechanical health monitoring and fault diagnosis field have entered the era of big data. Definite harmonic signals of the line current are located by a popular method known as motor current signature analysis. Different faults of an induction motor such as rotor, stator, bearing, vibration, air gap eccentricity and their different diagnosis techniques are also explored. In fact, the actual fault detection also has a deep development in the artificial intelligence. It is truly evident that the scope of this area is vast. Hence, acknowledging the need for future research, this review paper presents a birds eye view on different types of traction induction faults and their diagnostics schemes.

Key Words: Traction induction motors, fault diagnosis, model-based approach, current analysis, artificial intelligence

1 Introduction

Traction induction motors are a critical component of many industrial processes and are most widely used electric machines in various industrial sectors and home appliances due to their compactness, ruggedness, and reliability features. Therefore, assessments of the running conditions and reliability of the induction motors is crucial to avoid unexpected and catastrophic failures. Consequently, the issue of preventive maintenance and fault diagnosis of the condition of these induction motors drives is of great concern, and is becoming increasingly important [1] [2]. There are many published techniques and many commercially available tools to monitor induction motors to insure a high degree of reliability uptime. In spite of these tools, many companies are still faced with unexpected system failures and reduced motor lifetime. Environmental, duty, and installation issues may combine to accelerate motor failure far sooner than the designed motor lifetimes.

The common faults of induction motors can be classified as stator faults, rotor faults and bearing failures. Approximately 40-50% of faults of induction motors are bearing related faults, 30-40% are stator faults, and 5-10% are rotor faults. Other possible faults can be external faults due to incorrect connection of stator winding or utility supply. Main failures of IM can widely be arranged as follows [3]:

1) Faults in the stator, due to opening or shorting of one or more of a stator phase winding;
2) Improper stator windings connections;
3) Rotor field winding shorted;
4) Broken bar in the rotor or cracked rotor end rings;
5) Eccentricity (Static or dynamic air gap irregularities);
6) Bent shaft;
7) Bearing and gearbox failures.

For the purpose of detecting such fault-related signals, many diagnostic methods have been developed so far. These methods to identify the above faults may involve several different types of fields of science and technology. They can be divided into three fundamental categories [3]-[4]: 1) signature extraction based approach; 2) model based approach; 3) knowledge-based approach. In this paper, an extensive literature review is conducted for state-of-the-art fault diagnosis techniques for induction motors. The three fundamental categories are discussed in detail serving as the backbone of the paper. These approaches are applied to detect several critical faults of induction motors including stator winding interturn fault, broken rotor bar and bearing fault. The objective of this review is to strike a balance between accuracy of methodology and implementation constraint with economic advantage in view.

2 The model-based approach

The model based approach relies on machine's mathematical modeling. Traditional approaches use the model to generate residuals with an observer, or with a parity space approach. The main practical difficulties result from the model precision and unknown disturbances. This leads to a tradeoff between false alarm rate and missed detection rate. Various approaches have been proposed to model the behavior of the induction motor under fault diagnosis.

In [5], the authors presented a unique parameter estimation technique for the detection of stator winding short circuit fault detection in induction motors. In reference [6], a new model-based diagnostic technique, which is the so-called virtual current technique (VCT), for the diagnosis of rotor faults in direct rotor field oriented controlled induction motor drives. By measuring the amplitude of the oscillations and having a knowledge of the controller and some motor parameters, this model based approach can reconstruct the oscillation that would appear in the reference magnetizing current component which is quite independent of the control parameters as a fault indicator. In reference [7], the authors proposed a parameter estimation technique for fault detection simply by measuring the motor's input and output signals. Comparing the nominal with the computed parameters, faults can be detected. Similarly, [8] also gave a fault diagnosis for the stator and rotor fault by using parameter estimation. A weak point of model-based techniques is pa-

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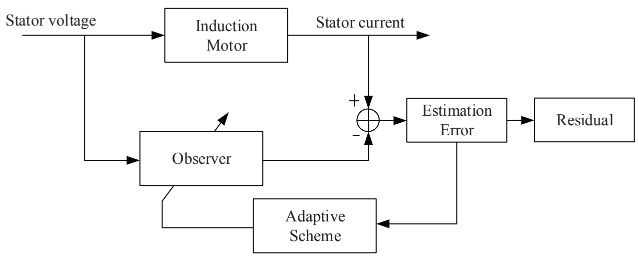

Fig. 1: Residual based induction motor fault detection

rameter dependence. To overcome this problem, a method to extract the component produced by the fault from the estimation error is proposed. [9] proposed a strategy based on the generation of a vector of specific residual using a state observer. This allows for a fast fault detection of incipient faults, independently of the phase in which the fault occurs. Fig. 1 shows the strategy which is the traditional innovation based residual generation for fault diagnosis. To obtain similar results, [10] proposed strategies need tree state observers, one for each motor phase. The classical estimation approaches for the unknown disturbances can be used for the induction motor in different environment [11] [12]. In [13], authors proposed the model-based and wavelet-based approaches for induction rotors, respectively. Both methods are applied to the same fault scenarios. The model-based approaches can give a better performance in accurate model. However, thermal effects make the parameter such as resistance and inductance vary. Therefore, the wavelet transform is very attractive approach to hierarchically extract information from signals and detection and isolation the failures. In [14], authors combined the advantage of both model-based and fuzzy logic, and let them complement the deficiency of each other. The residual generation is based on recursive least square parameter estimation and the residual evaluation is based on fuzzy inference.

3 Motor signature analysis

Modern measurement techniques in combination with advanced computerized data processing and acquisition show new ways in the field of induction machines monitoring by the use of spectral analysis of operational process parameters (e.g., temperature, pressure, steam flow, etc.). Time-domain analysis using characteristic values to determine changes by trend setting, spectrum analysis to determine trends of frequencies, amplitude and phase relations, as well as cepstrum analysis to detect periodical components of spectra are used as evaluation tools.

3.1 Stator Inter-turn Faults

Most induction motor stator faults is subjected to several stressful operating conditions like environmental, electrical, thermal, and mechanical. Stator winding faults namely open circuit, turn-to-turn, phase-to-phase, coil-to-coil, and coil-to-ground, are the most frequent and potentially disastrous faults. If timely diagnosis is not done, then it may ultimately cause terrible motor failure. Different methods used for diagnosis are insulation failures, partial discharge, surge testing, gas analysis, leakage current, air gap flux monitoring using search coils, vibration, temperature, acoustic noise, instantaneous angular speed, induced voltage, high frequency signal injection, instantaneous power, air gap torque, zero sequence voltage, negative sequence voltage, slot harmonics, angular fluctuations of current's space vector, negative sequence impedance and impedance matrix. The frequency components to detect in the axial flux component are given by

$$f_s = (k \pm n(1-s)/p)f \tag{1}$$

where is the number of pole pairs, f is the mains frequency, $k = 1, 3$ and $n = 1, 2, 3, ..., (2p-1)$ and s is the slip.

Motor Current Signature Analysis (MCSA) has been utilized for stator turn faults, and this technique is most feasible, cheapest and non-invasive for any electrical fault detection [15]. This method has been adopted by many researchers for studying and characterizing signals and faults, under different load conditions and abnormal operating conditions like supply voltage unbalance. Spectral analysis of stator currents, Negative and Zero sequence components of line currents, Radio frequency components of neutral currents and shaft currents has been taken as the fault indicators [16]. Classical Fast Fourier transform (FFT) is the most common method for stator current monitoring contains four processing sections: sampler, preprocessor, fault detection algorithm and postprocess. Generally, not denying the diagnostic value of classical spectral analysis techniques, induction motor faults detection, via FFT-based stator current signature analysis, could be improved by decreasing the current waveform distortions of the spectrum noisiness [17]. The amount of information carried by the instantaneous power, which is the product of the supply voltage and the motor current, is higher than that deducible from the current alone. Therefore, in some cases, the instantaneous power is used as a medium for the motor signature analysis oriented toward mechanical faults detection in a drive system [18]. However, the power spectra are vulnerable to noise. Bispectrum is defined in term of the two-dimensional Fourier transform of the third-order moment sequence of a process. It is capable of revealing both the amplitude and phase information of the signals. With these additional provided dimensions, the fault detection and diagnostic process can be enriched [19]. This technique should be particularly applied to detect electrical-based faults, such as stator voltage unbalance, because those faults do not have a well-identified harmonic frequency component [20]. A main disadvantage of the classical spectral estimation like FFT, is the impact of side lobe leakage due to the inherent windowing of finite data sets. A class of spectral techniques based on an eigenanalysis of the autocorrelation matrix has been promoted in the digital signal processing research literature. Two well-known eigenanalysis-based frequency estimators have been used: multiple signal classification (MUSIC) and ROOT-MUSIC for stator voltage unbalance [20]. The Fourier analysis is very useful for many applications where the signals are stationary. The Fourier transform is, however, not appropriate to analyze a signal that has a transitory characteristic such as drifts, abrupt changes, and frequency trends. To overcome this problem, it has been adapted to analyze small sections of the signal at a time. This technique is known as short-time Fourier transform (STFT) [21]. The fixed size of the window is the main drawback of the STFT. The wavelet transform was then introduced with the idea of overcoming the difficulties mentioned above [22].

Other signal processing approaches like Current envelope, Multiple reference frame theory, Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), Rough set theory based classifier, Park's Transform, Cross Wavelet Transform (CWT) [23], Extended Parks Vector, Concordia pattern [24], Empirical-Mode Decomposition (EMD) were found in literature for fault diagnoses and severity evaluation [25]. Of the above, the negative-sequence component of the motor's phase currents was widely used to study the stator inter-turn faults [26]. Negative sequence currents can also be caused by power supply unbalance and the intrinsic asymmetry, which is slip dependent [27], and complicates the diagnosis. The frequency components in the instantaneous power and air-gap torque analysis are basically same as the negative-sequence component methods. Wireless sensors for temperature and vibration measurement have been shown to be inferior to wired sensors, due to interference and conflict of electromagnetic fields between wireless devices and motors [28]. Although MCSA can detect these components, they may be confused with voltage unbalance in some machines. Fortunately, they can be unambiguously detected at the terminal voltages of the machine just after switching it off. In a healthy machine, the pole pair number associated with this time particular harmonic does not match that of a symmetrical three-phase winding. Hence, it is not detectable. Detection of stator voltage unbalances and single phasing effects using traditional and advanced signal-processing techniques have been described in [20].

3.2 Rotor Bar Faults

Unlike stator design, cage rotor design and manufacturing has undergone little change over the years. As a result, rotor failures now account for around 5%-10% of total induction motor failures. The reasons for rotor bar are several, such as thermal stresses, magnetic stresses, residual stresses and mechanical stresses. Since current cannot flow through broken rotor bar, it results in an unbalanced rotor flux. The current harmonics can be taken as the fault signature for rotor fault diagnosis [36]. Load oscillation can also induce the current harmonics at the same frequencies, which is the major problem of current spectrum-based methods [37].

[29]-[31] use MCSA to detect broken bar faults. They investigated the sideband components f_b around the fundamental for detecting broken bar faults.

$$f_b = (1 \pm 2s)f \tag{2}$$

While the lower sideband is specifically due to a broken bar, the upper sideband is due to consequent speed oscillation. In fact, [31] shows that broken bars actually give rise to a sequence of such sidebands given by

$$f_b = (1 \pm 2ks)f, \quad k = 1, 2, 3... \tag{3}$$

The motor-load inertia also affects the magnitude of these sidebands. Other spectral components that can be observed in the stator line current are given by

$$f_b = (\frac{k}{p}(1 - s) \pm s)f, \quad k = 1, 2, 3... \tag{4}$$

where f_b are detectable broken bar frequencies. In [30], the authors proposed to add a space dimension to the measured signal by using an array of Hall Effect Flux Sensors installed inside the motor air gap. Such an instrumentation brings significant advantages for some classes of specialised induction motors. [32] presents some experimental results obtained for the diagnosis of the rotor broken bars in three identical squirrel cage induction generators by the analysis of stator current signatures MCSA using Periodogram, Covariance, and MUSIC techniques respectively. [33] proposed using pattern recognition to detect broken rotor bars. The rotor speed is estimated from stator current and then the featured vector is extracted as an input to Baye's classifier. The time-stepping coupled Finite element-state space (TSCFE-SS) method has been used in [34] to compute core losses and copper losses with broken-bar faults in variable speed drives. Time-series data mining (TSDM) in conjunction with the TSCFE-SS method has been used to extract broken bar information from torque data [35]. Interestingly, while literature abounds with MCSA-based fault detection, it is shown that spectral components related to broken bar faults are stronger in per-phase partial power and total power than in stator line currents. The best result is obtained with partial power. The instantaneous power-based methods are capable of providing better sensitivity to broken rotor bar fault in [41].

Applications of current-based broken rotor detection algorithms are limited by their detection sensitivity. The intrinsic unbalance of the rotor also produces current harmonics at the same frequency, and reliable detection is required to separate those components. To assist the reliable detection of rotor cage fault especially at earlier stage, different fault severity techniques are proposed to estimate the number of broken rotor bars to avoid false alarm caused by intrinsic rotor unbalance [43]. For closed-loop drives, the current regulator greatly reduces the current harmonics at the characteristic frequencies and thus degrades the performance of current-based methods. High-frequency signal injection method is proposed to monitor rotor saliency [44]. However, the data acquisition system requirements are high frequency signal. Other approaches/indicators, used are the rotor resistance-based method, parameter estimation-based method, swing angle method, the startup current, the induced voltage after switch off, but incapable of providing continuous monitoring an protection. A scheme to detect broken rotor bars by estimating the rotor position is also proposed [45]. However, these methods still cannot discriminate broken rotor bar faults from load oscillations. Experimentation with reconfigurable motor for detection of stator winding inter-turn and broken bar faults using motor flux signature analysis [46], and online monitoring technique detecting differences in the flux spectrum are also identified [47].

3.3 Bearing fault

The majority of the electrical machines use ball or rolling element bearings. Each bearing consists of two ringsłone inner and the other outer. Bearing are the most affected component of any other faults of three phase induction motor, hence the possibility of its occurrence is also more. Local defects on bearing can be on ball, inner raceway or outer raceway and can be of crack, pit or spall in nature. The ball bearing related defects can be categorized as outer bearing race defect, inner bearing race defect, ball defect, and train defect. The vibration frequencies to detect these faults are given by [56]:

$$f_o = \frac{n}{2} f_r (1 - \frac{D_b}{D_p} cos\phi) \tag{5}$$

for outer race frequency;

$$f_i = \frac{n}{2} f_r (1 + \frac{D_b}{D_p} cos\phi) \tag{6}$$

for inner race defect frequency;

$$f_i = \frac{D_b}{D_p} f_r (1 - (\frac{D_b}{D_p})^2 cos^2\phi) \tag{7}$$

for ball defect frequency;

$$f_c = \frac{1}{2} f_r (1 - \frac{D_b}{D_p} cos\phi) \tag{8}$$

for cage defect frequency. Where f_r is the rotor speed in revolutions/minute, n is the number of balls, D_b is the ball diameter, D_p is the pitch diameter of the bearing and ϕ is the contact angle. Shaft rotational speed, fault location, and bearing dimensions determine the amplitude and period of these impulses.

Diagnostic studies of local defects are found more than that of distributed effects. Distributed faults give broadband signatures, and may not give specific frequencies in the harmonic spectrum. Advanced signal processing techniques such as high resolution frequency analysis, probabilistic models or enhanced wavelet decompositions are needed for the diagnoses of distributed effects. A general fault detection method based pattern recognition has three processes: acquire physical signal and calculate numerical features, feature reduction technique to compress data without removing useful information and to extract the hidden patters, which is the most important stage of any diagnostic procedure and classification [50]. [48] have proposed an adaptive, statistical time frequency method for the detection of bearing faults. Experiments were conducted on defective bearings with scratches on the outer races and bearing balls and cage defects. It has been claimed that all defective measurements were correctly classified as defective. However, the detection procedure required extensive training for feature extraction. Vibration analysis found to be dominated in the field of bearing fault detection [49]. A system which applies a variant of Curvilinear component analysis for feature extraction and artificial neural network for classification, found to be capable of diagnosing both local and distributed faults from the acquired vibration signal [50]. However, detection of bearing faults using vibration signals is affected by machine speed. Thermal sensors, chemical analysis, acoustic emission monitoring and sound pressure measurements are the other bearing failure detection methods. However, their applications are limited by the requirement of specialized devices and sensors [51].

It is reported that the bearing faults also will lead to rotor eccentricity and hence additional harmonics will also be present in the current spectrum [52]. Monitoring of general roughness of the bearing is more important to detect bearing faults at early stage in order to schedule maintenance and repair proactive. Standard deviation of the current spectrum can be used as fault signature. The current harmonics caused by power supply harmonics, load oscillation, broken rotor bar, rotor eccentricity etc., have to be removed for proper diagnoses. To improve the signal-to-noise ratio, a Wiener filter-based noise cancellation approach is proposed [53]. Hybrid time and frequency domain analysis is also used to obtain the bearing fault signature for inverter fed motors [54]. Methods which use the magnetic flux density in proximity of induction motor as a diagnostic signal for the detection of eccentricity and bearing faults are proposed in [55]. Vibration and stator current analysis of motor with externally induced vibration by an air cooled shaker shows that MCSA is not affected by the excitation method but vibration analysis is affected. But in this method MCSA is effective only for fault characteristic frequency lower than supply frequency like cage defect characteristic frequency [56]. Combined faults of static/dynamic eccentricity and bearing, is experimented with multiple sensors such as vibration, current and acoustic on a common wireless platform. The disadvantage of this system is data loss while transmitting [57]. Difficulties in fault signature extraction because of the fluctuations in characteristic frequency due to load variations, are reduced using an improved CLIQUE algorithm for fault signature extraction from the frequency spectrum of stator current signal [51].

4 Artificial Intelligence methods

Until recently, the prevalent fault detection technique has been MCSA. Artificial Intelligence (AI) are now used extensively for speed, torque estimation, and solid-state drive control of both dc and ac machines.. It can improve the robustness and efficiency of the fault diagnosis. Machine learning, deep machine learning, i.e. Artificial Neural Network (ANN), fuzzy logic and Particle Swarm Optimization (PSO) are AI methods that have been used for motor fault diagnosis.

As the data is generally collected faster than diagnosticians can analyze it, there is an urgent need for diagnosis methods that can effectively analyze massive amounts of data and provide accurate diagnosis results automatically. These types of methods are called intelligent fault diagnosis methods. [59] proposed a motor fault analysis technique for acoustic signals using the Coiflet wavelet transform and K-nearest neighbor classifier. [60] used the wavelet analysis method for decomposing the vibration acceleration signal of the motor, to obtain the energy ratio of each subfrequency band. Then, they used the energy ratio to train the optimized support vector machine (SVM). [61] proposed a fault diagnosis method for an asynchronous motor, which was based on kernel principal component analysis and particle swarm SVM. For other diagnostic objects, [62] utilized wavelet packet transform and SVM to diagnose induction motor multi-faults. [63] developed a fault classifier using the fusion of vibration data and acoustic signals for planetary gearboxes based on the Dempster-Shafer evidence theory. However, some obvious deficiencies were discovered by carrying out a literature review. The features input to the classifiers were extracted and selected by diagnosticians from measured signals largely depending on prior knowledge about signal processing techniques and diagnostic expertise. In addition, manual feature extraction often makes raw signals lose a certain part. Thus, it is necessary to adaptively mine the characteristics hidden in measured signals to reflect the different health conditions of the machinery, instead of manually extracting and selecting features.

Deep learning has the potential to overcome the aforementioned deficiencies in current intelligent diagnosis methods. In 2006, [64] proposed a deep learning method for the first time, and it set off a wave of interest in deep learning, in the academic and industrial fields. Presently, deep learning shows a clear advantage in processing large data volumes of images and speech [65]. Deep learning has also been applied in the field of mechanical fault diagnosis. [66] utilized singular value decomposition and deep belief networks in building a fault diagnosis system for rolling bearings. The system achieved a satisfactory result. [67] proposed a new method for gear fault diagnosis. Using this method, they established a stacked autoencoder network and then utilized the frequency domain as input, to train the network and realize gear fault diagnosis. In [68], the raw signal was converted into a time frequency map using STFT. Subsequently, the time frequency map was used as input to a convolutional neural network (CNN), where it utilized these preprocessed samples for carrying out supervised training to realize motor fault diagnosis.

5 conclusion

A brief review of bearing, stator, rotor, and eccentricity-related faults and their diagnosis has been presented in this paper. It is clear from various literature that noninvasive MCSA is by far the most preferred technique to diagnose faults. However, theoretical analysis and modeling of machine faults are indeed necessary to distinguish the relevant frequency components from the others that may be present due to time harmonics, machine saturation, etc. The different techniques for the detection of induction machine faults based on fuzzy-logic, genetic algorithm, neural networks, wavelet technique, Vienna monitoring etc. have also been discussed.

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