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Diagnosis Techniques for Electrical Machines: State of the Art

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Anotace v anglickém jazyce / Abstract

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List of symbols and shortcuts

Contents

1 Introduction

In recent years, the research activity in the electrical machines diagnosis area has experienced spectacular dynamism. This has been partially due to the incorporation of these elements in a vast number of industrial processes and applications. Moreover, these elements are often critical in those processes in which they operate. Large motors and generators, whose eventual failures may lead to severe repercussions in economic terms (repair costs and production shutdowns) as well as other less tangible costs (customer delivery delays, user hazard, and efficiency reduction) are particularly key issues for industry. All of these factors have justified increasing efforts to develop new techniques able to detect the development of any faults sufficiently in advance.

Traditionally, induction machines (IM) have attracted the most attention in electric machine fault diagnosis research due to their widespread usage. Now, other types of rotating electrical machines, such as permanent magnet synchronous machines (PMSM) and externally excited synchronous machines (EESM) are increasingly being used. This is due to the emergence of many applications (power generation, electric vehicles, cranes, elevators, high-speed trains, etc.). Consequently, the importance of new research lines in the aforementioned area is quickly increasing.

Faults of electrical machines can be classified into three categories: stator faults, rotor electrical/magnetic faults, and rotor mechanical faults. Other possible faults can be external faults due to incorrect connection of stator winding, failure of supply, etc. Main failures of electrical machines can widely be arranged as follow:

- Stator faults which are defined by open circuit, intern turn short circuit or short circuit phase;
- Rotor electrical/magnetic faults which include rotor winding open or short circuited for wound rotor machines, broken bar(s) or cracked end-ring for squirrel-cage machines and demagnetization of permanent magnet for permanent magnet synchronous machines;
- Rotor mechanical faults such as bearing damage, eccentricity (static/dynamic), bent shaft, and misalignment.

For the purpose of detecting such faults, many diagnosis methods have been developed so far. They can be categorized into offline testing and online monitoring methods. The former methods (offline testing methods) need to stop machines before any testing, and the later ones (monitoring methods) examine the machine while it is still in operation. In relation to sensor installation, diagnosis methods are grouped into non-intrusive and intrusive methods. The difference between two approaches is that while the non-intrusive methods require only measured stator voltages and currents, the intrusive methods require additional sensors for measuring other physical quantities such as vibration, flux, etc.

For the applied techniques, monitoring methods can be divided into four fundamental categories [1]:

- Sequence component analysis based diagnosis;
- Model based diagnosis;
- Signal based diagnosis;
- Artificial intelligence based diagnosis.

Signal processing is an enabling technology for the four methods diagnostic but with different impact and role. Moreover, with advances in digital technology over the last few years, adequate data processing capability is now available on cost-effective hardware platforms. They can be used to enhance the features of diagnostic systems on a real-time basis in addition to the normal machine protection functions.

2 Signal processing techniques

Faults detection takes place mainly in five different ways: temperature measurements, chemical measurements, mechanical vibration measurements, electrical measurements (current, voltage, flux, electromagnetic torque), and partial discharge detection. The most interesting technique is based on electrical measurements mainly because they are readily available in the power converter and for signal processing.

Measured quantities are processed in order to retrieve diagnostic induces related to the faults. The signal processing can be classified into three main classes:

1. Time-domain techniques;
2. Frequency-domain techniques;
3. Time-frequency domain techniques

Another major difference is the nature of the signal that may be stationary or non-stationary.

2.1 Time-domain methods

Time-domain methods are implemented through checking abnormal changes of interesting machine features along with time. These methods usually have advantages of simple calculation and implementation, but they generally suffer from low fault sensitivity. Thus, they could encounter difficulties when measuring fault indicative components of incipient faults or in noisy environments. Two main focuses of recent time-domain methods are finding fault sensitive time-domain features and increasing fault detectability.

Abbreviation	Faults detection diagnostic methods
CSVA	Current space vector analysis
HFSI	High frequency signal injection
K-L	Kullback-Leibler
PDF	Power density function
TCLA	Three-phase current locus analysis
TSZC	Time between successive zero crossings
TG	Thermography

Table 1: Abbreviation of faults detection diagnostic of Time-domain methods.

2.2 Frequency-domain methods

Frequency-domain techniques are widely adopted in machine diagnosis. Machine faults generate additional frequency components in various spectra due to resultant periodic vibrations of mechanical forces and air-gap spacing. The spectra include data signatures directly related to either electrical or mechanical faults and allow to perform a quantitative analysis of the fault severity. The most commonly adopted solution is referred to as MCSA (Machine Current Signature Analysis). Many diagnostic techniques are based on spectral analysis, most of them operating with one machine line current, others with flux, voltage (MVSA: Machine Voltage Signature Analysis used for synchronous generators), torque or vibration signals.

Abbreviation	Faults detection diagnostic methods

ESPRIT	Estimation of signal parameters via rotational invariance technique
FFT	Fast Fourier transform
HFTA	High frequency transient analysis
HOTA	Harmonic order tracking analysis
MUSIC	Multiple signal classification
MM	Mathematical morphology
REA	Reduced envelop analysis
SAA	Simulated annealing algorithm
SEA	Squired envelop analysis
SST	Spectrum synch technique
TK	Teager-Kaiser operator
WLC	Weighted linear combination

Table 2: Abbreviation of faults detection diagnostic of Frequency-domain methods.

2.3 Time-frequency domain methods

Time-frequency analysis consists of the 3-D time frequency, and amplitude representation of a signal, which is inherently suited to indicate transient events in the signal. Advanced signal processing techniques in time-frequency domain are not able for superiority in dealing with non-stationary signals. These methods provide more accurate inspection of a machine's dynamic features via continuous spectral analysis using a small moving time window, where non-stationary signals are treated as constant. Tradeoffs of these detailed inspections are more complex computation and implementation.

Abbreviation	Faults detection diagnostic methods
CWT	Continuous wavelet transform
DWT	Discrete wavelet transform
EMD	Empirical model decomposition
HED	Hybrid ensemble detector
IMF	Intrinsic mode function
PPT	Polynomial-phase transform
PSHT	Principal slot harmonic tracking
STFT	Short-time Fourier transform
WPT	Wavelet packet transform
WPD	Wavelet packet decomposition

WT	Wavelet Transform
XWT	Cross wavelet transform
HHT	Hilbert-Huang transform

Table 3: Abbreviation of faults detection diagnostic of Time-Frequency-domain methods.

3 Diagnosis methods for electrical machines

3.1 Testing methods

The term “testing” implies that they require specific devices/signals to test the machine and it is stopped from service. Usually, the testing methods can provide direct and accurate diagnosis results. Insulation resistance [2], polarization index [3], voltage surge [4], and partial discharges [5] tests are among the most common methods in industry. The two former methods are suitable for machines rated 400 V and above while the others are fitting for those rated at least 4 kV [6].

In the insulation resistance test, a DC voltage is applied between the winding copper and ground and the insulation resistance is calculated as the ratio between this voltage and the resultant current. The specific values of the applied voltage and the resistance threshold for evaluating the insulation condition follow industrial standards such as IEEE 43-2000 and NEMA MG1-1993. This insulation resistance method has simple test procedure. Nonetheless, it depends strongly on the operational temperature.

The polarization index can be used to overcome this drawback. It measures the time required for molecules of insulation to polarize in order to resist the flow of current. Therefore, it can be used for assessing the capability of ground wall insulation to polarize. It is calculated as the ratio of the insulation resistance at one-minute and ten-minute instances. The specific value of polarization index for testing is available at several standards such as IEEE 43-2000. Due to it easy implementation, this testing method is widely used. However, it is mainly used for testing phase-to-ground insulation.

The voltage surge test applies a high voltage between the tested turns, and hence, can probe inter-turn fault. The premise of this test is to create a voltage surge between the winding to charge and discharge the winding capacitor subsequently. Since the capacitor and the machine forms a RLC-series circuit, if the inter-turn insulation is deteriorated at certain level, there will be a change in the frequency and the magnitude of the impulse response. Although this method can test inter-turn fault, it has appearance drawback that the life time of the tested machine can reduce significantly due to effect of voltage stress.

The other method is the partial discharges test, in which an AC external voltage is applied between the winding and ground. This method requires an additional device to measure the partial discharges. In addition, it is only applicable to medium and high-voltage machines since the voltage magnitudes in low-voltage machines may not be high enough to generate a proper partial discharges indicator.

Insulation resistance, polarization index, voltage surge, and partial discharges tests are standardized for medium and high-voltage machines. However, they are not standardized for low-voltage machines. In addition, they are more suitable for testing purpose, i.e., to check if a machine is at healthy or failure conditions other than to continuously monitor the condition of a machine. High frequency impedance/inter-turn capacitance method [7] has the similar nature with the voltage surge test by exploiting the inter-turn capacitance effect for fault diagnosis. It is based on the principle that if a high frequency signal is injected in the stator winding and the frequency is close to the series resonance frequency of the system, the induced flux caused by the structured high frequency signal will vary the phase lag between the flux and the injected signal. Actually, this change represents the change in the resonance frequency caused by the corresponding change in the inter-turn capacitance. This has the advantage of considering the capacitance effect, which is neglected by most of other research. Nonetheless, the significant disadvantage of this method is its invasive nature requiring the injection of high frequency signal.

For the past few decades, various monitoring methods have been proposed for detecting faults in electrical machines based on different characteristics and behaviors of faulty machines. Moreover, due to the multi-physics nature of electrical machines, different physical quantities have been applied for generating diagnosis indicators.

3.2 Monitoring methods

3.2.1 Sequence component analysis based diagnosis

Symmetry analysis is one of the most common methods for fault diagnosis of rotating electrical machines and power systems. Under the healthy condition, the stator windings are symmetrical, and hence, the stator currents are also balanced. However, under the faulty condition, the stator windings are no longer symmetrical. As a result, the stator currents become imbalanced. Therefore, asymmetrical property of stator currents can be exploited for fault diagnosis. The sequence component analysis is the tool of symmetry analysis. The concept of sequence components analysis is proposed in [8]. Considering an induction machine (IM) of three phases, the sequence component analysis decomposes the multi-phase quantities such as stator currents, stator voltages, impedance in term of positive-sequence, negative-sequence, and zero-sequence components. Assuming three-phase quantities, such as the currents of stator phase a, phase b, and phase c, are represented by rotating vectors A, B, C, respectively. The positive sequence components are A+, B+, C+ of same magnitudes and 120o in phase difference, and rotating in clock-wise direction. On the other hand, the negative sequence components are A-, B-, C- of same magnitudes and 120o in phase difference, but rotating in the counter clock-wise direction. The zero sequence components A0, B0, C0 are static and identical vectors. The original vectors A, B, C can be derived back from the vector sum of their sequence components. Different quantities can be used in symmetry-based method. The most common quantity is the stator currents (the symmetry-based method is not only using current, but also other quantities (voltage, impedance)). One of the pioneering research exploring the sequence components of stator current for fault diagnosis is presented in [9]. In this work, it shows that the negative sequence current is less sensitive to speed variation. In [10] [11], both the magnitude and phase of negative and zero-sequence currents are proposed as fault indicators. The magnitude is used for evaluating the fault severity, while the phase is used to identify the faulty phase. However, the method is more suitable to balanced voltage supplies. In [12], the negative sequence stator current is found as sensitive to inherent motor asymmetry, supply voltage imbalance, and measurement errors. In [13], it is shown that the effects of both the supply voltage imbalance and fault are actually nonlinear. The negative sequence stator current becomes even more balanced under fault. Sequence components of higher order harmonic of stator current is also studied. In [14], a technique using the positive and negative-sequence third-harmonic components of line currents to identify the effect of inherent asymmetry. However, the estimated severity is not fully monotonic. The symmetry-based method has been also found in other electrical machines, such as permanent magnet synchronous machine (PMSM). Due to its high efficiency and high torque density, PMSM is widely used in modern wind energy conversion system and transportation system. The zero sequence voltage component and zero sequence current are applied in [15]. The negative sequence component is investigated in [16]. The sequence components are also used in [17], in hybrid approach, i.e., combining with Neural network, Fuzzy logic, or model-based methods. In overall, the symmetry-based method are non-intrusive, as only the measurements of terminal quantities are required. In addition, it provides a simple medium to model and analyze the asymmetrical characteristic of machines. However, the challenge with this technique is to discriminate the effect of fault from that of inherent asymmetry and voltage imbalance in a simple implementation.

3.2.2 Model based diagnosis

Model-based diagnosis was originated by Beard [18] in 1971 in order to replace hardware redundancy by analytical redundancy. In model-based methods, the models of the industrial processes or the practical systems are required to be available, which can be obtained by using either physical principles or systems identification techniques. Based on the model, fault diagnosis algorithms are developed to monitor the consistency between the measured outputs of the practical systems and the model-predicted outputs. Model-based diagnosis methods are classed in four categories: deterministic fault diagnosis methods, stochastic fault diagnosis methods, fault diagnosis for discrete-events and hybrid systems, and fault diagnosis for networked and distributed systems, which are classified in terms of types of the models used. It can also be classified as observer-based, parity equation, and parameter estimation approaches. Thanks to advance in control theory and control system applications, model-based diagnosis provides abundant tools for both robustness and sensitivity fault diagnosis.

While observer-based approach aims to design an observers, which are also dynamic systems, but other than process itself, the parity equation directly explores the process model, to form the residual. On the other hand, the parameter estimation approach attempts to estimate the model parameters and examine the deviation of parameters for residual generation. Observer-based approach plays a significant role in model-based methods, and substantial research has been studied for fault detection, isolation, and identification. In order to achieve incipient fault detection, under disturbances due to model uncertainty, process noise, and measurement errors, the fault detection is formulated as an optimization problem. The structure and parameters of the observers is optimized to guarantee that the residual signal is sensitive to fault, but robust against disturbances. Eigenstructure assignment has been proposed [19] [20] [21] to address this problem. The other approach is LMI-based method applicable to both nonlinear and linear systems [22] [23]. For fault isolation, a bank of observers are required. The idea is to make a residual only sensitive to its corresponding fault [24], or other faults [25], but robust against other faults and disturbances. The other idea is to decompose the different components in the residual signals, as discussed in [26] [27]. In fault identification, the observer-based approach is applied to estimate the fault parameters. They are modelled as augmented state variables, and the observer estimate both the states and fault parameters simultaneously. The approach is presented in [28] [29] [30] to name a few.

Parameter estimation approach tries to estimate the process parameters and compare them with the normal values for fault diagnosis. In the approach, the measured inputs and outputs, and model structure are employed for parameter estimation. The fault diagnosis is also formulated as optimization problem in which either equation or output error is minimized. Depending on the complexity of the problem, either direct estimation of the parameters or numerical optimization methods are required [31]. Parameter estimation has been found in applications where process parameters are closely linked to physical conditions or structure of the system, such as aerospace systems, as presented in [32].

The essence of parity equation approach is to check the consistency between the models and measured, i.e., process outputs [33]. The similarity of parity equation to observe base approaches has been discussed in [34]. In the parity equation approach, the residuals are under effect of model uncertainty, process noise, besides faults. However, the approach allows the flexibility to reorganize the model structure to improve the fault detection and isolation.

In Deterministic Fault Diagnosis Methods, Observer plays a key role in model-based diagnosis for monitored systems/processes characterized by deterministic models.

In parallel with the development of the fault diagnosis for deterministic systems, stochastic approaches were also developed for fault diagnosis in the early 1970s. The basis of the approach is to monitors the mean and variance of the innovation of a Kalman Filter. The fault is detected and diagnosed based on the statistical tests thereby. Similar to observer-based approach, banks of filters are applied for fault isolation and identification. Multiple model adaptive estimation (MMAE) is based on the idea of multiple models in order to estimate the probability for each model, providing confidence level to achieve fault isolation, as proposed in [35]. Further research studies have led to a couple of modified Kalman filter techniques for fault diagnosis, such as extended Kalman filters (EKF), unscented Kalman filters (UKF), adaptive Kalman filters, and augmented state Kalman filters.

Model-based methods of parameter estimation, observer design, and parity equation are applied for fault diagnosis of electrical machines. Related the models, dq-axis, sequence component analysis, and state-space models have been used.

Dq-model has been applied to analyze the behavior of an induction machine under fault, and also for fault indicator generation. In [36], a dq-model, which models a fault simultaneously occurring on multiple phases, is proposed. The parameter estimation, based on output error technique, is employed. Both the motor and fault parameters are estimated, and the fault phases are identified. The experimental results show interesting point that the change of motor parameters is negligible, while the fault parameters are more noticeable. However, the research is limited to the pure inter-turn fault, i.e., small value of fault loop resistance, representing relatively high severity level. In [37], both local and global search method has been applied to estimate the fault parameters and identify the faulty phase and compared. The local method applies the techniques of gradient descent and nonlinear least squares, while the global search method is based on pattern search method. It is shown that the global search method is insensitive to initial search and can converge to the global minima. However, its drawback is more computation time. Noise is added to the data to analyze the robustness of the methods. However, similar to many other works, the fault resistance is omitted in the work, implying that the research do not cover incipient fault represented by fault loop resistance component. In [38], an estimation method based on particle swarm optimization is proposed. The third harmonic component in the supply line current is used as the input for the estimator to estimate the percentage of shorted turn. In [39], the particle swam and bacterial foraging optimization have been explored for fault detection and severity estimation, and also faulty phase identification. The both methods have the advantage of not requiring prior knowledge of fault signatures. Nonetheless, they own inherent drawback of computational expensiveness.

In [40], EKF is applied for parameter and state estimations of brushless wound field synchronous generator (called also externally excited synchronous generator). The rotor field current, damper bar currents, and fault parameters are estimated in the work. Based on the estimates, the fault signatures of stator winding inter-turn short fault under load imbalance is proposed. The paper also helps demonstrates the advantage of KF-based approach on estimating unmeasurable quantities.

In [41], the sensor fault detection and isolation of interior permanent magnet synchronous machine is proposed, based on EKF. Three types of fault, which are faulty position sensor, DC-Link voltage sensor, and phase current sensor, are shown to be detected and isolated. The element of this approach is to use different quantities which are differently sensitive to different types of faults, and achieve the isolation thereby. However, it is assumed that only one sensor is faulty during operation, the probability of faults in more than one sensor is low though. The observer-based approach and parity equation are applied to calculate deviation between the simulated stator currents and measure stator currents. However, the effects of both non-idealities and fault are mixed in the generated signal. The inherent asymmetry is also not considered in this research. In addition, the experiment is only conducted on a small value of fault loop resistor, which implies the fault severity is relatively high. The system under fault is a bilinear system, in which an adaptive observer can be applied to estimate the fault parameters. In [42], a summary of disturbance/uncertainty estimation and attenuation (DUEA) techniques in PMSM drives is presented. It shows the existence of various DUEA techniques and the key differences between them.

3.2.3 Signal based diagnosis

Signal-based diagnosis utilize measured signals rather than explicit input–output models for fault diagnosis. The faults in the process are reflected in the measured signals, whose features are extracted, and a diagnostic decision is then made based on the symptom analysis and prior knowledge on the symptoms of the healthy systems. Signal-based fault diagnosis methods have a wide application in real-time monitoring and diagnosis for electrical machines, power converters, and mechanical components in a system in particular due to the abundance of signals and signal processing techniques. In electrical machines, the signals consist of stator current, voltages, axial and radial flux, electromotive force, vibration signal, and torque.

MCSA (Machine Current Signature Analysis) is one of the most commonly used method due to its non-intrusive and non-invasive nature and requiring only stator current measurement. The rotor slots harmonics [43], third harmonic [44], the lower sideband of field rotational frequency with respect to the fundamental frequency, the components relating to slots [45], suggest certain types of frequencies for fault detection. The study in [44] provides a detailed analytical analysis, using winding function approach, to arrive at the conclusion that under stator winding inter-turn short fault, there is no new frequency components emerging in the stator current spectrum, but only the rise in some frequency components instead. In the research, it is also verified by experiments. It is shown that these fault indicative frequency components are sensitive to voltage supply imbalance. In addition, the third harmonic is proved as a not reliable indicator because it also appears under magnetic saturation. Moreover, it is sensitive to machine non-idealities. A method using the positive and negative-sequence third harmonic components of line currents to address the effect of inherent asymmetry is proposed in [14]. However, the estimated severity is not fully monotonic.

Therefore, while MCSA is widely applied and easy to implement, it tends towards being fairly sensitive to voltage imbalance and machine non-idealities. The harmonics of stator voltages are also studied in [46] [47]. The rotor-slot-related harmonics, the third and other triple-related harmonic of terminal voltages switched off, are proven to be effective indicators for detecting stator winding inter-turn short fault. Because the fault signatures are calculated from the measured terminal voltages after they are switched off, there is no effect of voltage imbalance to the fault signatures. Due to this advantage, the method has potential to detect early fault, to extend of a few number of shorted turns. However, since the method is based on the transient voltages, it is only applicable to certain operational circumstances.

Axial leakage flux has been also used for fault detection. In [48], the flux is proposed, as the occurrence of inter-turn fault is associated to the flux. The premise of the approach is that the machine asymmetry, caused by stator winding inter-turn short fault, brings about a change in the air gap space harmonic distribution, which is rejected in the axial leakage flux. In details, when stator winding inter-turn short fault occurs, it establishes a closed-loop, and the circular current in the loop generates Electromagnetic Force (EMF). This results in a corresponding Magneto-Motive Force (MMF) pulse, superimposing on the main field distribution. This in turn modifies the harmonic of axial leakage flux. The spectrum component of voltage induced by leakage flux in the axial direction is used for fault diagnosis. In order to measure the leakage flux, a simple device called search coil is installed. Besides axial leakage flux, the leakage flux in the radial direction is also applied. For measuring this flux, the search coil is placed perpendicular to the machine radial direction near the vicinity of machine body [49]. The radial direction leakage flux based fault detection has been reported to be more reliable than MCSA [50]. To further improve the fault detectability, multiple search coils can be used to measure both axial and radial leakage fluxes, as presented in [51]. The flux-based method, however, is invasive and fairly dependent on load conditions.

Vibration signal is a mechanical quantity but it is well-known that there is interrelationship between it and electrical quantities. Owning to that fact, vibration signal has been also proposed for fault diagnosis. The second harmonic of bearing vibration is investigated in [52]. The research shows that the signal can provide information involving to the air-gap flux created by winding deterioration that may be unable to be captured by voltage and current quantities. In [53], electromagnetic anomalies in the induction motors based on the classical theory of electromagnetic vibration is explored. [54], complex wavelets is applied to discriminate stator winding inter-turn short fault from bearing fault. With that capability, the fault can be detected without concern of false fault detection due to other potential mechanical faults such as bearing and broken rotor bar faults. However, wavelet transform is relatively computationally expensive in general.

Electromagnetic torque also has close link to current and flux linkage quantities, and hence, it has been proposed for fault detection, as proposed in [55]. Nonetheless, the experimental results show that their performance does not outperform the other methods using other physical quantities. Both vibration and torque-based methods require the installation of additional sensors, which makes their application are fairly limited compared to other non-intrusive methods.

Besides standard techniques like Fast Fourier Transform (FFT), advanced techniques have been also applied for fault diagnosis. Bi-spectrum, also called third-order spectrum, is a high order statistics which can be suitable for detecting electrical-based faults, such as stator voltage imbalance [56]. Therefore, it application can be to evaluate the stator voltage imbalance condition or diversify to fault diagnosis of electrical faults like stator winding fault. Wavelet analysis is computationally expensive, but it can overcome the drawback of Fourier analysis, which is more suitable to stationary signals. In order to increase the resolution and also capture the sudden changes, wavelet is preferred, as proved in [54]. Wavelet transform (WT), Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT), Cross Wavelet Transform (XWT) is applied in [57] [58]. The zero crossing time signal of stator currents (TSZC) can be used to reduce volume of data acquisition and analysis for signature analysis approach [59]. The techniques based on the stator current space vector (CSVA) and its variances [60] [61], Park's vector modulus (PT) [62] are some other methods. In other works [63], techniques based on the instantaneous power is proposed. FFT combined with Principal component analysis (PCA) and Bayesian network is used in [64]. FFT combined with Discriminant Analysis (DA) is proposed in [65]. Other signal processing approaches like Current envelope (REA), Empirical-Mode Decomposition (EMD), Mathematical morphology (MM), Harmonics order tracking analysis (HOTA), Teager–Kaiser energy operator (TK), Estimation of signal parameters via rotational invariance technique (ESPRIT), Multiple signal classification (MUSIC), etc. were found in literature for fault diagnoses and severity evaluation [66].

3.2.4 Artificial intelligence based diagnosis

Artificial intelligence-based diagnosis has been also applied to diagnosis of electrical machines. Essentially, the AI-based diagnosis consists of three mains steps, including signature extraction, fault identification, and fault severity evaluation, as discussed in [67]. With the advance of computation software and hardware, AI-based approach has been also received substantial attention. In addition, AI-based diagnosis can be combined with other methods, usually signal-based diagnosis, to improve learning model and feature extraction, and hence, diagnosis performance. For electrical machines, AI-based methods are also found more commonly applied to mechanical faults such as bearing, broken-rotor bars rather than stator winding fault.

One of the most known AI-based diagnosis is the expert-system. The expert system emerged in the late 1960s as a branch of artificial intelligence, which is a rule-based system by presenting a human's expertise in a set of rules [68] [69]. Expert-system-based fault diagnosis was initialized in the 1980s [70], which was performed based on the evaluation of online monitored data in terms of a set of rules, which is learned by human experts from past experience.

In [71], a hybrid feature-reduction methodology based on Artificial Neural Network (ANN) is proposed to classify bearing, broken-bar rotor, and stator faults. The method combines Fishers discriminant ratio to maximize the separability between classes and error probability model to select an optimal number of extracted features. ANN is also widely applied to fault diagnosis of bearing fault. It is used for statistical-time features in [72].

Another AI-based method using Support Vector Machine (SVM) technique are proposed to classify rotor and bearing faults in [73], respectively.

In [74], the envelope analysis of vibration signals is explored for bearing fault diagnosis using FFT and PCA techniques The PCA method is also used for fault diagnosis of open-circuit faults in power inverters in [75].

A Feed Forward Neural Network (FFNN) method is proposed in [76]. In the training stage, the negative sequence current of a healthy machine under several different load conditions and supply voltage imbalance is used for offline training. In other words, the inputs to FFNN are of terminal quantities. In the monitoring stage, the measured negative sequence current is compared with the estimated value by FFNN, and the deviation between them is the indicator of fault severity. Experimental results show the technique can detect the incipient fault, and also is insensitive to supply voltage imbalance. However, to obtain the data for offline global training is a challenge in practice.

In [77], an ANN approach is applied to a wound-rotor induction generator. The ANN is trained directly by digital signals coming from sensors. Therefore, the diagnosis system can be implemented in a simplified architecture on a low-cost hardware. In [78], an ANN approach is applied to a squirrel-cage Induction Machine fed through an inverter. The variation of the phase shift between the phase voltages and the line currents is used for fault diagnosis.

Fuzzy logic-based approach is proposed fault detection and classification. It is also combined with other methods in fusion approach for fault identification. In [79], fuzzy logic-based approach based on the stator current Concordia patterns is validated as an effective method to detect stator fault. The fuzzy decision tree is proposed in [80] for fault classification of broken rotor bars and broken connector faults. The fuzzy decision tree approach is compared with Gaussian Mixture Models, ANN, and few other methods, and verified to provide better performance. The application of fuzzy logic-based approach for fault classification is found in [81] for bearing fault.

The AI-based methods have the advantage of learning capability under the lacking of quantitative domain knowledge, i.e., mathematical model. A few works have been proposed to reduce the computational load and complexity, such as the application of PCA for the unsupervised ANN method, proposed in [67]. The AI-based techniques are, however, computationally expensive, and not really suitable for online implementation.

Abbreviation	Faults detection diagnostic methods
AAC	Artificial and clustering
CCA	Curvilinear component analysis
DA	Discriminant analysis
DFA	Detrended fluctuation
DTCWT	Dual-tree complex wavelet transform
FMM-CART	Fuzzy max-min neural network using classification and regression tree
FZ	Fuzzy logic
ANN	Artificial Neural network
PCA	Principal component analysis
RBF-MLP	Radial basis function multilayer perceptron
RFE	Recursive feature elimination
SVM	Support vector machine
RUWPT	Recursive undecimated wavelet packet transform
ES	Expert System
FFNN	Feed Forward Neural Network

Table 4: Abbreviation of Artificial intelligence techniques.

3.3 Other approaches

All diagnostic approaches addressed in this paper concerns line-fed electric drive system and inverter-fed sensored control electric drive system. Sensorless control electric drive system without mechanical position or speed sensors is of high interest in several industrial applications, such as electrical vehicles, wind turbine energy conversion systems (WTECSs) [82]. For example, in new integrated motor drives, with power converter inside the machine, the space taken by the mechanical sensor represents a major problem. Using sensorless control strategies permit to reduce the size, and maintenance requirements of the electric drive. Regarding the WTECS, generally, the system operates under severe environmental conditions that act on the electric drive during the operation. Hence, the use of mechanical sensor increases the cost and failure rate. Repairing the faulty components leads to a significant loss in electric power production and requires additional cost.

Many investigations have been made so far on sensorless control electric drive system such as T.M Wolbank worked on sensorless control since 1993 [83]. Sensorless control electric drive system use the method INFORM (Indirect Flux detection by on-line Reactance Measurement) which works without mechanical sensors and yields hence cheaper and more robust drive solutions. The drive is able to produce full torque even at standstill without tachometer and position encoders. The basic idea is to evaluate saturation effects in the motor in real-time, yielding speed-independent information about the flux axis. The INFORM algorithm is coupled with well-known EMF-based flux models, providing optimal flux information for field-oriented control over the full operating range.

Diagnostic of sensorless control electric drive system use a kind of electrical excitation of the machine which may be transient or with high frequency signal. The response of the machine to this excitation has to be measured and evaluated during normal operation of the drive. This method uses a transient excitation or a high frequency signal injection of the machine with voltage test pulses impressed by the inverter and evaluates the transient current response. Only the electrical sensors which are already available in modern inverter fed drives are necessary to apply the method.

Using induction machine, in [84], a method of detecting rotor-bar defect at zero load and almost at standstill is proposed. The method uses the standard current sensors already present in modern industrial inverters by applying an excitation with a voltage pulses using the switching of the inverter and then measuring the resulting current, a fault indicator is obtained. [85] Investigates the influence of pole-pair number of the mixed eccentricity related fault indicators extracted by means of high-frequency or transient signal injection. In [86] a diagnostic technique for traction motor insulation condition monitoring is presented.

[87] present sensorless rotor temperature estimation technique for permanent magnet synchronous machine. The method implies an intermittent injection of a voltage pulse in the d-axis of the motor while keeping the load current zero.

In the domain of power generation, EPRI (Electric Power Research Institute) develop many projects to improve monitoring and diagnostics of turbo-generators and hydro-generators. In [88] a development of simplified analytical technique for electromagnetic signature analysis (EMSA) is in project. The objective of this project is to explore existing EMSA data analytical techniques and develop new techniques that can help simplify interpretation of data to provide actionable information for plant personnel. Electromagnetic Signature Analysis (EMSA) is a non-intrusive, on-line monitoring technology to diagnose anomalies in electrical machines. The EMSA process is used to evaluate electromagnetic interference (EMI) generated by anomalies in the energized electrical equipment. EMSA can identify sparking, arching, gap, discharge, and other types of electrical insulation-related anomalies in electrical equipment. The digital transformation of the power industry has been promoted as a significant opportunity to improve processes using digital tools and intelligence technologies. In the case of power generation, the practical value from adopting digital technologies has not been well defined. To realize value for power generation, in [89], a Digital Demonstration Facility (DDF) is being to:

• Establish scaling of digital technology solutions across a plant and fleet;

• Refine the infrastructure and resources needed to sustain connectivity and functionality of digital components;

• Understand the practical value from implementing select technologies;

• Discern good practices for evaluating and integrating new technologies into industrial power plant environments.

The “digitization” of a plant can encompass many areas and the DDF will initially focus the following technologies:

• Monitoring and control hardware;

• Computational algorithms to support process control, diagnostics and prognostics;

• Utilization of data management and analytic platforms to support advanced analysis of large data sets;

• Digitization of procedures, drawings, plant equipment and components;

• Use of mobility and digital worker technologies.

Another project of EPRI in [90] is I4GEN (Insight through the Integration of Information for Intelligent Generation. A key component of I4Gen is the transformation of data into actionable intelligence, with an ultimate goal to make the most useful information available at the time it is needed to perform an action. A power plant using the I4Gen concept produces, shares, and manages information at appropriate times, within proper context, and at a level of detail sufficient to support a decision/response. Adopting the I4Gen approach in totality will be a large and complex undertaking. In many cases, adoption of selected digital technology platforms and capabilities over time, with short-term tangible benefits, is a more realistic scenario. The I4Gen research and demonstration opportunities target:

• Advanced asset management through monitoring and diagnostics;

• Enhanced operations and maintenance through digital worker technologies;

• Improved information management and decision-making through data analytic and integration including prognostics and predictive maintenance, and operational actions;

• Quality data acquisition through low-cost sensor technologies and enhanced sensing capability;

• Improved communication using data visualization to display relevant information in a timely manner;

• Optimized operation and performance through adaptive controls and high levels of automation;

• Greater insights and options for system, plant and fleet performance.

4 Conclusion

This paper comprehensively reviewed diagnostic techniques of AC electrical machines. The diagnosis methods are classified into four categories and all four categories use the technology of signal processing to predict and detect faults. This diagnosis methods concern inverter-fed sensored control electric drive systems and line-fed electric drive systems.

Then, a diagnostic research advanced such as diagnostic of inverter-fed sensorless control electric drive systems is given. This method is based on signal injection.

Electric Power Research Institute (EPRI) develop projects on monitoring and diagnostic of synchronous generator such as development of simplified analytical technique for electromagnetic signature analysis (EMSA), Digital Demonstration Facility (DDF) and Insight through the Integration of Information for Intelligent Generation (I4GEN).

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[89] EPRI, Digital Demonstration Facility. California, USA: Electric Power Research Institute, March 2019.

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List of Figures

Revision history

Rev.	Chapter	Description of change	Date	Name