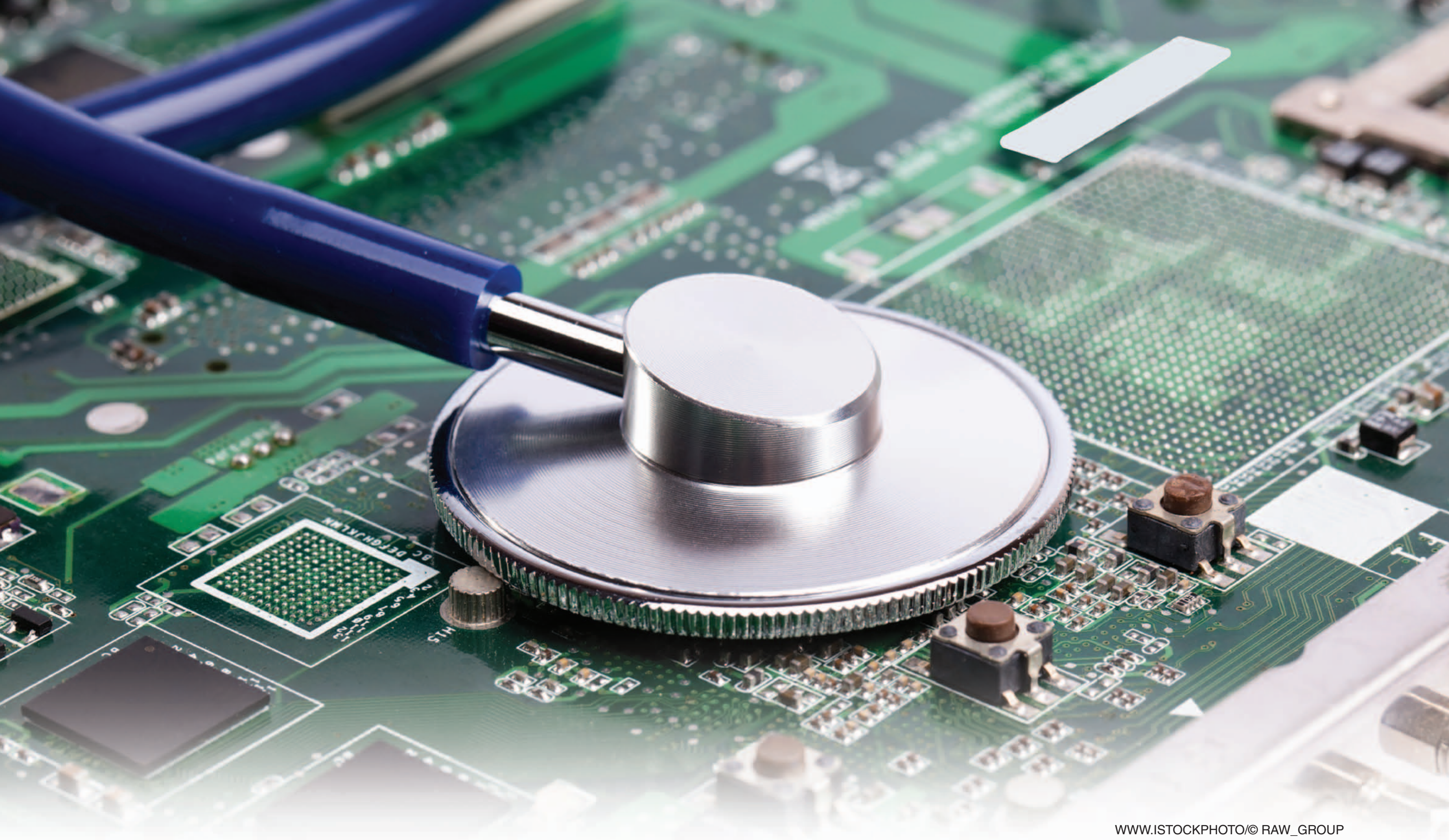
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Trends in Fault Diagnosis for Electrical Machines

A Review of Diagnostic Techniques

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The fault diagnosis of rotating electrical machines has received an intense amount of research interest during the last 30 years. Reducing maintenance costs and preventing unscheduled downtimes, which result in losses of production and financial incomes, are the priorities of electrical drives manufacturers and operators. In fact, both correct diagnosis and early detection of incipient faults lead to fast unscheduled maintenance and short downtime for the process under consideration. They also prevent the harmful and sometimes devastating consequences of faults and failures. This topic has become far more attractive and critical as the population of electric machines has greatly increased in recent years. The total number of operating electrical machines in the world was around 16.1 billion in 2011, with a growth rate of about 50% in the last five years [1].

Digital Object Identifier 10.1109/MIE.2013.2287651
Date of publication: 19 June 2014

AI is a powerful tool to improve the efficiency and effectiveness of fault diagnosis of electrical machines, especially during the maintenance decision process.

Electrical machines and drives are subject to many different types of faults. These faults include: 1) stator faults, which can be listed as stator open phase, stator imbalance due to short circuits, or increased resistance connections; 2) rotor electrical faults, which include rotor open phase, rotor imbalance due to short circuits or increased resistance connections for wound rotor machines and broken bar(s) or cracked end ring(s) for squirrel-cage induction machines, and rotor magnetic faults as demagnetization for permanent magnet synchronous machines (SMs); 3) rotor mechanical faults such as bearings damage, eccentricity, bent shaft, and misalignment; and 4) failure of one or more power electronics components of the drive system. Noninvasive condition monitoring is achieved by relying on easily measured electrical or mechanical quantities such as voltage, current, external magnetic field, speed, and vibrations. Other quantities, such as internal main air gap flux or torque, are often estimated in drives control loops. Acoustic noise, temperature, or other phenomena have seldom been investigated [2]–[4].

A brief review of diagnostic techniques begins with the widespread motor current signature analysis (MCSA) based on the spectrum analysis of the stator current signal, which is effective for electrical machines operating at both constant speed and rated load. Transient conditions are the most critical, and several methods have been proposed to deal with this situation. They are mainly based on the discrete wavelet transform (DWT) or the Hilbert–Huang transform (HHT) [5]–[8]. Artificial intelligence (AI) is a powerful tool to improve the efficiency and effectiveness of fault diagnosis of electrical machines, especially during the maintenance decision process. AI techniques, such as expert systems, neural networks, fuzzy logic, and fuzzy-neural networks and algorithms, have been widely developed in recent years [2], even though they are not yet used at the industrial level.

To give an insight into emerging new techniques related to condition monitoring and fault diagnosis for electrical machines, the following topics have been selected:

- diagnosis of stator winding insulation failures
- diagnosis of rotor faults
- diagnosis of rotor eccentricity (RE)
- diagnosis of gear and bearing faults
- fault diagnosis by stray flux analysis
- fault diagnosis by Park's vector approach
- diagnosis under nonstationary conditions
- efficient digital signal processing techniques (DSPTs).

Diagnosis of Stator Winding Insulation Failures

Initial studies have proved that interturn short circuits are one of the main root causes of insulation breakdown. As a consequence, a large number of researchers have focused their efforts on the online early detection and diagnosis of this type of failure. Most of the proposed methods have demonstrated their reliability when experimentally applied to test benches based on low-voltage motors. In fact, [3] provides a thorough survey of the techniques applied to low-voltage machines for turn insulation diagnosis, which perfectly summarizes the scientific knowledge for turn insulation fault diagnosis in this type of machine. However, these methods cannot be easily applied to large medium-voltage (MV) motors with form-wound stator coils for which few studies can be found [4]. In these machines, partial discharge analysis (PDA) is the most widely applied method. However, an important number of studies [9] that rely on the variables used for diagnosis can be grouped into 13 categories [10] and have been developed for large MV motors.

Offline analysis of stator insulation systems in rotating machines is performed using a set of tests that imply the machine disconnection from the power grid or power converter. The most relevant techniques are as follows: 1) measurement of both insulation resistance and polarization index, 2) ac and dc Hipot tests, 3) turn-to-turn insulation tests, 4) power factor (PF) tests, and 5) PDA. Particularly, PF tests allow the user to obtain information, in an indirect way, about the partial discharge activity taking place in the bosom of the insulation system. One limitation of this method is related to the semiconductive protective layers located close to the output of the slots in the bars or individual coils forming the stator winding. These layers may hide the actual presence of partial discharges caused by insulation degradation, preventing a reliable diagnosis of the insulation system [11]. The problem can be minimized by using guard terminals if individual bars or coils are being tested.

Figure 1 shows the electrical connections needed to perform PF tests on individual bars or complete coils. The slot is simulated by two electrodes firmly attached to the surface of the bars and ground connected in the same way as guard terminals. In the past, the testing instrument was a Krueger bridge, but this has been substituted by differential bridges electronically controlled to provide further information such as capacity, current, and power absorbed during the test. However, when the test is carried out on a complete machine, this solution is not feasible. According to the European standard [12], this test allows the user to analyze the dielectric behavior of the insulation system of rotating electrical machines with rated voltage of between 5 and 24 kV. Tetrault et al. [13] demonstrated the inactivity of partial discharges in electrical machines, rated at voltages below 4 kV, unless the internal status of the insulation is really poor. If this is the case, the partial discharge activity is a clear indicator of an imminent fault [13], [14]. Therefore, it can be concluded that, for voltages below 6 kV, it could be difficult to make a proper early diagnosis of the internal status of the insulation system.

Standards IEEE 1434 [58] and IEC 60034-27 [10] are the most specific guides for the development of offline PDA [10]. A certain degree of uncertainty exists in the application of this test to electrical machines whose rated voltage is below 6 kV, since in this range the detection of the partial discharge activity is linked to an extremely high level of wear in the insulation system, making the fault imminent [15].

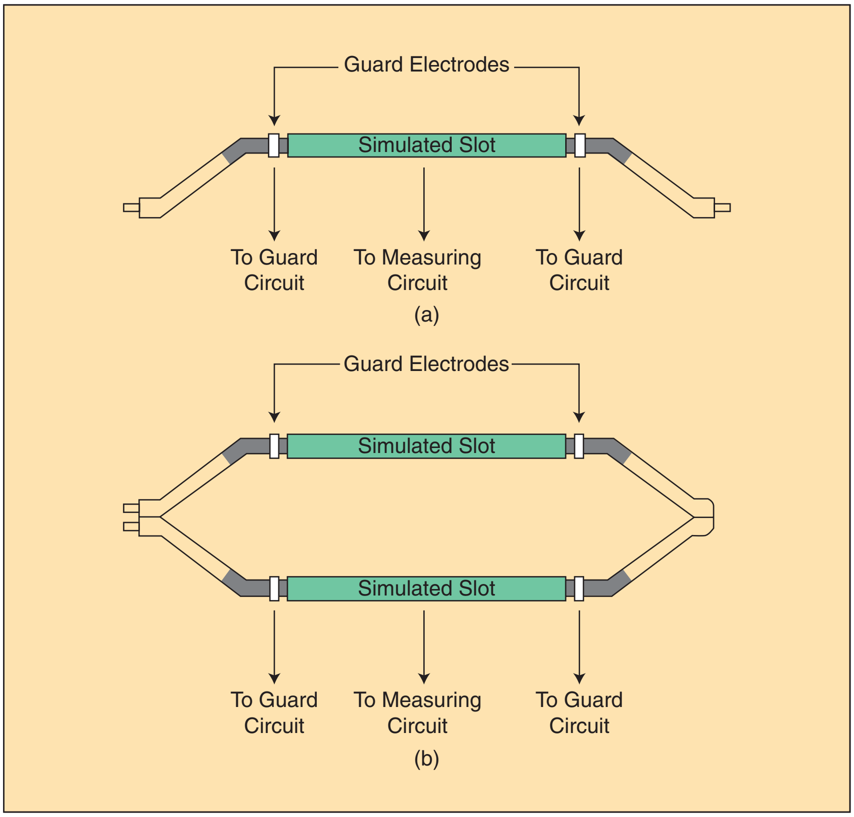

FIGURE 1 – The PF measurement using guard terminals according to IEEE Standard 286 [57]: (a) in a bar and (b) in an individual coil [15].

Diagnosis of Rotor Faults

Specifically, all electrical faults that occur in the rotor of an induction machine give rise to a common effect: asymmetry of the rotor circuits, both in the case of wounded rotor machines (asymmetry of windings impedances) and in the case of squirrel-cage machines (broken bars or cracked end rings). Rotor faults can be caused by thermal stress, electromagnetic forces, electromagnetic noise and vibration, centrifugal forces, environmental stresses (such as abrasion), mechanical stresses due to loss of laminations, fatigue parts, bearing failures, or simply defects in the connections. Rotor faults have been investigated considering constant and variable speed operating conditions, assuming power converter-based supplies. Fault diagnosis techniques are classified into signal-, model-, and data-based classes [2]. The signal-based methods commonly use the stator current as a measurement since it is sensitive to the rotor faults, and it is a suitable method to obtain a diagnostic index and a threshold stating the edge between faulty and healthy conditions. Conventional MCSA techniques based on the frequency

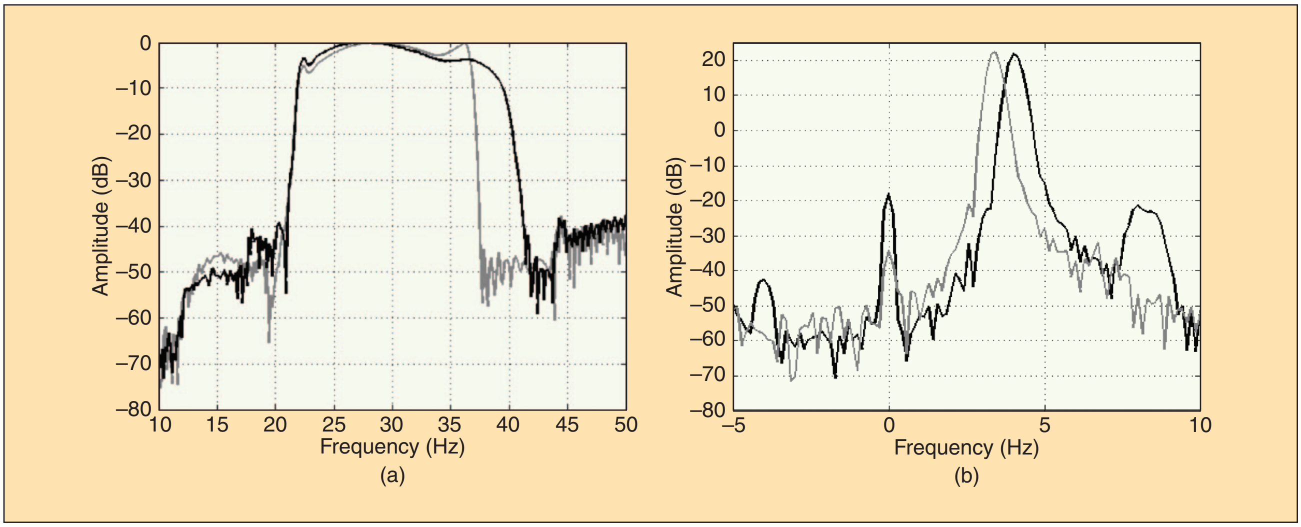

FIGURE 2 – The spectrum of the phase current of an induction machine during the shaft acceleration: (a) using conventional fast Fourier transform (FFT) in healthy (light gray solid line) and faulty (black solid line) conditions and (b) using demodulated current in healthy (light gray solid line) and faulty (black solid line) conditions.

The data-based methods are also interesting since they do not require any knowledge about the induction machine parameters and model.

analysis of the stator current are currently the most common and well-established methods. In fact, MCSA is simple and effective under suitable operating conditions. However, this technique has significant limitations because of the increased complexity of electric machines and drives. As an example, MCSA is the optimal choice for electrical machines under steady-state conditions and rated load.

Figure 2(a) reports the spectra of a phase current of a 7.5-kW squirrel-cage three-phase induction machine in healthy and faulty conditions during the shaft rotating acceleration. The spectra clearly show that no signature analysis can be possible for such cases because of the large spreading of both frequency and speed. Hence, the sideband frequency components related to the faults are spread across a wide frequency range and they are not detectable, leading to the failure of the MCSA technique under these conditions. Figure 2(b) illustrates the spectra of the phase current demodulated as in [6], showing that a suitable processing technique allows for effective condition monitoring, even in time-varying conditions, by frequency translation of the fault signature at the frequency $f = 0$ Hz. Condition monitoring for rotor faults in induction machines is a very attractive research topic with special references to quantitative, noninvasive methods, operating also in transient conditions [16].

The Vienna monitoring method is a model-based diagnosis technique that uses both voltage and current measurements for the rotor fault detection. It relies on the deviations in terms of the instantaneous electromagnetic torque obtained by both voltage and current models. This method is proposed as a quantitative diagnostic index independent of both inertia and load level [17]. The data-based methods are also interesting since they do not require any knowledge about the induction machine parameters and model. They only require a database of both healthy and faulty conditions for feature extraction and classification.

Diagnosis of REs

The rotors of ac electrical machines are usually heavily solicited in high-power applications [18]. Mechanical, thermal, and magnetic imbalances invariably

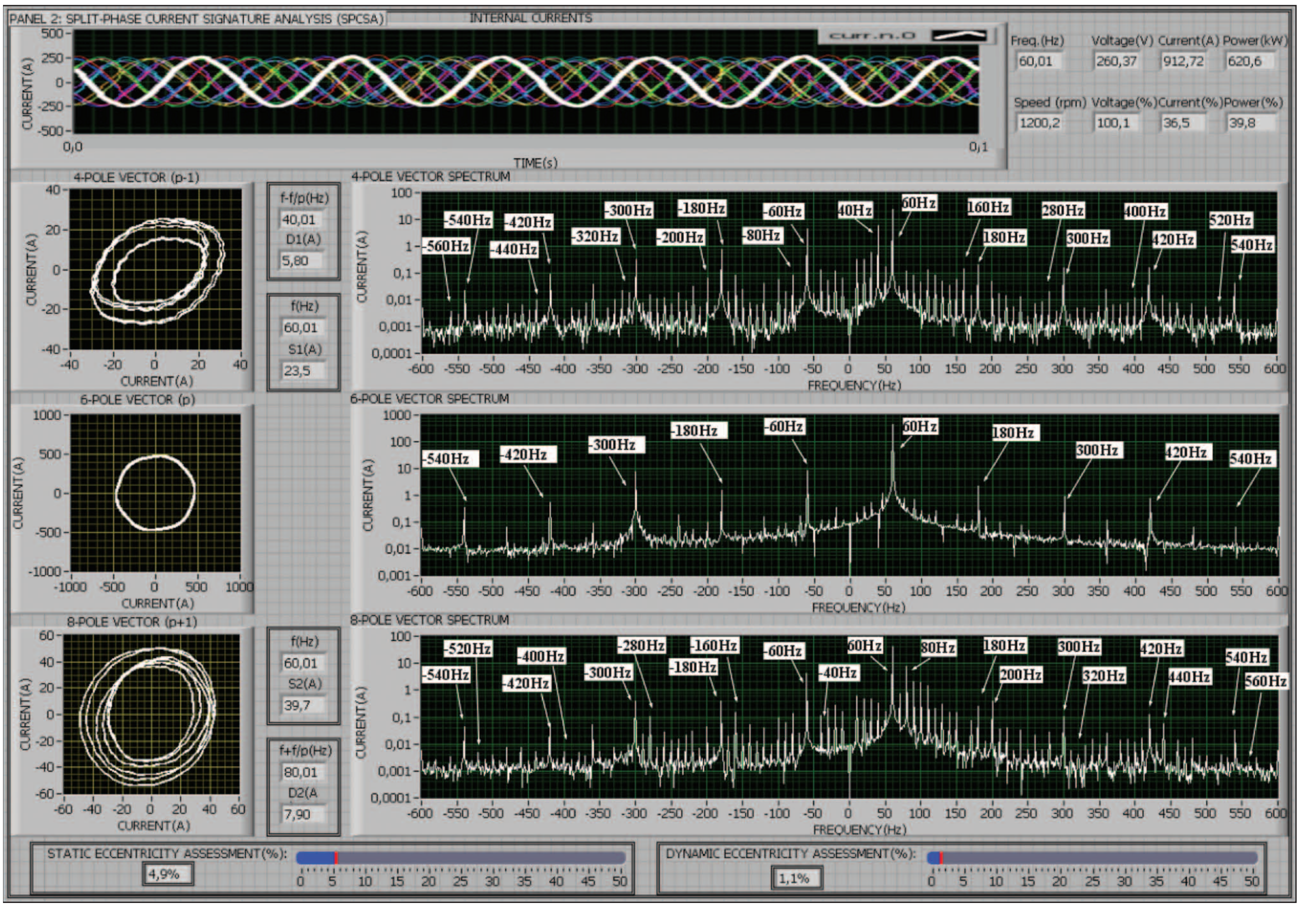

FIGURE 3 – The virtual instrument panel, showing the SPCSA applied to a 1,950-kVA six-pole stand-alone alternator with 36.5% of the rated load [24].

lead to REs. The REs should be carefully monitored in large machines and everywhere that damages would result in costly service disruption and repairs. The REs produce unbalanced magnetic pull, vibrations, and shaft currents, leading to bearing wear and damage, frame and winding loosening, insulation fretting, and stator–rotor rubs. The REs have been invasively monitored in large generators using capacitive, inductive, and fiber-optic sensors. Phase current monitoring is a viable alternative for condition-based maintenance because of easy measurement [2]. The rotor slot frequencies in the phase current of induction motors (IMs) [19] or the sideband frequencies $f \pm fr$ around the supply frequency [20] have been exploited.

Load influence and difficulty to distinguish a static RE (SRE) from a dynamic RE (DRE) are open problems. Consequently, indicators of mixed RE overall level have been tried. Separate detection of SRE and DRE by using terminal voltage analysis at the electrical machine switch-off is reported in [19], and detection of RE in the presence of load torque oscillations is reported in [21]. The external flux is used in [22], where a DRE-related slip-frequency signature is detected by an axial coil. Although some methods suitable for IMs could be adapted to other revolving-field machines with a cage, the zero-slip condition and the salient poles require specialized approaches for SM monitoring. Bruzzese and Joksimovic [23] studied SM phase current and voltage additive frequencies in the case of an SRE showing increasing non-homopolar triplen harmonics for series-connected stator windings. $2f$ and f/p frequencies have been detected in the field current of SMs with SRE and DRE, respectively.

The split phase current signature analysis (SPCSA) may be used in the case of parallel-connected windings [24]. The SPCSA exploits the air gap flux density modulation due to REs and resulting in additional $2(p \pm 1)$-pole flux density waves in $2p$-pole ac electrical machines. These waves affect phase currents only, thanks to the rotor cage whose reaction field increases $f \pm fr$ frequencies in the line current in case of mixed RE [20]. The $2(p \pm 1)$-pole flux waves cause a current circulation in the stator winding and an imbalance in the split-phase currents. The latter can be transformed in complex space vectors. Both SRE and DRE can be assessed based on the FFT of the $2(p \pm 1)$-pole space-vectors. Figure 3 reports the eccentricity fault assessment in a six-pole, 60-Hz, 1,950-kVA synchronous generator with 36.5% of the rated load by using the SPCSA. Figure 3 shows currents of 18 pole-phases groups (top) that are used to compute 4-, 6-, and 8-pole current space-vectors trajectories (middle-left) and the corresponding spectra (middle-right). Then, these last spectra are used to estimate both static and dynamic eccentricities (bottom).

Phase current monitoring is a viable alternative for condition-based maintenance because of easy measurement.

Diagnosis of Gear and Bearing Faults

Detecting and identifying mechanical faults and separating them from each other are major challenges in electrical drive systems. Although vibrations and acoustic noise are commonly used for this purpose, it is necessary to detect these faults by using as few standard sensors as those used for other purposes, such as current and voltage sensors. The questions addressed in ongoing works are as follows:

- Is it possible to determine the presence of a fault from measurements only at the drive terminals instead of both bearings and gears? In [25], on bearing faults, and in [26], on gear faults, such comparisons are presented, and they have been rather pessimistic when it comes to the use of the stator current.
- Is it possible to separate faults with similar signatures? What techniques can be applied online with limited data storage capability and processing in low-cost applications?

Types of mechanical faults in bearings and gears connected to electrical drives can be: bearings failures as pits may be created through bearing currents and voltages; uniform wear due to both use and environment; gear wear resulting in backlash or individual damage due to an unpredicted impact or a manufacturing shock.

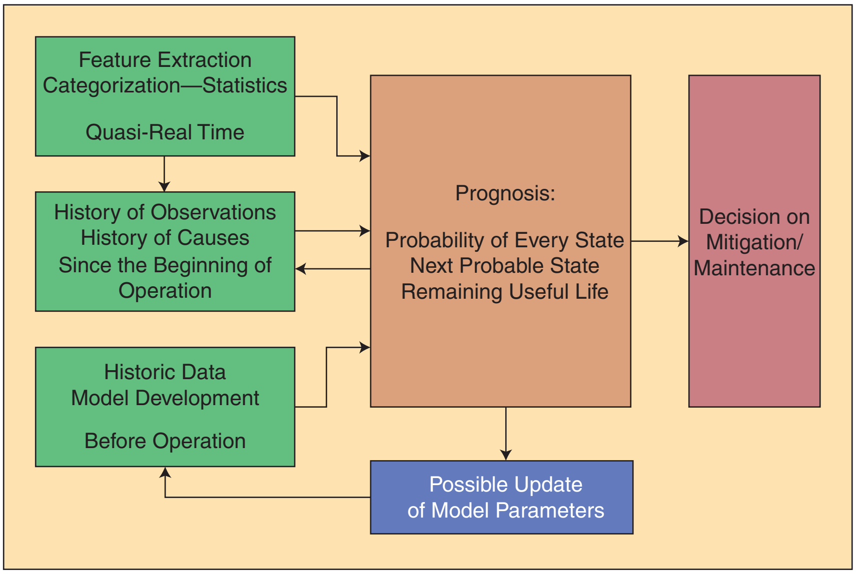

FIGURE 4 – A flowchart of information acquisition and processing for prognosis [31].

MCSA is the optimal choice for electrical machines under steady-state conditions and rated load.

Mechanical faults translate into rotating eccentricities, torque pulsations, and electric quantities. Current variations are dependent not only on the fault but also on the supply. A fast current-controlled inverter may well decrease the effects of eccentricity and signs of bearing fault. Bearing or gear faults are characterized by three effects: 1) frequency with which an impulse repeats, which depends on the rotation frequency; 2) generation of vibrations from the impulse, which can be established experimentally; and 3) increase in the total level of noise.

The closer the sensors are to damaged bearings or gears, the lower the damping and the clearer the relationship between the fault and the sensed variables. Hence, determining the presence of these faults from the acceleration on the electrical machine housing is the most accurate method. However, the most convenient detection method is the use of existing sensors, e.g., for current or voltage of the drive system. When the signal is stationary, the FFT is enough to give features for further processing. Time-frequency analysis methods are preferred for feature extraction in nonstationary cases, such as the continuous wavelet transform (CWT), as well as the short-time Fourier transform (STFT), the Wigner–Ville distribution (WVD), and the HHT [27]. Alternatively, time-domain rather than time-frequency features are used to estimate thresholding, root mean square, crest factor, and distribution measures [28], [29].

Some methods have the possibility to lead to fault prognosis from diagnosis [30]. Figure 4 gives a very simple flowchart to show of how a prognosis scheme must work. In this flowchart, it is clearly specified that the use of models of fault creation and development, whether based on fatigue or bearing currents, as well as observed external factors such as periodic and static loads and temperature, improve the statistics. A prognosis requires a large number of samples or a clear trend consequently leading to a reliable extrapolation. In the same way, model parameters adaptation based on online measurements may be adequate to replace extensive a priori testing and collection of data, which is seldom feasible. For data-based models, physics-based models that connect features to faulty states and predict fault developments have been proposed. Among them, particle filters and hidden Markov methods have been developed [30].

A wide range of fault diagnosis algorithms, based on models and signal processing methods, have been compared, but no clear general choices seem to emerge. Physical models can be useful, but their parameters are not easily determined before use. Adaptation of the model parameters over time is a promising solution. The trends in the diagnosis of mechanical faults using this technique have been analyzed [31]. The following points have been highlighted:

- The use of more than one sensor for prognosis leads to more accurate indicators, e.g., the power to the inverter or the transfer function between torque and speed as modified by the fault.
- A combination of data-driven and model-based techniques is used to follow the fault development and estimate the confidence in predictions.

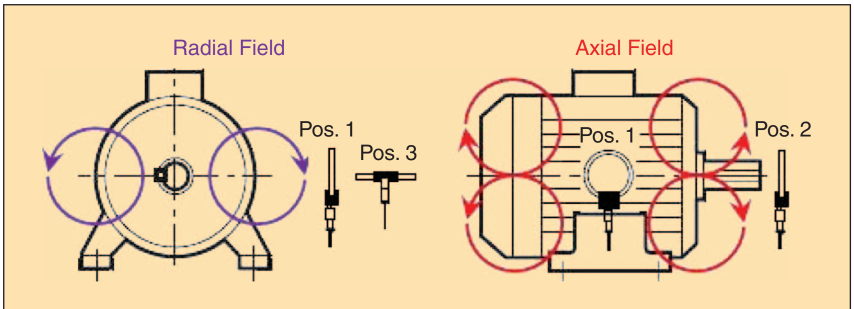

FIGURE 5 – The stray flux sensor in different measurement positions [38].

Fault Diagnosis by Stray Flux Analysis

Techniques based on vibrations or current signature analysis are widely used for electrical machine diagnosis because these variables are directly tied to both electrical or mechanical states of the electrical machine. However, Over the last few decades, methods based on the analysis of external magnetic fields have been developed [32]–[35]. Their main advantages are the noninvasive investigation and the simplicity in the implementation. The drawback of these methods is related to the difficulty of modeling the magnetic field, which strongly depends on the electromagnetic behavior of the stator yoke and the motor housing, which have important shielding effects. The determination of the external magnetic field requires the modeling of the internal sources and both ferromagnetic and conducting materials of the machine that have an influence on the external stray flux. The computation of such a problem can be made using a finite elements approach, but many simplifications are necessary, and the modeling requires much computational effort [36]. Another approach consists of adapting analytical solutions existing for simple geometries that lead to define attenuation coefficients, which can be easily combined with an analytical model of the electrical machine [37].

The external magnetic field can be studied by means of its axial and radial decompositions. In this approach, the axial field is in a plane that includes the machine axis. It is generated by currents in the stator end windings or rotor cage end rings. The radial field is located in a plane perpendicular to the machine axis; it is an image of the air gap flux density, which is attenuated by the stator magnetic circuit (package of laminations) and by the external machine frame. Both fields can be measured separately by a convenient sensor location. Figure 5 shows the different positions of a stray flux sensor derived from the presumed circulation of the field lines. It enables measuring of both axial (Pos. 2) and radial fields (Pos. 3). Indeed, in Pos. 3, the stray flux sensor is parallel with the longitudinal plane of the machine, and the linked flux of the sensor concerned by the axial field is equal to zero. In Pos. 1, the sensor measures the radial field and also a part of the axial field. The pure axial field measurement can be done in Pos. 2.

A stator interturn short-circuit fault produces an asymmetry in the air gap flux density and therefore in the external magnetic field. This asymmetry generates flux density components that clearly appear in the stray flux as it is not strongly attenuated by the stator iron. It can be pointed out that the sensitivity of the external magnetic field is higher than the line current as far as these spectral lines are concerned. It should also be noted that the lower part of the spectrum with frequency less than the slotting effect is not very sensitive to the fault [38].

It is well known that a broken bar in induction machines generates a negative sequence on the rotor fundamental air gap flux density. Both direct and indirect consequences are based on the appearance of spectral lines in the line current spectrum, which also appear in the stray flux. It can be shown that the eccentricity also has an influence on the phenomenon. It should be pointed out that this phenomenon is specific to the axial field and does not appear in the radial field or the line current [38].

Fault Diagnosis by the Park's Vector Approach

This section reviews recent advances in fault diagnosis by the Park's vector approach with special emphasis being given to the most recent developments concerning power converter fault diagnosis in variable-speed ac drives. With the aim of demonstrating the suitability of such an approach for power converters self-diagnostic, an experiment-based assessment of four algorithms intended for real-time diagnosis of switch open-circuit faults is presented.

The Park's vector approach has been used successfully for conditioning monitoring of electromechanical systems including three-phase power transformers, synchronous and induction machines, and power converters.

The Park's vector approach has been used successfully for conditioning monitoring of electromechanical systems including three-phase power transformers, synchronous and induction machines, and power converters. This technique allows for diagnosis of several types of malfunctions [39]–[43]. As main merits, this approach is noninvasive and requires inexpensive sensors and measurement systems. The first studies were based on the recognition of the pattern associated with the current Park's vector representation. For instance, the extended Park's vector approach relies on the spectral analysis of the ac level of the current Park's vector modulus, whereas through the average-current Park's vector approach, converter power switch faults are detected when the vector modulus is different from zero. However, load dependency and sensitivity to transients, which were major drawbacks in converter diagnosis, were finally overcome by the use of the Park's vector approach in recently proposed techniques [42], [43].

Concerning the power converter self-diagnosis based on the Park's vector approach, the modulus of Park's vector is used in [42] to normalize phase currents and the absolute value of the absolute Park's vector phase derivative is used in [43] as a detection variable. With further signal processing and additional variables, both techniques are able to diagnose multiple faults. The technique reported in [42] is called *errors of normalized currents average absolute values* (*ENCAAV*), and the technique reported in [43] is called *the current Park's vector phase and currents polarity* (*CPVPCP*). Both techniques

TABLE 1 – A FAULT DIAGNOSTIC METHODS KEY FEATURES EVALUATION.

		ENCAAV [42]	CPVPCP [43]	NCAV [44]	NRCE [45]
Localization capabilities (fault signatures)		15	27	27	27
Effectiveness		High	High	High	High
Robustness (robustness factor)		0.76	1.00	0.23	0.94
Detection speed (% currents period)	Min	11.3	37.8	25.9	4.8
	Max	77.3	92.4	88.6	66.5
	Avg	39.6	71.2	58.3	28.7
Implementation effort (file size in kB)		64.9	73.1	74.7	63.4
Computational burden (execution time in μs)		3.40	4.25	4.89	3.37
Tuning effort (parameters number)		2	4	3	3

The CPVPCP method is endowed with a remarkable robustness against false alarms as a consequence of load and speed transients.

fulfil the major requirements for integration into the drive controller for real-time diagnosis such as the lack of need for extra hardware, simple implementation, operating condition independence, and low computational demand. With identical features, two other distinct techniques have been proposed, the normalized currents average values [44] and the normalized reference current errors (NRCEs) [45].

A comparison of the four aforementioned techniques [42]–[45] constitutes a valuable contribution for assessing their applicability to a specific drive system. The four methods have been integrated into a digital controller of a permanent magnet synchronous motor drive, and the experimental results obtained have been used to evaluate their performances. In summary, the most relevant information from the performance comparison is shown in Table 1. All methods demonstrate very high diagnostic effectiveness even for low load levels. The CPVPCP method is endowed with a remarkable robustness against false alarms as a consequence of load and speed transients. The fastest detection can be achieved by using the NRCE method. The NRCE and ENCAAV methods are the less computational demanding methods. Finally, the ENCAAV method involves the lowest tuning effort.

Diagnosis Under Nonstationary Conditions

An electrical machine works under nonstationary conditions when its normal duty cycle consists of continuous and random load fluctuations and/or changes in supply conditions (Figure 6). Wind generation, electrical vehicles, or any other industrial processes involving variable speed drives, are examples of actual applications in which electrical machines work under nonstationary conditions. Traditional approaches based on stationary analysis, such as the MCSA, usually lead to unsatisfactory results when they are applied under such conditions. On the other hand,

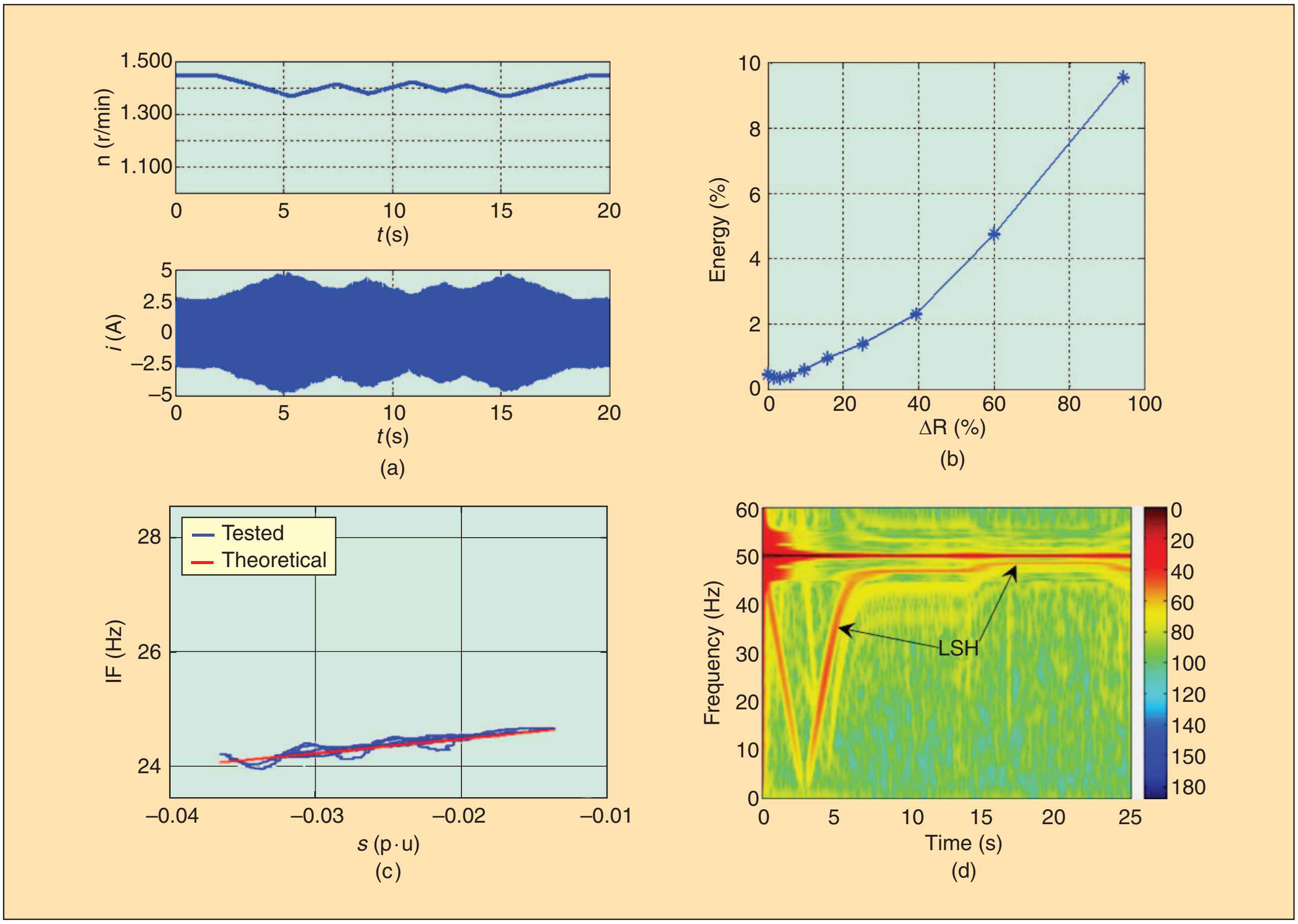

FIGURE 6 – Diagnosis under nonstationary conditions: (a) fluctuating speed and current, (b) increase of energy in the frequency bandwidth (0 Hz, 39 Hz) in case of stator phase asymmetries, (c) diagnosis in the slip-frequency domain of a cage machine with mixed eccentricity, and (d) diagnosis of a bar breakage in time-frequency domain through an adaptive transform [51].

more recent approaches based on transient analysis, which are usually focused on start-up, cannot be applied to diagnose under nonstationary conditions. Therefore, new diagnostic methodologies have been developed. A summary of recently proposed methods for performing diagnostics in nonstationary conditions is described:

- *Frequency domain approaches*: When speed oscillations are small, Fourier analysis can be applied provided great accuracy in diagnosis is not needed. The unavoidable smearing effect in the spectrum could be limited, shortening the time of capturing the signal, to reduce the slip changes. This leads to bad-quality spectra with low-frequency resolution and high spectral leakage. To solve this conflict, methodologies based on the estimation of signal parameters via the rotational invariance technique have been proposed [46].
- *Time domain analysis*: Under nonstationary conditions, different failures introduce fault components into analyzed signals with both magnitude and frequency changing with time in an unpredictable way since the rotational speed varies randomly. Consequently, there are no specific fault-related patterns in the time domain that support the diagnosis. Nevertheless, the appearance of components related to the fault whose related frequency changes in a limited interval produces increases of energy in the signal within this frequency range [Figure 6(b)] [47]–[49]. Proposed to diagnose and quantify faults through the computation of the signal energy in specific frequency bands, the DWT has been used as a filtering tool for extracting frequency bands of interest and then computing the signal energy into them.
- *Diagnosis in the slip-frequency domain*: This kind of analysis is complementary to time domain approaches since it allows for characterizing the faults components under nonstationary conditions with high reliability. This analysis is based on the description of the instantaneous frequency of an extracted fault component against slip. It is easy to demonstrate [49] that this plot is a straight line with a specific slope and an offset for every kind of fault. This fact allows for identifying faults and discriminating them from other phenomena as both load and voltage fluctuations or noises that can increase the signal energy. The analysis in the slip-frequency domain has been successfully applied to the diagnosis of rotor and stator asymmetries [49] as well as eccentricities in induction machines [50]. An example of this kind of analysis is shown in Figure 6(c).
- *Diagnosis in the time-frequency domain*: This kind of analysis can be performed through different continuous transforms such as STFT, CWT, WVD, Choi–Williams distribution (CWD), and Zhao–Atlas–Marks distribution. The standard result of these transforms is a three-dimensional graph usually plotted as a two-dimensional colored map. For each time, this map informs about how the signal energy is distributed among different frequencies. This enables tracking of the evolution of fault components during transients and nonstationary operating conditions. A recent improvement in the field of linear transforms has been proposed in [51], where an adaptive transform is introduced taking into account the characteristics of the presumed fault component in each point [Figure 6(d)]. Regarding quadratic transforms, in [52], a method based on a pretreatment of the diagnosis signal through optimized notch filters is proposed for reducing cross terms but avoiding the use of kernels, keeping the characteristic high resolution of the WVD unaltered.

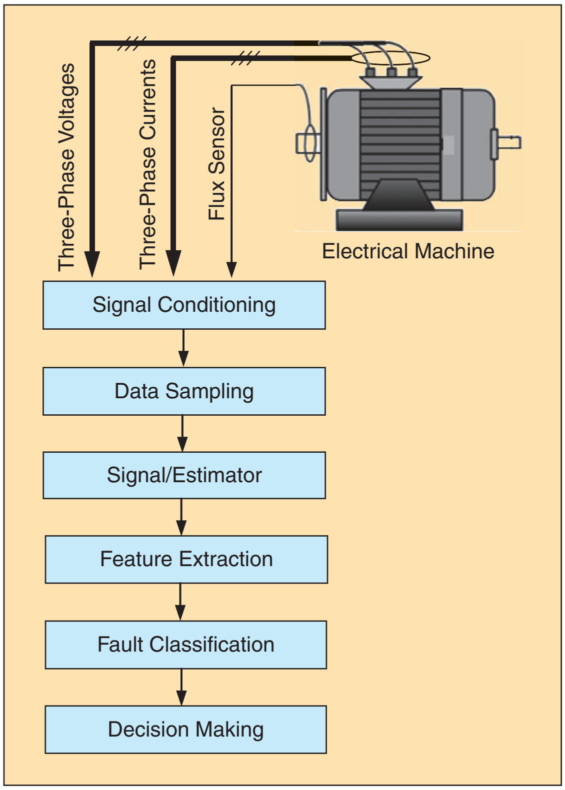

FIGURE 7 – A general implementation scheme for noninvasive electrical machines fault diagnosis [53].

Fault Diagnosis and Efficient DSPTs

The early detection of incipient faults with minimum required measurements is the main purpose of an ideal diagnosis. In this sense, noninvasive techniques are good candidates because they do not require any change in the system design. A general scheme of noninvasive electrical machine fault diagnosis is shown in Figure 7. It consists of an initial stage for signal conditioning to enhance the signal-to-noise ratio (SNR) and avoid aliasing. In the second stage, the data sampling converts the analog signal into a discrete one. These two parts are integrated in one module in modern data acquisition systems. Sampled three-phase voltages and currents can be used directly or for estimation/observation of other quantities such as mechanical speed and electromechanical torque. To cover a large number of faults, different features should be extracted from a signal or its estimation/observation to allow for accurate fault classifications. A reliable decision-making procedure is important at the final stage to avoid missing or false alarms.

Classical DSPTs such as the discrete Fourier transform, which is known to be an efficient algorithm in terms of computation time, have been used for feature extraction for a long time [54]. Any type of fault in electrical machines may yield to asymmetries in its electromagnetic field, adding characteristic fault frequencies to any initial sensor signal and depending on the type of fault. This can be well explored by means of frequency domain analysis. Despite their effectiveness, the classical DSPTs have several limitations to be evaluated for a reliable fault diagnosis. The main restriction is the practical use of classical techniques on real signals because of additional noises, which are always present in any industrial environment. This may result in an erroneous decision-making process. The study of advanced DSPTs plays a crucial role, as it can be used to enhance SNR and, consequently, improve extraction performance. By handling time-varying conditions, this leads to more consistent fault-detection techniques. Furthermore, thanks to recent advances in digital signal processing technology, adequate DSPTs can be implemented on cost-effective real-time platforms. Advanced DSPTs, which have been recently proposed for improving the performance of fault diagnosis in induction machines for feature extraction (Figure 7), can be classified into three different categories [53]: 1) frequency domain analysis, 2) time-frequency/time-scale domain analysis, and 3) time domain analysis.

In the frequency domain, the frequency resolution is an important factor, since any accurate frequency tracking in a spectrum is essential for a consistent diagnosis, as the fault-related frequency components in electrical signatures are commonly load dependent. The modern DSPTs, which are used for improving the frequency resolution of the spectrum, are classified into nonparametric, parametric, and subspace techniques. It is shown that the application of subspace methods can significantly improve the performance of fault diagnosis in induction machines in the frequency domain, in comparison with nonparametric and parametric methods, because of their ability to estimate frequencies with high resolution using smaller sample measurement and reducing the noise influence [53].

Electrical machines working in nonstationary operating conditions have nonstationary voltage, current, vibration, and so on. A straightforward solution for processing a nonstationary signal is to represent it in the time-frequency plane. A well-known method, which has been widely used because of robustness and simplicity for electrical and mechanical fault detection in induction machines, is the windowed Fourier transform (WFT). Quadratic time-frequency analysis techniques are efficient alternatives to the WFT because of their independence from the type and size of the window function. The WVD and its variants, particularly the pseudo-WVD (PWVD) and the smoothed pseudo-WVD (SPWVD), have been used for mechanical fault detection in electrical machines. The WVD produces large undesirable frequencies, the so-called inner interference terms, which can interfere with fault-related frequency components by decreasing the ability to evaluate fault severity. The PWVD and SPWVD methods attempt to reduce the magnitude of inner interference terms by smoothing in both the time and frequency planes. To achieve a strong reduction of inner interference terms in addition to high-frequency resolution, the CWD and the Zhao–Atlas–Marks technique have been applied. Another concept extensively used for electrical machine diagnosis is the wavelet transform (WT). The fundamental idea is to replace the frequency shifting operation, which occurs in the WFT by a time-scaling operation. This makes the WT a time-scale representation rather than a time-frequency one. This method has been applied to the stator current of induction machines during plugging and removal of the grid connection modes of operation to extract a general pattern for fault characteristic frequencies [53].

The AI methods can help during fault classification and decision-making procedures after feature extraction of a signal or its estimation/observation (Figure 7). In the initial stage of any classification procedure, the feature reduction process is essential to keep only most significant features. A typical method of feature reduction is principal component analysis. Fault classification using reduced features space is a common task in machine learning, which can be either supervised or unsupervised. The label of all objects and the number of classes are known in a supervised classification, whereas they are unknown in an unsupervised classification. The clustering methods based on *k*-means and hierarchical techniques are known as *unsupervised classification.* The self-organizing map is a neural network model that uses unsupervised learning algorithms. At the final stage, expert systems can perform the decision-making process since they can emulate human expertise by building online updating of system knowledge bases. The application of AI tools in condition monitoring and fault diagnosis of electrical machines is a great help in the automation of the diagnosis process, which results in both early and accurate fault detection [55], [56].

Conclusions

Although condition monitoring of electrical machines was initially dedicated to purely internal electrical and mechanical fault detection, today, it covers monitoring in voltage source inverters, load, and some other elements of mechanical transmission systems as well. The first techniques have been implemented to be applied on stationary conditions of electrical machine drives using the FFT to localize the frequency components associated to different faults. This conventional technique is still used as a first diagnostic approach, but the real conditions of industrial applications are such that it cannot be the only support for the development of diagnosis tools. New techniques based on the assessment of physical phenomena produced by fault conditions, advanced digital signal processing, and reliable decision-making procedures show the state of the art of recent methodologies for the efficient condition monitoring of electrical machines. However, the reliable identification and isolation of faults is still under investigation, and there are several open issues. Among them, the insensitivity to operating conditions, fault detection for drives in time-varying conditions, evaluation of fault severity, and fault-tolerant control for drives have recently been under focus.

Acknowledgments

We would like to thank the following individuals who participated in the writing of this article: José Antonino-Daviu, Alberto Bellini, Jean-François Brudny, José Manuel Cano, Vicente Climente-Alarcon, Nuno Freire, Jean-Philippe Lecointe, Joan Pons-Llinares, Antonio Marques-Cardoso, Manuel Garcia-Melero, Joaquin Norniella, Gonzalo Orcajo, Francisco Pedrayes, Juan Perez-Cruz, Manuel Pineda-Sanchez, Ruben Puche-Panadero, José Roger-Folch, Carlos Hiram-Rojas, Raphaël Romary, and Francisco Vedreño-Santos.

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