A Review of Induction Motors Signature Analysis as a Medium for Faults Detection

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***Abstract*—This paper is intended as a tutorial overview of induction motors signature analysis as a medium for fault detection. The purpose is to introduce in a concise manner the fundamental theory, main results, and practical applications of motor signature analysis for the detection and the localization of abnormal electrical and mechanical conditions that indicate, or may lead to, a failure of induction motors. The paper is focused on the so-called motor current signature analysis which utilizes the results of spectral analysis of the stator current. The paper is purposefully written without "state-of-the-art" terminology for the benefit of practicing engineers in facilities today who may not be familiar with signal processing.**

***Index Terms*—Fault detection, induction motor, motor current signature analysis.**

I. Introduction

INDUCTION MOTORS are a critical component of many industrial processes and are frequently integrated in commercially available equipment and industrial processes. Motor-driven equipment often provide core capabilities essential to business success and to safety of equipment and personnel. 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. Critical induction motor applications are found in all industries and include all motor horsepowers. It have been found that many of the commercial products to monitor induction motors are not cost effective when deployed on typical low- to medium-horsepower induction motors. Advances in sensors, algorithms, and architectures should provide the necessary technologies for effective incipient failure detection [1], [2].

In this context, a variety of sensors could be used to collect measurements from an induction motor for the purpose of failure monitoring. These sensors might measure stator voltages and currents, air-gap and external magnetic flux densities, rotor position and speed, output torque, internal and external temperature, case vibrations, etc. In addition, a failure monitoring system could monitor a variety of motor failures. These failures might include conductor shorts and opens, bearing failures, cooling failures, etc. It is apparent then that a failure monitoring system should be capable of extracting, in a consistent manner, the evidence of many possible failures from measurements from many physically different sensors [3]–[6].

In general, condition monitoring schemes have concentrated on sensing specific failures modes in one of three induction motor components: the stator, the rotor, or the bearings. Even though thermal and vibration monitoring have been utilized for decades, most of the recent research has been directed toward electrical monitoring of the motor with emphasis on inspecting the stator current of the motor. In particular, a large amount of research has been directed toward using the stator current spectrum to sense rotor faults associated with broken rotor bars and mechanical unbalance [7]–[18].

All of the presently available techniques require the user to have some degree of expertise in order to distinguish a normal operating condition from a potential failure mode. This is because the monitored spectral components (either vibration or current) can result from a number of sources, including those related to normal operating conditions. This requirement is even more acute when analyzing the current spectrum of an induction motor since a multitude of harmonics exist due to both the design and construction of the motor and the variation in the load torque. However, variations in the load torque which are not related to the health of the motor typically have exactly the same effect on the load current. Therefore, systems to eliminate induction motors arbitrary load effects in current-based monitoring have been proposed [19], [20].

Condition monitoring of the dynamic performance of electrical drives received considerable attention in recent years. Many condition monitoring methods have been proposed for different type of rotating machine faults detection and localization [21]–[26]. In fact, large electromachine systems are often equipped with mechanical sensors, primarily vibration sensors based on proximity probes. Those, however, are delicate and expensive. Moreover, in many situations, vibration monitoring methods are utilized to detect the presence of incipient failure. However, it has been suggested that stator current monitoring can provide the same indications without requiring access to the motor. This technique utilizes results of spectral analysis of the stator current (precisely, the supply current) of an induction motor to spot an existing or incipient failure of the motor or the drive system [27]–[34].

II. Faults Effect on Stator Current Spectrum

A. Air-Gap Eccentricity

Two methods have been proposed for the detection of an air-gap eccentricity. The first monitors the behavior of the cur-

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rent at the sidebands of the slot frequencies [9]. The sideband frequencies associated with an eccentricity are

$$f_{\mathrm{slot+ecc}} = f_s\left[(kR \pm n_d)\left(\frac{1-s}{p}\right) \pm n_\omega\right] \tag{1}$$

where

f_s electrical supply frequency;
k $= 1, 2, 3, \cdots$;
R rotor slots number;
n_d rotating eccentricity order;
s per-unit slip;
p number of pole pairs;
n_ω stator MMF harmonic order.

While this scheme has the advantage of separating the spectral components produced by an air-gap eccentricity from those caused by broken rotor bars, it has the disadvantage that it requires an intimate knowledge of the machine construction, i.e., the rotor slots number.

The second method monitors the behavior of the current at the fundamental sidebands of the supply frequency [5]. These frequencies of interest are given by

$$f_{\mathrm{ecc}} = f_s\left[1 \pm m\left(\frac{1-s}{p}\right)\right] \tag{2}$$

where $m = 1, 2, 3, \cdots$. This scheme provides the advantage of not requiring any knowledge of the machine construction.

B. Broken Rotor Bars

Broken rotor bars are detected by monitoring the motor current spectral components produced by the magnetic field anomaly of the broken bars [5], [32]. The broken rotor bar frequencies are given by

$$f_{\mathrm{brb}} = f_s\left[k\left(\frac{1-s}{p}\right) \pm s\right] \tag{3}$$

where, due to the normal winding configuration, $k/p = 1, 5, 7, 11, 13, \cdots$.

Even though the predicted frequencies are the same for both air-gap eccentricity (2) and broken rotor bars (3) the frequency corresponding to a particular harmonic number is different, allowing the two faults to be distinguished. The amplitude of the left sideband frequency component is proportional to the amount of broken rotor bars [35]. In fact, the amplitude I_{brb} of frequency component $f_s(1-2s)$ can be evaluated by [36]

$$\frac{I_{\mathrm{brb}}}{I_s} \cong \frac{\sin\alpha}{2p(2\pi-\alpha)} \tag{4}$$

where I_s is the stator current fundamental frequency component

$$\alpha = \frac{2\pi R_b p}{R}.$$

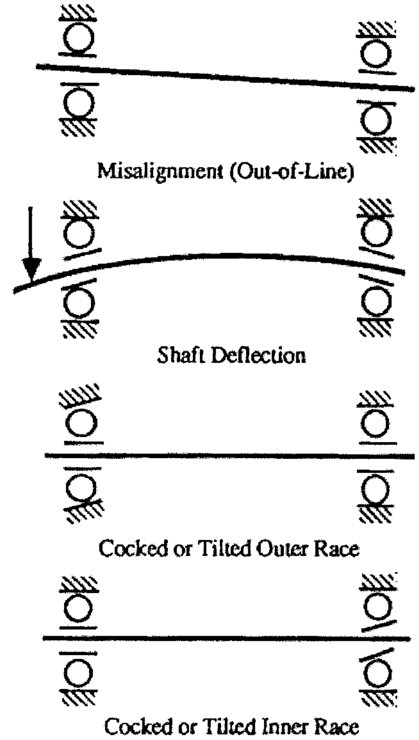


Fig. 1. Four types of rolling-element bearing misalignment [12].

R_b is the number of broken bars. With analyzing the stator current, it is just possible to evaluate the general condition of the rotor. If there are broken bars in various parts of the rotor, the current analysis is not capable of providing information on the configuration of noncontiguous broken bars. For example, the frequency component $f_s(1-2s)$ does not exist if broken bars are electrically $\pi/2$ radians away from each other. It should be noted that some experimental studies have demonstrated that both skewing and noninsulation of rotor bars lead to reduce the broken rotor bars harmonic components. Moreover, it seems that when the amplitude of these harmonics is over 50 dB smaller than the fundamental frequency component amplitude, the rotor should be considered healthy [36].

The right sideband component $f_s(1+2s)$ could also be used in monitoring fault severity. Its importance is clearly demonstrated in [37], [38].

C. Bearings Damage

Installation problems are often caused by improperly forcing the bearing onto the shaft or in the housing. This produces physical damage in the form of brinelling or false brinelling of the raceways which leads to premature failure. Misalignment of the bearing, which occurs in the four ways depicted in Fig. 1, is also a common results of defective bearing installation. The relationship of the bearing vibration to the stator current spectra can be determined by remembering that any air-gap eccentricity produces anomalies in the air-gap flux density. Since ball bearings support the rotor, any bearing defect will produce a radial motion between the rotor and stator of the machine. The mechanical displacement resulting from damaged bearing causes the machine air gap to vary in a manner that can be described

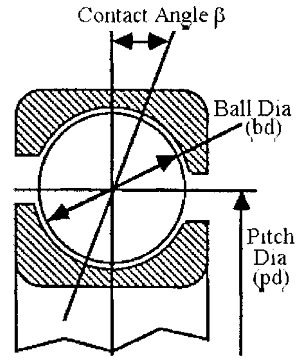


Fig. 2. Ball bearing dimensions.

by a combination of rotating eccentricities moving in both directions. As with the air-gap eccentricity, these variations generate stator currents at frequencies given by

$$f_{\mathrm{bng}} = |f_s \pm m\, f_{i,o}| \tag{5}$$

where $m = 1, 2, 3, \cdots$ and $f_{i,o}$ is one of the characteristic vibration frequencies which are based upon the bearing dimensions shown in Fig. 2

$$f_{i,o} = \frac{n}{2}\, f_r \left[1 \pm \frac{bd}{pd} \cos\beta\right] \tag{6}$$

where

- n number of bearing balls;
- f_r mechanical rotor speed in hertz;
- bd ball diameter;
- pd bearing pitch diameter;
- β contact angle of the balls on the races [12].

It should be noted from (6) that specific information concerning the bearing construction is required to calculate the exact characteristic frequencies. However, these characteristic race frequencies can be approximated for most bearings with between six and twelve balls [39]

$$\begin{cases} f_o = 0.4 n f_r \\ f_i = 0.6 n f_r. \end{cases} \tag{7}$$

This generalization allows for the definition of frequency bands where the bearing race frequencies are likely to show up without requiring explicit knowledge of the bearing construction.

D. Load Effects

If the load torque does vary with rotor position, the current will contain spectral components which coincide with those caused by a fault condition. In an ideal machine where the stator flux linkage is purely sinusoidal, any oscillation in the load torque at a multiple of the rotational speed mf_r will produce stator currents at frequencies of [19]

$$f_{\mathrm{load}} = f_s \pm m f_r = f_s \left[1 \pm m\left(\frac{1-s}{p}\right)\right] \tag{8}$$

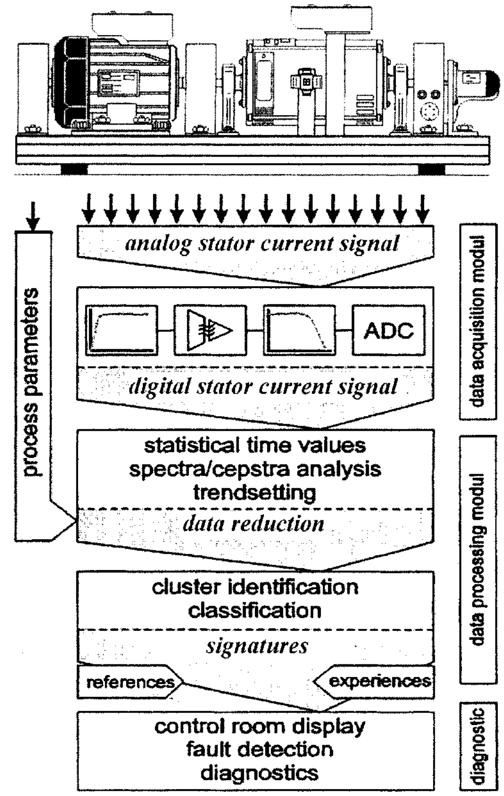


Fig. 3. Basic stator current monitoring system configuration.

where $m = 1, 2, 3, \cdots$. Since the same frequencies are given by (2) and (3), it is clear that when the induction machine operates with a typical time-varying load, the torque oscillation results in stator currents that can obscure, and often overwhelm, those produced by the fault condition. Therefore, any stator current single phase spectrum based fault detection scheme must rely on monitoring those spectral components which are not affected by the load torque oscillations. However, broken bars detection is still possible since the current typically contains higher order harmonics than those induced by the load [10].

III. Faults Detection Techniques

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.

In many situations, vibration monitoring methods were utilized for incipient fault detection. However, stator current monitoring was found to provide the same indication without requiring access to the motor [5], [10]. A basic stator current monitoring system configuration is illustrated by Fig. 3. In what

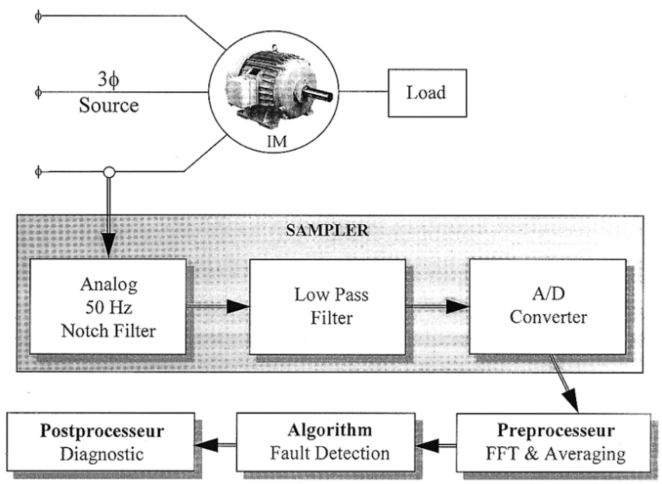


Fig. 4. Single-phase stator current monitoring scheme.

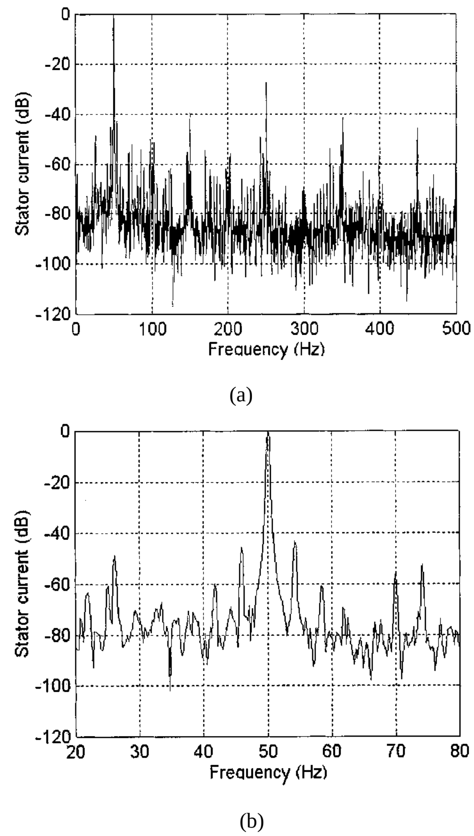


Fig. 5. Stator current power spectra of supposedly healthy motor [6]. (b) Power spectra around 50 Hz.

follows, some of the main stator-current- signature-based techniques are presented.

A. Classical Fast Fourier Transform (FFT)

For this method, the stator current monitoring system contains the four following processing sections shown in Fig. 4.

1) *Sampler*: Its purpose is to monitor a single-phase stator current. This is accomplished by removing the 50-Hz excitation component through low-pass filtering, and sampling the resulting signal. The single-phase current is sensed by a current transformer and sent to a 50-Hz notch filter where the fundamental component is reduced. The analog signal is then amplified and low-pass filtered. The filtering removes the undesirable high-frequency components that produce aliasing of the sampled signal while the amplification maximizes the use of the analog-to-digital (A/D) converter input range. The A/D converter samples the filtered current signal at a predetermined sampling rate that is an integer multiple of 50 Hz. This is continued over a sampling period that is sufficient to achieve the required FFT.
2) *Preprocessor*: It converts the sampled signal to the frequency domain using an FFT algorithm. The generated spectrum includes only the magnitude information about each frequency component.

   Signal noise that is present in the calculated spectrum is reduced by averaging a predetermined number of generated spectra. This can be accomplished by using either spectra calculated from multiple sample sets or spectra computed from multiple predetermined sections (or windows) of a single large sample set. Because of the frequency range of interest and the desired frequency resolution, several thousand frequency components are generated by the processing section.
3) *Fault Detection Algorithm*: In order to reduce the large amount of spectral information to a usable level, an algorithm, in fact a frequency filter, eliminates those components that provide no useful failure information. The algorithm keeps only those components that are of particular interest because they specify characteristic frequencies in the current spectrum that are known to be coupled to particular motor faults. Since the slip is not constant during normal operation, some of these components are bands in the spectrum where the width is determined by the maximum variation in the motor slip.
4) *Postprocessor*: Since a fault is not a spurious event but continues to degrade the motor, the postprocessor diagnoses the frequency components and then classifies them (for each specified fault).
5) *Discussion*: 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 as illustrated by Fig. 5 [6], [40].

B. Instantaneous Power FFT

In this case, in place of the stator current, the instantaneous power is used as a medium for the motor signature analysis oriented toward mechanical faults detection in a drive system [41]–[43]. It was shown that 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. In fact, besides the fundamental and the two classical sideband components, the instantaneous power spec-

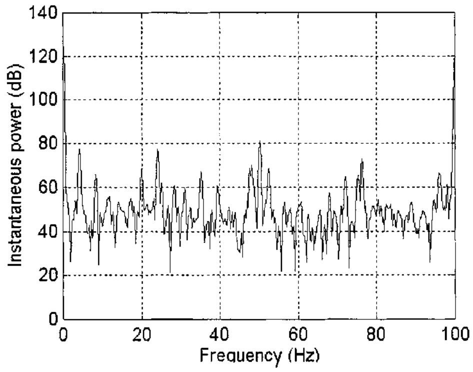


Fig. 6. Power spectrum of the instantaneous power [40].

trum contains an additional component directly at the modulation frequency as shown by the following:

$$\begin{aligned} p(t) =& p_0(t) + \frac{MV_{LL}I_L}{2} \left\{ \cos\left[(2\omega + \omega_{\rm osc})t - \varphi - \frac{\pi}{6}\right] \right. \\ &+ \cos\left[(2\omega - \omega_{\rm osc})t - \varphi - \frac{\pi}{6}\right] \\ &\left. + 2\cos\left(\varphi + \frac{\pi}{6}\right)\cos(\omega_{\rm osc}t)\right\} \end{aligned} \tag{9}$$

where

- p instantaneous power;
- M modulation index;
- V_{LL} rms value of the line-to-line voltage;
- I_L that of the line current, while ω and ϕ denote the supply radian frequency and motor load angle, respectively;
- $\omega_{\rm osc}$ radian oscillation frequency.

As illustration, Fig. 6 shows clearly the differences with Fig. 5(b). In fact, all the fault harmonics are translated into the frequency band 0–100 Hz. This constitutes a great advantage because the fault harmonics domain is well bounded. However, the power spectra are still noisy, so as instantaneous power FFT, at this stage, does not bring important improvement. Therefore, the stator current should be maintained as the main medium for the motor signature analysis.

C. Bispectrum

Bispectrum, also called third-order spectrum, emerges from higher order statistics. The bispectrum is defined in term of the two-dimensional Fourier transform of the third-order moment sequence of a process [13]–[16].

1) *Definition*: The fundamental definition of the bispectrum and its evaluation from the sampled signals are illustrated by the simplified flow diagram shown in Fig. 7(a) [14], where $\{x(k)\}$ is a sequence of a random signal with zero mean, k is a time index, and τ_1 and τ_2 are lag variables.

It is clear from (11) (see Fig. 7) that the bispectrum is periodic with a period of 2π, and preserves both the magnitude and phase information. It is then 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 [16].

2) *Some Results*: Very promising results were obtained, as illustrated by Fig. 7(b) and (c). In fact, experimental results indicate that the bispectrum magnitude of the dominant component, caused by the machine rotation, increased with the fault level increase. These results clearly indicate that stator current bispectrum is capable of providing adequate and essential spectral information for induction motors condition monitoring and faults detection. 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 [44].

D. High-Resolution Spectral Analysis

The classical spectral estimation techniques which have been used are among the most robust ones, allowing computationally efficient algorithms like the FFT. However, a main disadvantage of the classical spectral estimation is the impact of side lobe leakage due to the inherent windowing of finite data sets. Window weighting allows us to mitigate the effect of side lobes at the expense of decreasing the spectral resolution which can be no better than the inverse of acquisition time (i.e., 1/4.096 s ≈ 0.25 Hz).

In order to improve the statistical stability of the spectral estimate, i.e., to minimize the estimate variance, pseudo ensemble averaging by segmenting the data was introduced at the price of further decreasing the resolution. Therefore, tradeoffs among stability, resolution, and leakage suppression are necessary.

A class of spectral techniques based on an eigenanalysis of the autocorrelation matrix has been promoted in the digital signal processing research literature. They may improve or maintain high resolution without sacrificing as much stability, allowing us to keep only the principal spectral components of the signal and to decrease noise influence.

1) *Eigenanalysis-Based Frequency Estimators*: The principle of these estimators is briefly reviewed in the following. The data are assumed to consist of L pure sinusoids in white noise, a suitable model for the stator current

$$d(n) = \sum_{k=1}^{L} A_k \exp(j2\Pi f_k n + \phi_k) + e(n) \tag{12}$$

where

- $d(n)$ data;
- $e(n)$ additive complex white noise sample of variance σ^2;
- $A_k,\ f_k,\ \phi_k$ amplitude, frequency, and phase of the kth sinusoid, respectively.

These frequency estimation techniques are based on an eigenanalysis which divides the information in the autocorrelation matrix R_M, where M is the matrix order, into two vector subspaces, one a signal subspace and the other a noise subspace. The M eigenvalues are $\{\lambda_1+\sigma^2,\ \lambda_2+\sigma^2,\ \cdots,\ \lambda_L+\sigma^2,\ \sigma^2,\ \cdots,\ \sigma^2\}$.

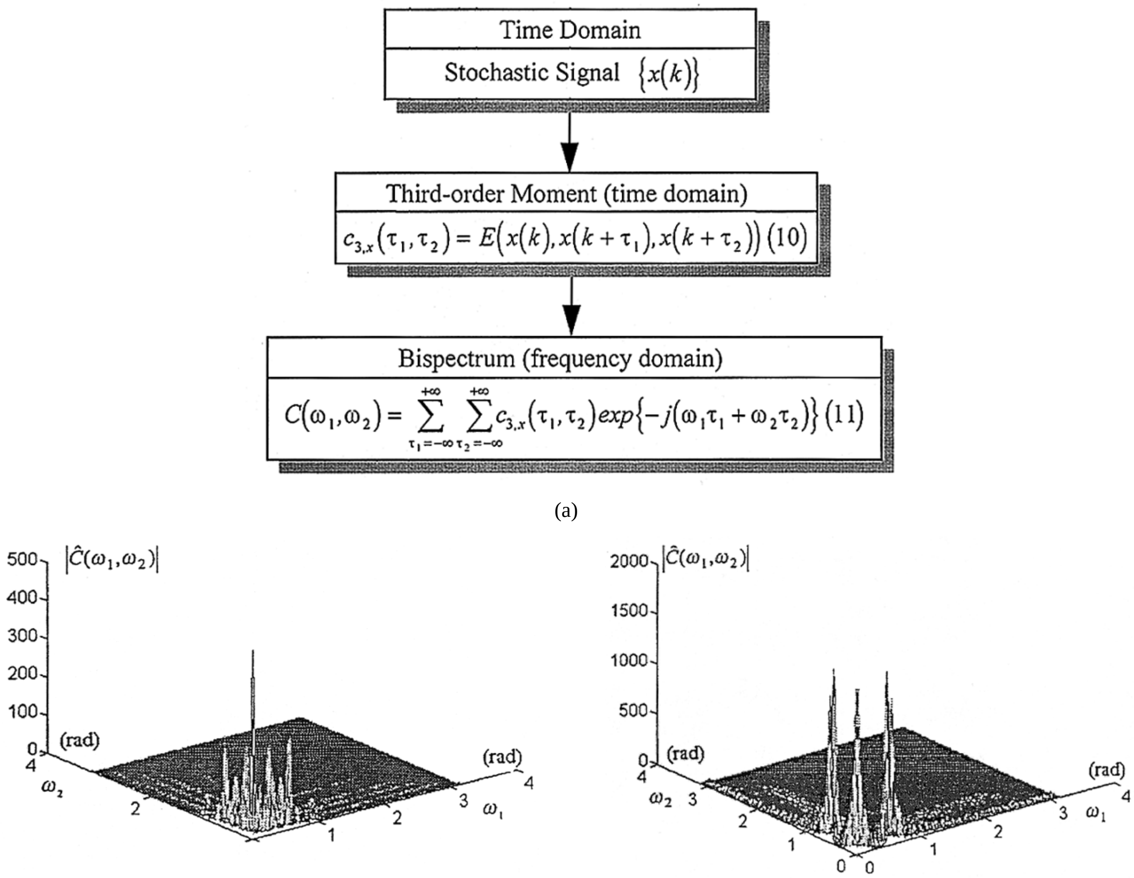


Fig. 7. Bispectrum [16]. (a) Bispectrum evaluation from the discrete time-domain signal. (b) Reference condition (healthy machine). (c) Stator winding faults condition.

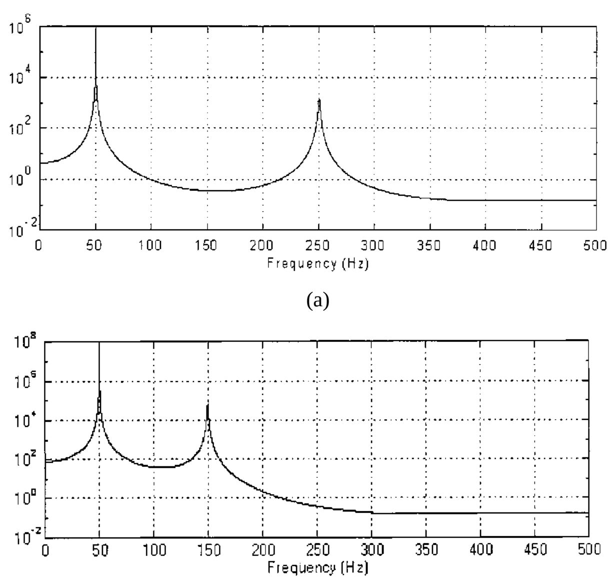
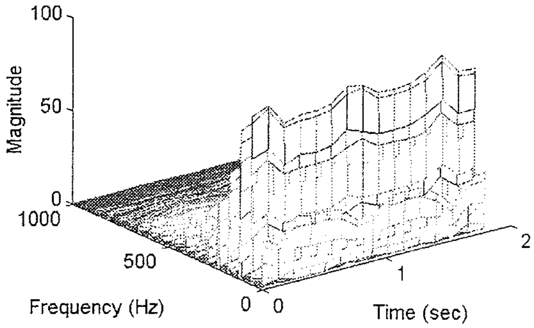


Fig. 8. Music frequency estimate [44]. (a) Healty machine. (b) Stator voltage unbalance.

2) *Some Results*: As illustration, two well-known eigenanalysis-based frequency estimators have been used: multiple signal classification (MUSIC) and ROOT-MUSIC for stator voltage unbalance underscoring [44]. In this case, one of the principal spectral components modified by the electric fault is the supply frequency third harmonic (i.e., 150 Hz), whose amplitude increases in a significant way, whatever the load. The two principal spectral components of the stator current spectrum are the first and the fifth harmonics (50–250 Hz) for a healthy motor, and the first and third harmonics (50–150 Hz) for a stator voltage unbalance. The MUSIC algorithm has been applied for each case and results are given in Fig. 8. With regard to these results, MUSIC and ROOT-MUSIC methods allow us to keep only the main frequencies without other spectral information. Moreover, stator current high-resolution spectral analysis, used as a medium for induction motors faults detection, will be useful in all faults modifying main spectral components.

E. Wavelet Analysis

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), or windowing



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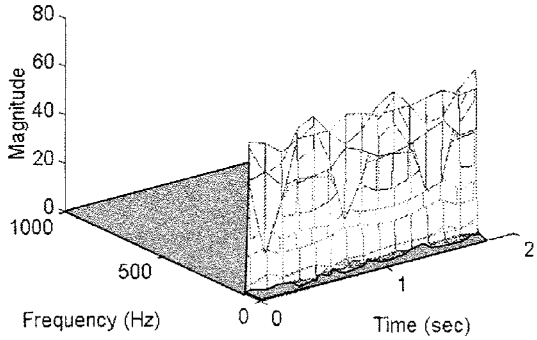


(b)

Fig. 9. Misalignment detection using STFT and the wavelet technique [45]. (a) STFT. (b) STFT and wavelet technique.

technique. The adaptation maps a signal into a two-dimensional function of time and frequency. The STFT represents a sort of compromise between time- and frequency-based views of a signal and it provides some information about both. However, we can only obtain this information with limited precision, and that precision is determined by the size of the window. The fixed size of the window is the main drawback of the STFT [45]. The wavelet transform was then introduced with the idea of overcoming the difficulties mentioned above. A windowing technique with variable-size region is then used to perform the signal analysis, which can be the stator current. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. The ability to perform local analysis is one of the most interesting features of the wavelet transform [46].

The advantages of using wavelet techniques for fault monitoring and diagnosis of induction motors is increasing because these techniques allow us to perform stator current signal analysis during transients. The wavelet technique can be used for a localized analysis in the time-frequency or time-scale domain. It is then a powerful tool for condition monitoring and fault diagnosis. As illustration, Fig. 9 provides the result where STFT and the wavelet technique are combined. These results show the improvements introduced by the wavelet technique for the signal frequency monitoring [47].

F. Techniques to be Associated to Motor Current Signature Analysis (MCSA)

In what follows, techniques which can be associated to the MCSA will be briefly presented.

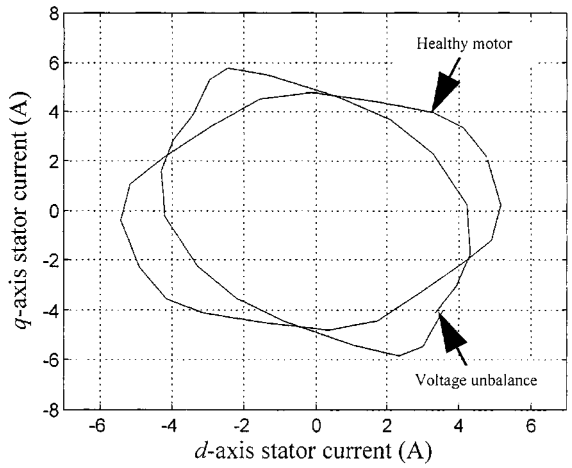


Fig. 10. Stator current Park's vector pattern [48].

1) *Park's Vector Approach*: A two-dimensional representation can be used for describing three-phase induction motor phenomena, a suitable one being based on the stator current Park's vector [18]. As a function of mains phase variables (i_a, i_b, i_c), the current Park's vector components (i_d, i_q) are

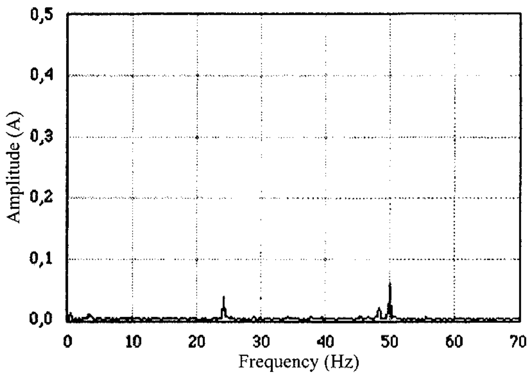
$$\begin{cases} i_d = \sqrt{\dfrac{2}{3}}\, i_a - \dfrac{1}{\sqrt{6}}\, i_b - \dfrac{1}{\sqrt{6}}\, i_c \\ i_q = \dfrac{1}{\sqrt{2}}\, i_b - \dfrac{1}{\sqrt{2}}\, i_c. \end{cases} \tag{13}$$

Under ideal conditions, three-phase currents lead to a Park's vector with the following components:

$$\begin{cases} i_d = \dfrac{\sqrt{6}}{2}\, i_M \, \sin \omega t \\ i_q = \dfrac{\sqrt{6}}{2}\, i_M \, \sin\left(\omega t - \dfrac{\pi}{2}\right) \end{cases} \tag{14}$$

where i_M is the supply phase current maximum value and ω_s is the supply frequency. Its representation is a circular pattern centered at the origin of the coordinates. This is a very simple reference figure, that allows the detection of faulty conditions by monitoring the deviations of the acquired patterns as illustrated by Fig. 10. The healthy pattern differs slightly from the expected circular one, because supply voltage is generally not exactly sinusoidal.

Recently, a new implementation of the Park's vector approach has been proposed [49]. In fact, under abnormal conditions, for example, in the presence of rotor cage faults, such as broken bars, (13) and (14) are no longer valid, because the induction motor supply current will contain sideband components, namely, at frequencies differing from the fundamental by the double slip frequency. These additional components at frequencies of $(1-2s)f_s$ and $(1+2s)f_s$ will also be present in both motor current Park's vector components (i_d, i_q). In these conditions, it can be shown that the spectrum of the stator current Park's vector modulus is the sum of a dc level, generated mainly by the fundamental component of the induction motor supply current, plus two additional terms, at frequencies



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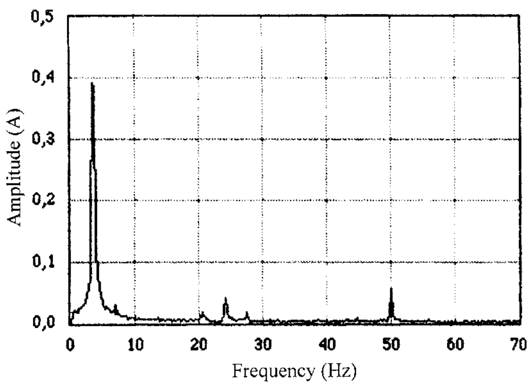
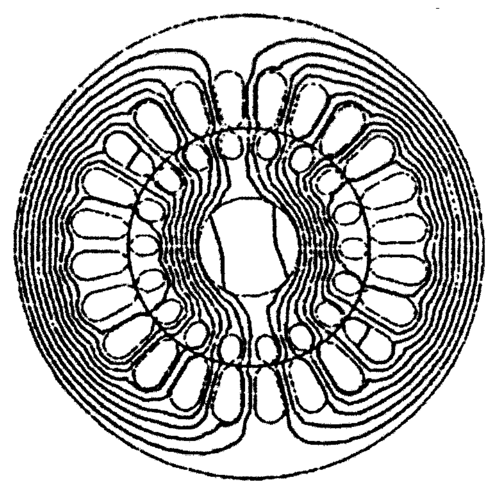


(b)

Fig. 11. Spectrum of the stator current Park's vector ac level [49]. (a) Healthy induction motor. (b) Four continguous broken rotor bars.

of $2sf_s$ and $4sf_s$. In this way, the spectrum of the stator current Park's vector modulus ac level is clear from any component at the fundamental supply frequency, making it more useful to detect the components directly related to the induction motor fault. This new implementation of the Park's vector approach is intended to eliminate some of the technical limitations of the conventional MCSA. In fact, Fig. 11(a) shows that, in the absence of faults, the behavior of the induction motor is mostly characterized by the absence of any relevant spectral component. Moreover, results obtained by the extended Park's vector approach are more discriminative than those obtained by the traditional FFT-based MCSA [Fig. 11(b)].

2) *Finite-Element Method*: The above-cited works were mainly developed from an experimental standpoint. However, accurate analysis of an induction motor under faulted conditions (particularly transient) is very difficult. Some works have then reported on the introduction of numerical methods to aid in understanding faults manifestation. Once known faults are accurately simulated, the technique can be used to predict how other, more difficult to identify, faults can be detected via MCSA [50]–[53]. The finite-element method, which is well established for induction motors modeling, could be used to provide an accurate evaluation of the magnetic field distribution inside the motor. Perturbation in this field distribution would indicate fault presence, e.g., a broken rotor bar, as illustrated by Fig. 12. Less common rotor faults, such as broken end rings and faults in double-cage designs could be investigated using a finite-element model. To asses the magnetic saturation effect on faults detection, the time-stepping finite-element method is recommended [52].



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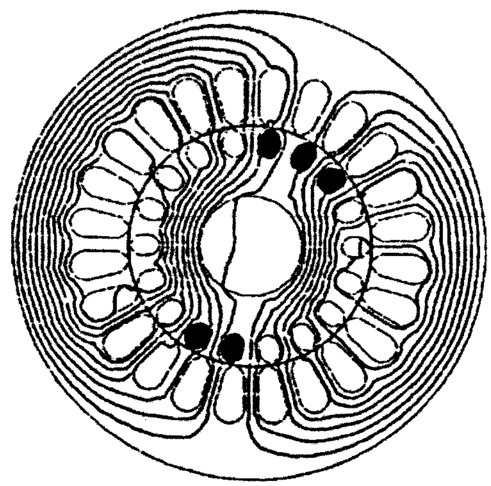

(b)

Fig. 12. Magnetic field distribution [51]. (a) Healthy rotor cage. (b) Five broken bars.

IV. Comments

A review of publications on MCSA, or diagnosis based on induction motors current passive analysis, reveals the ironic fact that there is an inverse relationship between the fault detection ease and the importance to the user of that fault detection. In fact, there are dozens of published papers on broken rotor bars and only two or three on the use of MCSA for bearing faults detection, in spite of several studies that show bearing faults to account for almost 50% of induction motor failures as opposed to around 10% for rotor cage problems [27]–[30], [54], [55].

V. Conclusion

This paper has attempted to review fundamentals, main results, and practical applications of the MCSA used for induction motors faults detection. It is hoped that this account will be of help to those who are interested in understanding the powerful capability of MCSA. The reference list is intended to contain all significant papers published to date. However, due to page limitations, the author would apologize to those whose papers are not included.

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