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Bearing Fault Detection in Induction Machine Using Squared Envelope Analysis of Stator Current

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Additional information is available at the end of the chapter

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Abstract

In this chapter, motor current signature analysis based on squared envelope spectrum is applied in order to identify and to estimate the severity of outer race bearing faults in induction machine. This methodology is based on conventional vibration analysis techniques, however, it is, non-invasive, low cost, and easier to implement. Bearing fault detection and identification in induction machines is of utmost importance in order to avoid unexpected breakdowns and even a catastrophic event. Thus, bearing fault characteristic components are extracted combining summation of phase currents, prewhitening, spectral kurtosis and squared envelope spectrum analysis. Experimental results with a 0.37 W, 60 Hz, and three-phase induction machine demonstrated the methodology effectiveness.

Keywords: bearing fault detection, induction machine, motor current signature analysis, squared envelope analysis, spectral kurtosis

1. Introduction

In an industrial scenario, three-phase induction machines have several applications due to their reliability, availability, and cost-effectiveness. Unexpected faults in these machines

could lead to unexpected breakdowns, losses at industrial production, or have catastrophic consequences. In this context, rolling element bearings are responsible for more than 40% of induction machine faults [1]. Rolling bearings are critical mechanical components, which allow relative movement between systems, supporting radial and thrust load. Bearing faults could be associated to contamination, corrosion, inadequate lubrication, installation problems, and misalignment or overloading [2]. In general, a fault affects only one bearing component—inner race, outer race, cage, or ball; as the fault evolves, it spreads to other components; moreover, these faults could be described based on fault mechanism, location, or on a combination of these [3, 4].

Maintenance of electrical machines is an activity of the utmost importance. Moreover, considering a scenario of cost reduction and production efficiency, the development of an effective maintenance program has been gaining more attention and several tools have been implemented to support and encourage best practices. In this sense, advanced methods for data acquisition and processing have been developed in order to allow an effective machine condition monitoring and early fault detection and identification, avoiding unexpected breakdowns and even catastrophic failures, especially for critical systems. Whenever possible, condition monitoring should be done non-invasively and without interrupting machine operation [5–7].

Over the years, the concept of maintenance became more comprehensive, reducing fault occurrence and increasing industrial system availability. Besides, requirements of reliability, safety, and criticality were associated with the system or equipment under analysis. Maintenance strategies or schemes can be classified as corrective (run-to-break), preventive (time-based) and predictive (condition-based maintenance) [8]. Corrective maintenance is only performed after an occurrence of a fault and therefore involves unexpected breakdowns, high costs, changes in the production chain, and in addition, it could lead to catastrophic events. Preventive maintenance and interventions occur based onto a scheduled maintenance plan or based on the equipment mean time between failures. Although it is more effective than corrective maintenance, by preventing most failures, unexpected failure may still occur. Additionally, the process cost is still high, especially, the costs associated with labor, inventory, and even with unnecessary replacement of equipment or components [8, 9].

On the other hand, predictive maintenance analyses the equipment condition so that a possible fault can still be identified at an early stage. Predictive maintenance aims to identify a machine anomaly so that it does not result in a fault. Such maintenance involves advanced technique of monitoring, processing, and signal analysis, that are generally performed non-invasively and, in many cases, in real time. In case of induction machines, these techniques can be developed based on vibration, temperature, acoustic emission, or electrical current signal monitoring [9]. It should be noted that the monitoring of such signals or parameters, in order to verify the operating condition of a machine, is called condition monitoring. In fact, condition monitoring aims to not only observe machine current operational condition, but also to predict machine future condition, keeping it under a systematic analysis during the machine's remaining life [8]. In this sense, from a systematic machine condition monitoring, a fault condition can be detected and identified, such that, a diagnosis procedure can be established, whereby properly investigating the fault symptoms and prognosis [10].

In general, the machine's monitored signals are the result of a combination of different sources, which can vary according to machine environmental and operational conditions, monitoring and acquisition systems, among others. Besides, some faults, such as bearing faults, can produce a signal modulation, which give rise to other signals (sidebands and harmonics) [8]. Thus, a great challenge in machine diagnosis consists of separating and identifying these sources. In case of bearing fault detection in induction machines, the motor current signature analysis (MCSA) has emerged as one of the leading condition monitoring techniques. This approach is an advantageous alternative (or complementary) to condition monitoring based on vibration analysis. Many machines already have current monitoring for control or protection purposes, not requiring the installation of other types of sensor, therefore, this approach can be considered non-invasive and cost-effective. Over the years, the spectral estimation using techniques based on Fourier transform has been widely applied for analysis of the stator current [11–13]. This analysis methodology considers the use of stationary signals, that is, considers that the machine is operating at constant speed and load. On the other hand, advanced techniques take into account the nonstationary signals [11].

In this context, this work consists of applying a methodology for analyzing the electrical signature for the diagnosis of point defects in bearings induction motor, based on spectral kurtosis and squared envelope spectrum analysis, in order to increase the fault detection capability even in an incipient stage [14].

2. Bearing fault diagnosis in induction machine

Rolling bearings are one of the most important mechanical components in induction machines. Therefore, it is necessary to assess the health condition of these components, especially by means of signal processing methodologies for bearing fault diagnosis. Bearing fault diagnosis comprises a series of processes performed in order to detect, isolate, and identify the bearing condition based on the machine monitoring [10]. Although there are several techniques for monitoring of bearing condition in induction machine, i.e., vibration, acoustic emission, and ultrasound, this section describes an approach based on electrical stator current analysis or current signature analysis. This approach has been gaining attention since bearing failure causes a modulation in electrical current signal, which can be identified in a similar way, as it is done in vibration analysis [15].

This section aims to describe some of the most used methodologies for induction machine fault detection based on electrical current signature analysis. In this context, it is important to know the machine to be monitored, and often the system in which it is inserted, since practical considerations are essential to allow a proper fault diagnosis. Some of these considerations are mainly related to machine technical specifications; load variations; rotor speed variations; power supply characteristics; failure mode to be analyzed (electrical or mechanical); sensors (physical quantity to be monitored, specification, amount), among others [16, 17].

Bearing fault detection is a technique mainly based on feature extraction from acquired signal, and condition identification based on the analysis of these features [10]. In the case of a

fault localized on the inner or outer race, whenever a rolling element passes through the fault surface, a series of impulses are generated. This almost periodic series of impulses present characteristics that vary with bearing geometry and fault localization; in addition, they excite resonances in the bearing and in the machine structure as a whole [8, 16].

The series of generated impulses are still amplitude modulated as the fault passes by the load zone and they are influenced by the transfer function from the fault to the sensor. The impulses are generated at a rate which varies according to: the fault position (inner race, outer race, and cage), the bearing dimensions, and the machine shaft speed (f_r). Thus, it is possible to estimate the so called bearing characteristic frequencies, i.e., ball pass frequency of the outer race (BPFO), ball pass frequency of the inner race (BPFI), fundamental train frequency (FTF), which is related to cage speed rotation, and ball spin frequency (BSF). The following equations represent these frequencies [3]:

$$\text{BPFO} = \frac{n f_r}{2} \left(1 - \frac{d}{D} \cos \alpha \right) \quad (1)$$

$$\text{BPFI} = \frac{n f_r}{2} \left(1 + \frac{d}{D} \cos \alpha \right) \quad (2)$$

$$\text{FTF} = \frac{f_r}{2} \left(1 - \frac{d}{D} \cos \alpha \right) \quad (3)$$

$$\text{BSF} = \frac{D}{2d} \left[1 - \left(\frac{d}{D} \cos \alpha \right)^2 \right] \quad (4)$$

where n corresponds to the number of rolling elements; α is the angle of the load from the radial plane; d is the ball diameter and D is the pitch diameter. When such characteristic frequencies appear (or its amplitude increase) in the analyzed signal spectrum, it is possible to identify a bearing fault and its location [10]. However, it is very difficult to extract these components, since they have low amplitude and are merged with other spectral components and background noise.

Therefore, it is possible to affirm that fault detection based on the current analysis is great a challenge, especially in industrial environments mainly due to low signal-to-noise ratio of the characteristic frequency components associated with these faults, even though several studies have shown promising results in this area [6, 18]. On the other hand, in many situations, motor current signature analysis (MCSA) becomes a useful alternative to traditional fault detection methods, e.g., vibration analysis, particularly considering the sensor installation, risks, costs associated with process, and degree of criticality of the system or machine under analysis [11].

2.1. Motor current signature analysis—MCSA

MCSA is one of the most commonly used techniques to fault detection in induction motors, since it allows identifying electrical and mechanical faults. It performs a spectral analysis of stator electrical current, which is usually monitored at one of three power supply phases. Studies related to mechanical faults effects on motor stator current mainly consider: load torque oscillations, rotating eccentricities, and air gap eccentricity [11, 15, 19].

In case of bearing faults, it is possible to consider that machines inductances can vary due to rotating eccentricities at bearing characteristic frequencies f_c , i.e., BPFO, BPFI, etc., which produces a stator current modulation, described by [11]:

$$f_E = f_s \pm k \cdot f_c \quad (5)$$

where f_E is the frequency related to a bearing fault; f_s is the power supply frequency; and $k = 1, 2, 3, \dots$ is the harmonic number. Thus, f_c appears in the current spectrum as sidebands.

In this context, it is import to observe that rotor inertia and winding inductances produce an electromechanical filtering effect in stator current, such that, this current is mainly affected by low frequency components [20, 21].

Other studies show that load torque oscillations can occur each time the rolling elements reach a localized fault on the outer or inner race, or when a fault on a rolling element reaches a race. These oscillations cause phase modulations in electrical current as described by Eq. (5) [22].

Finally, another approach considers that the effect of a localized bearing fault in stator current can be modeled as air gap eccentricity. In this case, a magnetic flux density variation affects stator current as a function of the fault location. Thus, frequencies related to the bearing faults are expressed by [19]:

$$f_{E \text{ outer race}} = f_s \pm k \cdot \text{BPFO} \quad (6)$$

$$f_{E \text{ inner race}} = f_s \pm f_r \pm k \cdot \text{BPFI} \quad (7)$$

$$f_{E \text{ ball}} = f_s \pm \text{FTF} \pm k \cdot \text{BSF} \quad (8)$$

where $f_{E \text{ outer race}}$, $f_{E \text{ inner race}}$ and $f_{E \text{ ball}}$ are the frequencies related to a fault in outer race, inner race, and ball respectively, which correspond to an amplitude modulation of the fundamental power supply frequency (f_s). It is important to observe that this modulation is caused by a permeance variation on the rotor fundamental magnetomotive force [11].

2.2. Power spectral density

Generally, the MCSA is carried out using classical or nonparametric spectral estimation methods. Nonparametric methods require little information regarding the signal to be analyzed and its computational complexity is low, especially compared to modern spectral estimation methods [16, 23].

Among the most common nonparametric techniques are the periodogram and its refined variations, i.e., Bartlett, Welch, and Daniell methods [22]. Periodogram can be obtained by [23]:

$$\hat{\Phi}_p(\omega) = \frac{1}{N} \left| \sum_{n=0}^{N-1} y(t) e^{-j\omega t} \right|^2 \quad (9)$$

where $y(t)$ is signal under analysis and its samples could be represented by $[y(t)]_{t=1}^N$.

Mean squared error, represented by the sum of the bias squared and the variance, is a parameter commonly used to evaluate the performance of an estimator. In this sense, bias reduction is obtained by applying a window. In order to reduce periodogram variance, Bartlett method uses an average of several periodograms obtained from different segments of

the signal. In this case, the original signal $[y(t)]_{t=1}^N$ with N samples is split into K segments, such that, an average of $L = N/K$ periodograms is computed. Welch method can be seen as evolution of Bartlett method; since the estimation is performed considering that the signal segments are overlapped and windowed. Thus, variance is reduced, but also the resolution [23].

3. Envelope analysis

Bearing faults can be classified as localized (single-point) or extended. Incipient localized faults produce sharp impulses that cover a large bandwidth. These faults, in general, are associated with small pits or spalls. On the other hand, extended faults effect is not so apparent or highlighted in the spectrum and its bandwidth is limited. Brinelling and corrosion are examples of extended bearing faults. It is also possible that a small localized fault becomes an extended fault as the fault evolves over time. Regardless of the type of fault, in general, bearing failure can be detected using envelope analysis [3].

It is also important to observe that signals produced by bearing faults (localized or extended) are typically nonstationary, i.e., signals whose statistical parameters vary in time. More specifically, localized bearing faults signals can be modelled as cyclostationary or pseudocyclostationary [8, 24].

Over the years, the envelope analysis or high frequency resonance demodulation has been widely used for identifying localized faults in rolling bearings. Each time a bearing component strikes the fault surface, a mechanical shock occurs. Consequently, an impulse is generated and structural resonances of the system are excited by it. In addition, these impulses are modulated in amplitude. This way, through the envelope analysis, it is possible to obtain demodulated signals, which are directly related to the bearing condition [8].

The following steps perform envelope analysis. First, digital bandpass filtering of acquired signal in a suitable frequency band, in general, around the machine mechanical resonance is performed. Following, the filtered signal is demodulated. Finally, the resulting signal frequency spectrum is estimated, resulting in the envelope spectrum, whereby it is possible to identify the periodic components associated with a fault in a bearing component [16, 25]. In other words, it is possible to identify the repetition frequency of the impulses caused by a fault simply analyzing the envelope signal spectrum, which, in general, it is not possible by using the raw spectrum [17]. Fourier transform is applied in order to obtain the envelope spectrum.

One of the most used tool for demodulation or envelope extraction is Hilbert transform [26, 27]. First, the acquired signal is bandpass filtered around a machine resonance frequency, and then Hilbert transform is applied. This digital technique reduces the data length and allows flexibility for bandpass filter specification [28].

However, it is important to observe that a suitable frequency band to filter the signal must contain impulses generated by the fault and amplified by machine mechanical or structural resonances [8]. Therefore, one of the main difficulties in using envelope analysis is undoubtedly the choice of an appropriate frequency band for filtering the signal. In order

to circumvent this drawback, algorithms based on spectral kurtosis have been successfully applied, which is discussed later in the chapter.

3.1. Hilbert transform

As mentioned before, bearing fault signals can be seen as amplitude modulated signal, such that, carrier frequency, represented by high frequency resonances are modulated by bearing characteristic frequencies. Hilbert transform can be used for the demodulation process in envelope analysis when modulated signal is proved to be analytic [8].

When envelope analysis is performed based on Hilbert transform, the frequency band to be demodulated can be properly separated from adjacent components that could interfere with the analysis. Impulse response function produced by bearing faults has real and imaginary parts of its corresponding frequency function related by Hilbert transform [8].

In general, signal-to-noise ratio is used as an indication of the frequency band where the modulated signal should be filtered. After filtering, selected frequency band is shifted at low frequencies in the spectrum and padded with zeros to double the length in order to obtain a one-side spectrum. When computing the inverse Fourier transform of this one-side spectrum, an analytic signal is obtained, such that, its imaginary part is the Hilbert transform of the real part. In this way, envelope corresponds to the modulus of real and imaginary parts. However, it is more interesting to analyze the squared envelope, since it can improve signal-to-noise ratio by removing extraneous components in practical situations [28].

3.2. Kurtogram

A rolling bearing fault excites high frequency resonances in the rotating machine, which can produce modulations at bearing characteristic frequencies. Therefore, characteristic frequency components should be demodulated using an optimal selection of frequency and bandwidth (f, Bw) for bearing fault identification based on envelope analysis. In this sense, spectral kurtosis based algorithms, such as kurtogram, aims to find this combination in a computationally efficient way [25].

Initially, spectral kurtosis (SK) was defined based on short-time Fourier transform (STFT) for impulsivity measurement as a function of frequency, and it was mainly applied to sonar signal analysis [17]. Some years ago, SK was also considered and applied for bearing fault analysis [29].

Thus, spectral kurtosis of a signal $x(t)$, i.e., kurtosis value for each frequency (f), can be computed based on the STFT ($X(t, f)$) of this signal, such that [8, 30]:

$$SK(f) = \frac{\langle X^4(t, f) \rangle}{\langle X^2(t, f) \rangle^2} - 2 \quad (10)$$

where $X(t, f)$ corresponds to the envelope as a time-frequency function; $X^2(t, f)$ represents the power spectrum values calculated for each time (t); and the average of all these power spectral values ($\langle X^2(t, f) \rangle$) corresponds to the power spectrum of the analyzed signal as a whole. In addition, the constant factor 2 is subtracted, so that, for Gaussian signal, Eq. (2) turns to zero [8]. In this sense, spectral kurtosis can be understood as a filter so that its value is maximum in the

frequency bands containing impulsive signals and zero for that frequency bands dominated by stationary signals [29].

Since using short-time Fourier transform, parameters, such as window length, can directly affect the spectral kurtosis calculation; therefore, considering an impulsive signal, the window shorter than the spacing between two consecutive pulses and longer than an individual pulse shall provide a maximum kurtosis value. A detailed investigation about the relation between spectral kurtosis value and window length was conducted in Ref. [28]. Additionally, in Ref. [29], it was depicted that the square root of the spectral kurtosis is equivalent to the optimum Wiener filter and it demonstrated a close relation between optimum matched filter and spectral kurtosis value. For envelope analysis, in order to obtain an optimum result, it is of utmost importance to specify properly filter center frequency and bandwidth. For this purpose, the concept of kurtogram emerges as a tool to find the optimum filter for envelope analysis based on spectral kurtosis values. Kurtogram displays the spectral kurtosis values as a function of frequency and windows length, which define the spectral resolution. Experiments showed that the filter set from kurtogram was more efficient for outer race fault detection, when compared with Wiener and matched filters [28].

Fast kurtogram algorithm was developed as an extension of the kurtogram, especially considering that it was costly and inefficient to analyze all possible combinations of frequency and windows length. Fast kurtogram computes spectral kurtosis using digital filters, instead of short-time Fourier transform, following a dyad-decomposition so-called 1/3-binary tree. This decomposition is similar to discrete wavelet packet transform, where frequency bands are divided into bands with one half of their previous width, but here, divisions by 1/3 are also included [30].

As an alternative for fast kurtogram, the wavelet kurtogram algorithm was developed. In this case, nonorthogonal complex Morlet wavelets are used for signal decomposition and it is considered that the optimum combination center frequency and bandwidth for envelope analysis could be found based on a 1/nth-octave wavelet analysis. In general, the sequence $1/1, 1/2, 1/3, 1/4, 1/8, 1/12, \dots, 1/n$ th-octave is used, although, any sequence could be applied. Besides, before wavelet decomposition, the original signal power spectral density is prewhitened by an autoregressive model in order to enhance the fault detection into the envelope spectrum. Additionally, applied complex Morlet wavelet was optimized, since several filter banks are tested and the selected for envelope analysis is the one that maximizes the SK. The scheme of signal decomposition by means of filter bank for SK optimization is similar to that one used in kurtogram [17].

Wavelets are used because they present an impulse response with a constant damping ratio, which is more suitable for impulsive signals analysis in comparison with STFT. Besides, complex Morlet wavelet is analytic; therefore, its Fourier transform presents only positive frequencies. Thus, SK for each wavelet filter can be calculated considering that the product of the Morlet wavelet coefficients and their complex conjugate corresponds to the squared envelope of the filtered signal [17]. Here, it is also important to notice that using the quadratic envelope has been more advantageous for bearing signal analysis [28], which will be discussed in the next section.

The SK calculation could be enhanced by prewhitening the spectrum of the signal to be analyzed. Through the prewhitening, signal spectrum becomes almost constant, similar to the white noise spectrum. This process reduces variations that could occur in transient signals spectrum, which can lead to inaccurate SK calculations [17]. An autoregressive model can be used for signal spectrum prewhitening. In this case, the model error corresponds to the noise, but especially to the nonstationary part of the signal, which contains information related to bearing fault. In other words, it is possible to say that a digital filter (linear prediction filter), which is designed based on an autoregressive signal model, predicts the deterministic part of the signal; and the prediction error, which contains an impulsive signal that will be used for machine condition analysis [31].

An autoregressive model (AR) of order p can be represented by [32]:

$$AR(k) = -\sum_{i=1}^p a(i)x(i+k) + \text{error}(k) \quad (11)$$

where $a(i)$, $i = 1, 2, 3, \dots, p$, corresponds to the linear prediction filter weighting coefficients; $\text{error}(k)$ is a whitened signal, which is the difference between the original and the predicted signals. Minimum least square error is used to find the coefficients of the linear predictor. Model order (p) will be one that maximizes the kurtosis of the $\text{error}(k)$, such that, this residual signal will contain fault related impulse signals. Besides, (p) must be smaller (in number of samples) than that the space between two consecutive bearing faults impulses [17].

3.3. Squared envelope analysis

During the envelope analysis, existing random or discrete noise components can make it difficult to identify components related to bearing failure. That is why a major constraint of envelope analysis is related to signal-to-noise ratio. A way to overcome this limitation is by using squared envelope. In this case, envelope spectrum presents a higher harmonic reduction, which cannot be obtained by a common filtering operation [28].

A method for computing squared envelope from an analytic signal was depicted in Ref. [28]. There, squaring envelope process is defined as a convolution of an analytic signal and its complex conjugate. Thus, squared envelope spectrum can be calculated by the convolution of the analytic signal and its complex conjugate corresponding spectra. In this case, spectrum of squared envelope does not present a sum of frequency components, since the analytic signals have only positive frequency components. Besides, the squared envelope spectrum has the same frequency range as if it was calculated using Hilbert transform and zero padding [8].

It is also important to highlight that the integral of spectral correlation of all considered frequencies is equivalent to spectrum of the squared envelope, where the spectral correlation is a two-dimensional Fourier transform calculated on the two-dimensional autocorrelation function [33].

4. Bearing fault detection methodology

Despite major advances in bearing fault detection techniques, such as MCSA, current methodology still has limitations that make it difficult to identify incipient faults, impairing the fault prognosis. Depending on the operational environment and machine specifications, there may be a reduction in the analysis reliability as a whole.

A way to mitigate this problem consists in separation of signals coming from different sources. In general, the components in the machine vibration or current signals have specific characteristics that allow their separation and identification in order to detect changes in machinery health condition. Noise, eccentricity, gear, cavitation, rolling bearing characteristic frequencies, and broken bars are examples of components that may be present in vibration signals or electric current signals [8].

In this scenery, several techniques have been proposed to support signal separation and identification in machine fault detection. Among these techniques, it is possible to mention, for example, time synchronous averaging (TSA), which is used to remove signal components that are not synchronous with rotor speed. In this situation, a minimal disturbance could occur in the resulting signal, but it is necessary an angular sampling for each harmonic family to be separated. This technique removes harmonics, but not lateral modulation bands. Techniques related to noise cancelling, also could be used in order to mitigate noise contamination. In addition, linear prediction filtering could be used to separate the predictable deterministic signal, which must be removed from the original signal in order to highlight the signal component related to bearing fault [1]. Linear prediction was also considered for electrical signature analysis.

Another technique that was evaluated in Ref. [14] to improve the detection of fault related components was the sum of the electric currents. A common operation in three-phase circuit analysis is to obtain the current or voltage phase using information from other phases. In the case of a three-phase induction machine connected to a delta system, considering that the sum of all currents entering a node is equal to the sum of all the currents out of the node (1st Kirchhoff's Law), it is possible to assume that $I_A + I_B + I_C = 0$, where I_A , I_B , and I_C are the measured currents of the phase A, B, and C, respectively. In this sense, the current of any phase (I_A , I_B , or I_C) can easily be defined by the other two. For example, $I_C = -(I_A + I_B)$.

This procedure is similar to the synchronous average calculation. Any mechanical effect related to the machine condition (nominal or under a fault), including periodic or random components, can be observed in any of the three phases' current, or alternatively, in the numerically obtained current, i.e. (I_C). On the other hand, any other uncorrelated random effect will be attenuated using this procedure [14].

This way, the methodology that guided this work follows five steps:

1. Sum of the electric currents.
2. Prewhitening (linear prediction filtering).
3. Spectral kurtosis based algorithm.
4. Squared envelope spectrum.
5. Bearing fault identification based on bearing characteristic frequency detection.

It is also important to highlight that since faults are identified in the envelope spectrum, its amplitude can be used as severity index. Thus, a fault evolution can be analyzed as function of increases in the bearing characteristic frequency amplitude [34].

4.1. Experimental issues

In this section, damaged rolling bearings (model 6203-ZZ) are installed on a three-phase induction motor; for each bearing, stator current signals are acquired and squared envelope spectrum was analyzed in order to detect outer race faults by means of ball pass frequency outer race (BPFO) identification. Rolling bearings were artificially damaged, such that, through holes of 1.0 mm, 2.0 mm, and 3.0 mm diameter were drilled on the outer race to simulate localized faults with different levels of severity. Experiments were performed using 6203-ZZ shielded metric radial bearings, also described as deep groove ball bearing, single row, double shielded, pressed steel cage, normal clearance, prelubricated with grease, with inner (bore) diameter: 17mm; outside diameter: 40mm; and overall width: 12mm.

Experimental test rig (**Figure 1**) consists of a three-phase squirrel cage induction motor with 0.37 kW power, four poles, and 60 Hz supply frequency, coupled to an electric machine working as a power generator (constant mechanical load), without any speed or torque control. A 24-bit/4-channel data acquisition board (National Instruments NI 9239) and current probes were used to acquire electric current signals at 50 kHz sample rate. Prior to any processing, data was filtered using a low pass filter of 25 kHz.

Two of the three stator currents (I_A and I_B) were measured, and the third one (I_C) was numerically obtained, such that $I_C = -(I_A + I_B)$, and used in the fault detection process. **Figure 2** shows the damaged bearings used in the experiments. Rotational speed was estimated to be 28.80 Hz (1728 rpm), and the characteristic frequency for a fault on the bearing outer race was estimated in (BPFO = 87.93 Hz \pm 2%).

The methodology was applied to calculate electric stator current. Following, prewhitening was performed, such that the AR model order was chosen by using the kurtosis maximization criterion of the residual signal. In this work, it is proposed as a simplified methodology, where the healthy

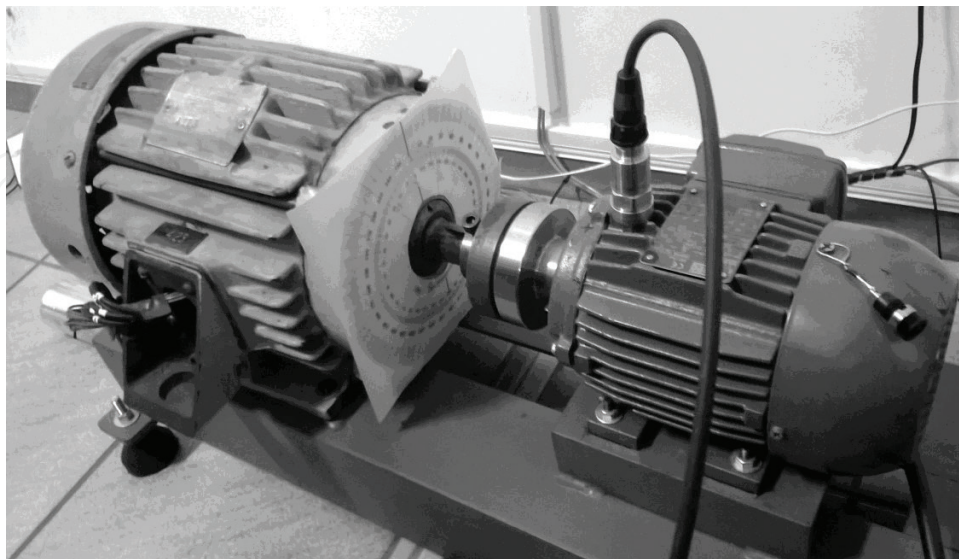


Figure 1. Experimental test rig.

bearing is initially tested and the resulting AR model order is also used for the faulty bearings analysis. Therefore, an AR model order ($p = 32$) is used for all experiments. Following, fast kurtogram algorithm was applied at five levels of decomposition. It is important to notice that this process, including sampling, signal processing, and feature extraction, lasts about 2 minutes on a modern computer. Although the wavelet kurtogram algorithm has been analyzed, only the results obtained with the fast kurtogram are presented, mainly due to its performance in this application, as explained in Refs. [14, 34]. The signal processing is performed offline using Matlab®.

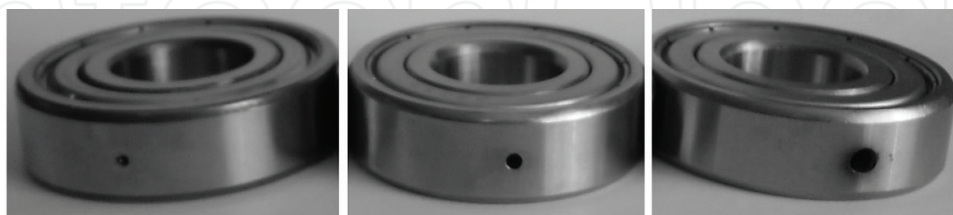


Figure 2. Damaged bearings used in the experimental tests. From left to right holes of 1.0 mm, 2.0 mm, and 3.0 mm.

Thus, the described methodology was applied for all damaged bearing cases. The fast kurtogram color map was similar to that in **Figure 3**; then, only the resulting squared envelope spectrum was shown for the other experiments. The bandpass filter with center frequency $f_c = 6250$ Hz and bandwidth $Bw = 4167$ Hz, at decomposition level ($k = 2.6$), indicated by black circle in **Figure 3**, was used in all squared envelope calculations, which was very useful for comparisons. In the Figures, an arrow indicates the amplitude of the bearing outer race characteristic frequency (BPFO).

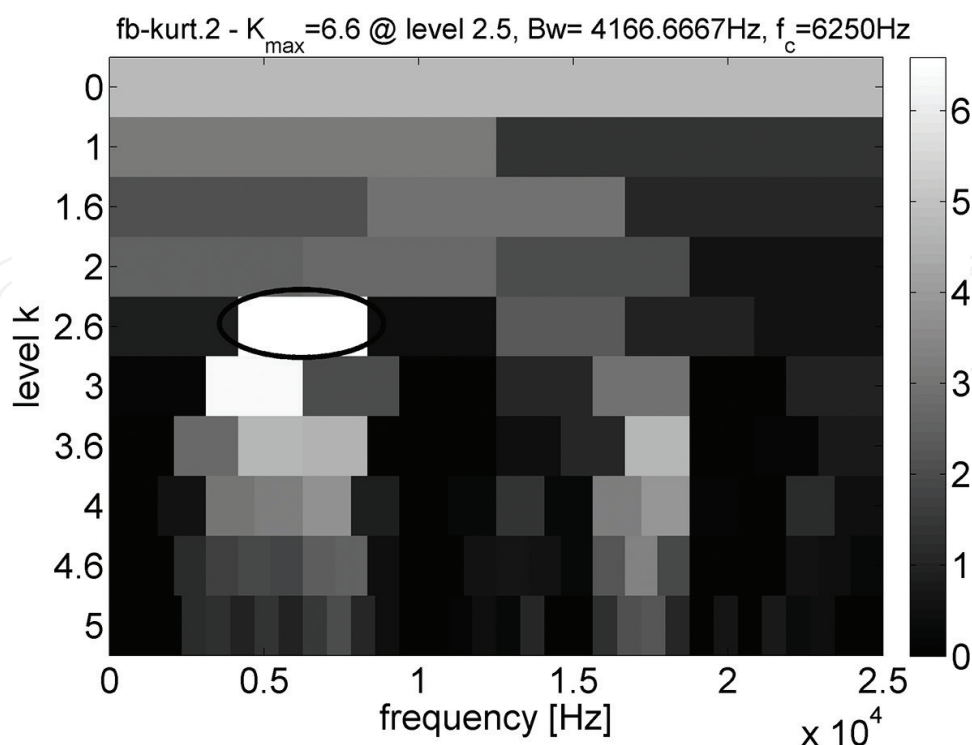


Figure 3. Fast kurtogram color map.

Figure 4 shows the squared envelope spectrum of the electric current for the damaged bearing with the 1.0 mm hole. In this case, the envelope spectrum clearly shows the fault signature around the estimated BPFO, with amplitude $A = 2.9 \times 10^{-9}$.

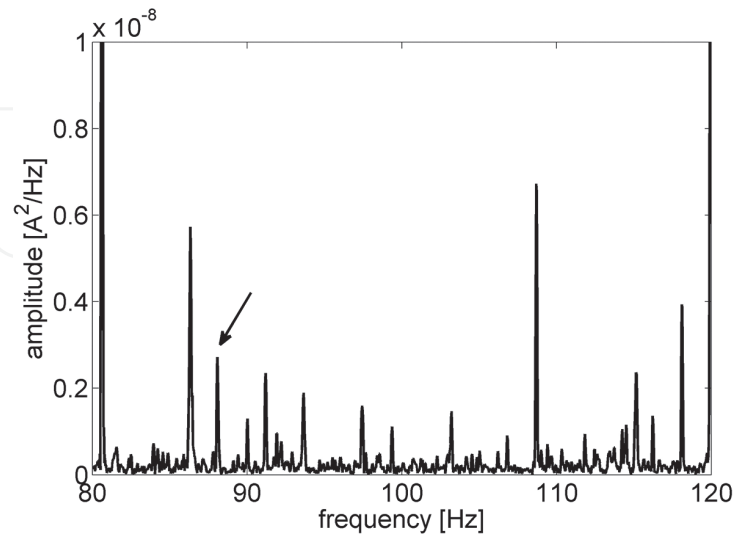


Figure 4. Squared envelope spectrum of the electric current for the damaged bearing with the 1.0 mm hole.

The same procedure was applied to the damaged bearing with 2.0 mm hole, as presented in **Figure 5**. Here, a significant increase in the bearing characteristic fault frequency amplitude ($A = 7.9 \times 10^{-9}$) was observed, confirming the fault effect in the stator current envelope spectrum amplitude.

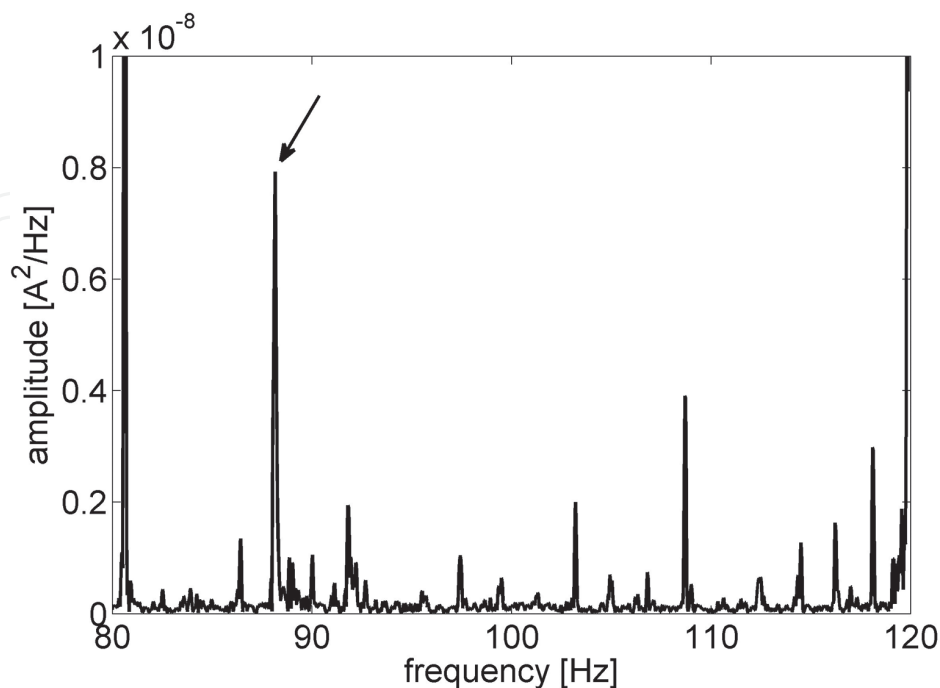


Figure 5. Squared envelope spectrum of the electric current for the damaged bearing with the 2.0 mm hole.

The last experiment assessed the damaged bearing with 3.0 mm hole. In this case, it is important to observe a change in the envelope spectrum graphic scale (**Figure 6**), due to the increase in amplitude ($A = 11.3 \times 10^{-9}$) in the observed fault frequency.

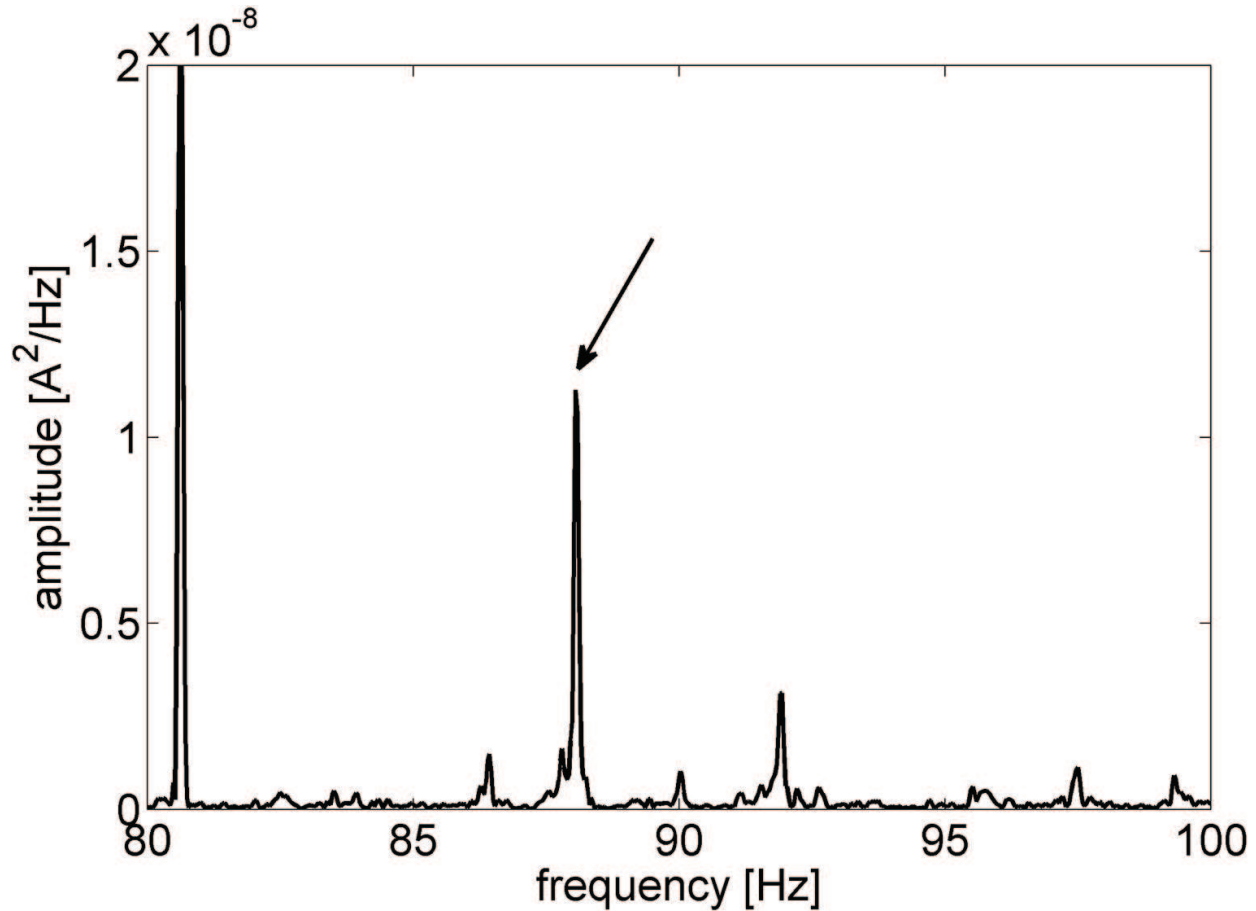


Figure 6. Squared envelope spectrum of the electric current for the damaged bearing with the 3.0 mm hole.

The obtained results validate the methodology, and therefore, the involved theoretical concepts. A BPFO frequency (at 88.1 Hz) was detected for each damaged bearing experiment, strongly indicating a bearing outer race fault. Besides, the characteristic frequency amplitude increases with the fault severity, which could be used as a prognosis indication. In the envelope spectra, it was also observed that as the amplitude of BPFO increased, the amplitude of another frequency component decreased. Thus, as in Ref. [11], it is possible to conclude that, although the stator current analysis is more complex than the vibration analysis, it is an important alternative to bearing fault detection in induction motors, mainly due to its advantages related to cost, availability and applications.

5. Conclusions and comments

This work describes a methodology to enhance MCSA for bearing fault detection and identification in induction machines by combining electrical currents sum, prewhitening based on linear

prediction filtering, spectral kurtosis, and squared envelope analysis. This methodology is based on successful methodologies and algorithms, initially proposed to be applied to vibration signals. An experimental test of such methodology was depicted using a test rig where artificially damaged bearings were created in order to simulate faults at different severity levels. Results show that the methodology improves MCSA in comparison with traditional spectrum analysis. Besides, the methodology provides an indication of fault severity based on bearing characteristic frequency (e.g. BPFO) amplitude in squared envelope, which can be used for prognosis purposes. For real industrial applications, the authors believe that this methodology could be easily carried by a professional predictive maintenance team, given adequate equipment and analysis software.

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