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Diagnosis of broken-bars fault in induction machines using higher order spectral analysis

L. Saidi [a,b,*], F. Fnaiech [a], H. Henao [b], G-A. Capolino [b], G. Cirrincione [b]

[a] Université de Tunis, Ecole Supérieure des Sciences et Techniques de Tunis, SICISI, 5 avenue Taha Hussein, BP 96, Montfleury, 1008 Tunis, Tunisie
[b] University of Picardie "Jules Verne", Department of Electrical Engineering, 33 rue Saint Leu, 80039 Amiens cedex 1, France

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A B S T R A C T

Detection and identification of induction machine faults through the stator current signal using higher order spectra analysis is presented. This technique is known as motor current signature analysis (MCSA). This paper proposes two higher order spectra techniques, namely the power spectrum and the slices of bi-spectrum used for the analysis of induction machine stator current leading to the detection of electrical failures within the rotor cage. The method has been tested by using both healthy and broken rotor bars cases for an 18.5 kW-220 V/380 V-50 Hz-2 pair of poles induction motor under different load conditions. Experimental signals have been analyzed highlighting that bi-spectrum results show their superiority in the accurate detection of rotor broken bars. Even when the induction machine is rotating at a low level of shaft load (no-load condition), the rotor fault detection is efficient. We will also demonstrate through the analysis and experimental verification, that our proposed proposed-method has better detection performance in terms of receiver operation characteristics (ROC) curves and precision-recall graph.

1. Introduction

For several decades both correlation and power spectrum (PS) have been most significant tools for digital signal processing (DSP) applications in electrical machines diagnosis area. The information contained in the PS is sufficient for a full statistical description of Gaussian signals. However, there are several situations for which looking beyond the autocorrelation of a signal to extract the information regarding deviation from Gaussianity and the presence of phase relations is needed. Higher order spectra (HOS), also known as polyspectra, are spectral representations of higher order statistics, i.e., moments and cumulants of third order and beyond. HOS can detect deviations from linearity, stationarity or Gaussianity in any signal [1,2]. Most of the electrical machines signals are non-linear, non-stationary and non-Gaussian in nature and therefore, it can be more interesting to analyze them with HOS compared to the use of second-order correlations and power spectra. In this paper, the application of HOS on stator current signals for different rotor broken bars fault severities and shaft load levels has been discussed.

So far, the large usage of induction machines (IM) is mainly due to their robustness, to their power efficiency and to their reduced manufacturing cost. Therefore, the necessity for the increasing reliability of electrical machines is now an important challenge and because of the progress made in engineering, rotating machinery is becoming faster, as well as being required to run for longer periods of time. By looking to these last factors, the early stage detection, localization, and analysis of faults are challenging tasks. The distribution of IM failures has been reported in many reliability survey papers [3–8]. These main faults include: (a) stator faults, which define stator windings open or short- circuits and stator inter-turn faults; (b) rotor electrical faults, including rotor winding open or short-circuits for wound rotor machines or broken rotor bars (BRB) or cracked end ring for squirrel cage machines; (c) rotor mechanical faults such as bearing damages, static or dynamic eccentricities, bent shaft, misalignment, and any load-related abnormal phenomenon [3].

Issues of preventive maintenance, on-line machine fault detection, and condition monitoring are of increasing importance [3–9]. During the last twenty years or so, there has been a substantial amount of research dealing towards new condition monitoring techniques for electrical machine and drives. New methods have been developed for this purpose [5]. Monitoring machine line current and observing the behavior in time-domain and frequency-domain characteristics, from healthy to faulty condition, has been always the first step of analysis. This technique is known as machine current signature analysis (MCSA).

The MCSA technique has been widely used for fault detection and diagnosis and it is considered as the most popular not only

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[*] Corresponding author at: Université de Tunis, Département de Génie Electrique, Ecole Supérieure des Sciences et Techniques de Tunis, SICISI, 5 avenue Taha Hussein, BP 96, Montfleury, 1008 Tunis, Tunisie. Tel.: +216 22169567; fax: +216 72486044.
E-mail address: lotfi.saidi@u-picardie.fr (L. Saidi).

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for electrical faults but also for mechanical faults. Moreover, it can easily detect machine faults by using only current sensors which are not really invasive. Other signals to be monitored could be stator voltages, instantaneous stator power, shaft vibration, stray flux, electromagnetic torque, speed, temperature, acoustic noise and much more [3–9]. Features extracted from one or more of these signals could be used as the fault diagnosis indexes.

This paper focuses on BRB fault in IM which represent about 10% of total industrial induction motor faults [3], by using both spectral and bi-spectral analysis of the stator current. MCSA has been extensively used to detect BRB and end ring faults in IM [9–11]. The side-band frequency components at $(1\pm 2ks)f_s$ have been used to detect such faults, (s is the rotor slip and f_s is the fundamental supply frequency, and one integer $k=1, 2, 3, \ldots$).

Although, the MCSA gives efficient results when the motor operates under rated or high load conditions, some drawbacks have been observed when the load shaft is light. Since the side-band frequency components $(1\pm 2s)f_s$ are very close to the grid frequency f_s, a natural spectral leakage can hide frequency components characteristics of the fault [12]. In this case, the standard MCSA method fails to detect BRB faults. This problem can be solved by increasing the sampling frequency but load variations during sampling may decrease the quality of the spectrum [9]. Hence a trade-off must be performed between spectrum leakage and frequency resolution which is difficult to be reached when using the Fast Fourier transform (FFT). Consequently, MCSA method is strongly dependent on the rotor slip condition and it has not been applied to BRB faults under no-load condition.

Due to those limitations of FFT, in the literature other methods for spectral analysis become potential options to the detection of BRB such as the zoom-FFT (ZFFT) [9–11], in [11] a method based on the multiple signal classification (MUSIC) has been proposed to improve diagnosis of BRB fault in IM, by detecting a large number of frequencies in a given bandwidth. This method is called zoom-MUSIC, wavelet approaches [13], neural network [14]. In those techniques, the computational time and the accuracy in a particular frequency range are increased. However, as expected, the frequency resolution is still affected by the time acquisition period and the load effect (especially no-load condition) was not studied.

The analysis of faults at low slip is important in industrial applications and would provide the following benefits [12]:

- Improving quality control of new motors,
- Allowing no-load analysis of all type of motors,
- Preventing confusion of faults with load-induced current oscillation,
- Reducing the cost of fault analysis.

In this context, the MCSA method based on a Hilbert transform (HT) was used to detect BRB faults at very low rotor slip conditions [15]. The effectiveness of the method was confirmed by experimental data on an induction motor with one BRB fault. The performance of the method was not evaluated for different numbers of BRB. Besides this method requires high computation and large amount of data is required for the high frequency resolution. In another study [16], the HT is used to extract signal envelop and then the wavelet transform is applied to estimate fault index around $2sf_s$ frequency component which reflects the energy variation of the phase current related to the BRB fault. The main drawback of this approach is that no clear methodology is proposed for the wavelet decomposition.

Various DSP techniques [4–9] have been extensively used for feature extraction purposes and HOS has been one of them [17–24]. The bi-spectrum is the third order spectrum and it results in a frequency–frequency–amplitude relationship which shows coupling effects between signals at different frequencies [19]. This tool has already demonstrated its efficiency in many detection applications including machinery diagnosis for various mechanical faults [20]. Other applications include the usage of the bi-spectral analysis to detect the fatigue cracks in beams [21], stator inter-turn faults [22], and bearings [23]. It has been also used in the case of the coupling assessment between modes in a power generation system [19]. The application of HOS techniques in condition monitoring has been already reported [24,25] and it is clear that multi-dimensional HOS would contain more useful information than traditional two-dimensional spectral analysis for diagnostics purposes.

The next section will give a brief development of the basic bi-spectrum theory followed by a description of the experimental set-up. The third section will develop the PS and the bi-spectrum signal processing tools in order to characterize the stator current frequency components in presence of BRB. The last section will be dedicated to the analysis of experimental results, and ends with a comparison of the two higher order spectra techniques (PS and proposed BDS methods) by means of the ROC curves, before giving some conclusions on the implementation of this advanced DSP technique for electrical machines fault detection.

2. HOS analysis

2.1. Basic definitions

In this section, the theoretical concepts of the bi-spectrum method will be recalled. Let us assume that: $x(n)$, $n=0, 1,\ldots,N-1$ is a discrete current signal, zero-mean and locally stationary random process with a length N. The autocorrelation function of a stationary process $x(n)$ is defined by:

$$R_{xx}(m)=E\{x(n)x(n+m)\} \tag{1}$$

where $E\{.\}$ is the expected mean operator (or equivalently the average over a statistical set) and m is a discrete time-delay. The PS is formally defined as the Fourier transform (FT) of the autocorrelation sequence:

$$P_{xx}(f)=\sum_{m=-\infty}^{+\infty} R_{xx}(m)\, e^{-j2\pi fm} \tag{2}$$

where f denotes the frequency.

An equivalent definition can be given by:

$$P_{xx}(f)=E\{X(f)X^{*}(f)\}=E\{\left|X(f)^2\right|\} \tag{3}$$

where X^*denotes the complex conjugate of X and $X(f)$ is the discrete Fourier transform (DFT) of $x(n)$, given by:

$$X(f)=\sum_{n=0}^{N-1} x(n)\, e^{-j\frac{2\pi fn}{N}} \tag{4}$$

where N is the number of samples.

The third-order spectrum, called the bi-spectrum $B(f_1, f_2)$ is defined as the double DFT of the third order moment. It can be defined as:

$$B(f_1,f_2)=\sum_{k=-\infty}^{+\infty}\sum_{l=-\infty}^{+\infty} M_3^x(k,l)W(k,l)e^{-j\frac{2\pi}{N}(f_1k+f_2l)} \tag{5}$$

where $W(k, l)$ is a two-dimensional window function used to reduce the variance of the bi-spectrum and $M_3^x(k,l)$ is the third-order moment of the process $x(n)$, given by:

$$M_3^x(k,l)=E\{x^*(n)x(n+k)x(n+l)\} \tag{6}$$

where k and l are discrete time delays.

As equivalence, Eq. (5) can be expressed in terms of the FT of $x(n)$ as:

$$B(f_1,f_2)=E\{X(f_1)X(f_2)X^{*}(f_1+f_2)\}. \tag{7}$$