



Rotor unbalance and broken rotor bar detection in inverter-fed induction motors at start-up and steady-state regimes by high-resolution spectral analysis

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ARTICLE INFO

Article history:

Received 25 July 2015

Received in revised form

12 November 2015

Accepted 10 December 2015

Available online 6 January 2016

Keywords:

Fault diagnosis

Induction motors

Inverter

Multiple signal classification

Complete ensemble empirical mode

decomposition

Spectral analysis

ABSTRACT

Fault detection in induction motors operated by inverters is an actual industrial need. Most line-fed machines are being replaced by inverter-fed drives, due to their improved speed regulation, and fast dynamic response, despite the insertion of undesired harmonics. Under this particular operating condition, most of the detection techniques so far developed are unable to distinguish induction motor faults. This paper presents a detection methodology based on the combined use of two techniques: Complete Ensemble Empirical Mode Decomposition and the Multiple Signal Classification. The proposed methodology is applied to an inverter-fed induction motor during a start-up followed by a steady-state regime, where it is verified its capability to identify a single broken rotor bar, mixed eccentricity in the form of motor-load misalignment, and the combination of both faults. From the experimental results, the proposed methodology is proven to be sensitive enough to detect the fault evolution in the time-frequency plane of single and combined faults under different operating regimes (start-up and steady-state) in inverter-fed induction motor.

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1. Introduction

Induction motors (IM) are the main source of mechanical power in modern industry. Since the early 1990s, it is recognized the need of continuous monitoring for detecting faults in IM, being this need the origin of much research in the field during the last three decades [1–6]. Rotor asymmetries caused by broken bars and mixed eccentricity are some of the most common faults and it has received a renewed attention, mainly due to the importance of their possible effects. There is always a certain level of eccentricity due to manufacturing tolerances, which produces a misalignment of the rotor and stator. But usually, the unbalanced operation of the rotor is explained by other causes, such as: misalignment of the load axis and rotor shaft, wrong placement or rubbing of ball bearing, mechanical resonance or unbalanced load [7–9].

Some techniques and methods have been proposed to detect these faults, but those based on non-invasive measurements are preferable to the rest. Among them, the most used is the Motor Current Signature Analysis (MCSA) [10], which is based on the measurement of the stator current. Early applications of MCSA relied on the Fast Fourier Transform (FFT) to analyze the stator current during a steady state operation of the motor as described in [11,12]. The FFT based analysis is only suitable when the motor operates in steady state, which is not the case in many industrial applications, including those where the IM operates under continuous load variations or oscillations, voltage fluctuations, or in the presence of undesired harmonics.

Additional harmonic content is always present in the stator current when an IM is fed by an inverter as is the case when IMs are used in industrial machinery. These applications are characterized by changing or nonstationary operating conditions, where most of the developed techniques are unable to detect faults in the IM. Even in steady state, inverter-induced harmonics might overlap with fault-related spectral components, making difficult their detection with the same methodologies used in line fed IM. Despite the

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mentioned difficulties, some authors have been able to detect BRB and MECC operation in inverter-fed IM operating in steady-state [13–26], as well as during the start-up regime [27–34]. However, it is still necessary to explore other methodologies that could detect faults under the operating conditions imposed to the IM by an inverter supply. An interesting and promising methodology is the application of high-resolution spectral analysis [13,35,12,36], such as the multiple signal classification (MUSIC) method.

In searching for a more universal fault detection method, it is desirable that the technique be able to detect several types of faults either in the steady-state, the start-up transient, or in both regimes in the same analysis. With this objective in mind, this paper presents an extension of a previous work presented at ICEM'14 [33], having the novelty of developing a methodology where the fusion of the complete ensemble empirical mode decomposition (CEEMD) and MUSIC are used to analyze the stator current of an inverter-fed IM during the start-up transient followed by the steady-state regime, and the steady-state with no inverter-fed IM and other variable loads. Experimental results demonstrate the excellent capability of these tools to identify the fault evolution in the time-frequency plane for one BRB and mixed eccentricity faults in the form of motor-load misalignment (MECC), and also their combination. The obtained results show a good resolution in both operating regimes, which is a great advance compared to other time-frequency transforms.

2. Background

This section presents the mathematical background of the proposed techniques for the current stator analysis during the start-up transient and steady-state regimes.

2.1. Complete ensemble empirical mode decomposition (CEEMD)

The CEEMD is a noise-assisted method [37] that improves the IMF decomposition of a signal to avoid the undesired mode mixing problem, present in the Empirical Mode Decomposition EMD [38], having the following procedure:

First, add a fixed percentage of Gaussian white noise onto the target signal and obtain the first EMD component of the data with noise. Repeat the decomposition I times using different noise realizations and compute the ensemble average to define it as the first IMF₁ of the target signal. Then,

$$\text{IMF}_1 = \frac{1}{I} \sum_{i=1}^I E_1 [x(t) + \varepsilon w_i] \quad (1)$$

where IMF₁ is the first EMD component of the target signal $x(t)$, w_i is zero-mean Gaussian white noise with unit variance, ε is a fixed coefficient, $E_i(\bullet)$ is an operator that produces the i th IMF component of the EMD, and I is the number of realizations. Then calculate the first signal residue r_1 ,

$$r_1 = x(t) - \text{IMF}_1 \quad (2)$$

Next, decompose realizations $r_1 + \varepsilon E_1[w_i]$, $i = 1, 2, \dots, I$; until they reach their first IMF conditions and define the ensemble average as the second IMF₂.

$$\text{IMF}_2 = \frac{1}{I} \sum_{i=1}^I E_1 [r_1 + \varepsilon E_1[w_i]] \quad (3)$$

For $k = 2, 3, \dots, K$, calculate the k th residue: $r_k = r_{(k-1)} - \text{IMF}_k$, then extract the first IMF component of $r_k + \varepsilon E_k[w_i]$, $i = 1, 2, \dots, I$ and

compute again their ensemble average to obtain IMF_(k+1) of the target signal

$$\text{IMF}_{(k+1)} = \frac{1}{I} \sum_{i=1}^I E_1 [r_k + \varepsilon E_k[w_i]] \quad (4)$$

The sifting process is continued until the last residue does not have more than two extremes, producing

$$R = x(t) - \sum_{k=1}^K \text{IMF}_K \quad (5)$$

where R is the final residual, and K is the total number of IMF. Therefore, the target signal can then be expressed as

$$x(t) = \sum_{k=1}^K \text{IMF}_K + R \quad (6)$$

Eq. (6) makes the CEEMD a complete decomposition method, and compared with EMD method, the CEEMD not only solves the mode mixing problem, but also provides an exact reconstruction of the original signal. Consequently, it is more suitable than EMD to analyze transitory signals as the stator current in an inverter-fed IM.

2.2. MUSIC algorithm

The MUSIC algorithm estimates the frequencies of the complex sinusoids that best approximates a noisy signal by using an eigen-based decomposition method [39]. First, consider a signal $c(t)$ as a sum of P complex sinusoids and white noise as the following equation:

$$c(t) = \sum_{k=1}^P A_k e^{j(2\pi f_k t + \phi_k)} + w_n(t) \quad (7)$$

where A_k , f_k , and ϕ_k are the amplitude, the frequency and the phase of the k th current-space vector, respectively; j is $\sqrt{-1}$ and $w_n(t)$ is white noise. The MUSIC pseudo-spectrum Q of the current space vector follows the orthogonality of the noise and signal subspaces and is given by the following equation:

$$Q_c^{\text{MUSIC}}(F) = \frac{1}{\sum_{k=P+1}^N |s^H(F)\eta_k|^2} \quad (8)$$

where $s_k^H(F_k)$ is the signal vector given by $s_k^H(F_k) = [1 \ s^{-j2\pi F_i} \ \dots \ s^{-j2\pi F_i(N-1)}]$, and η_k is the noise eigen-vector. Expression (8) exhibits the peaks that are exactly at the frequencies of the principal sinusoidal components where the projections of signal and noise subspaces are zero ($s_k^H(F_k)\eta_k = 0$).

2.3. IM faults considered

In steady-state, the analyzed IM faults are identified by the presence of some harmonics in the stator current spectrum. The detection of BRB in IM can be realized by the observation of the following space harmonics (f_{BRB}) [40]:

$$f_{\text{BRB}} = f_c (1 \pm 2s) \quad (9)$$

where s is the per-unit motor slip and f_c is the fundamental frequency of the voltage supply. Mixed eccentricity fault related harmonics (f_{ecc}) are given by the following equation:

$$f_{\text{ecc}} = f_c \left[1 \pm \left(\frac{1-s}{p} \right) \right] \quad (10)$$

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