Fused Empirical Mode Decomposition and MUSIC Algorithms for Detecting Multiple Combined Faults in Induction Motors

D. Camarena-Martinez[1], R. Osornio-Rios[2], R. J. Romero-Troncoso[3] and A. Garcia-Perez*[4]

[1,2,3] HSPdigital-CA Mecatrónica, Facultad de Ingeniería
Universidad Autónoma de Querétaro
San Juan del Río, Querétaro., México
[3] HSPdigital-CA Telemática, DICIS
[4] HSPdigital-CA Procesamiento Digital de Señales, DICIS
Universidad de Guanajuato
Salamanca, Guanajuato., México
*agarcia@hspdigital.org

ABSTRACT
Detection of failures in induction motors is one of the most important concerns in industry. An unexpected fault in the induction motors can cause a loss of financial resources and waste of time that most companies cannot afford. The contribution of this paper is a fusion of the Empirical Mode Decomposition (EMD) and Multiple Signal Classification (MUSIC) methodologies for detection of multiple combined faults which provides an accurate and effective strategy for the motor condition diagnosis.

Keywords: Empirical mode decomposition, high-resolution spectral analysis, induction motors, multiple-fault diagnosis.

1. Introduction

Induction motors are the most commonly used prime movers for many equipment in industrial applications; thus, they are popular because of their reliability and simplicity of construction. Several approaches have been proposed for monitoring and diagnosis of induction motors, unfortunately most of them focus on single fault or multiple faults that are not present at the same time [1-2]. However, in a real rotary machine, two or more faults can be present at the same time, so one faulty condition could affect the detection of a differing fault and a wrong decision about the operational condition of the motor could be made. Several techniques have been developed for the diagnosis and monitoring of motors, the classic method used for detection of motor faults is based on the Fast Fourier Transform (FFT) [3]. Unfortunately, the disadvantage of the classic method is that the FFT diagnosis considers the signal linear and stationary, but it is common that numerous natural phenomena have a stringent tendency to behave in a nonlinearly and nonstationary way. Therefore, in recent studies, several advanced signal-processing techniques such as the high-resolution spectral analysis and wavelet analysis have been applied for detection of motor faults. For instance, Grili et al. [4] use de Discrete Wavelet Transform (DWT) to detect a broken bar in squirrel cage motor under speed–varying condition. Antonino-Daviu et al. [5] present a methodology based on the application of the DWT to the stator startup current for detection of four faults (rotor bar breakages, torque fluctuations, mixed eccentricities and inter-coil short-circuits). However, one of the main problems with the wavelet methods is the Wavelet Transform (WT) is not a self-adaptive method. Therefore, it is necessary to choose properly and carefully the mother wavelet, where the contents of her daughter wavelets are largely similar to that of the analyzed signal to ensure suitable results. Further, the multiple signal classification (MUSIC) method provides a high-resolution, improving the diagnosis by detecting frequencies characteristics. Garcia-Perez et al [6], use a bank of filters with a specific frequency band in combination with the MUSIC algorithm, for analysis of the related frequencies with the different faults of the induction motor.

In recent years, the use of the techniques such as the Hilbert Huang Transform (HHT) and the Empirical Mode Decomposition (EMD), introduced by Huang

[7], have been used for different applications in sciences and engineering. The EMD method whose function is to decompose signals in their intrinsic mode functions (IMF), where each IMF represents the natural oscillatory mode embedded in the signal. The EMD method has several advantages, such as: it is an adaptive method and it can deal with nonlinear and non-stationary signals [8]. The EMD method is used for detection of different motor faults, as bearings [9-10], short circuit fault [11] and broken rotor bars [12-13]. The works mentioned analyze a single fault; however, it is common to find two or more faults at the same time, as result, a methodology to detect multiple faults is needed. The contribution of this paper is a fusion of the EMD and MUSIC methods for detection of multiple combined faults that provides an accurate and suitable strategy for the motor condition diagnosis.

2. Background

2.1 EMD method

The EMD is an adaptive method introduced by Huang [7], to decompose nonlinear and non-stationary signals, where each signal obtained by the decomposition is called Intrinsic Mode Function (IMF). The process of obtaining IMF follows the steps below:

(1) Extract the local maxima and minima to create the upper and lower envelopes

(2) Designate the mean of the upper and lower envelope as m_1 and the difference between the signals $x(t)$ and m_1 as the first component ($h_1 = x(t) - m_1$).

If h_1 satisfy the conditions of the IMF, take it as the first IMF of $x(t)$. But if h_1 is not an IMF; then take it as original signal and repeat the first two steps until h_{1k} satisfies the conditions of IMF, and designate it as $c_1 = h_{1k}$.

(3) Subtract c_1 from the original signal $x(t)$ and let $r_1 = x(t) - c_1$

(4) Treat r_1 as the original signal and apply the same process again as above to obtain the others IMFs, $c_2, c_3, \ldots c_n$

The decomposition process can be stopped when r_n becomes a monotonic function from which no more IMF can be extracted. At the end of the process, the resulting formula is shown in Eq. 1.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n \tag{1}$$

(5) Then, the signal x(t) is decomposed into n intrinsic modes $c_i(t)$ and a reminder r_n.

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. First, consider the signal $c(t)$ as a sum of P complex sinusoids and white noise as Eq. 2.

$$c(t) = \sum_{k=1}^{P} I_k e^{j(2\pi f_k t + \phi_k)} + c_n(t) \tag{2}$$

where I_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 $c_n(t)$ 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 Eq. 3.

$$Q_c^{MUSIC}(F) = \frac{1}{\sum_{k=P+1}^{N} \left| s^H(F)\eta_k \right|^2} \tag{3}$$

where $s_k^H(F_k)$ is the signal vector given by $s_k^H(F_k) = \begin{bmatrix} 1 & s^{-j2\pi F_i} & \cdots & s^{-j2\pi F_i(N-1)} \end{bmatrix}$, and η_k is the noise eigen-vector. Expression (3) exhibits the peaks that are exactly at the frequencies of the principal sinusoidal components where the projection of signal and noise subspaces are zero $\left(s_k^H(F_k)\eta_k = 0 \right)$.

2.3 Treated Faults

Three different induction motor faults are considered in this work: unbalance, bearing defect and one broken rotor bar.

Broken rotor bar (BRB) fault is possible to detect by locating the frequency components of the current due to the broken rotor bar in the frequency spectrum, which can be determined by Eq. 4.