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EEMD-based notch filter for induction machine bearing faults detection

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ABSTRACT

This paper deals with induction machine bearing faults detection based on an empirical mode decomposition approach combined to a statistical tool. In particular, it is proposed an innovative fault detector that is based on the dominant intrinsic mode function extraction, through an ensemble empirical mode decomposition, then its cancellation. The validation of this approach is based on simulations and experiments. The achieved simulation and experimental results clearly show that the proposed approach is well suited for bearing faults detection regardless the rank of the intrinsic mode function introduced by the fault.

1. Introduction

Fault detection in electrical machines is certainly the most important key in maintenance cost reduction. Despite the long experience accumulated by several technologies applied in electric machines, the task of fault detection is still an art, because induction machines are widely used in variable speed drives and in renewable energy conversion systems. So, new challenges arise particularly with regard to maintenance. In this context, cost-effective, predictive, and proactive maintenance assume more importance. Condition monitoring systems (CMS) provide then an early indication of component incipient failure, allowing the operator to plan system repair prior to complete failure. Hence, CMS will be an important tool for lifting uptime and maximizing productivity, when cost-effective availability targets must be reached. Experience feedback and a survey of condition monitoring for induction motors show important features of failure rate and index the four types of motor faults, which are considered as the most prevalent: stator intern-turn fault; bearing failures; broken rotor bar/end-rings; and air gap eccentricity [1,2]. Many techniques and tools are developed for condition monitoring of electrical machines in order to prolong their life span as reviewed in [1]. Some of the technology used for monitoring includes existing and pre-installed sensors, such as speed sensor, torque sensor, vibrations, temperature, flux density sensor, etc. These sensors are managed together in different architectures and coupled with algorithms to allow an efficient monitoring of the system condition. From the theoretical and experimental point of views, well-established methods are: electrical quantities signature analysis (current, power…), vibration monitoring, temperature monitoring, and oil monitoring. The advantage of signature analysis of the motor electrical quantities is that it is a non-invasive technique as those quantities are easily accessible during operation [3]. Moreover, stator currents are generally available for other purposes such as control and protection, avoiding the use of extra sensors [4]. Hence, most of the recent researches on induction machine faults detection have been focused on electrical monitoring with emphasis on current analysis [5,6].

For steady-state operations, current spectral estimation based on Fast Fourier Transform (FFT) and its extension, the Short-Time Fourier Transform (STFT), have been widely employed, such as FFT based bispectrum/bicoherence [6]. Due to these techniques frequency resolution limitation [7], high resolution technique: MUltiple SIgnal Classification (MUSIC) [8] and ESPRIT [9,10] were afterwards investigated. However, these techniques have several drawbacks since they are difficult to interpret and it is difficult to extract variations features in time domain for non-stationary signals. To overcome this problem and under non-stationary behavior, procedures based on time-frequency representations (Spectrogram, Quadratic Wigner Ville,…) [11–13], or time-scale analysis (wavelet) have been proposed in the literature of the electric machines community [14,15]. There are also parametric methods based on parameters estimation of a known model [7]. Nevertheless, these methods are formulated through integral transforms and analytic signal representations [16], so their accuracy depends on data length, stationarity and model accuracy. In the above-discussed context, this paper proposes then an approach based on the induction motor stator current data collection and attempts to highlight the use of a non-parametric and data driven method for bearing fault detection. This approach exploits the information extracted through the

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Nomenclature

EMD	Empirical Mode Decomposition
EEMD	Ensemble Empirical Mode Decomposition
$e_{min}(n)$	lower envelope
$e_{max}(n)$	upper envelope
IMF	Intrinsic Mode Function
IMF_c	closest or dominant intrinsic mode function
AM	Amplitude Modulation
PM	Phase Modulation
M	number of trials of EEMD algorithm
a	noise amplitude for EEMD algorithm
N	number of samples
r(X, Y)	Pearson correlation score
x_c	remaining signal after dominant *IMF* subtraction

EEMD algorithm regardless the rank of the *IMF* introduced by the fault. The proposed technique is validated through simulations and experiments on a specific 0.75 kW test bench. This paper is organized as follows. Section 2 highlights the characteristic of rolling-element bearing faults and focuses on mechanical failures that lead to stator current amplitude modulation. Section 3 describes the signal processing technique used for multi-component signal decomposition, and describes the Pearson correlation-based cancellation of the dominant *IMF*. Section 4 describes the fault detector approach based on statistical feature of the remaining signal. Finally, the performances of the proposed method are reported in Section 5 through simulations and experiments.

2. Rolling element-bearing faults

Failure of rolling-element bearings is electric machines most common failure mode associated with its long downtime. Defects in rolling element bearings can be caused by fatigue, wear, poor installation, improper lubrication, and occasionally manufacturing faults in the bearing components. A schematic view of a typical rolling-element bearing is shown in Fig. 1.

Because of their construction, rolling-element bearings generate precisely identifiable signature on vibration [17,18]. The characteristic frequencies of rolling-element bearings depend on the geometrical size of various elements, and can be found in the literature. Those frequencies present an effective route for monitoring progressive bearing degradation. It is therefore possible to detect on the stator side the frequencies associated with the bearings using an accelerometer mounted directly on the bearing housing, which is not often easily accessible [18]. It is also true that vibration monitoring has make out its efficiency; and it is highly suitable for rolling-element bearings, however it represents an issue when requiring a good vibration baseline [19]. If no baseline is available, no history has been built-up, and the background noise has risen, then it will be impossible to detect specific faults [18]. To tackle this problem, many works have proposed an alternative procedure for bearing wear detection in electric machines by analyzing the stator side electrical quantities, such as the current [19,20], or the instantaneous power factor [21]. Indeed, a bearing fault is assumed to produce an air-gap eccentricity [12], and consequently an unbalanced magnetic pull. Hence, this gives rise to torque oscillations, which lead to amplitude and/or phase modulation of the stator current [12,19,22]. Therefore, it is sufficient to demodulate the current for bearing faults detection.

3. Signal processing tools

Most of electric machine faults lead to current modulation (amplitude and/or phase) [23]. This is the particular case of bearing faults [24]. So, for failure detection, a possible approach relies on the use of amplitude demodulation techniques. The most investigated and popular amplitude demodulation techniques include Hilbert Transform (HT), Teager Energy Operator TKEO [25], and synchronous demodulation. Furthermore for three-phase system, three phase transformations such as Concordia Transform (CT) [26,27] and Park vector approach [28–30] have been employed to perform demodulation. However, TKEO is less robust against noise, HT is valid only for mono-component signals, while CT and Park vector approachs are reliable only for balanced three-phase system and require the use of three-phase currents. To go besides those constraints, innovative techniques are investigated to track the fault component by source separation such as principal components separation (PCA) [31], noise cancellation [32], and spectral features extraction and linear discriminant analysis (LDA) [33]. Besides, in typical electric machines, stator current components are the supply fundamental, harmonics, additional components due to slot harmonics, saturation harmonics, other components from unknown sources such as environmental noise and design imperfection, and eventually effect introduced by bearing faults. In typical electric machines, the stator current is multi-components and can be expressed by a temporal model as:

$$x(t) = \sum_{k=1}^{M} a_k(t)\sin(\phi_k(t)), \tag{1}$$

with: $a_k(t) = a_k(1 + m_{ka}\sin(2\pi f_{ka} t + \varphi_{ka})$,

and: $\phi_k(t) = 2\pi f_k t + m_{kp}\sin(2\pi f_{kp} t + \varphi_{kp})$.

where m_{ka} and m_{kp} are the AM index, and the PM index respectively, that can be introduced by a fault as an AM/PM effect. This work considers only the *AM* effect. Therefore, $m_{kp} = 0$ and $\phi_k(t) = 2\pi f_k t$, where $f_k = kf_0$ with f_0 is the fundamental frequency and k is the harmonic order. Hence, for fault detection, a possible approach relies on the use of amplitude demodulation techniques to extract fault related features. In this multi-component signal context, the EEMD is considered.

3.1. Empirical mode decomposition method

The EMD is an emerging signal processing algorithm for signal demodulation. It has been first introduced in [34], and has since become an established tool for the analysis of non-stationary and nonlinear data [35]. This approach has focused considerable attention and has been widely used for rotating machinery fault diagnosis [36,13,37]. It is an adaptive time-frequency data analysis method for nonlinear and non-stationary signals [34], and behaves like an adaptive filter bank [38]. Conversely to FFT or wavelets that decompose a signal into a series of *sine* functions or scaled mother wavelet; the aim of the EMD is to decompose the multi-component signal into a series of *IMFs* based on the local characteristic time-scale of the signal. This decomposition can be described as follows:

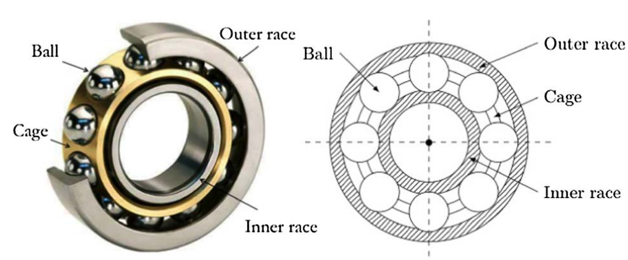

Fig. 1. Typical rolling-element bearing.