Broken-Rotor-Bar Diagnosis for Induction Motors

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Abstract. Broken rotor bar is one of the commonly encountered induction motor faults that may cause serious motor damage to the motor if not detected timely. Past efforts on broken rotor bar diagnosis have been focused on current signature analysis using spectral analysis and wavelet transform. These methods require accurate slip estimation to localize fault-related frequency. This paper presents a new approach to broken rotor bar diagnosis without slip estimation, based on the ensemble empirical mode decomposition (EEMD) and the Hilbert transform. Specifically, the Hilbert transform first extracts the envelope of the motor current signal, which contains broken rotor fault-related frequency information. Subsequently, the envelope signal is adaptively decomposed into a number of intrinsic mode functions (IMFs) by the EEMD algorithm. Two criteria based on the energy and correlation analyses have been investigated to automate the IMF selection. Numerical and experimental studies have confirmed that the proposed approach is effective in diagnosing broken rotor bar faults for improved induction motor condition monitoring and damage assessment.

1. Introduction

As an essential component in the industrial process, condition monitoring and damage assessment of induction motors has received considerable attention in recent years [1, 2]. One of the most commonly seen motor faults is the broken rotor bar, which can cause serious motor damage if not detected in time [3, 4]. Various techniques have been developed for broken rotor bar fault diagnosis, including vibration [5], rotor speed [6], motor axial flux [7] and radial flux analysis [8], Park’s Vector current monitoring [9], and stator current analysis [10]. Among these methods, motor current signature analysis (MCSA) is the most widely used method, due to its low cost and non-invasive nature [11]. In spectral analysis of the stator current signal, broken rotor bar is reflected in the rise in magnitude at the side band frequency, defined by

\[
\pm (1 \pm 2ks)f_S,
\]

where \( f_S \) is the supply frequency, \( k = 1, 2, 3, \ldots \), and \( s \) is the slip of the motor [6]. The change in lower sideband is specifically due to the broken bar, whereas changes in the upper sideband are due to consequent speed variations. The amplitudes of these sidebands are related to the number of broken bars and motor loads.

Spectral analysis of motor current was firstly used to detect a broken rotor bar through the sideband harmonics near the fundamental supply frequency [10, 12]. This method has shown limitation due to spectrum resolution and the inherent constraint of not being applicable to analyze non-stationary signals. The sideband harmonics in the current spectrum are affected by the motor’s mechanical load, which causes motor slip. Besides load condition, variations in the supply frequency, regulated by a variable speed controller, also affect the effectiveness of spectral analysis for non-stationary current signal analysis. Time-frequency techniques such as wavelet transform [13] have
been introduced to address these limitations. In [14], the discrete wavelet transform is applied to the current signal. Following decomposition, the band which is related to fault frequency is selected for further analysis. In [15], slip and working conditions are first estimated to calculate the sideband harmonics, and then a discrete wavelet transform decomposes the current signal according to the predefined fault frequencies. The power spectral density technique is used to calculate energy in the fault frequency band, obtained using the wavelet transform. The above techniques require slip estimation to localize the fault related frequency for diagnosis. However, accurate slip estimation requires complex signal processing [16, 17].

To overcome the limitation, this paper presents a new approach to current signature analysis of broken rotor bar without requiring slip estimation, based on the ensemble empirical mode decomposition (EEMD) method. EEMD is an adaptive analysis technique for processing nonlinear and non-stationary signals [18], which has been investigated in various engineering applications such as ocean wave analysis [19], gearbox [20] and bearing fault diagnosis [21]. However, this technique is not directly applicable to motor current signal for identification of fault-related intrinsic mode functions (IMF), because EEMD would interpret the amplitude-modulated narrow band signal as an IMF [22]. Since motor current induced by the broken rotor bar is such a kind of signal, modulated by both the supply frequency and fault-related frequencies [23], direct application of the EEMD method would cause mode mixing in the signal decomposition result.

In this paper, Hilbert transform is first applied to extracting the envelope of the motor current signal, which contains broken rotor fault-related frequency information [24-26]. The extracted envelope is then adaptively decomposed into a number of IMFs using EEMD. Two criteria, the energy measure and correlation analysis, have been investigated to automatically determine the representative IMFs that characterize broken rotor bar-related information. With the assistance of post-spectral analysis of the selected IMFs, broken rotor bar fault can be identified.

The rest of the paper is constructed as follows. After introducing the theoretical background of EEMD in Section 2, details of the broken rotor bar diagnosis method based on EEMD are discussed in Section 3. Additionally, numerical simulations are presented, which quantitatively evaluate the developed technique. The effectiveness of the technique is experimentally validated in Section 4, based on data acquired online using an experimental fault simulator. Finally, conclusions are drawn in Section 5.

2. Ensemble Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is an adaptive signal processing method for nonlinear and non-stationary data analysis [27]. EMD reveals local characteristics of the signal being analysed through decomposition of it into a set of complete and almost orthogonal components, termed intrinsic mode functions (IMFs). The IMFs represent the natural oscillatory mode of the signal and serves as the basis functions. EMD has been applied to various scenarios [19]. However a drawback of EMD exists, which is known as mode mixing. To alleviate the problem, the ensemble empirical mode decomposition or EEMD has been realized through the addition of white noise into the IMF decomposition process. The enhanced decomposition of IMFs in EEMD is achieved through the sifting process [18], which can be summarized as follows:

1. Sum a white noise series with the signal;
2. Decompose the noise-mixed data into IMFs through the sifting process:

\[
x(t) + \text{Randn}(t,1) = \sum_{i=1}^{N} c_i(t) + r_n(t)
\]

where \(x(t)\) is the signal of interest, \(\text{Randn}(t,1)\) represents the noise signal added to the signal. The variable \(t\) represents the signal length, the term \(c_i(t)\) stands for the IMFs obtained through decomposition during the first trial, and the symbol \(i\) represents the number of IMFs. \(r_n(t)\) is the residue of the decomposition process, which is usually a constant or a monotonic function.
3. Continue to repeat steps 1 and 2, using different white noise series in each iteration. It can be
formulated as shown in Eq. (2) that:

\[ x(t) + \text{Randn}(t,1) = \sum_{i=1}^{N} c_{i1}(t) + r_{i1}(t) \]

\[ x(t) + \text{Randn}_{,2}(t,1) = \sum_{i=1}^{N} c_{i2}(t) + r_{i2}(t) \]

\[ \vdots \]

\[ x(t) + \text{Randn}_{,j}(t,1) = \sum_{i=1}^{N} c_{ij}(t) + r_{ij}(t) \]

Here, \( \text{Randn}(t,1) \) represents the noise added to the signal during each trial. The term \( c_{ij}(t) \) stands for the IMF obtained during each trial, the symbol \( i \) represents the number of IMFs, and \( j \) represents the trial number associated with the signal decomposition process.

(4) Obtain the ensemble means of corresponding IMFs as the final IMFs.

\[ c_{i} = \frac{\sum_{j=1}^{M} c_{ij}(t)}{M} \]  

During each decomposition trial, white noise with zero mean and a constant standard deviation is added to the signal. Since the noise series in each trial is different and low correlation exists among the various series, the noise will be cancelled out in the ensemble means statistically, given sufficient number of trials. The reason that EEMD alleviates mode mixing is that the added, normally distributed white noise constitutes an entire time-frequency space. When the signal of interest is summed with the white noise, its components at different frequency scales can be projected into the proper frequency scales of the reference established by the white noise. In the sifting process, the signal component at different frequency scales can reside in the corresponding IMFs. Through this alleviation of the mode mixing problem, the IMF becomes physically meaningful.

2.1 Number of Ensemble and Amplitude of Added White Noise

EEMD is an iterative process of EMD, realized through the addition of white noise into the signal being analyzed. Two parameters - the number of ensemble trials and the amplitude of added white noise, can be optimized to improve the performance of EEMD in terms of computation efficiency and accuracy. The relationship among the ensemble number, the amplitude of the added white noise, and the effect of the added noise is given in the following equation [18]:

\[ \xi_{n} = \frac{\xi}{\sqrt{M}} \]  

or

\[ \ln \xi_{n} + \frac{\xi}{2} \ln M = 0 \]

In the above equations, \( M \) is the number of ensemble, \( \xi \) is the amplitude of the added noise, and \( \xi_{n} \) is the final standard deviation error, which is defined as the difference of the input signal and the corresponding IMFs. Generally, the standard deviation of the added white noise is taken to be about 20% of the standard deviation of the input signal. When the signal is dominated by high frequency components, the standard deviation of the added noise should be smaller. Conversely, when the signal is dominated by lower frequency components, the standard deviation should be increased [28].

2.2 IMF Selection Criterion

After performing EEMD, a series of IMFs is obtained, though only a few of them may be relevant to the purpose of defect diagnosis. To select the IMFs of interest, two criteria - energy based and correlation-based IMF selection methods [29] have been utilized. The energy contained in all IMFs can be calculated by:
where $N$ represents the number of all IMFs, and $E_{E_i(t)}$ represents the amount of energy contained in the $i$th IMF, which is defined as

$$E_{E_i(t)} = \sum_{t=0}^{T} |c_i(t)|^2$$

Since fault-related IMFs contain a higher amount of energy than the rest of the IMFs [29], the IMFs that contain the relatively the highest amount of energy are selected as the representative IMFs.

Another method for IMF selection is based on the correlation analysis, which describes the similarity between two signals. Since the IMFs are decomposed from the original signal, they are inherently correlated with each other. Therefore, a correlation based IMFs selection criterion can be formulated. The IMFs that have the highest correlation coefficient with the original signal are chosen as the representative IMFs. The correlation coefficient is represented as:

$$\rho_{x(t)c_i(t)} = \frac{\sum_{t=1}^{T}(x(t) - \bar{x})(c_i(t) - \bar{c}_i)}{\left(\sum_{t=1}^{T}(x(t) - \bar{x})^2\right)^{1/2} \left(\sum_{t=1}^{T}(c_i(t) - \bar{c}_i)^2\right)^{1/2}}$$

Here, $T$ is the number of the data samples, $\bar{x}$ and $\bar{c}_i$ are the mean value of $x(t)$ and $c_i(t)$, respectively.

3. Formulating of Diagnosis Method

Motor current induced by the broken rotor bar is modulated by both the supply voltage frequency and fault-related frequencies $f_{BR}$, and the envelope of the current signal contains the defect information. Thus the defect identification process can be achieved through a multi-step signal decomposition and feature extraction process, as illustrated in Figure 1. The envelope of the signal is first extracted using a digital bandpass filter and Hilbert transform. Next, the envelope signal is decomposed through the EEMD. Based on the IMFs selection criteria, the IMFs that are most correlated with the defect features are chosen for the Hilbert spectrum analysis.

To quantitatively evaluate the EEMD-based diagnosis method, a synthetic motor current signal is constructed for numerical simulations. When a broken rotor bar defect occurs, the line current signal is modulated by both the supply frequency and fault-related frequencies $f_{BR} = (1 \pm 2ks)f_s$ [30]. To simulate the current signal of a motor with a broken rotor bar, a synthetic current signal is built as:

$$I(t) = \cos(2\pi ft)(1 + 0.1 \cos(2\pi f_B(t)) + 0.1 \cos(2\pi f_s(t)) + 0.1 \cos(2\pi f_{2s}(t))$$

Here, $s$, slip of the motor, has the assumed value of 0.03, and supply frequency $f_s$ is set as 60 Hz. The signal in Eq. (9) and its spectrum are displayed in Figure 2, from which it is seen that spectral analysis
of the signal alone isn’t effective in revealing broken rotor bar fault related frequencies. These frequencies are calculated to be 49.2 Hz, 52.8 Hz, 56.4 Hz, 63.6 Hz, 67.2 Hz, and 70.8 Hz.

This signal is then processed using the EEMD-based diagnosis method. For this purpose, the envelope of the synthetic signal is first extracted by the Hilbert Transform, as shown in Figure 3a. Then EEMD is applied to decompose the signal into a number of IMFs, as shown in 3b-3f. According to the energy or correlation-based IMF selection criteria, C3, C4 and C5 are selected as the representative IMFs that correlate with the broken rotor bar. In their corresponding Fourier spectra as shown in Figure 3i-l, the frequency components at 3.6 Hz, 7.2 Hz, and 10.8 Hz are dominant. These are related to the 2sf, 4sf, and 6sf fault frequencies known in the synthetic signal. This result demonstrates the effectiveness of the EEMD based method in identifying motor defect features.

To evaluate the performance of the EEMD-based method for diagnosis of current signals of varying frequencies, a similar synthetic motor current signal as shown in Eq. (9) is constructed, with the varying frequency (from 56 Hz to 48 Hz in two seconds) profile illustrated in Figure 4. The
envelope of the synthetic signal extracted by the Hilbert transform, and its Fourier spectrum, are shown in Figure 5a and 5g, respectively. It is noted that the smear caused by the varying frequency in the supply current make it hard to identify the defect-related frequency components. As a solution, the envelope of the current signal is then decomposed by EEMD into a number of IMFs as shown in Figure 5b-5f. Using the energy and/or correlation-based IMF selection criterion, C3, C4 and C5 are selected as the representative IMFs. The instantaneous frequency components in the Hilbert spectrum (time-frequency spectrum) are shown in Figure 5i, which are related to the 2sf, 4sf, and 6sf fault frequencies contained in the synthetic signal, with the slip \( s \) set as 0.03. The effectiveness of the diagnosis method for varying frequency supply current is thus verified.

![Figure 4](image1.png)

**Figure 4.** A synthetic signal for broken rotor bar fault motor with varying speed profile and its spectrum

![Figure 5](image2.png)

**Figure 5.** IMFs extracted from the envelope of synthetic varying speed signal, with their corresponding spectra

### 4. Experimental Studies

Experiments for diagnosing motor broken rotor bar defects were conducted on a motor tested system, as illustrated in Figure 6. The system is driven by a 1-hp induction motor, with the speed...
range varied from 0 to 6,000 rpm. A current probe (Fluke i200s) is clamped on one of the three-phase wires to the motor, which provides the current signal. The shaft rotation speed is controlled by a speed controller. Static load is applied through two load discs, and a variable load is applied by a magnetic brake system through a bevel gearbox and a belt drive. A data acquisition system (NI-PCI 6259) is employed for signal collection.

Figure 6. Experimental setup: (1) Tachometer, (2) Motor, (3) Bearing, (4) shaft, (5) Load disc, (6) Belt, (7) Data Acquisition Board, (8) Bevel Gearbox, (9) Magnetic Load, (10) Reciprocating Mechanism, (11) Variable Speed Control, (12) Current Probe

In the experiment, two motors, one healthy and one with a broken rotor bar have been investigated. Both motors are power supplied under the same frequency of 60 Hz and loading conditions. Current signals from the healthy and defective motors are shown in Figure 7a and Figure 7c, respectively. From the corresponding spectrum of these two current signals (in Figure 7b and Figure 7d), no defect features are clearly identified. Especially in Figure 7d, it is difficult to see the sideband harmonic signal, which is related to the broken rotor bar characteristic frequency.

Figure 7. Current signals from healthy motor and motor with broken rotor bar and their spectra

Applying the developed method, the envelopes of the current signals from these two motors are extracted using the Hilbert transform, as shown in Figure 8a and Figure 9a, respectively. These two current envelope signals are further decomposed into a number of IMFs, as shown in Figure 8b-f and Figure 9b-f.
According to the energy or correlation based IMFs selection criteria as introduced in section 2.2, the IMFs C3 (Figure 8d), C4 (Figure 8e) and C5 (Figure 8f) are chosen as the representative IMFs for the healthy motor. The related dominant frequency components are at 0.3 Hz, 3 Hz, and 19 Hz in the spectra, as shown in Figure 8j-8l. Since they do not match the sideband harmonic characteristics of the broken rotor bar, this motor is identified as free from a broken rotor bar.

Using the same selection criteria, the IMFs C3 (Figure 9d), C4 (Figure 9e), C5 (Figure 9f) are identified as the representative IMFs for the motor containing a broken rotor bar. From their corresponding spectra, the dominant frequency components are found to be 3.6 Hz, 7.2 Hz and 10.8 Hz, respectively. These components are consistent with the known broken rotor bar sideband harmonics $2kfs$, $k = 1, 2, 3$, thus indicating the motor as defective. Based on these three frequencies, and the current supply frequency $f = 60$ Hz, the motor slip is found to be 0.03, which is within the normal range.

To enable a clear comparison between the broken rotor bar motor current signal with that of the healthy motor, the spectra of the two representative IMFs are overplayed in Figure 10. From the spectra, the sideband harmonic frequencies of 3.6 Hz, 7.2 Hz, 10.8 Hz in the motor with a broken rotor bar can be clearly differentiated. Additionally, the envelope of the broken rotor bar motor current signal has sparser energy concentration in the frequency domain than that of the healthy motor. Based on the energy definition in Eq. (7), the energy in the current signal envelope in the case of the defective motor is calculated as $0.04$ mw, as compared to $5*10^{-4}$ mw in the healthy motor. This means that power density can also be used as an indicator for diagnosing broken rotor bar in motors.
5. Conclusions

In this paper, an EEMD-based motor current analysis method is presented for broken rotor bar diagnosis. The proposed method identifies broken rotor bar related sideband harmonic frequencies without the need for slip estimation. Theoretical framework of the method is described, and two criteria for representative IMFs selection are illustrated. Both numerical simulation and experimental results have demonstrated the effectiveness of the diagnosis method in identifying broken rotor bar defect features. Research is being continued to examine the robustness of the technique for defect diagnosis under a broader range of operation conditions.

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