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APPLICATION OF THE COMBINATION OF BOTH WAVELET MULTI-RESOLUTION ANALYSIS AND EMPIRICAL MODE ANALYSIS TO DETECT INDUCTION MOTOR DEFECTS

Nabil Talbi[1,*], Abderrezak Metatla[1], Nouredine Ouelaa[2]
Ramdane Younes[2,3], Louendi Fatmi[2] and Abderrazek Djebala[2]

[1]Department of Mechanical Engineering
University 20 août 1955
Skikda BP 26, Algeria
*Corresponding author: nabil_talbi@yahoo.fr

[2]Mechanics & Structures Laboratory
University 8 Mai 1945
P.O.Box 401, 24000 Guelma, Algeria

[3]Department of Mechanical Engineering
University of Badji Mokhtar
Annaba BP 12, Annaba, 23000, Algeria

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Abstract. *The work developed in this paper proposes a method to detect bearing defects and rotor bars breaking in induction motors based on a combination of two approaches: wavelet multi-resolution analysis (WMRA) and empirical mode decomposition (EMD). After applying these two methods to measured vibratory signals, we used the envelope analysis to identify the characteristic frequency corresponding to the inspected defect and the obtained results are satisfactory. To better identify the defects, a successive combination of these two methods was performed while using the highest energy value. The comparison between these two methods and their combination shows that successive application of the WMRA and the EMD gives better defect identification.*
Keywords: Induction motor, Diagnostics, Vibration analysis, Wavelet multi-resolution analysis, Empirical mode decomposition

1. **Introduction.** In modern industry, most engines are three-phase squirrel-cage induction motors mainly due to their robustness and low cost [1]. Despite these advantages, this type of engine is not free from failures as sometimes evidenced by bearing defects or breaking of rotor bars. Hence, it is necessary to look for an appropriate diagnostic method to identify defects.

Vibration analysis of electrical machines is the most common approach in modern industry, since it ensures detection, diagnosis and defects evolution [2,3]. The vibratory signal, captured by a piezoelectric accelerometer is often mixed with uncertainties, which makes identification of defects difficult or impossible. For this reason, it is necessary to use statistical indicators such as the RMS value, the peak factor and kurtosis [4]. Unfortunately, using of these indicators is limited since it does not allow diagnosing the type of defect. To overcome this difficulty, the measured signal must undergo other treatments. For a long time, the use of spectrum and cepstrum analysis has been reported in several studies [5-8]. Spectrum analysis is a very useful tool for stationary signal analysis while cepstrum analysis is a good complement to spectrum analysis. However, most of the vibratory signals are non-stationary and non-linear, which can be considered as stringent limitations. Such signals require a time-frequency analysis in order to locate the time

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periodicity [9]. This type of analysis reconciles the advantages of spectrum and cepstrum analysis but the last one does not give significant results in the case of noisy signals which have variable frequencies (non-stationary) [10]. In this case, a new approach based on new filtering methods must be introduced to extract the defect signature from measured signals. As an indication, we find the adaptive filtering [11], high frequency resonance technique (HFRT) [12] and the continuous wavelet technique (CWT) [13], discrete wavelet multi-resolution analysis (WMRA) [14] and the wavelet packet transform (WPT) [15,16]. A good review with applications of the wavelets for fault diagnosis of rotary machines is proposed in [17]. Wavelet multi-resolution analysis was used by Djebala et al. using the kurtosis as a criterion for optimization and evaluation. The obtained results show the validity of this method in detecting several defects affecting bearings [14]. In addition, Natu investigated bearing defects by using a two-level wavelet analysis [18]. However, one of the limitations of wavelet multi-resolution analysis is the need to predefine the basic functions for signal decomposition [19]. To overcome this difficulty, Huang et al. introduced empirical decomposition analysis as a method of sub-band decomposition [20]. The main advantage of the EMD is that the basic functions are derived from the signal itself [21]. For instance, Selami et al. used the EMD to detect gear defects [22]. In addition, in the work of Du and Yang carried out the decomposition of the real signal by both EMD and WMRA. Then the envelope method was applied in each case and the results show that the first method better locates frequencies of the bearing compared to the second one [23]. In the same vein, Zhang et al. employed the EMD and envelope analysis to extract the characteristic frequency of the rotor bars breaking in an induction motor [24]. So, to improve the efficiency of this method, it must be combined with other methods such as WPD and even more with intelligent methods such as neural networks. This combination offers a very efficient method for obtaining an intelligent diagnosis.

The main contribution of this paper is the new proposed approach of defects diagnosis, based on the successive combination of WMRA and EMD. This approach is validated with vibratory signals measured on a recently designed test bench and the results are compared with those obtained by EMD and WMRA. It has been found that the results obtained are conclusive compared with the methods mentioned above. In addition, another comparison made by recent research revealed that the proposed approach has better extraction of defect frequencies as it supports the benefits of both methods (WMRA and EMD) [22,25].

The rest of this paper is structured as follows. A description of the test bench with measuring equipment is presented in Section 2. Therefore, Section 3 presents a discussion of the vibratory signal and the result of the application of the test of frequency analysis. In addition, the theories of the two WMRA and EMD methods are briefly described in the same section. The results obtained are presented and discussed in Section 4 where the proposed approach to the diagnosis of defects by combining the two previous methods is presented and validated experimentally. Finally, conclusions and perspectives are mentioned in Section 5.

2. Description of the Setup and the Measuring Equipment.

The test bench is designed at the Laboratory of Mechanics and Structure (LMS) of the University of Guelma. It can simulate several defects on the induction motor such as rotor bar breaks, defects in the bearings that carry the motor shaft and some other defects. This test bench, illustrated in Figure 1, is a very simple design for the rapid assembly and disassembly of the rotors and bearings to be tested.

For every rotating machine, it is necessary to know the defect's specific characteristic frequencies which have a direct relation with the geometry of the organs and the rotation speed developed by the machine. Table 1 summarizes the characteristic frequencies of the two studied defects for two different rotation frequencies: F_R = [12.375 and 17.125] Hz. The induction motor power is 1.5 kW.

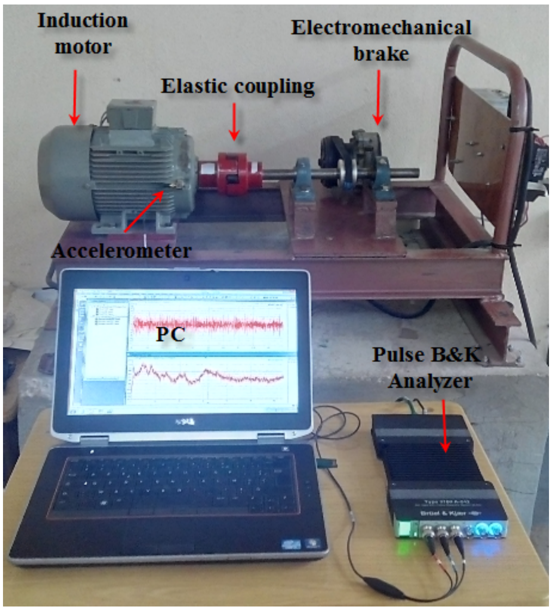


FIGURE 1. Test stand & measuring equipment

TABLE 1. Defect frequencies

Types of defect	Frequency signatures	Theoretical rotation frequency F_S (Hz)	Effective rotation frequency F_R (Hz)	Results (Hz)
Outer race	$F_{BE} = Z/2 \cdot [1 - (d/D_m)\cos\alpha] \cdot F_R$	12.5	12.375	42.94
		17.5	17.125	60.95
Break of bars	$F_B = F_R \pm 2 \cdot g \cdot F_A$	12.5	12.375	12.375 ± 0.50
	$g = (F_S - F_R)/F_S$, $F_S = F_A/P$	17.5	17.125	17.125 ± 0.49

Here F_R is the rotation frequency, Z is the number of balls, d and D_m are ball diameter and average diameter of the bearings respectively, α is the contact angle, F_A is the supply frequency, g is the motor sliding, F_S is the theoretical motor rotation frequency and P is the number of poles.

3. Results & Discussion.

We realized a defect on the outer ring of the bearing on which measurements were made in several frequency bands (low, medium and high frequency) and for two motor rotation frequencies [12.375 and 17.125] Hz. Among the measured signals, we used the one measured in the [0-6400] Hz band.

At first observation, the analysis of the measured signal and its spectrum do not show any information on the presence of a possible defect. To be able to analyze the measured signal, we proceed to their filtering to identify the defects by applying the two methods: the wavelet multi-resolution analysis and the empirical mode decomposition methods. In the continuation of this work we propose the application of these two methods, then their combination to better filter the signals to ensure better identification of defects.

3.1. Wavelet multi-resolution analysis (WMRA) theory.

A wavelet is a transformation allowing decomposition of a signal into several segments, and it is expressed by the following relation:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \left(\frac{t-b}{a} \right) \tag{1}$$

with a: scale parameter, b: translation parameter, $\psi(t)$: mother wavelet.

One can express the transformation in continuous wavelet by

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\psi^* \left(\frac{t-b}{a} \right) dt \tag{2}$$

The discrete form of the wavelet transformation is given by

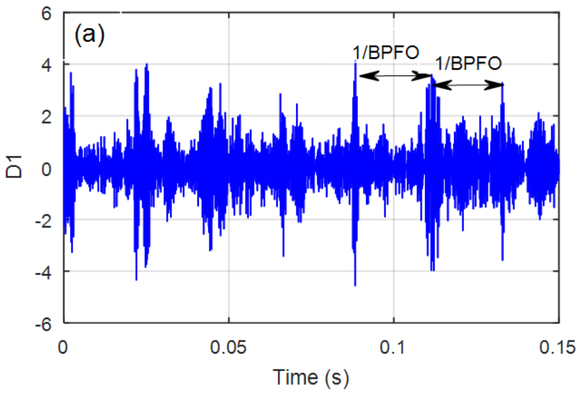
$$DWT(m,n) = 2^{\frac{-m}{2}} \int_{-\infty}^{+\infty} s\,(t)\,\psi^*\left(2^{-m}t - n\right)dt \tag{3}$$

Or, n and m: are integers.

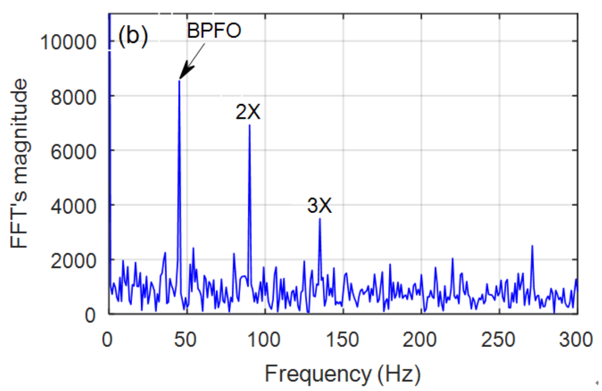
In 1989, Mallat developed a new version of the wavelet transform called wavelet multiresolution analysis [26]. It transforms the signal with different frequency bands and gives a view from the finest to the largest. When a signal is passed through the two low-pass (L) and high-pass (H) filters, two coefficients are obtained, one of approximation cA_k and the other of detail cD_k. The new passage of the two coefficients cA_k and cD_k through the two reconstruction filters (LR) and (HR) gives us the two new vectors of approximation (A_k) and of detail (D_k) [14].

3.1.1. *Case of a bearing defect.* The decomposition based on WMRA was applied to the measured signal in the frequency band [0-6400] Hz for a rotation frequency $F_R = 12.375$ Hz in three levels, 3 details and 3 approximations, followed by a calculation of energy for each case.

Figure 2(a) illustrates the reconstructed signal that was extracted from detail 1 (D1), having the greatest energy and covering the [3200-6400] Hz frequency band. We find that the impacts of the masked defect by the noise in the measured signal are very visible on the filtered signal. An envelope spectrum calculated from the Hilbert transform of the reconstructed signal clearly shows the frequency of the rolling fault at 42.94 Hz and two of its harmonics, Figure 2(b).



(a) Detail signal D1

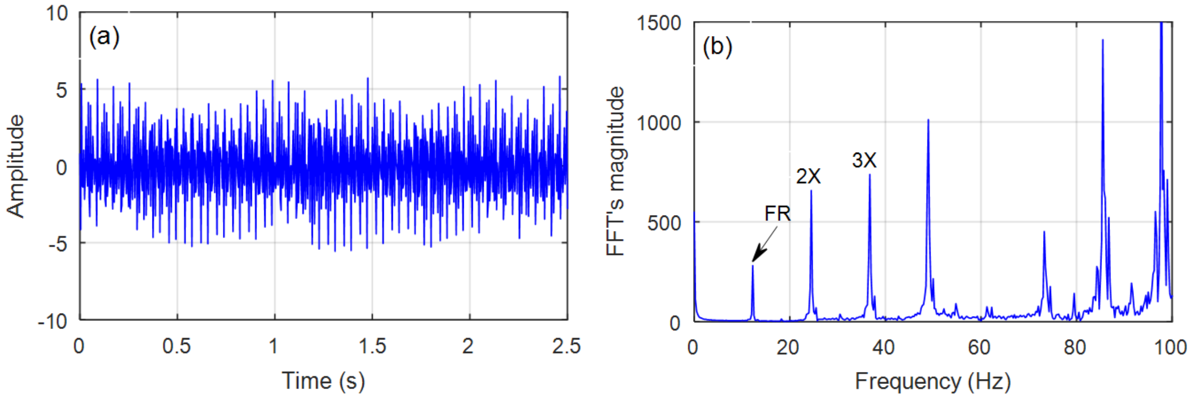


(b) Its envelope spectrum

FIGURE 2. Decomposition by WMRA (bearing defect)

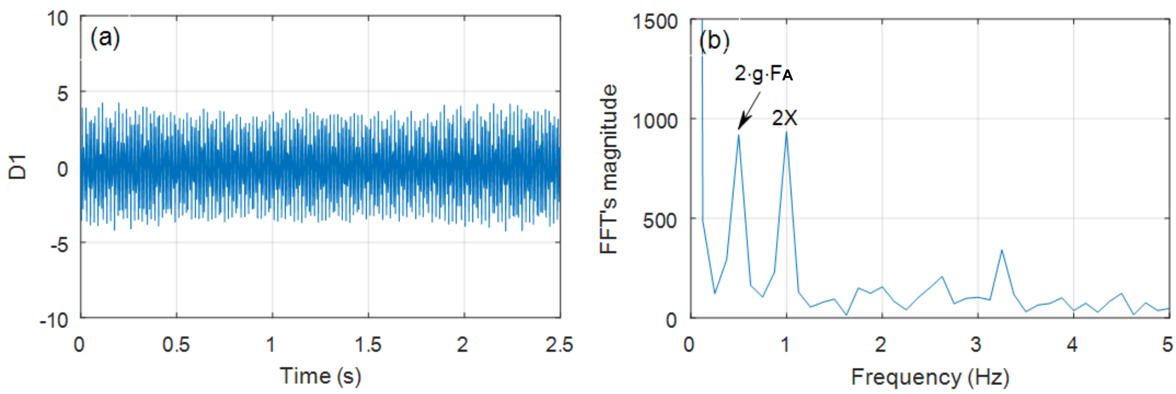
3.1.2. *Case of defect of bar breaks.* The signal of Figure 3(a) was measured at low frequency in the band [0-100] Hz for the rotation frequency of 12.375 Hz. The broken rotor bar defect was simulated by drilling the rotor. This signal does not reveal any information on the state of the rotor. The spectrum of Figure 3(b) shows only the presence of the motor rotation frequency and its harmonics. The increase of the amplitudes of the harmonics means the presence of a misalignment.

In the same way, we have decomposed with the WMRA the signal measured in the frequency band going from [0-100] Hz. The calculation of the energies of the details and the approximations obtained always shows that it is the detail 1 (D1) which has the greatest energy. Figure 4(a) shows the reconstructed signal of detail 1 (D1), and its frequency band is taken between [50-100] Hz. The application of the Hilbert transform on detail 1 is shown in Figure 4(b) clearly shows the appearance of two peaks corresponding



(a) (b)

Figure 3. (a) Measured signal; (b) spectrum



(a) Detail signal D1 (b) Its envelope spectrum

Figure 4. Decomposition by WMRA (bar breaks defect)

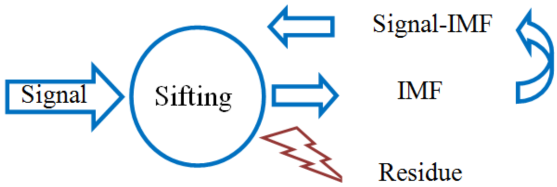


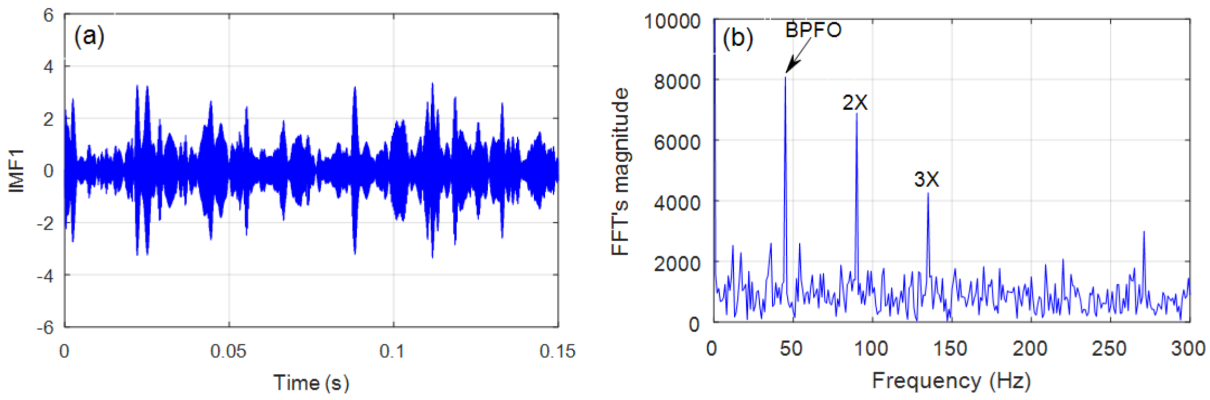
Figure 5. Principle of the empirical modes decomposition

to twice the slip frequency ($2 \cdot g \cdot F_A = 0.5$ Hz) and one of its harmonics, which confirms the presence of a defect of breaks of bars.

3.2. **Empirical mode decomposition analysis (EMD) theory.** The decomposition in empirical modes is a signal processing method created, in 1998 by the engineer Huang [20] to decompose the signal by going from the highest frequencies to the lowest frequencies into several oscillating components extracted directly from the signal adaptively and from a residue. These components are called intrinsic mode functions (IMF) and are interpreted as non-stationary waveforms, and they must satisfy two conditions [26]: (i) the number of zero crossings and the number of extrema are equal to or no more than one; (ii) the average value of the envelope produced by local extrema is zero.

The sieving process, corresponding to extraction of an IMF, from a given signal is illustrated in Figure 5.

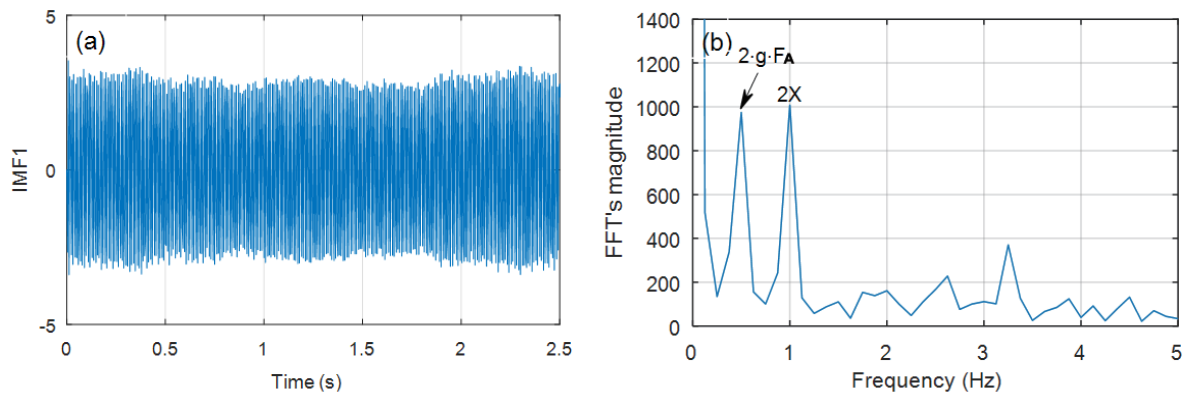
3.2.1. *Case of a bearing defect.* We decompose the signal of Figure 2(a) with the EMD method. This decomposition gives twenty-one IMF plus one residue. Figure 6(a) shows the first IMF1, having the highest energy. Its envelope spectrum Figure 6(b) clearly shows the frequency of a fault on the outer race, is 42.94 Hz and its harmonics.



(a) IMF1 signal (b) Its envelope spectrum

FIGURE 6. Decomposition by EMD (bearing defect)

3.2.2. *Case of defect of bar breaks.* In the same way, we decomposed using EMD the signal of Figure 3(a). Figure 7 shows the first IMF and its envelope spectrum showing the presence of the slip frequency ($2 \cdot g \cdot F_A = 0.5$ Hz) and one of its harmonics.



(a) IMF1 signal (b) Its envelope spectrum

FIGURE 7. Decomposition by EMD (bar breaks defect)

4. **Proposed Method and Its Application on the Measured Signal.** To better visualize and improve the results obtained by WMRA and EMD, we propose to combine the two methods successively, one after the other and see which can provide a better solution.

The three steps of the first combination are listed as follows.

1) The measured signal is decomposed by the WMRA in several details and approximations.

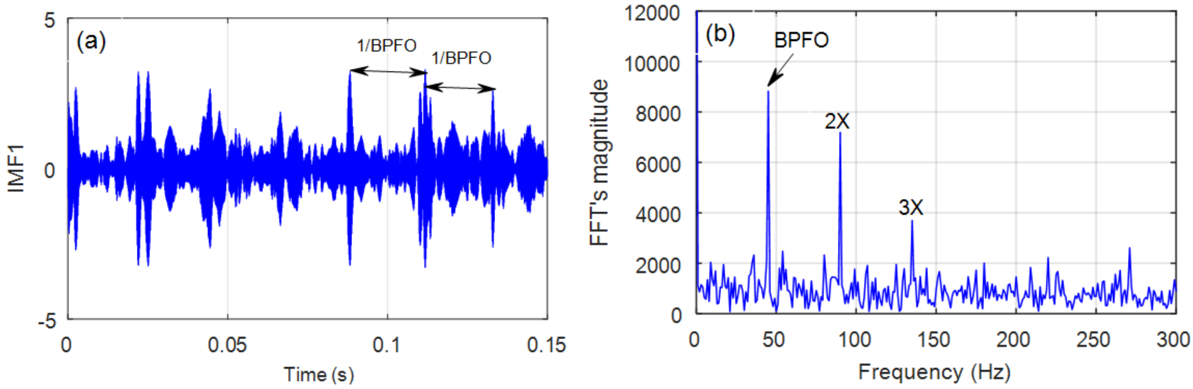
2) The detail or approximation with the highest energy value will be decomposed by the EMD.

3) An envelope signal of the IMFs is calculated from the Hilbert transformation by choosing the one that will highlight the characteristic frequency of the defect.

The same steps are applied for the second combination while first decomposing the signal measured by the EMD and selecting the IMF with the highest energy that will be treated by WMRA.

4.1. **Case of a bearing defect.** First, begin with the successive application of WMRA and EMD, choosing the detail or the approximation with the greatest energy. In this case, the first detail is then selected and it will be processed by the EMD.

Results of the WMRA-EMD combination are shown in Figure 8. They show that the first reconstructed IMF is more filtered, because its envelope spectrum clearly identifies the presence of the frequency of a defect on the outer race at 42.94 Hz and two of its harmonics. The results obtained are slightly improved compared to those obtained by EMD alone.

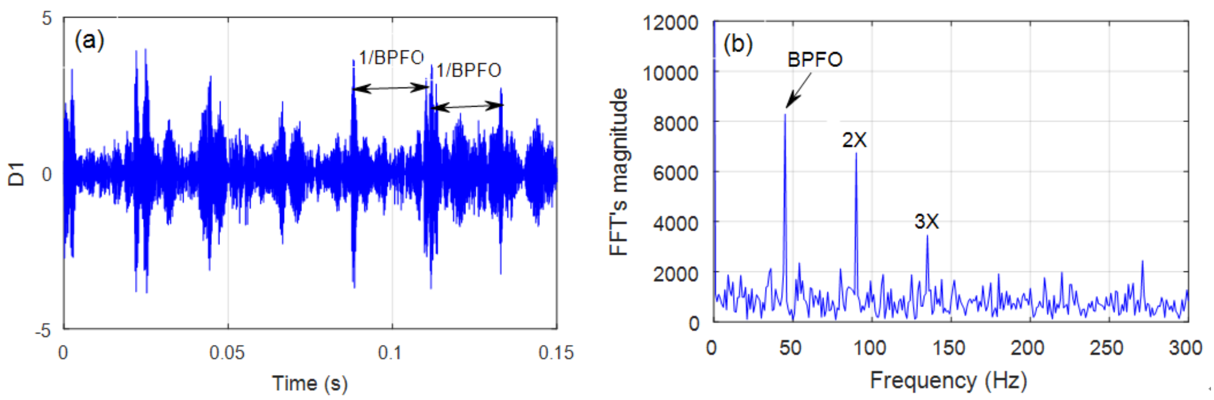


(a) IMF1 signal (b) Its envelope spectrum

FIGURE 8. Decomposition by WMRA-EMD

Now, we apply to the measured signal the EMD then the WMRA. In the same way, we choose the MFI with the highest energy. In this case, the first MFI is selected and will be broken down by WMRA.

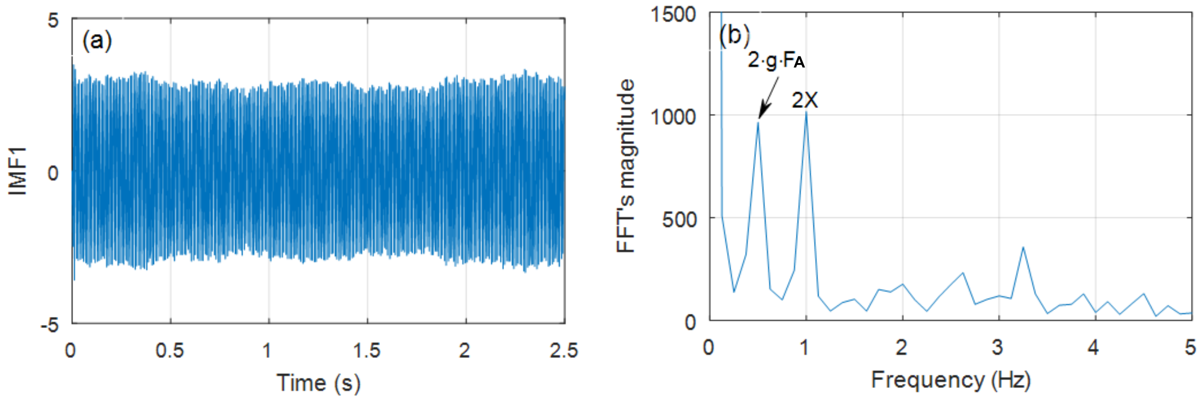
The results obtained from the EMD-WMRA combination are shown in Figure 9. They show that the first reconstructed detail is more filtered. After being subjected to an envelope analysis, we find that the envelope spectrum clearly identifies the presence of a defect. On the outer ring, it manifests itself by the frequency of a defect of the order of 42.94 Hz as well as two of its harmonics.



(a) Detail signal D1 (b) Its envelope spectrum

FIGURE 9. EMD-WMRA decomposition

4.2. **Case of defect of bar breaks.** The application of the WMRA-EMD to the measured signal allows us to select the first detail (D1), its treatment by EMD, has enabled us to obtain the results illustrated in Figure 10.

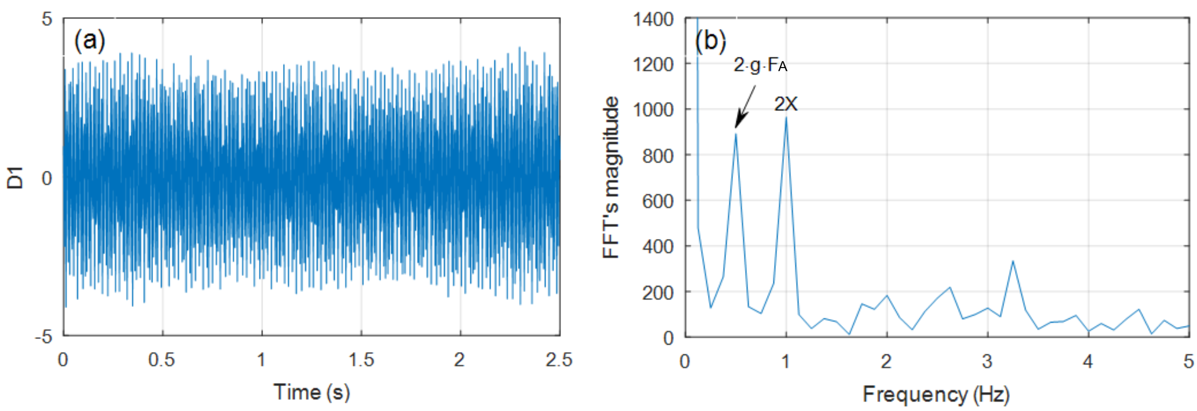


(a) IMF1 signal (b) Its envelope spectrum

Figure 10. Decomposition by WMRA-EMD

The envelope spectrum of the first reconstructed IMF clearly shows the presence of twice the slip frequency ($2 \cdot g \cdot F_A = 0.5$ Hz) and its harmonic.

In the same way, we apply the EMD-WMRA to the measured signal. The first IMF with the highest energy is treated by WMRA. The results obtained are shown in Figure 11. Only the first detail (D1) highlights the presence of the bar break defect by the appearance of twice the slip frequency and one of its harmonics.



(a) Detail signal D1 (b) Its envelope spectrum

Figure 11. Decomposition by EMD-WMRA

Results obtained by the two consecutive WMRA-EMD and EMD-WMRA combinations, for the two types of defects studied, confirm the results obtained by the application of WMRA and EMD separately. In addition, the results obtained by the combination of the two methods are slightly more informative, but they may be more effective in the case of emerging defects.

5. **Conclusions.** In this paper, we have proposed a method based on the successive combination of wavelet multi-resolution analysis and empirical mode decomposition analysis to ensure a good filtering of noisy signals; thus, better detection of defects that affect induction motors is assured.

The application of this combination on the two studied defects allows reconstructing clearer signals, which makes the extraction of the characteristic frequencies and their harmonic significant.

The proposed approach is, only, adapted to the two studied defects. It, also, concerns all the defects that affect rotating machines, because it takes account of the non-stationarity of the measured signal.

It is, ideally, suited for extracting signal characteristic parameters to perform automatic diagnosis of defects through intelligent techniques such as support vector machine (SVM) and adaptive neuro fuzzy inference system (ANFIS) which will be the subject of our future works.

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