Research Article

Induction Machine Bearing Fault Detection Using Empirical Wavelet Transform

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Abstract

The detection of faults related to the optimal condition of induction motors is an important task to avoid the malfunction or loss of the motor, thus avoiding high repair or replacement costs and faults in the efficiency of the process to which they belong. These faults are not limited to a single area; mechanical and electrical problems can cause a fault. Specifically, the bearing of a motor is subjected to several effects that cause bearing faults, which cause significant breakdowns in the machinery. This article proposes a methodology for detecting bearing faults on an induction motor. The first part of the methodology uses a signal processing method called empirical wavelet transform (EWT), which decomposes the vibration signal into multiple components to extract a series of amplitude and frequency modulated components (AM-FM) with a Fourier spectrum. First, the vibration signal data are collected in a normal operating condition and the other with bearing damaged due to perforation. Then, three types of goodness-of-fit tests are used, Kuiper, Kolmogorov–Smirnov, and Pearson chi-square, to classify the signals and determine which ones belong to a damaged engine. Finally, the experimental results show that the EWT in conjunction with the proposed goodness tests achieves competitive precision and efficiency in diagnosing induction motor-bearing faults.

1. Introduction

Induction motors are one of the most used rotary machines in the industry due to their simple design, easy operation, low cost, and maintenance. Although this type of machinery is reliable, it has different types of faults due to various tensions that are found. Different types of induction motor faults have been discussed in the literature, such as broken bars, bearing faults, an unbalanced rotor, and stator and winding faults [1, 2]. Diverse studies have been done on fault diagnostics in recent years. Early detection of problems is vital to save time and costs; necessary measures need to be taken to avoid failures, as worst-case scenarios can cause the entire system to break down. Fault diagnostics methods can be broadly classified into signal-based, model-based, and knowledge-based methods [3–6]. Therefore, the diagnostics of motor-bearing faults play a crucial role in the operation of induction motors. A motor must be monitored and diagnosed to ensure safe operation and prevent more severe faults. When a faulty bearing rotates at a constant speed, this provokes tiny periodic impulses due to defects in the raceway or ball, generating mechanical vibration signals with much information and dynamic characteristics about the fault. Therefore, the vibration-based signal processing method is one of the main tools to diagnose the malfunctioning of an induction motor.

Nowadays, various research works can be found in which multiple techniques for detecting faults in induction motor bearings are addressed. Hsueh et al. [3] proposed a methodology with which the induction motor faults can be
detected using an EWT-based pattern recognition technique. This methodology transforms the raw current signal to two-dimensional (2-D) signals in grayscale that contains the necessary information to be used later in a CNN (convolutional neural network) model, to automatically extract specific features of the images to classify and give a fault diagnosis; this method achieved a significant precision of the 97.37%. However, the data set considered for this methodology is small and requires collecting a large sample of data for the different exposure conditions. Merainani et al. [7] proposed a hybrid method in induction motor fault diagnosis using the EWT to filter the vibration signals as well as to isolate the region of interest, while the S-transform was proposed to show how the amplitude and phase for specific frequencies contained in the filtered signal change with time and frequency. Eren et al. [8] used the empirical wavelet transform together with the Fourier transform to divide the vibration signal into segments adaptively, with the inverse Fourier transform obtains a signal in the time domain with the characteristic frequency band of the fault and makes a comparison of the RMS (root mean square) values of the segments of the vibration signal in good condition having the possibility to extract the segments of interest from the original vibration data. However, the sizes and locations of the segments may depend on both the type of fault and the bearing geometry. Thus, for using this method, it is necessary to have the bearing geometry. Deng et al. [9] proposed a method where EWT is used to decompose the vibration signals; then using the fuzzy entropy, the signal complexity can be measured, reflecting the intrinsic oscillation complexity changes, and the fuzzy entropy values are calculated of the AM-FM components. These values are used as input to train and build an SVM classifier in order to recognize fault patterns obtaining accuracy in the results between 95% and 100%, demonstrating the improvements of using EWT compared to empirical mode decomposition and demonstrating some limitations in the way of adaptive segmenting the Fourier spectrum and selecting the optimal filter banks.

The wavelet transform (WT) helps analyze nonstationary signals [10–16]. A wave has good frequency properties and can provide time domain and frequency domain information by internal production between the analyzed signal and a predetermined wave base. So, this method has already shown great capacity in diagnosing mechanical equipment failures due to the ability to analyze multiple resolutions [17].

These methods have obtained good results in engineering applications, although they are still limited in a subdivision system, and in some cases, they are not very adaptable, which can lead to severe damage to the characteristics of the vibration signals. The empirical wavelet transform (EWT) based on the combination of the advantages of the wave transform and the EMD method was proposed by Gilles [18]. It is used to extract a series of amplitude and frequency modulated (AM-FM) signals from a given signal. This method is widely used in fault diagnosis to identify weak and compound faults. The AM-FM components can be transformed into a compact support Fourier spectrum, whereby adaptive waves capable of identifying AM-FM components of the vibration signal can be constructed. The different modes are identified to segment the Fourier spectrum and filter for each detected support. Therefore, the EWT method can decompose a signal to be efficiently analyzed and extract the internal characteristics [9].

In this study, a failure diagnosis method for motor bearings is proposed to take full advantage of the benefits of EWT and goodness-of-fit tests. First, the EWT method is used to adaptive decompose the vibration signal into various AM-FM components. Next, three goodness-of-fit tests (Kuiper, Kolmogorov–Smirnov, and Pearson chi-square) are used and compared to determine if the motor has a fault in one of its bearings. Finally, the diagnostic results are compared with other diagnostic methods of faults in the literature. In this sense, a new methodology based on EWT for feature extraction and goodness-of-fit tests for faulty classification is presented for automatic bearing fault detection on an induction motor. With this methodology, up to 99.224% accuracy was reached, improving the classification rate over other similar techniques in the literature.

2. Theoretical Background

The EWT method was proposed by Jérôme Gilles [18] to extract the different modes of a signal, beginning by designing an appropriate wave filter bank. Gilles proposed an innovative approach in constructing adaptive waves capable of extracting the AM-FM components of a signal. In this method, the Fourier frequency spectrum is normalized and separated into an indefinite number of intervals, and then the bases of the waves are built with support in each segment; this segmentation is fundamental so that the wave can adapt to the sample signal.

The local maximums in the signal are detected using the Fourier spectrum. Then, the spectrum is segmented based on the maximums that have been detected, and the corresponding wave filter bank is built. Taking into account that the Fourier spectrum [0, π] is segmented into N continuous segments, and each of them is defined as \( \omega_n \), the limits between each segment are expressed as \( \omega_n = 0 \) and \( \omega_n = \pi \). The division of the Fourier axis is illustrated in Figure 1, and each segment is denoted in the form \( \Lambda_n = [\omega_{n-1}, \omega_n] \) and then it can be seen that \( \bigcup_{n=1}^{N} \Lambda_n = [0, \pi] \) centered around each \( \omega_n \) defining a transition phase \( T_n \) of width 2\( T_n \) [18].

The EWT employs the use of bandpass filters for each \( \Lambda_n \) \( \forall n < 0 \), and the scale function and the empirical wavelets are defined by (1) and (2), respectively.
the literature is as follows: Many functions satisfy this property; the most used in the literature is as follows:

\[
\tilde{\varphi}_n(\omega) = \begin{cases} 
1, & \text{if } |\omega| \leq (\omega_n - T_n), \\
\cos \left( \frac{\pi}{2} \beta \left[ \frac{1}{2T_n} (|\omega| - \omega_n) \right] \right), & \text{if } (\omega_n - T_n) \leq |\omega| \leq (\omega_n + T_n), \\
0, & \text{otherwise}, 
\end{cases} 
\]

(1)

\[
\tilde{\psi}_n(\omega) = \begin{cases} 
1, & \text{if } (\omega_n - T_n) \leq |\omega| \leq (\omega_{n+1} - T_{n+1}), \\
\cos \left( \frac{\pi}{2} \beta \left[ \frac{1}{2T_{n+1}} (|\omega| - \omega_{n+1} + T_{n+1}) \right] \right), & \text{if } (\omega_{n+1} - T_{n+1}) \leq |\omega| \leq (\omega_{n+1} + T_{n+1}), \\
\sin \left( \frac{\pi}{2} \beta \left[ \frac{1}{2T_n} (|\omega| - \omega_n + T_n) \right] \right), & \text{if } (\omega_n - T_n) \leq |\omega| \leq (\omega_n + T_n), \\
0, & \text{otherwise}. 
\end{cases} 
\]

(2)

The function \(\beta(x)\) is an arbitrary function \(C^k([0,1])\) such that

\[
\beta(x) = \begin{cases} 
0, & \text{if } x \leq 0 \wedge \beta(x) + \beta(1 - x) = 1 \forall x \in [0,1], \\
1, & \text{if } x \geq 1. 
\end{cases} 
\]

(3)

Many functions satisfy this property; the most used in the literature is as follows:

\[
\tilde{\varphi}_n(\omega) = \begin{cases} 
1, & \text{if } |\omega| \leq (1 - \gamma)\omega_n, \\
\cos \left( \frac{\pi}{2} \beta \left[ \frac{1}{2\gamma\omega_n} (|\omega| - (1 - \gamma)\omega_n) \right] \right), & \text{if } (1 - \gamma)\omega_n \leq |\omega| \leq (1 + \gamma)\omega_n, \\
0, & \text{otherwise}, 
\end{cases} 
\]

(5)

\[
\tilde{\psi}_n(\omega) = \begin{cases} 
1, & \text{if } (1 + \gamma)\omega_n \leq |\omega| \leq (1 - \gamma)\omega_{n+1}, \\
\cos \left( \frac{\pi}{2} \beta \left[ \frac{1}{2\gamma\omega_{n+1}} (1 - \gamma)\omega_{n+1} \right] \right), & \text{if } (1 - \gamma)\omega_{n+1} \leq |\omega| \leq (1 + \gamma)\omega_{n+1}, \\
\sin \left( \frac{\pi}{2} \beta \left[ \frac{1}{2\gamma\omega_n} (|\omega| - (1 - \gamma)\omega_n) \right] \right), & \text{if } (1 - \gamma)\omega_n \leq |\omega| \leq (1 - \gamma)\omega_n, \\
0, & \text{otherwise}. 
\end{cases} 
\]

(6)

Regarding the choice of \(T_n\), several options are possible. The simplest is to choose \(T_n\) proportional to \(\omega_n\): \(T_n = \gamma\omega_n\), where \(0 < \gamma < 1\). Therefore, \(\forall n > 0\), (1) and (2) simplify to (5) and (6):
The parameter $\gamma$ can guarantee no overlap between two consecutive transition areas. Then, the parameter $\gamma$ must comply with the following equation:

$$\gamma < \min \left( \frac{\omega_{m+1} - \omega_m}{\omega_{m+1} + \omega_m} \right). \quad (7)$$

The EWT method is defined similarly with the wavelet transform. The detailed coefficients $W^r_{f}(n, t)$ are given by the inner products with the empirical wavelets:

$$W^r_{f}(n, t) = \langle f, \psi_n \rangle = \int f(t) \psi_n^r (t - \tau) d\tau,$$ \quad (8)

and the approximation coefficients (we adopt $W^r_{f}(n, t)$ to denote them) of the inner product with the scale function is as follows:

$$W^s_{f}(n, t) = \langle f, \phi_n \rangle = \int f(t) \phi_n^s (t - \tau) d\tau,$$ \quad (9)

where $\psi_n^r$ and $\phi_n^s$ are defined by (5) and (6), respectively. The reconstruction is obtained by the following:

$$f_0(t) = W^s_{f}(0, t) \ast \phi_1(t),$$

$$f_k(t) = W^s_{f}(k, t) \ast \psi_k(t).$$ \quad (10)

### 3. Test of Goodness of Fit

#### 3.1. Pearson’s Chi-Square Test.

The Chi-square is a statistic test to determine if the numbers of the set $r_i$ are uniformly distributed in the interval $(0, 1)$. To perform this test, it is necessary to divide the interval $(0, 1)$ into $m$ subintervals, where it is recommended that $m = \sqrt{N}$. Then each pseudo-random number of the set $r$ is classified into $m$ intervals, with the number of numbers $r$. These classified in each interval is called the observed frequency ($O_i \in \mathbb{R}^m$), obtained from the probability density function (PDF) defined as follows:

$$F(r) = P(a < r \leq b), \quad (11)$$

where $P$ is a function that applies limits $a$ and $b$ (lower and upper limits, respectively). In this sense, $O = F(r)$, and the number of numbers $r$ expected to be found in each interval is called the expected frequency ($E = F(r)\in \mathbb{R}^m$). From the values of $O_i$ and $E_i$ (where $i$ denotes the $i$-th coefficient of PDF), the statistic value $\chi^2_0$ is determined using the following equation [19]:

$$\chi^2_0 = \sum_{i=1}^{m} \frac{(E_i - O_i)^2}{E_i}. \quad (12)$$

The critical value of the test $\chi^2_{\alpha, \nu}$ is obtained by the following equation:

$$\chi^2_{\alpha, \nu} = 1 - \int_0^{\chi^2_{\alpha, \nu}} \frac{t^{\nu/2 - 1/2} e^{-t/2}}{2^{\nu/2} \Gamma(\nu/2)} dt,$$ \quad (13)

where $\nu$ are the degrees of freedom, $\alpha$ is an integration variable, and $\Gamma$ is the gamma function [20].

In this way, rejecting the hypothesis $H_0$; $O_i = E_i$ is applied if the statistic value $\chi^2_{\alpha, \nu} \geq \chi^2_0$ is fulfilled; otherwise, the hypothesis $H_0$ is accepted. In other words, if $\chi^2_{\alpha, \nu} \geq \chi^2_0$, then $O_i$ and $E_i$ do not belong to the same distribution; otherwise, the test distribution belongs to the same distribution.

#### 3.2. Kuiper Test.

This is a statistical test to determine if a set $r_i$ fulfills the property of uniformity [21]. In this test, two distances are found: the most positive and the most negative values. So, the test statistic $D$ is obtained through the following equations:

$$D^+ = \max_{1 \leq j \leq m} |O_j - E_i|,$$

$$D^- = \max_{1 \leq j \leq m} |E_i - O_j|,$$ \quad (14)

$$D = \max (D^+, D^-),$$

where $D^+$ is the most significant positive distance and $D^-$ is the negative distance between each set; $O_i$ and $E_i$ are the observed and expected cumulative distribution function (CDF), respectively; and $n$ is the numbers of subclasses of the CDF, defined as follows:

$$G(r) = P(r \leq a),$$ \quad (15)

where $P$ is a function that applies the counting of coefficients of the set $r$ minor than $a$ limit. To obtain the $p$ value of this test, the following equation is used:

$$k_p = 2 \sum_{k=1}^{j} \left(4k^2 \lambda_p^2 - 1\right) e^{-2k^2 \lambda_p^2},$$

$$\lambda_p = D \left( \sqrt{\frac{m}{2}} + 0.24 \frac{\sqrt{2}}{m} + 0.155 \right),$$ \quad (16)

where $k_p$ is the value of the test, $j$ is a coefficient, and $\lambda_p$ determines the threshold value for the test. The critical value is calculated concerning (14). In case $D \geq k_p$, it is concluded that the set does not follow a uniform distribution ($H_0$ is rejected); otherwise, it is said that no significant difference has been detected between the distribution of the set and the distribution ($H_0$ is accepted) [21].

#### 3.3. Kolmogorov–Smirnov Test.

The KS test allows, like the Chi-square test, to determine the probability distribution of a series of data. It is essential to obtain at least 30 data of the random variable, the mean and variance of the data are calculated, and a histogram of $m = \sqrt{n}$ with $n$ intervals is created, and the frequency observed in each interval $O_i$ must be obtained [22]. Using (17), the observed probability is calculated in each interval $PO_i$:

$$PO_i = \frac{O_i}{n},$$ \quad (17)
where $O_i \in \epsilon$ is the observed frequency and $n$ is the total number of data. The probabilities $PO_i$ are pooled to obtain the observed probability up to the $N$ interval $POA_i$. The null hypothesis $H_0$ must be explicitly established. Then, a probability distribution is proposed that adjusts to the shape of the histogram. We proceed to calculate the cumulative expected probability for each interval, $PEA_i$, from the function of the proposed probability. The test statistic is obtained by the following:

$$c = \max |PEA_i - POA_i| \quad \forall i \in \{1, 2, \ldots, n\}.$$  \hfill (18)

As the Kuiper test, this test requires calculating $p$ values, which are obtained as follows:

$$k_s = 2 \sum_{k=1}^{j} (-1)^{k-1} e^{-2k\lambda_j^s},$$

$$\lambda_j = c \left( \frac{\bar{n}}{2} + 0.11 \left( \frac{7}{n} + 0.12 \right) \right),$$

where $k_s$ is the $p$ value of the test, $\lambda_j$ is a threshold value of this test, and $j$ is an index. The significance level is defined by the test and determines its critical value by using (20); the test statistic is compared with the critical value; if the test statistic is less than the critical value ($c < \alpha_s$), the null hypothesis $H_0$ cannot be rejected [22];

$$\alpha_s = F^{-1}(a/n)$$

$$= \{c : F(c/n)\},$$

where $\alpha_s$ is the critical value and $F^{-1}(a/n)$ is the well-known inverse function to obtain the significance level. For example, if the 5% of a set of 30 samples is considered, the maximum $p$ value to accept $H_0$ should be $\alpha_{0.05} = 0.2417$, that is to say $c \leq 0.2417$ $H_0$ should be $\alpha_{0.05} = 0.2417$, it is to say, $c \leq 0.2417$.

4. Methodology

A valuable and competitive method is proposed with the existing techniques in detecting faults in induction motors. This work focuses on the use of the empirical wavelet transform. It is used to obtain an adaptive wave capable of identifying components of interest in a signal; the EWT is based on the combination of the advantages provided by the wavelet transform and the empirical mode decomposition method. As a result, it can efficiently analyze characteristics extracted from a signal. On the other hand, goodness-of-fit tests can be easily implemented in the time domain. Moreover, they have noise tolerance with an easily adaptable design and deliver high-precision results; these factors are essential for selecting the joint use of these two techniques.

Figure 2 shows the functional structure of the proposed method. The vibration signal is received from the motor, and the signal is filtered and processed using the empirical wavelet transform. The signal is adjusted to stay in the range of $-1$ at $1$, and the decomposition mode is detected where the range of characteristic frequencies of the fault to be analyzed is found. The three goodness-of-fit tests are carried out to determine whether the analyzed signal relates to a motor that presents damage.

The data of the vibration signals of the tests shown here were obtained from two sources, so we aim to corroborate the correct operation of the method; the first group of signals was obtained from the Bearing Data Center of Case Western Reserve University [23]. These signals are obtained when the motor is connected to a dynamometer using a self-aligning coupling. Data were collected from accelerometers in the engine housing at the drive end of the engine, and the vibration signals were measured without a load (0 HP) at a rotation speed of 1797 RPM. The fault was introduced into the motor bearing using the electrocharge machining method. The hole diameter created was 0.1778 mm, and there were two different operating conditions: normal condition and an outer race fault. The signals were sampled at the frequency of 12800 Hz. The original vibration signals were divided into small groups of samples, and each sample contained 2048 data points.

The second group of signals has been obtained from an asynchronous induction motor WEG 00118ET3EM143TW 1HP 1800 RPM 3F that operates with a three-phase power supply (220 V AC @ 60 Hz). Bearing 6204 is used in optimal operating conditions, and a bearing with generated damage on the outer race through a 1.6 mm diameter hole. The motor is powered from the power line (220V @ 60 Hz). The vibration signals were obtained from a low-cost triaxial accelerometer ADXL345 13-bit resolution at ±16 g connected to a custom FPGA-based data acquisition system to manage and save the signals. The sensor was installed in the drive end position on the motor, and the mechanical load was simulated with a car alternator connected to the motor through a band-coupling system. The sampling rate was set to 3600 samples per second.

Chandra and Sekhar [24] proposed a method that details the estimation of the characteristic frequency of the various failures of the elements that make up a bearing, including the one analyzed in this publication. The results are presented in Table 1.

The main idea behind EWT is to extract the different modes of a signal based on the Fourier supports detected from the spectrum information of the processed signal, so the Fourier transform of the signal to be processed must be found. The spectrum is segmented to detect the local maximums, ordered in decreasing order. Then, it proceeds to define the limits of each segment as the center between two successive maximums, and the Meyer wavelet construction is used to obtain a set of adjusted frames; finally, the filters of the corresponding signal are obtained as defined in [18].

The frequency spectra and time-domain signal of the faulty and optimal motor signals are shown in Figure 3.

Figure 4 shows the periodogram created using the filtering of the empirical wavelet transform and a smoothed estimate of the power spectrum; unlike Figure 3, it can be seen how the EWT eliminates the noise in the vibration signal while maintaining the valuable information for this method.
Using the Fourier transform and the EWT, the frequency that characterizes the failure of the outer race of the bearings is sought; when using the EWT method to divide the frequency band, the Gilles threshold method [18] is used to determine the value of $N$; in these tests, the value is established as $N = 8$.

Since the EWT method is applied, the multiresolution analysis (MRA), a type of signal decomposition, where the most concentrated energy is found is sought, based on the method reported by Chandra [24], to calculate the characteristic frequency of the fault. It is known that the frequency is around 107.29 Hz, so when performing the signal decomposition, the MRA that contains the frequencies range near to reported in theory. As a result, the most prominent amplitude peak at 109.74 Hz, according to the experimental analysis results, shows that the EWT is an accurate method to be able to extract the characteristics of the fault since it was possible to locate the frequency of the failure with just a couple of Hz difference between what was calculated and what was analyzed. For this reason, the EWT method is combined with goodness-of-fit tests to propose a novel and adaptable fault diagnosis method for the analyzed signal.

Analyzing the vibration signals, Figure 4 shows that the local maximum number in the spectrum is extensive, and some frequencies in the maximum values are very close to each other, in the case of selecting all these maximum points to calculate the frequency bands.
The intervals generated are too many, which would cause a decrease in computational time consumption and high demand for computer memory. According to the results presented by Deng et al. [9], the optimal value for the magnitude threshold should be set at 30% since this improves precision without increasing the temporal complexity of the threshold. The filter banks are built according to equations (5) and (6), and the results are shown in Figure 5.

The EWT method decomposes the signal into multiple components to extract its local maximum points in the frequency domain; with this, the Fourier spectrum is adaptively divided, and the different modes are obtained for normal signal and the fault signal of the outer race; this is shown in Figures 6 and 7.

Next, the modes of interest are taken where the theoretical frequency of the characteristic failure is found, and the goodness-of-fit tests described above are carried out. The distribution proposed for the comparison is obtained by grouping each signal in a histogram of 64 classes. Then, an average distribution of the signals is obtained, thereby establishing a critical value for the decision-making of the method.

When performing the Kolmogorov–Smirnov and Kuiper tests, the graphs in Figures 8 and 9, respectively, are obtained to confirm the decision of the test by making a visual comparison of the cumulative distribution function (CDF), the amplitude has been previously established in a range from −1 to 1, and the probability is 0 to 1; thus, it is possible to appreciate the similarity between the cumulative probability and the cumulative relative frequency of the healthy motor. In contrast, the cumulative relative frequency of the motor that presents a bearing failure shows a deviation for the cumulative probability of the base signal of the test in both cases.

Figure 10 shows the number of classes concerning the incidence of the data set within each class’s lower and upper limits according to the analysis method presented in [19]. Thus, obtaining the graph where it can visually corroborate the results of the Pearson’s chi-square test, it can be done a visual comparison about the frequency of incidence data of the signal used as a basis to detect if a motor is in good condition and when it presents a fault in its bearing.

The tests are randomly repeated using the 13,500 test signals.

5. Results and Discussion

There are two groups of test signals to corroborate that the method is functional; first, using the proposed methodology, using (21), the precision of each applied goodness-of-fit test is obtained.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \times 100\%, \quad (21)
\]

where \(TP\) is the number of true-positive results, \(TN\) is true negative, \(FP\) is false positive, and \(FN\) is false negative [19].

In total, 12,500 tests were carried out with the signals from group A and 1000 tests with the group B signals, and the percentages of the results obtained are presented in Table 2.
At present, various research works can be found in which multiple fault detection techniques are addressed in induction motors; they have a better precision compared to other works [9, 25–27], and shaft deflection, friction between stator and rotor, and poor insulation [3]. Table 3 shows part of the works reported in recent years.

The experimental results show that the proposed methodology achieves a competitive precision in diagnosing induction motor failures. In the case of the results obtained through the Kuiper test in conjunction with the use of the EWT, there is better precision compared to other works [3, 7, 25–27] (see Table 3), even matches the results obtained in [9] of the three goodness-of-fit tests applied in this...
method; the Kolmogorov–Smirnov test is the test that presented a lower precision. However, it was shown that it could competitively detect different levels of bearing outer ring damage, and the use of Pearson’s chi-square test outperformed traditional statistical methods and other deep learning methods.

6. Computational Complexity Analysis

The computational complexity is one of the highlighted features of algorithms, which allows us to know the use of computational resources and time consumption. The estimated computational complexity of this work is provided in Table 4.
Figure 9: Comparison of the cumulative probability with the cumulative relative frequency of a healthy motor and a faulty motor using the Kuiper test.

Figure 10: Comparison of the cumulative probability with the cumulative relative frequency of a healthy motor and a faulty motor using the Chi-square test.

Table 2: Accuracy of results.

| Test                     | Signal A (%) | Signal B (%) |
|--------------------------|--------------|--------------|
| Kolmogorov–Smirnov test  | 89.912       | 89.950       |
| Kuiper test              | 99.194       | 99.224       |
| Pearson Chi-square test  | 91.960       | 92.066       |
As Table 4 suggests, the main computational complexity is on the EWT algorithm, which lies in the MRA due to segmentation on different scales. Apart from that, the significant computational complexity to apply the complete procedure for goodness-of-fit tests relies on the distribution obtaining PDF or CDF using a sorting algorithm \[28,29\]. In applying the goodness-of-fit test (considering the obtention of PDF or CDF previously), the most complex algorithm is Pearson’s chi-square test.

However, this quick analysis gives an idea of the computational cost of implementing the proposed methodology. The computational complexity shown in Table 4 is subject to the used platform and programming language because the algorithms implemented can differ from those used in this paper. The methodology was tested and implemented on MATLAB software.

### 7. Conclusion

In recent years, numerous methods and techniques have been proposed to evaluate the performance of motors; in this case, a methodology with competitive results is presented for the diagnosis of failures in the outer race of the bearings of an induction motor based on the use of the empirical wave transform and three types of goodness-of-fit tests. There are two different groups of signals in which different motors were used and the level of damage is different (0.1778 mm and 1.6 mm). When analyzing the results, it can be appreciated that the use of the EWT and Kuiper provides the best results while the use of the EWT with Kolmogorov–Smirnov and Pearson chi-square shows a lower but still competitive precision with different methods analyzed. In the same way, a more negligible difference can be seen in the 0.1% between the results obtained from the group of signals A and B, taking into account the difference between the number of samples analyzed and the difference in dimension. Due to the damage in the bearing of each group of signals, there is a very small variation in the results, which proves the efficiency of the method in both cases.

The EWT method eliminates much of the limitations compared to the traditional DWT method and allows the Fourier spectrum to be segmented adaptive; in the same way, it can efficiently extract the AM-FM components with a compatible Fourier spectrum of vibration signals with a loud noise. The goodness-of-fit tests present favorable results when used in conjunction with the EWT; the results obtained show that the information on the damage generated in the outer race of the motor bearings can be detected in the vibration signals.

### Data Availability

The data used to support the study are included within the article.

### Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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