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BEARING INNER RACE DEFECT DIAGNOSIS USING SPECTRAL KURTOSIS (SK), AUTOREGRESSIVE (AR) MODEL AND WAVELET DENOISING

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Abstract- Fault diagnosis plays a very important part of industrial processes today, in order to increase the availability of equipment to ensure the safety of machines and people. The methods of advanced surveillance have been acquiring importance for various systems, vibration measurement being the most popular surveillance technique due to its reliability. It is often used to detect and diagnose faults in rotating systems. This article highlights one of the techniques of vibration analysis and signal pre-processing, ensuring the diagnosis of ball bearing faults, specifically the inner ring fault. The four techniques applied are: envelope analysis, which is the most widely used vibration analysis technique, and three signal pre-processing techniques, namely autoregressive model (AR), wavelet denoising and Spectral Kurtosis (SK), which are chosen to demonstrate the process of ball bearing diagnosis. The procedures are then implemented on real CWRU-generated data sets, known as a normalized benchmark for evaluating diagnostic tools. The comparison of the results obtained shows a complementarity between the different techniques manipulated, the results are quite reliable and the techniques will be ranked among the most recommended tools for monitoring different ball bearing defects. This study will allow engineers and technicians to anticipate any stoppage of the production line in a rotating system and to proceed in an earlier way.

Keywords: Vibration Analysis, Diagnostics, Ball Bearing, Inner Ring Defect, Envelope Analysis, Autoregressive (AR) Model, Wavelet Denoising, Spectral Kurtosis (SK).

1. INTRODUCTION

To date, predictive maintenance has mainly focused on techniques based on vibration signals for rotating components such as ball bearings [2] and gears [1, 2], as they commonly result in severe defects [2, 3]. Taking the case of ball bearing diagnostics, the subject of our article, by regularly diagnosing the condition of bearings to avoid downtime, improving the safety of people and machines, saving costs as well as predicting the Remaining Useful Life (RUL) of bearings [3].

Overall, the diagnosis of ball bearings is essential to ensure the functioning of machines and systems [4], by identifying potential problems early on, maintenance teams can take proactive steps to resolve them and ensure the smooth operation of equipment [5]. In this context, a lot of work has been done to ensure the diagnosis of ball bearings, taking for example: Azevedo studied tools for detecting the condition of bearings in wind turbines [6], Rai's group have applied some signal processing approaches for the diagnosis of bearing faults [7], Cerrada et al dealt with methods for fault severity assessment [8], Hamadache et al. reviewed artificial intelligence algorithms, including deep learning [9].

However, vibration analysis is most commonly used to detect bearing faults including bearing loosening, unbalance, misalignment and damage to rolling elements, inner and outer rings and to make an estimate of the residual life of rotating machines [10]. In most cases, bearing failures start with a local loss of material on a dull surface (inner ring, outer ring and rolling elements) [11]. About 60-70% of bearing defects can be detected by vibration analysis [12] (Figure 1). For example, bearings are the cause of about 21% to 70% of generator faults in the wind industry [6] and 70% of gearbox faults.

The remaining percentages of defects can be detected by other monitoring techniques (Figure 1), such as thermal analysis, oil analysis and acoustic analysis. Each of these techniques has its own advantages and can detect specific types of defects that may not be easily detected by vibration analysis.

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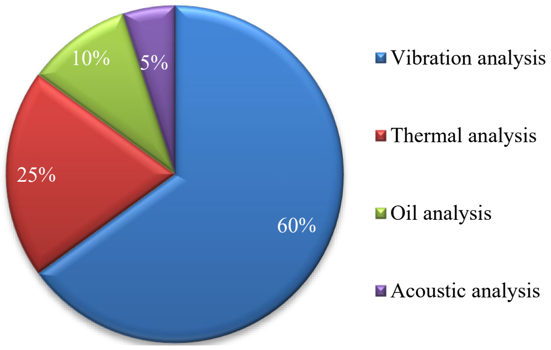

Figure 1. Percentages of defects caused by rolling element bearings according to specific monitoring techniques [12]

Other statistics show that bearing faults account for 44% according to IEEE [13], 40% according to EPRI [14] and 52% according to Thorsen and Dalva [15] of have medium-sized in induction motors. These percentages are presented in the diagram in Figure 2.

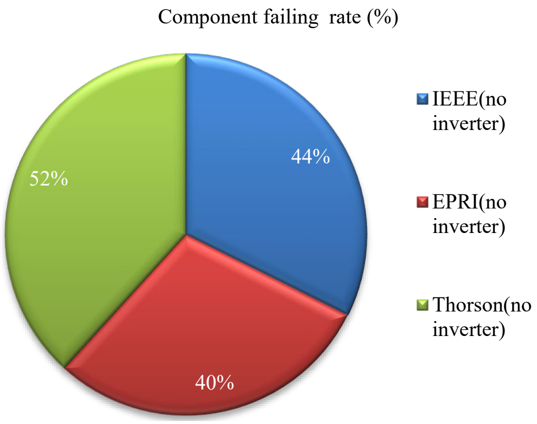

Figure 2. Percentage of ball bearing defects in medium-sized induction machines [13, 14, 15]

The defects produced in bearings are often concentrated in the outer and inner races [16]. The question is to find a way to detect and identify the different defects. To answer this question, in this paper we are interested in diagnosing ball bearings, in particular the inner ring defect, we will implement envelope analysis, one of the more common vibration signal analysis techniques applied to locate defects in controlled systems, by corresponding the envelope spectrum with characteristic defect frequencies. It is important to remember that the signal detected during measurement is usually embedded in resonance noise and noise from other components (e.g. gears, electric motors, etc.): gears, electric motors and others ...), hence the need to filter the measured signal as a first step, using a combination of autoregressive (AR) and spectral Kurtosis (SK), are classified among the most commonly applied techniques [16], let's add a wavelet denoising (DWT decomposition) in order to make a necessary comparison between the pre-processing tools used, and to validate and confirm the feasibility of the techniques used for a reliable diagnosis.

The techniques are applied to digital data measured by the CWRU group [17], which provides a database for testing appropriate signal processing algorithms for reliable diagnosis. In the following, we explain the basic principles and algorithms of the techniques used, the results obtained based on real data are discussed and compared while exploiting the figures, we end with a conclusion that highlights the reliability and simplicity of the techniques used to diagnose ball bearing failures, specifically the inner race failure.

2. METHODS

Vibration analysis focuses on the analysis of acquired vibration signals, it's one of the most widely used techniques for detecting bearing faults. There are several analysis procedures, including temporal analysis, frequency analysis and time-frequency analysis, can be combined to obtain a more accurate diagnosis [18], in this first part we will discuss the procedure of bearing fault diagnosis and the principles of the techniques used in our paper.

2.1. Bearing Failure Diagnosis Procedure

The different steps implemented in our paper to ensure the diagnosis of the ball bearing fault precisely the inner ring fault are implanted in Figure 3.

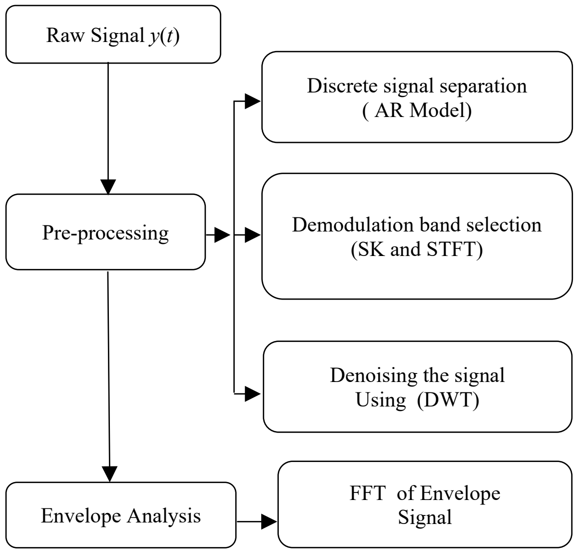

Figure 3. Protocol for bearing fault diagnosis

It is composed of four phases:

- The first is to isolate discrete waveforms, using an autoregressive (AR) model [19] to eliminate undesirable signals derived from mechanical sources, e.g. electrical machines, gears, etc.
- The second is the selection of the demodulation band using the SK and STFT to determine the frequency band where rolling resonance dominates;

- The third is the denoising of the signal by wavelet decomposition (DWT);
- The fourth concerns the analysis of the envelope to find the source of the failure signal, in our case failure created by inner race of the ball bearing.

The first three phases necessary for pre-treatment. The measured raw acceleration signal integrates three signals, namely the rolling fault signal, the discrete signal and the resonance frequencies containing the noise floor, hence the need for band-pass filtering to obtain only the in-band signal while suppressing those elsewhere.

2.2. Principles of Methods

In this part we outline the principles underlying the different techniques discussed in the article.

2.2.1. The Autoregressive (AR) Model

The AR model has been used in the diagnosis of rotative machines to detect gear and bearing faults [20, 21]. The separation of discrete signals involves the elimination of signals derived from other sources such as shafts, gears and others, known as deterministic signals. Autoregressive (AR) modelling, defined by the regression order p, is a parametric method that represents the time signal $y(t)$ as a linear combination of its previous values plus an error term [22]. Given a signal $y(n)$ of order N, for $0<n<N$, where, N, s the total number of measurements, general form the model takes $AR(p)$ is given in the following Equation (1) [23]:

$$y(n)=\sum a(i)\times y(n-1)+e(n) \quad i=1,...,p \quad n=0,...,N-1 \tag{1}$$

where, $y(n)$ current value in time series, a_i are the autoregressive coefficients AR, $e(n)$ is white noise (a random term) with a constant variance σ^2.

Based on the Yule-Walker approach [23, 24] to find the AR coefficients, a (1), a (2) ..., $a(p)$ which minimize the prediction error of the model, i.e. the residual signal $e(n)$: We begin by calculating the autocorrelation of the signal up to order p, as follows: $R(0)$, ..., $R(p\text{-}1)$. The autocorrelation $R(K)$ of order k is defined by Equation (2) [24]:

$$R(k)=\frac{1}{N}\sum y(n)y(n-k) \quad n=0,...,N-1 \quad k=0,1,...,p-1 \tag{2}$$

We can now rewrite the AR model equation in terms of autocorrelation. Replacing $y(n)$ by $y(n\text{-}i)$ in the AR model Equation (1) and multiplying both sides of the equation by $y(n)$, we obtain Equation (3) [19]:

$$y(n)y(n)=a(1)y(n)y(n-1)+...+a(p)y(n)y(n-p)+ +e(n)y(n) \tag{3}$$

Taking the mean over n ranging from p to N-1, we can redefine the autocorrelation of the signal by the following Equation (4) [25]:

$$\sum a(i)R(k-i)=-r(k) \quad i=1,...,p \quad k>=0 \tag{4}$$

where, $r(k)$ is the autocorrelation of the time sequence at a lag of k, for k=0,1,..., p.

We can write this equation in matrix form Equation (5) [12]:

$$R\bullet a=-r \tag{5}$$

where, R is a Toeplitz matrix of size $p\times p$, with elements $R(0)$, ..., $R(p\text{-}1)$ in the first row and elements, $R(1)$, $R(0)$, …, $R(p\text{-}2)$ in the next rows, a is a matrix of dimension p that includes the coefficients AR: $a(1)$, $a(2)$, ..., $a(p)$, r is a vector of size p containing the negative values of the autocorrelations of order 1 to p, i.e. $-r(1)$, $-r(2)$, ..., $-r(p)$.

We can solve this equation using numerical methods such as matrix inversion or Cholesky decomposition. The Yule-Walker Equation (5) can be solved to obtain the (AR) coefficients an Equation (6) [12]:

$$a=R^{-1}\bullet r \tag{6}$$

where, R^{-1} is the inverse matrix of R.

After finding the coefficients of the AR model, the signal is predicted using these coefficients, forming a moving mean process as shown in Figure 4 [19]. The discrete signal is defined by Equation (7) [19]:

$$\hat{y}(n)=-\sum_{k=1}^{P}a_k y(n-k) \tag{7}$$

Then the differential signal $e(n)$ is calculated by removing the discreet signal from the raw signal $y(n)$, as shown in the following Equation (8) [12]:

$$e(n)=y(n)-\hat{y}(n) \tag{8}$$

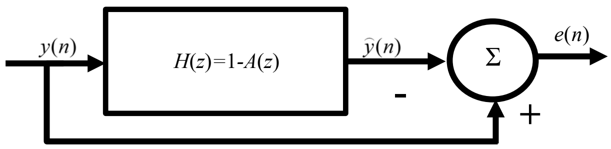

Figure 4. Signal prediction [19]

The residues can be analyzed for abnormal variations that could indicate faults in the machine [19]. It is important to note that the Yule-Walker method can be sensitive to the choice of the order of the AR model [12]. If the order p is too small, the model will not be able to capture all the information contained in the signal and the residual noise will be large, if the order p is too large, the model will be over-fitted to the data and the AR coefficients will not be generalizable to other similar data. There are several methods for choosing the optimal order of the AR model, such as the Akaike criterion (AIC) or Bayes criterion (BIC) [26]. In the diagnosis of bearing failures, the p-Order is determined in such a way that the kurtosis of the residual signal is maximal [24].

2.2.2. Wavelet Denoising

Wavelet denoising is a method of removing noise from a vibration signal. This method uses a raw signal decomposition based on wavelets to isolate the different components of signal at different scales and frequencies

[27]. Then, the wavelet coefficients corresponding to each scale and frequency are thresholder to remove the noise correspondents. The coefficients that are below a certain threshold are considered noise or interference and are removed, coefficients that are above the threshold are represented as important signal components and are retained.

The WT wavelet transform characterizes a signal by employing the correlation with the translating and expanding function named the mother wavelet [28], and includes CWT and the DWT. Given a waveform $y(t)$, the wavelet decomposition is calculated using the CWT of $y(t)$, defined by Equation (9) [28]:

$$CWT(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} y(t)\Psi^*(\frac{t-b}{a})dt \tag{9}$$

Often the discrete wavelet transform (*DWT*) is often used, which is a common and rapidly computable discretization. It is defined mathematically as Equation (10) [27, 28]:

$$DWT(m,k) = \frac{1}{\sqrt{2^m}} \int_{-\infty}^{+\infty} y(t)\Psi^*(\frac{t-2^m k}{2^m})dt \tag{10}$$

where, $\Psi^*(t)$ the conjugate function of the master wavelet, $\Psi_{a,b}(t)$, a and b are the scaling and translating (offset) variables are replaced by 2^m and $2^m k$; m and k are integers, $\Psi_{a,b}(n)$ is the discrete wavelet defined by Equation (11) [29]:

$$\Psi_{a,b}(n) = \frac{1}{\sqrt{a}}\Psi(\frac{n-b}{a}) \tag{11}$$

Wavelet coefficients are calculated for each level of decomposition using DWT to represent the different frequent features of the signal. This decomposition allows the signal to be separated into different frequencies and temporal resolutions. It should be noted that the wavelet function is defined using a base signal called the mother wavelet and a sequence of shifted and extended wavelets. A number of wavelet functions can be used, for example Haar, Daubechies, Morlet, etc., Note that the choice of an appropriate wavelet results in a reliable analysis.

In our paper, in this paper, we employ the Daubechies wavelet (db2) to diagnose inner race faults in a ball bearing. Next, the wavelet coefficients are thresholder to remove features corresponding to noise, specifically those coefficients whose magnitude is less than a predefined thresholding value. The thresholding threshold can be calculated using different methods, the most common method being the universal thresholding threshold of Donoho and Johnstone, defined by Equation (12) [27]:

$$\lambda = \sqrt{2\log n\sigma} \tag{12}$$

where, n is length of a signal, σ is the displayed standard error of the noise or interference.

Finally, the resulting signal is obtained by applying the IDWT to the thresholder wavelet elements. The IDWT formula is given by Equation (13) [28]:

$$x(t) = \sum_{m,k} C'_{m,k}\Psi_{m,k}(t) \tag{13}$$

where, $C'_{m,k}$ are the thresholder wavelet coefficients.

Wavelet denoising is a commonly used method of removing background noise and high frequency interference from vibration signals, while preserving important low frequency components.

2.2.3. Spectral Kurtosis (SK)

The Spectral Kurtosis permits the identification of the optimum frequency band for demodulation. of non-stationary signals such as machine vibrations. The determination of the appropriate frequency range is important for accurate demodulation and identification of machine faults. This method uses a STFT to calculate the SK, which represents a statistical measure of the form of the frequency spectrum [30]. The principle of spectral kurtosis based on STFT is detailed as follows [30]:

➢ Calculation of the STFT: STFT is a signal treatment procedure that calculates the frequency spectrum associated with a non-stationary signal over a short period of time. STFT is calculated by splitting the signal into short time segments and applying a Fourier transform to each segment.

➢ Calculation of Kurtosis: Kurtosis is a statistical measure of frequency spectral shape, indicating how flat or pointed the spectrum is relative to a Gaussian distribution. To calculate kurtosis, the frequency spectrum of each segment should be normalized to have zero mean and unit variance. Then, the kurtosis is determined for each frequency based on the STFT, as shown in Equation (14) [16]:

$$K(f) = \frac{\left\langle |S(t,f)|^4 \right\rangle}{\left\langle |S(t,f)|^2 \right\rangle} - 2 \tag{14}$$

where, <.>: represents time mean operator, $S(t,f)$ defines the STFT of residual signal evolved by the autoregressive AR model.

➢ Frequency band selection: The optimum frequency band for demodulation is selected by searching for the highest peak in the spectral kurtosis. This peak represents the frequency band where the form of the spectrum is most no-Gaussian, indicating the presence of faults in the machine.

The best way to achieve spectral Kurtosis is to filter the signal before analysis in order to extract as much of the bearing fault signal as possible from the background noise.

2.2.4. Envelope Analysis

Envelope analysis is a diagnostic technique that extracts the vibration envelope to detect operating faults. The different stages of this analysis [29]:

➢ Vibration acquisition: Vibration is acquired by sensors installed on the equipment. It is important to choose quality sensors to obtain accurate data.

➢ Data pre-processing: Raw data is filtered and pre-processed to remove noise and interference.

➢ Hilbert transform calculation: The Hilbert transform is a mathematical technique used to calculate the analytical signal of a given signal [29]. The analytical signal contains both the envelope and the phase of the original signal.

➢ Calculates the amplitude of the analytical signal to obtain the corresponding amplitude modulated signal envelope.

➢ Calculation of the envelope spectrum: represents the frequency distribution of the envelope of the analytical signal. It is used to visualize the variations of the vibration at different frequencies.
➢ Analyze the envelope spectrum to identify significant frequencies that show anomalies or unusual peaks. These frequencies may indicate the presence of specific faults in the machine.
➢ Use diagnostic techniques such as frequency signature analysis, spectral analysis or correlation analysis to identify the type of fault and its severity.
➢ Make a comparative analysis between the data obtained and the specifications of the machine (kinematics of the machine) to confirm the defect and estimate its evolution.

In terms of mathematical equations, the Hilbert transform is calculated using Equation (15) [29]:

$$H(f) = \frac{1}{\pi f} \int y(t) y(t - \tau) d\tau \quad (15)$$

where, $H(f)$ is denotes the hilbert transform of $y(t)$, f is frequency, t is time index, τ is integration variable. On the other hand, the analytical signal can be calculated from Equation (16) [29]:

$$a_x(t) = y(t) + jH(t) \quad (16)$$

where, $a(t)$ is the analytical signal, j is the imaginary unit; and $H(t)$ is the Hilbert transform of $y(t)$.

3. EXPERIMENTAL STUDY

3.1. Description of the Bearing Data Centre Test Unit (CWRU)

The CWRU test bench is composed of [17]:
- A tow horsepower motor (left);
- A sensor and encoder (center);
- A dynamometer(right);
- SKF type bearings: fan end and drive end bearings, supporting motor shaft.

The photo of the experimental set-up and its schematic diagram are shown in Figures 5 and 6.

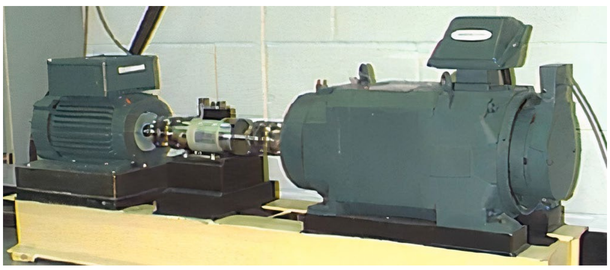

Figure 5. The CWR Bearing Test Stand [17]

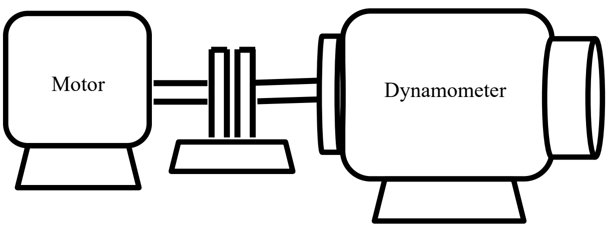

Figure 6. Synoptic diagram [17]

3.2. Bearing Geometry and Frequency Characteristics

In this paper we consider the fan-end (FE) ball bearing (SKF 6203-2RS JEM) as the controlled component in our study. The information concerning the geometry of the bearing considered is evaluated in Table 1.

Table 1. Bearing geometry 6203-2RS JEM SKF [12]

Bearing Name: Fan end bearing: 6203-2RS JEM SKF, rigid ball bearing	
Parameter Name	Value (inch)
Pitch diameter (D)	1.222
Ball diameter (d)	0.2656
Number of rolling element (n)	13
Inner diameter	0.6693
Outside diameter	1.5748
Thickness	0.4724

To diagnostics the bearing failure, the characteristic frequencies of the failure must be available. The set of failure frequencies is presented through Table 2.

Table 2. Fault frequencies: (multiple of operating speed in Hz) [17]

Fault frequencies: (multiple of operating speed in Hz)			
Ball Pass Frequency Inner BPFI	Ball Pass Frequency Outer BPFO	Fundamental Train Frequency FTF	Ball Spin Frequency BSF
4.9469	3.0530	0.3817	1.994

3.3. Defects Specification

Various experiments have been developed to examine damaged bearings [17]. The CWRU group caused local defects in SKF test bearings on the drive end (DE) and fan end (FE) by electrical discharge machining (EDM). The defect diameter studied in our study is 0.007 inch (1 inch = 1000 mil). In our study we are interested in diagnosing faults in the SKF fan-end (FE) test bearing (SKF 6203-2RS JEM) with a produced fault diameter of size 7 mils (0.007 inch) whose motor is driven by a constant speed of 1772 rpm.

3.4. Signals Measurement

The temporal random signals (vibrations) were measured through accelerometers mounted on motor casing by a magnetic foundation. The sensors are placed vertically on the motor housing [17]. The signatures have been acquired using advanced technology, a 16-channel digital recorder. The sampling rate is 12 kHz (12000 samples per second).

The defective bearings were reinstalled in the test motor, the vibrations were measured under the condition that the controlled system is in working state, the motor is rotated by a speed comprised between 1797 and 1720 rpm [17]. Our paper focuses on the vibration acquired by the accelerometer installed on the fan end bearing (FE), with a sampling frequency 12 kHz and a rotation speed 1772 rpm.

3.5. Results and Discussions

In this section, only significant results are considered: The data set for the (FE) bearing (SKF 6203-2RS JEM) is taken, the motor is rotated at a speed of 1772 rpm and a vertical load of 1N. Figure 7 shows the measured raw signal, whose kurtosis is 2.2344.

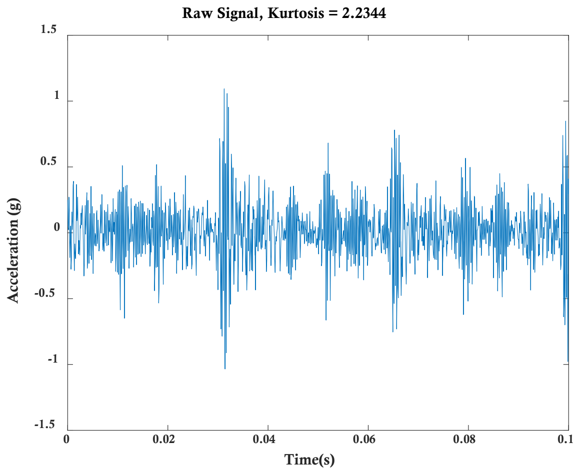

Figure 7. Raw vibration signals

It is clear that the raw signal is modulated in amplitude, this is because of the contact produced between the rolling elements and the outer or inner race, the impact will modulate the characteristic frequencies of the bearing (Table 2).

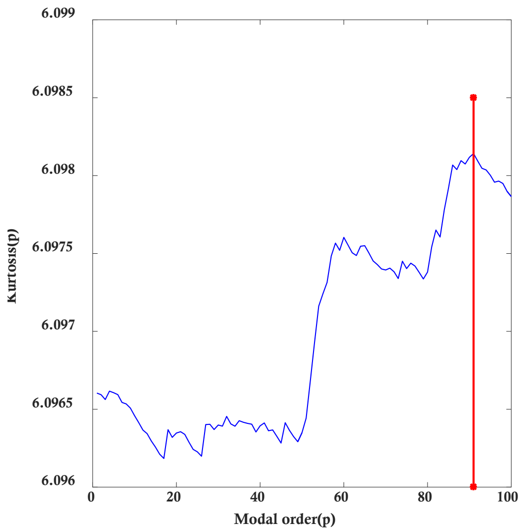

Figure 8. AR model order selection based on maximum kurtosis

3.5.1. Discrete Signals Separation

3.5.1.1. Autoregressive (AR) Model

To perform the separation of the discrete signals from the raw signal based on the AR model, the maximum order of the AR model is set to 100, with the optimal order calculated at 91 (Figure 8). The residual signal resulting from the AR model under these conditions, shown in Figure 9, has a kurtosis of 6.0966, an increase of about 3-fold over the kurtosis of the raw signal.

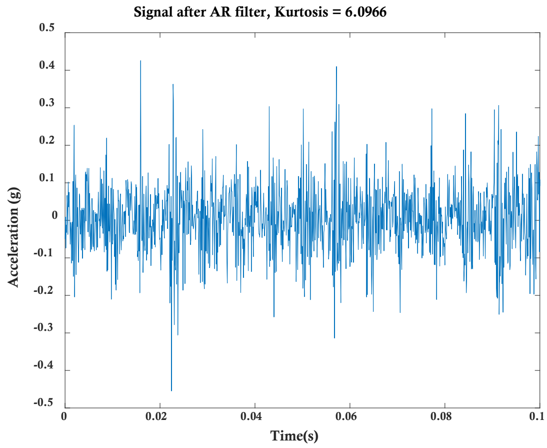

Figure 9. Residual signal after AR filtering

3.5.1.2. Wavelet Denoising

For the same reason and to remedy the separation results of the discrete signals, we performed a denoising of the measured signal based on the DWT wavelet decomposition, the threshold coefficient used for this technique is 0.4, the mother wavelet used for the reconstruction of the signal is the Daubechies4 (db4). The result obtained is shown in Figure 10, the raw signal has a kurtosis of 27.5, a 13-fold increase compared to the raw signal.

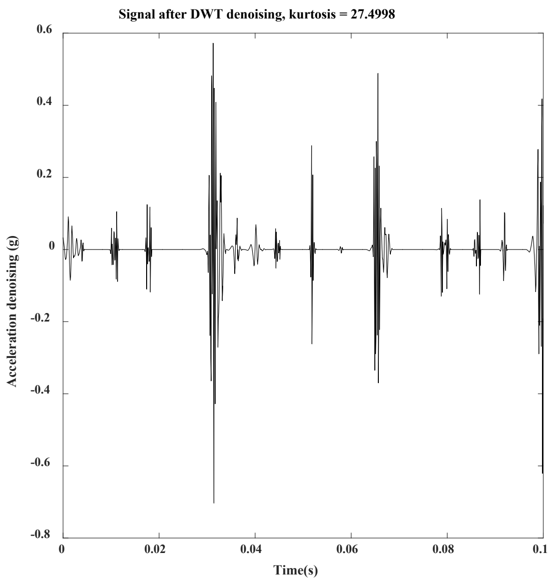

Figure 10. Time signal after denoising by wavelet decomposition (DWT)

This increase in the kurtosis value explains the existence of the more intense frequencies. Viewing the zoomed-in signal (Figure 11) which represents the time domain data of the wavelet decomposed signal (DWT).

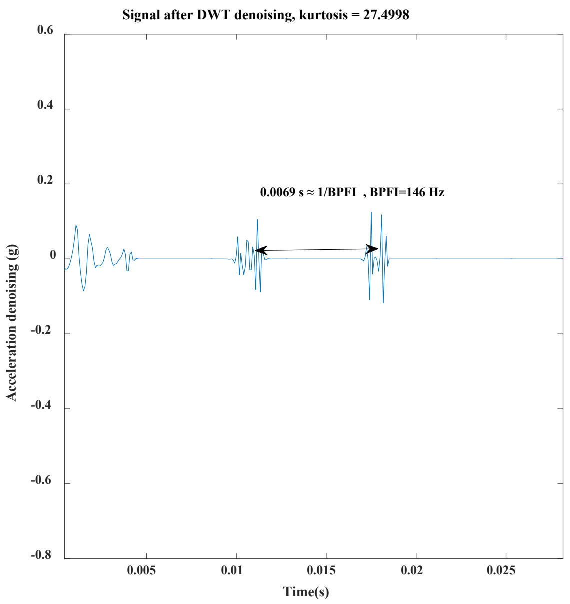

Figure 11. Signal after DWT denoising (zoomed)

It is observed that the signal is amplitude modulated, the modulation frequency being about 1/0.0069 ≈ 145Hz. Based on the controlled group kinematics (Table 2), the frequency at which the rolling element encounters a local inner race fault noted as BPFI is 146.1 Hz, a comparison between these two frequencies clearly proves that the bearing has a potential inner race defect.

3.5.2. Demodulation Band Selection

The remarkable increase in kurtosis, explains the existence of dominant frequencies (resonance frequencies or others), which cause the amplitude modulation of the frequencies of the rolling defects studied (Table 2), hence the need to determine the demodulation band based on the evolution of the spectral kurtosis. In our study the selection of the demodulation band is carried out using the three sets of kurtoses (SK) realized with three window lengths [2^4 2^5 2^6], which are mentioned in Figure 12.

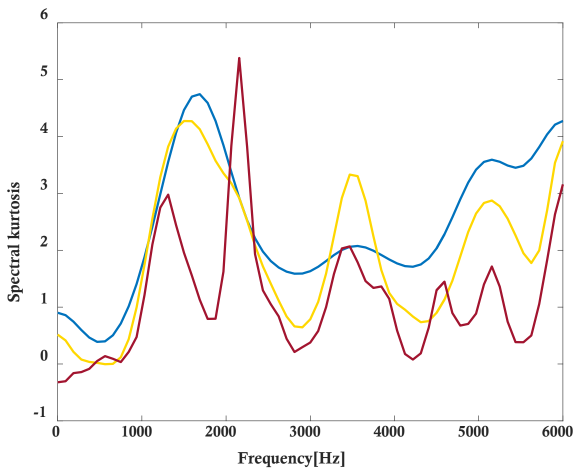

Figure 12. Spectral Kurtosis

The Fast Fourier Transform (FFT) is shown in Figure 12. It can be represented by the spectrogram (2D form) as well, which shows the evolution of frequency as a function of time, the STFT and SK spectral kurtosis are considered powerful tools for locating the frequency range with the highest kurtosis (highest signal to noise ratio) [30].

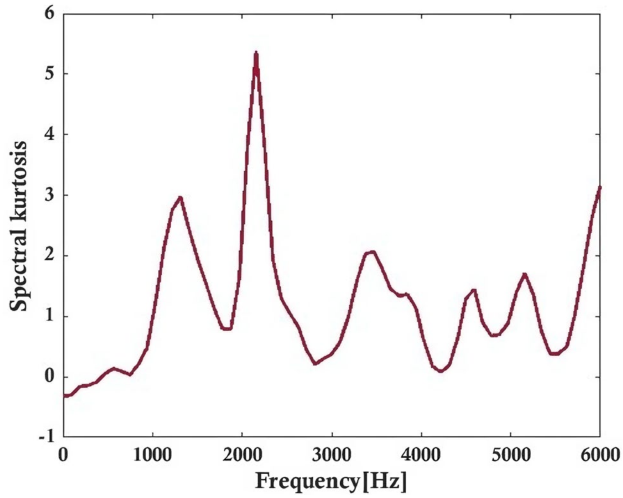

Figure 13. Spectral Kurtosis

Based on Figure 13, the frequency range for the SK kurtosis to be high can be selected visually, which is about 1.875-2.156 KHz in our case study.

3.5.3. Envelope Analysis

After determining the frequency range, the envelope analysis continues, the results obtained are shown in Figure 14, which represents the envelope spectrum of the residual measurement obtained by the AR autoregressive model, filtered in the selected demodulation band.

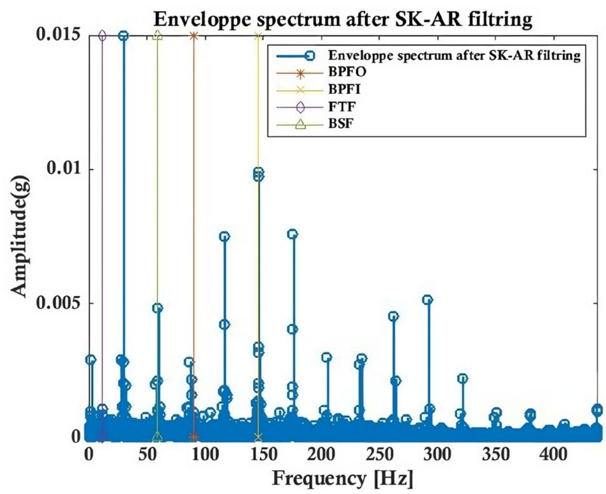

Figure 14. Envelope spectrum of the filtered residual signal in the band [1.857-2.156 K Hz]

On the other hand, Figure 15 illustrates the envelope spectral analysis of the signal decomposed by wavelets:

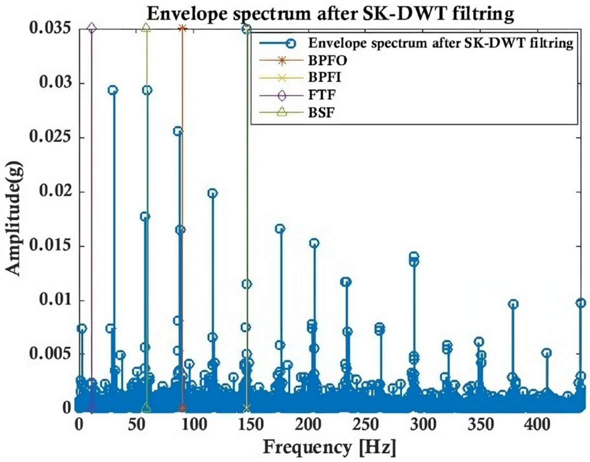

Figure 15. Envelope spectrum of the signal denoised wavelet decomposition

In both figures, the four characteristic fault frequencies [BPFO BPFI FFT BSF] (Table 2) are represented by vertical lines, at which the peaks are examined to determine whether or not the fault has occurred. The envelope spectra obtained are richer in significant frequencies, they show in the low frequencies a dominant peak at the rotating frequency of the shaft RPM (RPM=29.5 Hz = 1772 rpm) with its harmonics, a slight increase observed at the third harmonic (3RPM), which prove the existence of the following faults: an unbalance and a misalignment [31].

A more intense, energetic peak is still observed at the characteristic BPFI bearing frequency (146Hz) and its harmonics, spaced by sidebands equal to the rotational frequency (RPM=29.5Hz), which reflects the existence of the inner ring defect in the bearing under study [12]. It can be clearly seen that the signal envelope spectrum denoised by the DWT wavelet decomposition has more energetic and significant frequency peaks with large amplitudes and good frequency resolution, while the signal envelope spectrum obtained from the combination of the AR model and the SK kurtosis spectrum has high frequency resolution, less energetic frequency peaks with fairly low amplitudes. By comparison, wavelet denoising gives very accurate results, a perfect diagnosis of the inner ring of the bearing.

6. CONCLUSIONS

Bearings are equipment that provide rotational guidance for many rotating systems, hence the need to control them. This paper presents an approach to the diagnosis bearing defects, specifically the inner race default of a ball bearing, based on envelope analysis and signal pre-processing techniques such as the AR autoregressive model, the SK spectral kurtosis and the DWT wavelet decomposition signal noise.

The results obtained conclude that:
Wavelet decomposition has good temporal and frequency resolution, which can help to detect small bearing faults, it is able to separate the different frequency components of the vibration signal, which can allow a more accurate identification of bearing faults at different frequencies. In contrast, the autoregressive AR model combined with the spectral kurtosis SK uses an analysis of the spectral distribution of the signal, which may limit its frequency resolution. Both methods reliably allowed us to detect the inner ring defect of ball bearings, note that the reliability of each method depends on the specific application and the type of defect detected. In general, the envelope spectrum of wavelet decomposition is more reliable for detecting early-stage defects, while the envelope spectrum of the signal obtained via AR-SK may be more reliable for detecting more advanced defects.

In terms of simplicity, the signal envelope spectrum derived by DWT is relatively simple to implement, as it involves a straightforward process of extracting the signal envelope after noise removal. In contrast, the AR-SK method is more complex, as it involves estimating the spectral kurtosis of the signal using an auto-regressive model, which can be computationally intensive. In sum, wavelet decomposition can offer finer frequency resolution, but requires additional expertise to interpret the results. The choice between these two approaches will depend on the specific characteristics of the vibration signal and the needs of the diagnostic application.

NOMENCLATURES

1. Acronyms

AR	Auto-Regressive
SK	Spectral Kurtosis
RUL	Remaining Useful Life
EPRI	*Electric Power Research Institute*
STFT	Short Time Fourier Transform
DWT	Decomposition Wavelet Transform
CWT	Continu Wavelet Transform
IDWT	Inverse Decomposition Wavelet Transform
KHz	Kilo Hertz
DE	Drive End
FE	Fan End
SKF	Svenska Kullager Fabriken
RPM	Rounds per minute
FFT	Fast Fourier Transform
AIC	Akaike criterion
BIC	Bayes criterion

2. Symbols / Parameters

p: The regression orders
n: The length of the signal
a_i: The autoregressive coefficients AR
N: The number of samples
m: The integer variable
k: The integer variable
j: The imaginary unit
a: The dilation (scaling) parameter
b: The translation (offset) parameters
λ: The universal thresholding threshold of Donoho and Johnstone
f: The frequency
t: The time variable
τ: The integration variable
$y(t)$: The time signals

$AR(p)$: The Autoregressive (AR) model
R: The Toeplitz matrix of size $p \times p$
σ: Constant variance
g: Acceleration unit
R^{-1}: The inverse matrix of R
$e(n)$: The residual signal
$CWT(a, b)$: The continuous wavelet transforms CWT of $y(t)$
$DWT(j, k)$: The Discrete Wavelet Transform
$Y_{a,b}(t)$: The master wavelet
$\Psi^{*}(t)$: The conjugate function of $\Psi_{a,b}(t)$
$\Psi_{a,b}(n)$: The discrete wavelet
$x(t)$: The inverse wavelet transforms (IDWT) to thresholder wavelet coefficients
$C'_{j,k}$: The thresholder wavelet coefficients
$K(f)$: The kurtosis
$S(t,f)$: The short-time Fourier transform of residual signal evolved by the autoregressive AR model

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