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Conditional Maintenance by Vibratory Analysis: An Overview of Some Methods

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Abstract

Rotating machines such as motors, reducers, compressors, pumps or alternators are used in various fields of industrial production. These machines are subject to forces of mechanical origin generated by the moving parts. These forces can cause vibrations that can propagate throughout the machine. As a result, vibrations can be used as a tool to detect defects in machines in order to guarantee productivity, reduce maintenance costs and ensure the proper functioning of the machines. Today, more and more machines are monitored by sensors (acceleration, temperature, sound, etc.) that deliver signals on the internal state of the machine's vibration. The signals are analyzed to detect or diagnose failures. Several analysis methods exist, including acoustic analysis, temperature analysis and vibration analysis. In this work, we focus on the vibration analysis of signals delivered by an accelerometer placed at a preferred location on the machine. These signals can be analyzed in the temporal domain or in the frequency domain. The objective of this work is to provide an overview of the existing methods in the field of vibration analysis monitoring and show the limits and progress made in this field.

Keywords

Conditional Maintenance, Machine Monitoring, Vibration Analysis, Temporal Analysis

1. Introduction

Conditional maintenance is necessary and even essential to keep machines in working order and to increase productivity. In particular, the machine is monitored using data collected regularly and analyzed, in order to intervene at the appropriate time to avoid an incident. Several scientific and technical analysis methods are possible, for example vibration analysis [1], oil analysis [2], infrared thermography or sound perception [3] [4]. In our case, we limit ourselves to vibration analysis. In this area, work has been carried out by the authors Djebala *et al.* [5]-[7]. Moreover, a synthesis of their work was made by Djebala [8]. In this work, they proposed a method based on multiresolution wavelet analysis and the Hilbert transform to detect single and multiple gear defects. They showed from an experimental result and from a signal simulation containing a phase and amplitude modulation, that on the one hand, small defects are neither detected by the spectrum nor by the cepstrum [9], but that the envelope spectrum has made it possible to highlight the modulating frequency and several of its harmonics, even in the case of combined pinion-wheel defects. On the other hand, they show that Kurtosis is a tool that better detects defects in shock signals than the crest factor. They also show that detection is better when the bearing is greased or when the gears are loaded, and that Kurtosis increases according to the size of the defect.

In parallel with their work, in this paper, we show that Kurtosis is not able to detect the severity of a bearing defect compared to another defect on the bearing. Other criteria are also evaluated in this work. Antoni and Sidahmed [10] briefly presented different methods for fault diagnosis in acoustic and vibration signals, applicable to stationary or non-stationary signals. In the case of non-stationary signals, especially cyclostationary signals where the speed is variable, direct analysis of the signal would not give a correct result, because the number of points is not the same in each period of the signal. Specific signal processing techniques are required to complement or improve the presented methods [11]. To analyze signals in this context, one approach is to resample the signal (angular resampling), apply synchronous averaging to eliminate first-order components of the signal, apply filtering [12], and finally apply spectral correlation to detect second-order faults. Lejeune *et al.* [13] also present work on first- and second-order cyclostationarities applied to gear vibration signals. In the following sections, we present our approach to the work.

2. Materials and Methods

2.1. Materials

To record vibration signals, sensors are connected to the channels of the signal analyzer-recorder. In our case, it is the CoCo-80X signal analyzer from National Instruments (see **Figure 1**).

Figure 1. Data acquisition equipment and National Instruments CoCo-80X vibration analyzer.

The test bench allowed us to experiment with twelve tests with different configurations of defects carried out on the gear and on the bearing mounted on the bench. Table 1 below shows the tests carried out.

Table 1. Configurations of defect (twelve tests).

Twelve Gear and Bearing Fault Configurations		
Outer ring fault	Cage fault	Gear fault (1 tooth broken)
		
Config. 1: Healthy bearing (Rs)		
Config. 2: Healthy bearing and healthy gear (Rs_Es)		
Config. 3: Healthy Bearing and Defective Gear (Rs_Ed)		
Config. 4: Defective outer ring bearing (Rd_bext)		
Config. 5: Defective outer ring bearing and healthy gear (Rd_bext_Es)		
Config. 6: Defective outer ring bearing and defective gear (Rd_bext_Ed)		
Config. 7: Defective inner ring bearing (Rd_bint)		
Config. 8: Defective inner ring bearing and healthy gear (Rd_bint_Es)		
Config. 9: Defective inner ring bearing and defective gear (Rd_bint_Ed)		
Config. 10: Defective cage bearing (Rd_cage)		
Config. 11: Defective cage bearing and healthy gear (Rd_cage_Es)		
Config.12: Defective cage bearing and defective gear (Rd_cage_Ed)		

2.2. Methods

2.2.1. Temporal Analysis

1) Scalar indicators

Temporal domain analysis of vibration signals is a method of analyzing stationary signals in the time domain. This type of analysis makes it possible to highlight the presence of faults in machines. Indeed, the presence of faults and, if applicable, their severity in rotating machines is detected. Temporal domain methods are based on the statistical analysis of the collected signal and use well-known scalar indicators to monitor the evolution of a quantity derived from the power or peak amplitude of the signal.

These indicators include, among others, the RMS (effective value) is calculated by:

$$\text{RMS} = \sqrt{\frac{\sum_{i=1}^{N} X(i)^2}{N}} \tag{1}$$

The Kurtosis is obtained by:

$$\text{KURT} = \frac{\dfrac{\sum_{i=1}^{N}\left(X(t)-\bar{x}\right)^4}{N}}{\left(\dfrac{\sum_{i=1}^{N}\left(s(i)-\bar{x}\right)^2}{N}\right)^2} \tag{2}$$

The Crest factor is calculated by:

$$FC = \frac{\operatorname{Sup}\left|X(i)\right|}{\sqrt{\frac{\sum_{i=1}^{N} X(i)^2}{N}}} \tag{3}$$

The peak-to-peak value of the vibration signal is calculated by:

$$ACC = ACC\max - ACC\min \tag{4}$$

The peak value of the vibration signal is obtained by:

$$AC = ACC\max \tag{5}$$

And the K factor is obtained by:

$$K = \text{Acccrete} * \text{Acceff} = \operatorname{Sup}\left|X(i)\right| \times \sqrt{\frac{\sum_{i=1}^{N} X(i)^2}{N}} \tag{6}$$

To detect a defect, we look at the value of the indicators, if there is a change in the signal, then there will be a variation in the indicator. For example, a bearing in good condition generates a vibration signal with a Kurtosis close to 3. For a degraded bearing, with flaking, indentations or significant clearances, the shape of the distribution of the signal amplitude is modified and the Kurtosis is greater than 3.

2) Combined scalar indicators

In this subject, we proposed in [14] a new indicator obtained by linear combination of two traditional scalar indicators such as $I = aX + bY + c$, with a, b and c constants, and X and Y are traditional scalar indicators. The results showed that the best combined scalar indicator is obtained by the linear combination of RMS and crest factor:

$$Ic = -0.0099356 * RMS + 0.44901 * FC - 2.0601 \tag{7}$$

Avec $a = -0.0099356$, $b = 0.44901$ and $c = -2.0601$.

Tests were performed with defects on the bearing and gear created on a test bench. The results of defect detection by the indicators are presented in the results and discussion section.

2.2.2. Frequency Analysis

1) Spectral analysis or (Fourier analysis of the signal)

The vibration signal taken from a rotating machine is very complex, and originates from different parts of the machine. The Fourier transform is a mathematical calculation tool [15] that allows these complex signals to be processed appropriately, to decompose them into several basic sinusoidal components and to represent them in the form of an "Amplitude-frequency" spectrum [16]. The Fast Fourier Transform (FFT) developed by James Cooley and John Tukey requires a low calculation time to perform the discrete Fourier transform. The fast Fourier transform is widely implemented in diagnostic systems for rotating machines. Formulas (8) and (9) represent the Fourier transform and its discrete variant respectively.

$$X(f)=\int_{-\infty}^{+\infty}x(t)\mathrm{e}^{-i2\pi ft}\mathrm{d}t \tag{8}$$

$$X(f)=\sum_{k=0}^{N-1}x(t)\cdot\mathrm{e}^{-i2\pi f\frac{k}{N}} \tag{9}$$

2) Cepstral analysis

In its most common definition, the cepstrum of a signal is the result of the inverse Fourier transform of the decimal logarithm of the Fourier transform. Algebraically, the operation of cepstral analysis allows performing a Fourier transform on the spectrum of the signal in decibels (dB) (Equation (10)).

$$c(t)=F^{-1}\left[\log\left(\left|X(f)\right|^2\right)\right] \tag{10}$$

$$X(f)=F\left[X(t)\right] \tag{11}$$

where $c(t)$ is the cepstrum, F is the Fourier transform and F^1 is the inverse transform.

The purpose of the cepstrum is to recognize and analyze all the periodic structures present in the spectrum. It allows defining indicators adapted for the early detection of defects inducing at different stages of evolution, vibrational energies that indicators from traditional methods would have difficulty in highlighting. The cepstrum and its derivatives illustrate the amplitudes of the components whose frequencies are associated with the repetition periods of the shocks caused by the faults of the monitored machine. It is used to identify gear faults and, to a lesser extent, bearing faults [17].

3) Envelope analysis

Envelope analysis allows us to look at the evolution of a harmonic on a given frequency to identify abnormal and repetitive shocks. It consists of filtering the signal and then processing it by the Hilbert transform, and then by the inverse Fourier transform. The signal obtained (envelope) allows us to calculate a spectrum called the envelope spectrum. The Hilbert transform of a time signal x is defined by the following equation [15]:

$$\tilde{x}(t)=H\left(x(t)\right)=\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{x(\tau)}{t-\tau}\mathrm{d}\tau \tag{12}$$

$$\tilde{x}(t)=x(t)\times\frac{1}{\pi\tau} \tag{13}$$

where H is the Hilbert transform.

4) Multiresolution wavelet analysis

Multiresolution wavelet analysis is a signal analysis technique that has been widely used recently for fault diagnosis in rotating machines. It was used in vibration analysis by Djebala *et al.* [5]-[8], among other things, to overcome the problem of random noise that can be associated with low fault severity.

Multiresolution wavelet analysis decomposes the original signal into wavelets and then performs an approximation to reconstruct the signal for better localization in time and frequency. It allows for amplitude and phase modulation. In our study, we will perform a level 3 wavelet decomposition (see **Figure 2**) available in MATLAB®, then analyze the spectrum of the reconstructed signal to search for possible faults.

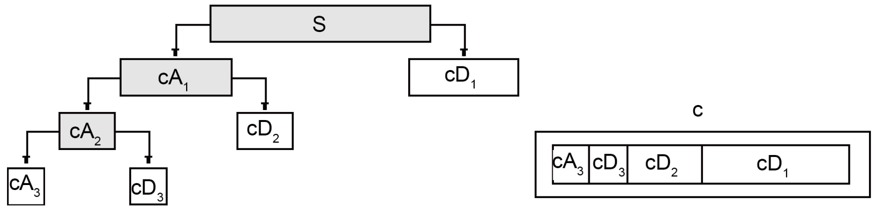

Figure 2. Level 3 wavelet decomposition (MathWorks® source). S: starting signal; cA*i*: level *i* approximation; cD*i*: level *i* details.

3. Results and Discussion

3.1. Results of the Temporal Analysis

3.1.1. Results of Scalar Indicators (e.g. RMS)

Temporal analysis has been studied in particular by exploiting scalar indicators. We have chosen to compare on several signals, some relevant indicators, in order to evaluate their fault detection capacity and their severity according to the type of fault.

As we mentioned previously, temporal analysis makes it possible to highlight the presence of faults in machines. Machine operating parameters, such as speed or load, can influence the result of fault detection. Figure 3 and Figure 4 present the results of the RMS [18] and the combined scalar indicator that we proposed in [14].

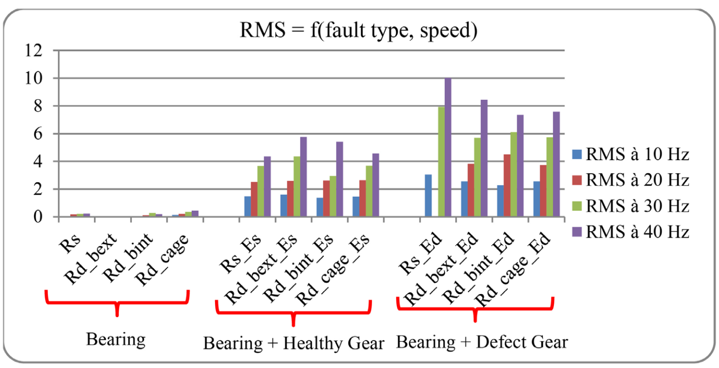

Figure 3. RMS for different speeds for different defects (without loading).

In this figure, we can see that when there is meshing, the signal is modified. When the gear is defective, we can clearly see a modification of the average value of the acceleration, which increases considerably because of the shock generated by the broken tooth on the pinion.

3.1.2. Results of Combined Scalar Indicators (see Boukar and Abakar Moussa [14])

The results in Figure 4 show that the combined scalar indicator given by Equation (7) above detects defects in all twelve configurations of defect. This result of the combined scalar indicators is a notable advance in the field of signal analysis in the time domain, because we manage to detect defects in several configurations. However, simple scalar indicators are limited in detecting defects in different configurations. Some are better in detecting shock defects (like Kurtosis or RMS), others are better in detecting bearing defects (like K factor or Crest factor) and others are better in detecting gear defects (Kurtosis for example).

There are fifteen combined scalar indicators obtained that we proposed by Boukar and Abakar Moussa [14]. But the best combined scalar indicator is given by Equation (7). Figure 4 below shows the result of this indicator on twelve tests carried out.

In this figure, we show that the value of the indicator obtained is greater than the value of initial indicator fixed. In this condition, the fault is detected when Ic > Iinitial.

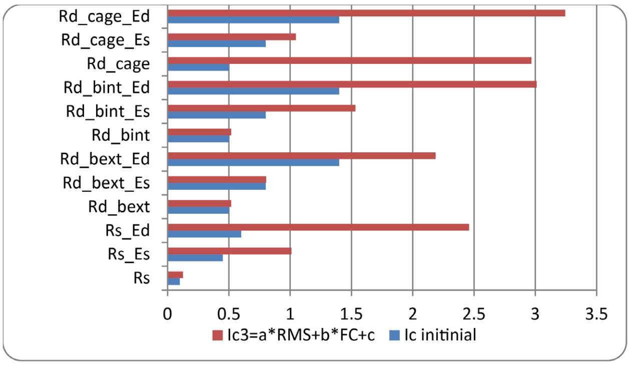

Figure 4. Combined scalar indicators Ic = f(RMS, FC).

3.1.3. Influence of Load on Scalar Indicators

Gear loading reduces the influence of the defect on the Kurtosis. Its value actually decreases. This shows that the vibrations are attenuated and stabilized when the gear is loaded. Figure 5 shows the influence of the load on the Kurtosis (a) and the RMS (b). Unlike the Kurtosis, whose value decreases when the load increases, the RMS on the other hand decreases (Figure 5). It is indeed shown that when the load increases, the Kurtosis decreases and thus the bearing defect is better detected. Figure 5 shows the evolution of the indicators according to the load in the case of the test with a "Defective cage bearing + Healthy gear".

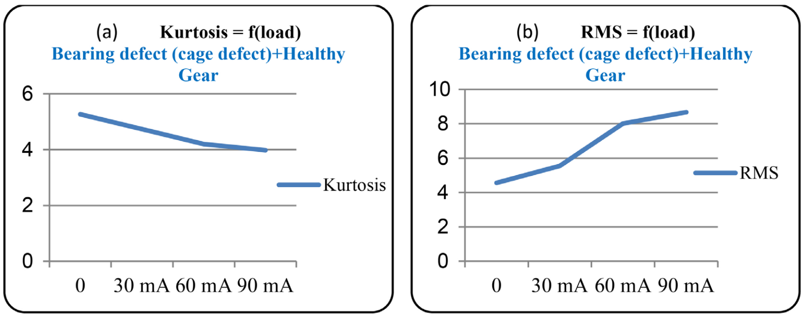

Figure 5. Influence of load on Kurtosis and RMS.

3.2. Results of Frequency Analysis

To monitor a rotating machine, it is essential to know the geometry and kinematics of this machine. Thus, in the frequency domain, to detect defects on a bearing or a gear, it is necessary to know the characteristic frequencies of each component of the machine.

In this section, given the large number of figures per method and per test, we deemed it necessary to present the results of only three tests (configuration 10, configuration 11, and configuration 12).

Before that, we will present the resonance test results used to determine the resonance frequencies, which can be distinguished from the defect frequencies on the bearing and gear.

3.2.1. Analysis of Resonance Spectra

To analyze defects in the frequency domain, the frequencies obtained from the frequency spectrum of each signal are examined. The presence of a defect on a bearing or gear is highlighted by the appearance of its characteristic frequency and several of its harmonics. It is also necessary to separate the natural frequencies of the structure, *i.e.* the resonance frequencies from the characteristic frequencies of the defects. To know the resonance frequencies, a resonance test is carried out on the test bench.

Figure 6 below shows the resonance frequencies of the structure, at motor shaft rotation frequencies of 0 Hz (machine at rest), 5 Hz, 10 Hz and 15 Hz.

In general, we avoid these resonance frequencies coinciding with the rotation frequency of the machine to avoid a possible catastrophe of the rotating machine. These are the frequencies of 8 HZ, 14 Hz, 18 Hz, 114 Hz, 178 Hz, etc.

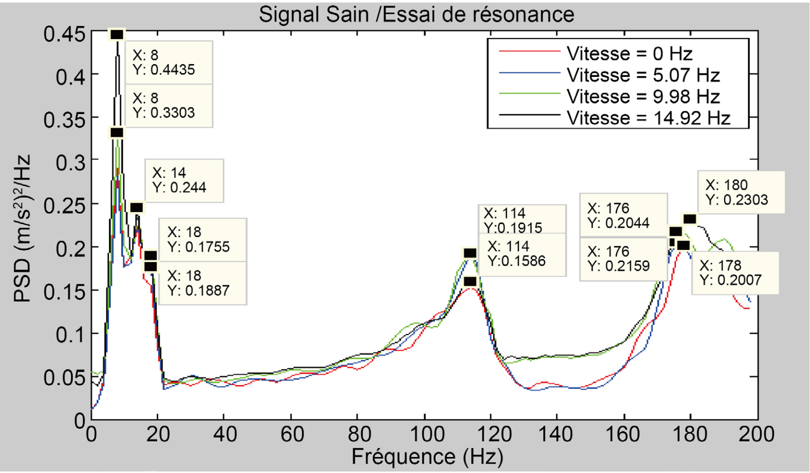

Figure 6. Resonance frequencies of the system.

3.2.2. Results of Spectral Analysis

In the following figures, the results obtained by Fourier spectral analysis are presented. Figure 7 shows the spectrum signal of "defective cage bearing at 10 Hz".

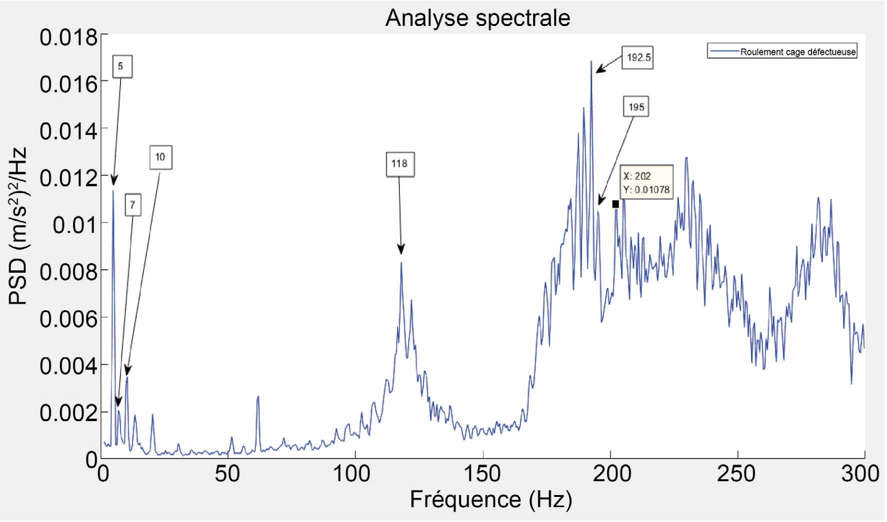

Figure 7. Spectrum signal of "defective cage bearing at 10 Hz".

In Figure 7 above, it is the signal of the defective bearing on the cage, the gear not being coupled. The cage defect of frequency 3.81 Hz is not detected, because the frequency of the cage does not appear. Depending on the size of the defect, the Fourier analysis of the signal does not detect the defect. Also, as there was the problem of shaft misalignment mentioned previously and which constitutes a mask for this defect. Figure 8 shows the spectrum signal of "defective cage bearing and healthy gear at 8.5 Hz".

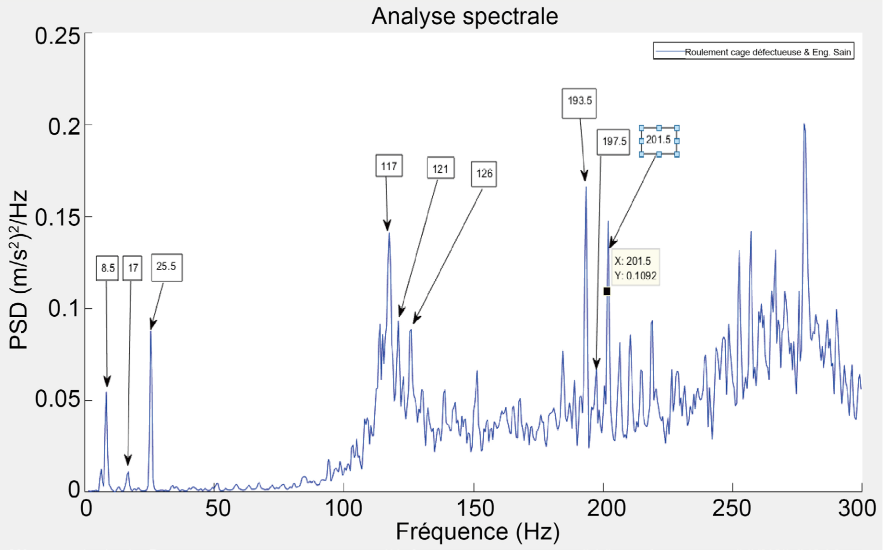

Figure 8. Spectrum signal of "defective cage bearing and healthy gear at 8.5 Hz".

In Figure 8 above, there is the defect on the cage and a healthy gear without defect. The cage defect, which has a frequency of 3.24 Hz, is not detected, but a probable shaft misalignment is detected, highlighted by the presence of the rotation frequency and its harmonics.

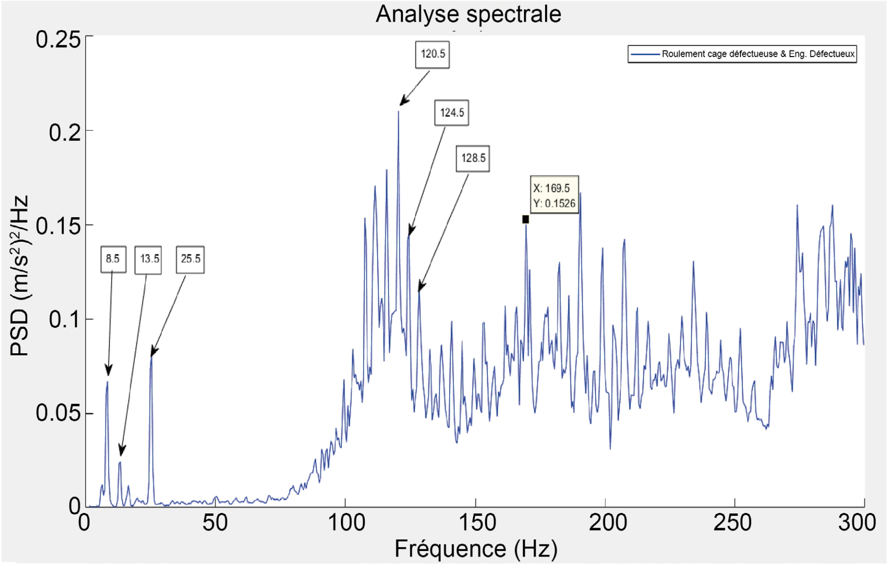

Figure 9. Spectral of the signal "bearing cage defect and gear defect at 8.5 Hz".

Figure 9 above shows the result of the signal analysis with a defect on the cage and on the gear. The cage defect, which has a frequency of 3.24 Hz, is not always detected, but the gear defect with a frequency of 8.5 Hz and its harmonics.

3.2.3. Results of Envelope Analysis

In the following figures, the results obtained by envelope analysis of configurations 10, 11, and 12 are presented in Figures 10-12.

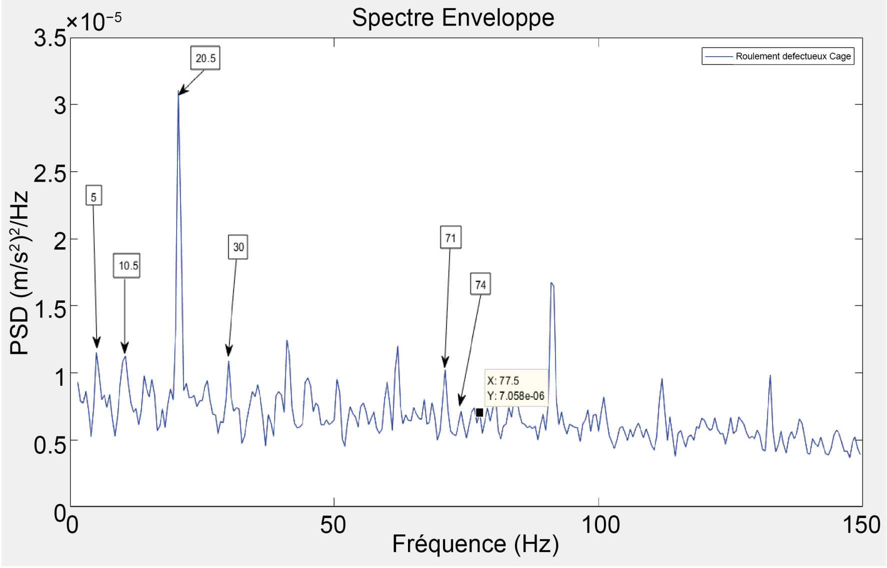

Figure 10. Envelope spectrum of "defective cage bearing at 10 Hz".

In Figure 10 above, the cage defect is not detected by the envelope. The frequency of the cage defect is a modulating frequency masked by the shaft alignment problem, which is the carrier frequency.

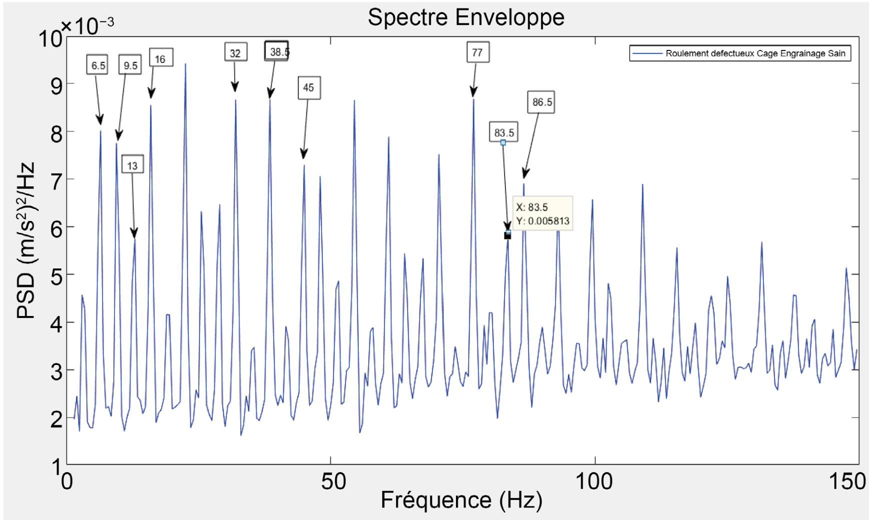

Figure 11. Envelope spectrum of "defective cage bearing and healthy gear".

In **Figure 11**, when the gear is healthy and with a defective bearing, the envelope analysis has made it possible to highlight the cage defect, which corresponds to the regular spacing of 3 Hz between the frequency peaks.

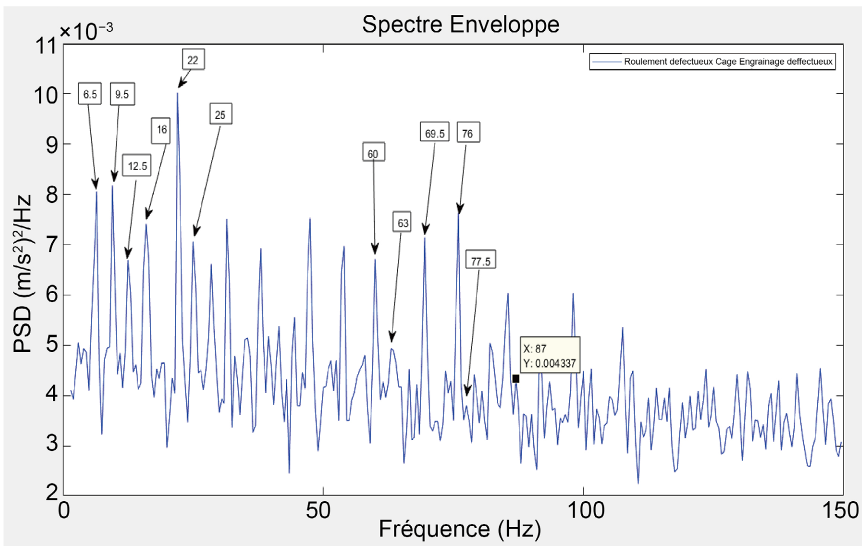

Figure 12. Envelope spectrum of "defective cage bearing and defective gear".

Figure 12 above shows that when there are two defects, *i.e.* two distinct frequencies in the signal, it is the modulating frequency that stands out (cage defect). The carrier frequency (gear defect) is not visible.

In conclusion, signal envelope analysis can highlight the modulating frequencies in a multiple defect configuration. When there is a single defect, this is not a problem; it is detected for both the bearing and the gear.

3.2.4. Results of the Multiresolution Wavelet Analysis

In the following figures below, the results obtained by multiresolution wavelet analysis of configurations 10, 11, and 12 are presented in Figures 13-15.

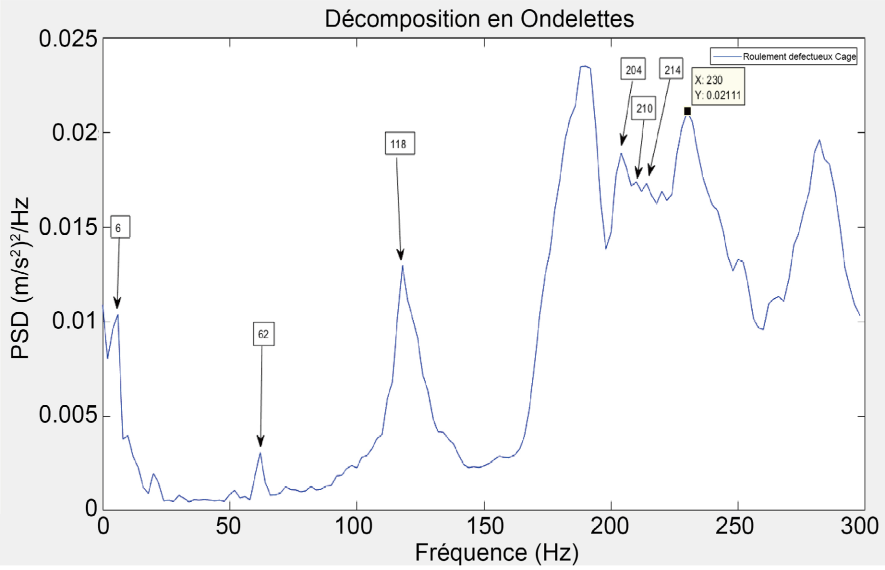

Figure 13. Multiresolution wavelet analysis of a "defective cage bearing".

In Figure 13, the wavelet analysis revealed a frequency (62 Hz) that is a multiple of the ball frequency of 7.62 Hz (approximately 8 times 7.62 Hz). This may be a ball-spalling problem caused by the cage defect. The 118 Hz frequency is the resonant frequency of the structure.

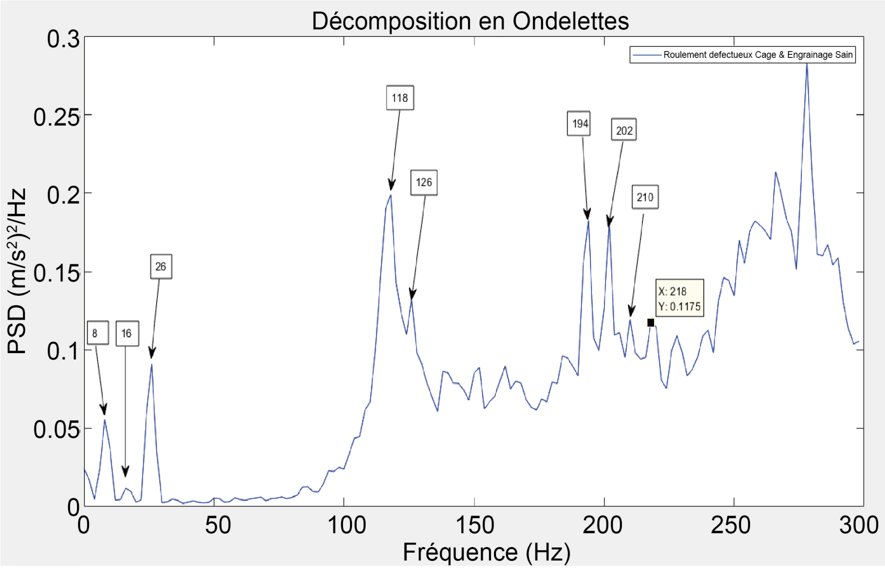

Figure 14. Multiresolution wavelet analysis of "defective cage bearing and healthy gear".

Figure 14 shows the rotation frequency and its harmonics. The cage defect is not detected when there is meshing. The frequencies of 8 Hz, 18 Hz, 118 Hz, etc. are the natural frequencies of the system.

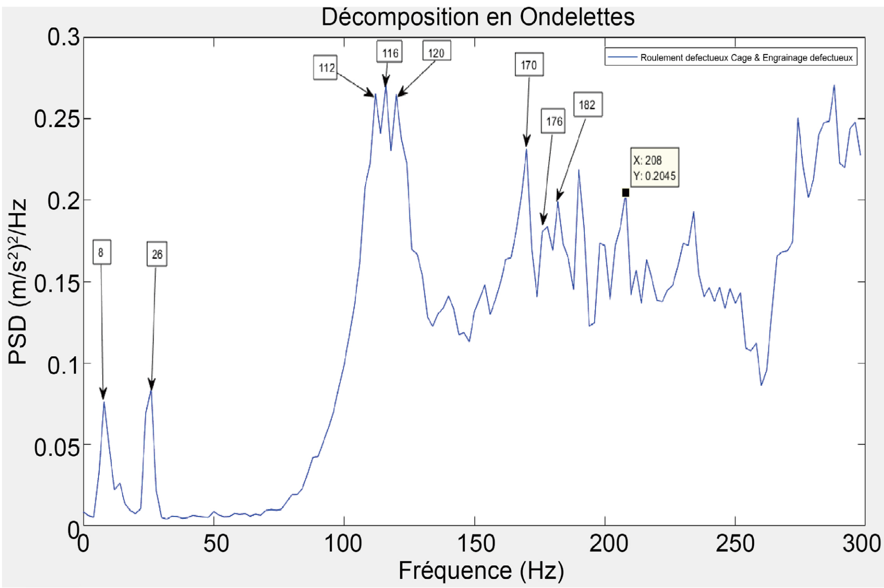

Figure 15. Multiresolution wavelet analysis of "defective cage bearing and defective gear".

As in the previous figure, the analysis failed to detect the cage defect.

3.2.5. Results of Cepstral Analysis

In the following figures below, the results obtained by cepstral analysis of configurations 10, 11 and 12 are presented in **Figures 16-18**.

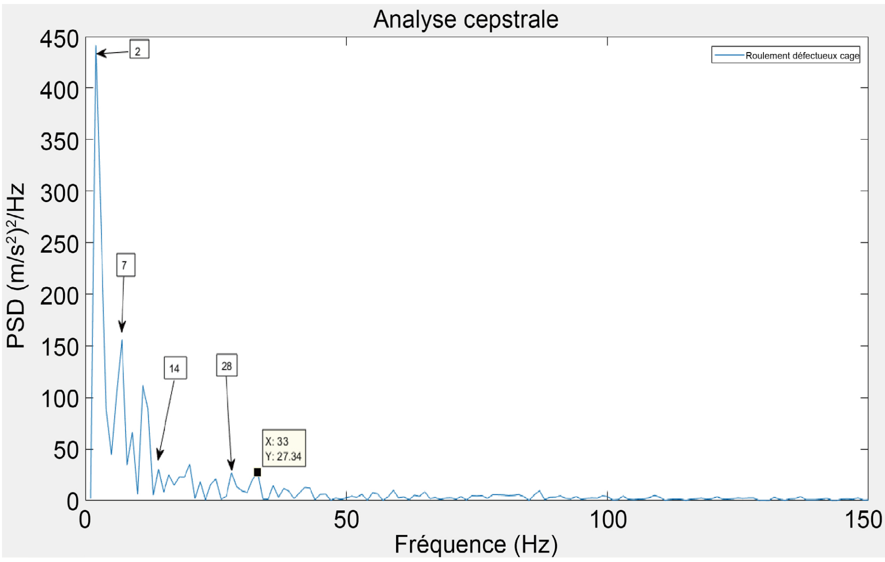

Figure 16. Cepstral analysis of "defective cage bearing at 10 Hz".

In the figure above, we note the presence of harmonics of the cage defect frequency of 3.81 Hz (7 Hz, 14 Hz, etc.). Cepstral analysis allows the detection of simple cage defects.

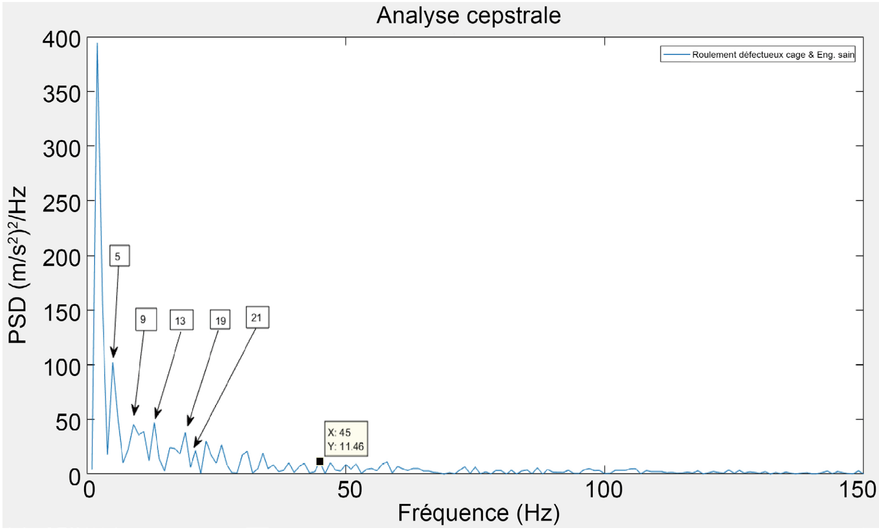

Figure 17. Cepstral analysis of "defective bearing, cage, and healthy gear".

In the figure above, there are two defects: a cage defect and a gear defect. Cepstral analysis does not clearly detect either of these defects. However, in principle, the function of cepstral analysis is to highlight harmonics in a signal.

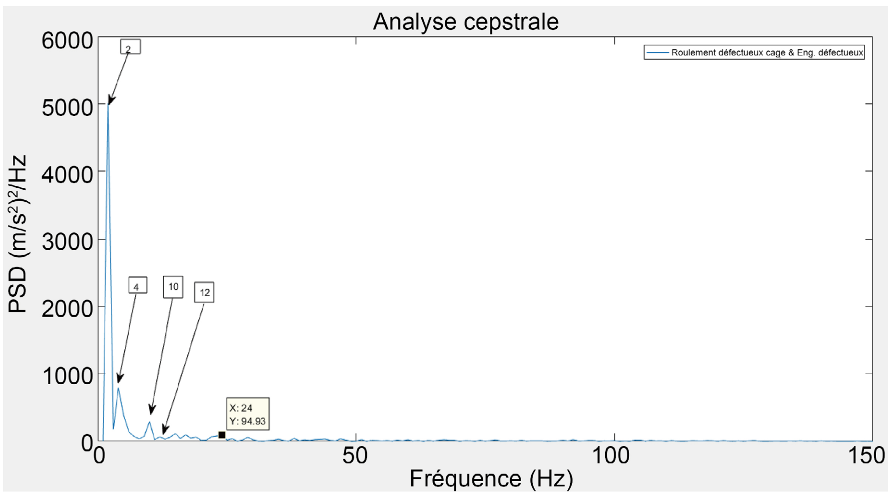

Figure 18. Cepstral analysis of "defective bearing, cage, and gear".

In the figure above, when there are two or more defects (multiple defects, in bearing and gear), cepstral analysis is unable to detect them.

In conclusion, cepstral signal analysis, in the case of our work, was able to detect simple bearing defects or shaft misalignment. However, it has limitations when it comes to detecting multiple defects in a system. Low-amplitude defects are not detected when there are two or more defects in a signal.

4. Limits and Progress in This Field

In terms of progress in the field of time domain analysis, several researchers have proposed improvements to defect detection using scalar indicators. To improve detection, it is advisable to lubricate or load the bearing. Also, we recently proposed in [14] a combined scalar indicator obtained from the linear combination of traditional scalar indicators, which yields satisfactory results across all defect configurations. In the frequency domain, we presented the results of spectral analysis, cepstral analysis, envelope analysis, and multiresolution wavelet analysis. Indeed, only cepstral analysis did not truly detect the gear defect, but did detect the cage defect when there were two defects (bearing cage defect and gear defect). Multiresolution wavelet analysis, on the other hand, identified a defect on the ball, while the tested defect was on the cage. This could be a ball-chipping problem caused by the cage defect. As for spectral analysis, the results showed that it is unable to detect a defect when the defect size is small. This is the case for the cage defect and the observed alignment defect. Furthermore, the envelope analysis revealed modulating frequencies that were not the frequencies of the tested defects. However, the most likely hypothesis is that the observed frequency modulation is due to a shaft alignment problem at the motor coupling; no unbalance defect is present in the system.

Multiresolution wavelet analysis highlights the dependency relationship between the ball defect and the cage defect. By decomposing the signal into wavelets, we can observe a ball defect when the cage is defective. The impact of the cage on the ball is highlighted. This has not been done before and nor in the work of Djebala *et al*. [7].

However, the methods presented have limitations or are even obsolete when the rotation frequency of the motor is variable. In the frequency domain in particular, it will be necessary to carry out studies on cyclostationary signals, that is to say when the speed is variable, because now, more and more machines operate at variable speeds and in this case, the methods presented become obsolete, it is therefore necessary to resample the signal to use it because the number of points is not the same in each period of the signal and thus find other more adequate means of signal processing.

5. Conclusion

In this article, we have presented an overview of maintenance by vibration analysis. We first addressed the problem of fault detection by analyzing signals in the time domain, that is to say, using scalar indicators such as RMS, crest factor, peak value, etc. The results obtained by many researchers in this field have proven interesting and have made it possible to understand the evolution of the sensitivity of these scalar indicators. Then, the transition to the frequency domain has made it possible not only to detect the appearance of a defect but also to find its source by identifying the active frequencies, unlike time analysis, which only gives global information. Frequency analysis, in particular, shows the vibration frequencies and their respective amplitudes. Today, the challenge is to process signals in the case of a cyclostationary regime, *i.e.* when the speed is variable in time. In this case, Fourier and other methods become obsolete. This requires resampling of signals and other approaches to be able to detect defects in this context.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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