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A NOVEL APPROACH TO FEATURE EXTRACTION FROM GEAR CONDITION MONITORING SIGNALS

Lina Bouhafs[a,*], Salah Tamalouzt[a], Ahcene Bouzida[b]

[a] *Université de Bejaia, Faculté de Technologie, Laboratoire de Technologie Industrielle et de l'Information (LTII), 06000 Bejaia, Algérie*

[b] *Université de Bouira, Faculté des Sciences et des Sciences Appliquées, Département de Génie Electrique, 10000 Bouira, Algérie*

[*] corresponding author: lina.bouhafs@univ-bejaia.dz

Abstract. Extracting features from condition monitoring signals of rotating machines is challenging, primarily due to the many potential sources of noise and interference that can corrupt the signals. Additionally, these signals can vary significantly depending on the operating conditions of the machine, making it difficult to develop consistent diagnostic methods. However, an effective feature extraction remains crucial for proper maintenance scheduling and for preventing unexpected machine breakdowns, which can result in costly repairs and operational disruptions. Gear faults, if left unchecked, can be extremely dangerous, particularly in critical applications such as wind turbines, where a failure can lead to significant operational losses. Vibration signals from machinery are often complex, consisting of many different components, making it challenging to isolate the fault-related features from the noise. In this paper, an Envelope-Derivative Operator (EDO) is proposed to overcome these challenges by achieving a balance between the signal amplitude and frequency. The EDO measures the rate of change of the envelope, which is useful in detecting shifts in both the amplitude and the frequency of the signal. To identify the impulsive-like behaviour often associated with gear faults, the EDO analyses the energy content of the signal in both the time and frequency domains. By isolating the fault-related components and filtering out irrelevant noise, the proposed operator shows high efficiency in diagnosing gear faults under various experimental conditions, with no data fitting required and minimal computational resources. In addition, the non-destructive nature of this method can significantly reduce downtime and associated maintenance costs, making it an ideal tool for real-time fault detection in rotating machinery.

Keywords: Condition monitoring, feature extraction, envelope-derivative operator, gear faults, vibration.

1. Introduction

Gearboxes are among the most common mechanisms for power transmission in rotating machinery due to their high power-to-weight ratio, reduced cost, and high reliability. Due to the essential role of the gearbox, gear deterioration can reduce efficiency and cause production disruptions. As a result, identifying gearbox failures early is critical to prevent abnormal system operation and minimising financial losses from damage [1].

During recent years, the demand for fault diagnosis methods based on vibration data analysis has risen in several industries [2]. Is simple to measure any mechanical quantity using relatively inexpensive equipment. It is therefore encouraging for researchers to develop signal-processing methods that are suitable for analysing signals produced by more complex machinery, which is often affected by significant noise. Over the last few decades, many approaches for condition monitoring equipment have been developed. Nowadays, the Fourier Transform (FT) is one of the most commonly used traditional tools for spectral analysis. The periodicity of the signal can be seen in the frequency domain. However, additional harmonics and sidebands can also be present in the frequency domain [3]. For instance, it has been established that the vibrations caused by gear teeth faults differ from those produced by healthy gears. As described by Bozchalooi [4], these variations can be observed as modifications in the amplitude and phase of the gear meshing vibrations, and the presence of additional impulsive vibration components. Consequently, by analysing these fault-specific characteristics, it is possible to monitor the condition of the gears. A technique that can extract multiple types of fault features would likely be more suitable for detecting gear faults. The demodulation is a necessary step in revealing the faults in monitoring signals [5]. For this reason, it has become a very effective method for diagnosing faults in rotating machines [6]. Several methods using a signal averaged synchronously with the rotation of the gear under consideration are described in [7]. Synchronous averaging techniques can reveal AM and PM signatures related to distributed faults but remain inadequate for extracting impulsive fault signatures. The high-frequency resonance technique (HFRT) is also widely used, as it allows information regarding defects of rotating machinery to be collected, as discussed in [8]. This technique, which is sensitive to noise and random fluctuations in rotational frequencies, allows the extraction of information on the components representing the defects and the determination of their severity. However, this approach completely ignores the AM and PM linked with distributed faults and only focuses on additive impulsive signal components. The main difficulty in implementing the technique is selecting the correct centre frequency and bandwidth. In [9], the non-linear Teager-Kaiser Energy Operator (TKEO) contains an energy tracking algorithm that converts a raw signal to the Teager-Kaiser Energy signal to extract the amplitude and instantaneous frequency. Furthermore, a variety of time-frequency analysis methods, such as the short time Fourier transform, developed in [10, 11], and the continuous wavelet transform, as presented in [12, 13], have been used to extract useful diagnostic information from vibration signals [14]. Despite their advantages, these methods, which can distinguish local features of signals and monitor how energy distribution over frequencies changes in time, can cause interference when a multi-component signal is analysed, as in the case of the Wigner-Ville distribution, as presented in [15]. The demodulation of vibration signals is considered a key element of target recognition [16]. However, classical methods, including HT and TKEO, are unable to detect the fault characteristic frequency in the presence of significant noise and vibration interferences, as illustrated in [17]. In [18], authors have proposed a novel technique for diagnosing gearbox compound faults. It is based on the demodulation of optimal resonance components by the energy operator, and it can diagnose gear and bearing faults. In [19], the authors use the envelope derivative operator (EDO) as an alternate energy operator approach, to demodulate the vibrating screen's retrieved vibration signal. The vibration signal extracted from the vibrating screen. This method can effectively extract fault characteristic frequencies compared to TKEO. The Multipoint Optimal Minimum Entropy Deconvolution method (MOMED) and B-spline based on envelope derivative operator (EDO) tools are presented in [20]. This method is specifically designed to detect the fault characteristics in the noise environment of a rolling bearing. A new feature extraction technique called Weighted Multi-scale Fluctuation based Dispersion Entropy (WMFDE), is suggested in [21] for the condition tracking of planetary gear boxes. It works well for the signal denoising technique; However, the performance of this method strongly depends on the parameters used for feature extraction. Calculating of WMFDE can be computationally expensive, especially if the vibration signals are complex and large.

To overcome the problems and drawbacks of the methods mentioned above, this article proposes the envelope-derivative operator (EDO) method. It is characterised by several advantages, which can be summarised as follows: EDO is a powerful and versatile technique for signal analysis in signal processing that detects rapid changes, extracts peaks, measures variation speed, and analyses signal frequency, particularly when there is significant noise interference and various vibrations. The usefulness and effectiveness of the EDO method are thoroughly discussed and analysed by many researchers. The references [22–24] have focused on the early detection of faults in bearings by using an energy measure called the envelope derivative operator. However, the use of this approach for gear applications has never been mentioned in the literature. In this context, the primary goals of this paper are to study and analyse the envelope-derivative operator performance and effectiveness. In order to extract the gear fault features, this technique is also known as a frequency-weighted energy operator. The basic principle of the proposed approach is based on the discrete Hilbert transform, where the information contained in the amplitude and frequency modulations (AM and FM) are jointly derived by a simple mathematical basis. Then, a spectral analysis step is performed after the transformation to extract the exact information and evaluate the state of the gearbox. It provides an envelope rate of change measurement helpful in detecting amplitude and frequency shifts in a signal. In order to identify the impulsive-like behaviour associated with gear faults, the EDO analyses the energy content of the signal in the temporary and frequency domains. This paper describes the proposed EDO approach efficiency on gear fault diagnosis in various experimental conditions with no data fitting necessary and a minimal computational demands. The effectiveness and performance study of the proposed approach, applied for gear teeth defect diagnosis, is based on a methodology illustrated in two different steps: First, we tested and validated this approach in MATLAB. Then, experimental studies are carried out on a real gearbox in order to validate the proposed method for gear teeth defect on a system driven by an electric motor.

2. Theoretical background

The analytical signal is frequently used for a modulated signal $x(t)$, which is established by:

$$X(t) = x(t) + jH[x(t)] = A(t)e^{j\varphi(t)}, \tag{1}$$

where $H[x(t)]$ is the Hilbert transform of $x(t)$, $A(t)$ and $\varphi(t)$ are the instantaneous amplitude (envelope, magnitude) and instantaneous phase, respectively.

As described in [25, 26], the signal's amplitude square provides the instantaneous energy:

$$S[x(t)] = |X(t)|^2 = |x(t) + H[x(t)]|^2 . \tag{2}$$

The Teager-Kaiser Energy Operator (TKEO) is a method that was initially developed for non-linear speech processing as per [27], for a signal $x(t)$ that is continuous in time, TKEO is represented as:

$$\psi[x(t)] = \left(\frac{dx(t)}{dt}\right)^2 - x(t)\frac{d^2x(t)}{dt^2}. \tag{3}$$

Therefore, the TKEO is determined in a discrete format by [28, 29]:

$$\psi[x(n)] = [x(n)]^2 - [x(n+1)x(n-1)]. \tag{4}$$

The TKEO correlates the energy of a signal with its frequency composition for a given signal, for example $\psi(A\cos(\omega_0+\varphi)) = A^2\,\omega_0^2$. To maintain the similarity with TKEO, it is proposed in [30] to include the frequency information in the envelope by implementing a weighting filter. If the Fourier transform of $X(t)$ $x(t)$ is $X(\omega)$. Using the property of harmony that $\dot{x}(t) = j\omega X(\omega)$ and chosing the derivative function as the weighting filter. The Envelope Derivative Operator (EDO) is defined as:

$$\Gamma(t) = |\dot{x}(t) + jH[\dot{x}(t)]|^2 = \dot{x}^2(t) + H[\dot{x}(t)]^2. \tag{5}$$

For a discrete signal $x\,(n)$, the EDO is expressed as:

$$\begin{aligned}\Gamma[x(n)] = \frac{1}{4}&\left[x^2(n+1)+x^2(n-1)+h^2(n+1)+h^2(n-1)\right]\\ &+\frac{1}{2}\left[x(n+1)+x(n-1)+h(n+1)+h(n-1)\right],\end{aligned} \tag{6}$$

where $h\,(n)$ is the discrete Hilbert transform, defined as: $h\,(n) = [x\,(n)]$.

For a signal that is modulated in amplitude, expressed as:

$$X(t) = Ae^{at}\cos(\omega_0 t+\varphi). \tag{7}$$

The frequency domain representation can be analysed using the EDO. The two Fundamental components of the EDO extension are:

$$\dot{X}(t) = Ae^{at}\left[a\cos(\omega_0 t+\varphi) - \omega\sin(\omega_0 t+\varphi)\right], \tag{8}$$
$$H[\dot{X}(t)] = Ae^{at}\left[a\sin(\omega_0 t+\varphi) + \omega\cos(\omega_0 t+\varphi)\right]. \tag{9}$$

Then the EDO is applied to the amplitude-modulated signal, resulting in a calculation of:

$$\Gamma[X(n)] = A^2\,e^{2\alpha t}\left(\omega_0^2 + a^2\right). \tag{10}$$

As a result, the amplitude $e^{2\alpha t}$, which varies over time, is the term that the operator is interested in tracking. For a signal that is modulated in frequency, expressed as:

$$Y(t) = B\left(\cos[\varphi(t)]\right), \tag{11}$$

with:

$$\varphi(t) = \omega_0 t + \int_0^t f(\tau)d\tau. \tag{12}$$

The frequency domain representation can be analysed using the EDO. The two fundamental components of the EDO expansion are:

$$\dot{X}(t) = A\left[\omega_0 + f(t)\right]\sin\left(\varphi(t)\right), \tag{13}$$
$$H[\dot{X}(t)] = A\left[\omega_0 + f(t)\right]\cos(\varphi(t)). \tag{14}$$

Consequently, the amplitude-modulated signal's EDO is determined:

$$\Gamma[X(n)] = A^2[\omega_0 + f(t)]^2, \tag{15}$$

which varies over time, $\omega_0 + f(t)$ is the element that the operator is interested in tracking.

3. Gear fault simulation

3.1. Evaluation of the proposed method

First vibration signal produced from a healthy gearbox, which is controlled by gear meshing vibration needs to be simulated. This signal is accompanied by some modulation resulting from factors such as geometric inaccuracies, assembly mistakes, changes in gear speed, and load. Any alteration to the gear tooth profile can generate amplitude and phase modulations (PM) of the meshing vibrations. The healthy gearbox vibration signal associated with amplitude and phase modulations can be modelled as [31, 32]:

$$x(t) = \sum_{m=1}^{M} A_m\left[\,(1+a_m(t))\;\cos\left(2\pi f_m t + \varphi_m + b_m(t)\right)\right], \tag{16}$$

where M is the number of vibration harmonics, A_m the amplitude at the m^{th} harmonic frequency f_m, functions $a_m(t)$ and $b_m(t)$ are the amplitude and phase modulation functions, respectively, and φ_m is the initial phase of the vibration signal.

Hence, if a gear fault occurs in a specific location, such as cracked teeth or distributed faults, the strength of the associated modulations increases during one full rotation of the gear. The occurrence of a fault initiates an impact, which subsequently generates a mechanical resonance in the system. This resonance, a natural oscillatory response to the fault-induced disturbance, contributes additional frequency components to the signal. As described in Equation (1), these components capture the unique vibrational characteristics of the fault [33, 34]. This relationship can be mathematically expressed as follows [35]:

$$Z(t) = d(t)\cos(2\pi f_r + \theta_r). \tag{17}$$

The modulation, represented by $d(t)$ of the resonant vibration, is affected by the system's response to the gear's impact fault f_r represents the frequency of resonance and θ_r the corresponding initial phase of the impact. The simulation of vibrations for a single stage, gearbox, both in a healthy and defective state, has been carried out. The signal encompasses five

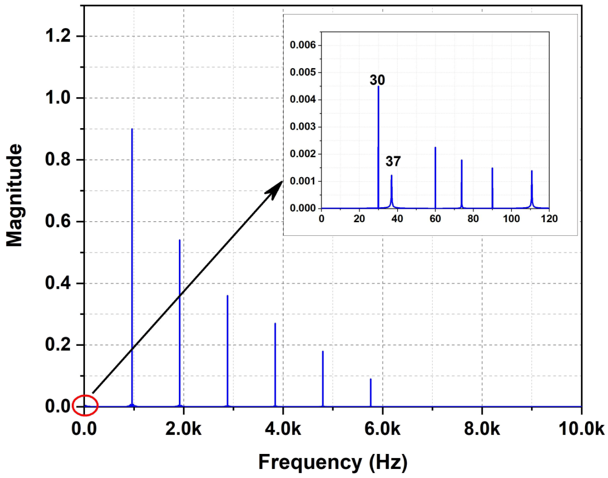


Figure 1. The vibration spectrum for a simulated single stage gearbox in a healthy state with the harmonics of the unbalance: Spectral analysis.

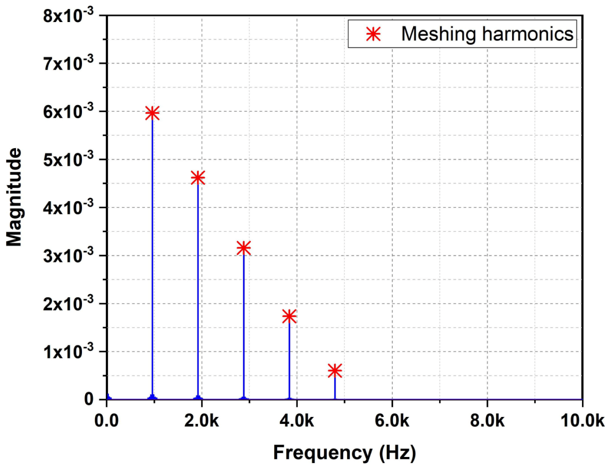


Figure 2. The vibration spectrum for a simulated single stage gearbox in a healthy state with the harmonics of the unbalance: EDO transformed signal.

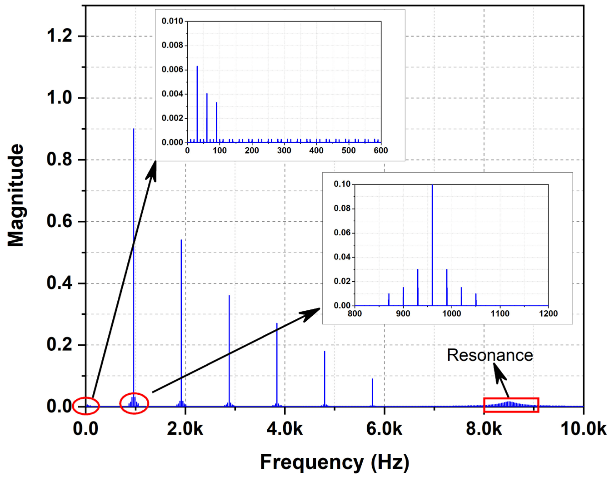


Figure 3. The vibration spectrum for a simulated single stage gearbox in a faulty state including multiplicative AM, PM, and impulsive signatures: Spectral analysis.

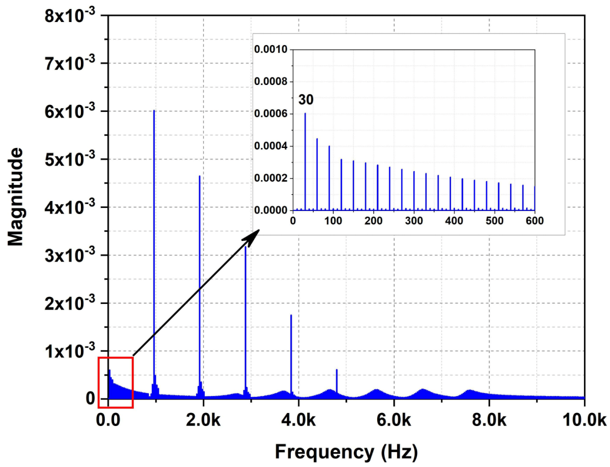


Figure 4. The vibration spectrum for a simulated single stage gearbox in a faulty state including multiplicative AM, PM, and impulsive signatures: EDO transformed signal.

harmonics of the frequency at which the gears mesh. It also includes components of unbalance stemming from the rotation of both the input and output shafts. This can be seen in the spectrum depicted in Figures 1 and 2.

The Figures 3 and 4 indicate, the spectrum of the faulty gear signal with amplitude modulation and an impact signal with its EDO transformer spectrum.

Figures 3 and 4 provide compelling evidence of the effectiveness of the EDO transformation in revealing the signature of defects within the system. In these figures, the presence of a distinct defect signature becomes clearly apparent, as it manifests as a set of rotational frequency harmonics associated with the defect in the driven wheel. Additionally, the presence of a frequency component at 8 500 Hz is noteworthy, as it corresponds to the resonance frequency of the system. This resonance frequency plays a critical role in understanding the dynamic behaviour of the system and can provide valuable insights into how the system responds to external forces or excitations.

In summary, Figures 3 and 4 underline the power of the EDO transformation in isolating and highlighting the rotational frequency harmonics of the driven wheel defect.

3.2. Proposed method to remove background noise

Figures 5 and 6 show the spectra of the EDO transform for the faulty gear signal under different conditions. In Figure 5, we observe the spectrum when the signal includes both amplitude modulation and the pulse signal, to which white Gaussian noise has been added at an SNR of 6.5 dB. In contrast, Figure 6 illustrates the spectrum of the same signal, but with an increased SNR value of 10 dB. Upon careful examination of Figures 5 and 6, it becomes evident that the impact of noise on the signal is significantly reduced as the SNR value increases. In Figure 5, where the SNR is 6.5 dB, the noise component is more pronounced,

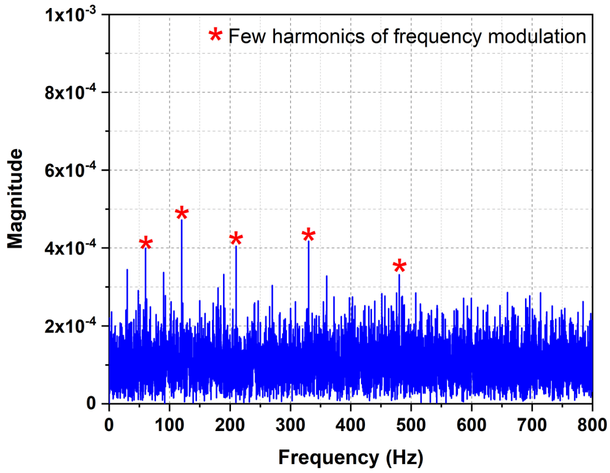


Figure 5. Spectrum of the EDO transformed simulated faulty gear signal mixed with white Gaussian noise: SNR = 6.5 dB.

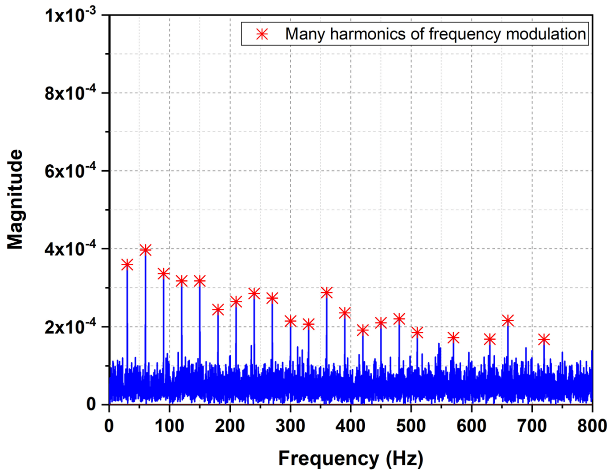


Figure 6. Spectrum of the EDO transformed simulated faulty gear signal mixed with white Gaussian noise: SNR = 10 dB.

leading to a relatively higher noise level in the signal. Conversely, in Figure 6, where the SNR is increased to 10 dB, the noise interference noticeably diminishes, resulting in a cleaner and less noisy signal.

This observation underlines the importance of SNR as a crucial parameter in signal processing and analysis. A higher SNR implies a stronger signal relative to the noise, making it easier to extract meaningful information and detect subtle variations or anomalies within the signal.

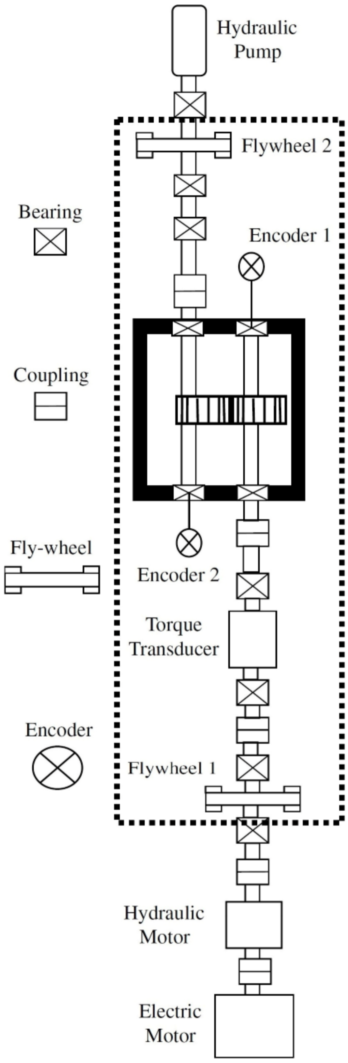


Figure 7. Experimental test of UNSW gearbox.

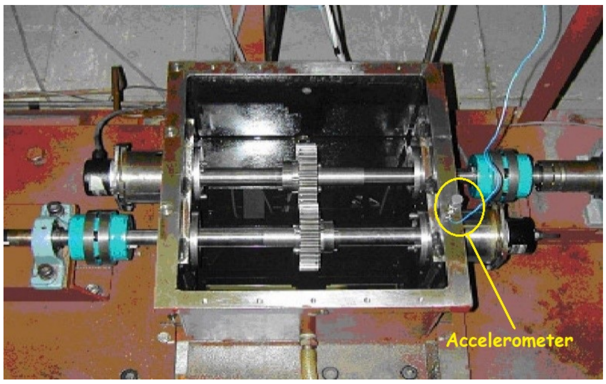


Figure 8. The defective gear.

4. Experimental evaluation

To verify the assessment, the proposed method is applied to the gearbox vibration signals from the experimental test conducted by [34] (University of New Wales, Kensington, Australia, and LASPI, Senlis) to investigate the impact of gear profile errors on transmission error (TE), as shown in Figures 7 and 8.

The rig features a single stage gearbox with a spur gear set containing 32 teeth on each gear and a 1:1 gear ratio. It is mainly driven by a three phase electric motor, with circulating power provided through a hydraulic pump/motor set. The input and output shafts of the gearbox are positioned parallel to each other, and are supported by two double row ball bearings (Koyo 1205) per shaft. Flywheels are used to reduce input and output shaft speed fluctuations. The focus is on the first set of tests, with a defective tooth on the

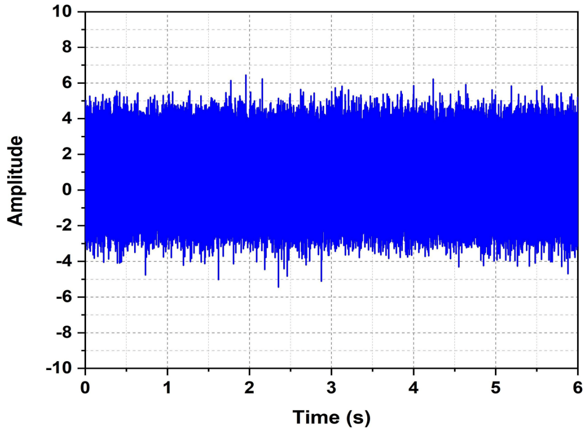


FIGURE 9. The healthy signal: The measured signal.

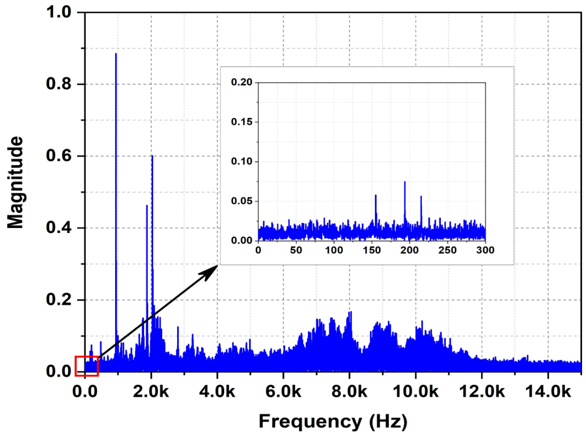


FIGURE 10. The healthy signal: Spectrum.

driven wheel. Two sensors were employed to record data signals on the gear reducer; an accelerometer and tachymeter. Two experimental applications are presented to evaluate the proposed approach. The first is a gear tooth defect. The second experimental investigation concerns the study of the effect of load variation in the same default case.

4.1. DETECTING FAULTS IN HIGH SPEED GEARBOX

In this testing setup, the gearbox is primarily driven by a three phase electric motor. However, the focus of this section is to use the EDO (Envelope Demodulation Order Tracking) method for the purpose of detecting faults specifically in gearboxes intended for use in wind turbines. To achieve this, a comparative analysis is conducted between the spectral characteristics of faulty gearboxes and those in a healthy state.

Figures 9–14 in the following sections present comprehensive visualisations of the temporal vibration signal, its corresponding spectrum, and its envelope for both healthy and defective gear scenarios. These visual representations serve as valuable tools in diagnosing and understanding the condition of the gearbox, aiding in the detection of any potential faults.

Wheels rotation frequencies, are measured and reported. These frequency values are crucial indicators

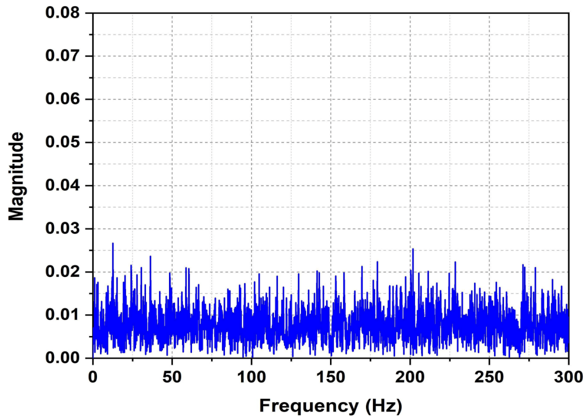


FIGURE 11. The envelope spectra of the healthy signal.

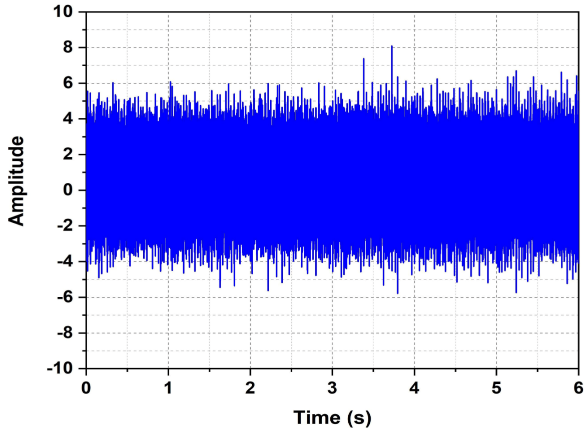


FIGURE 12. The faulty signal: The measured signal.

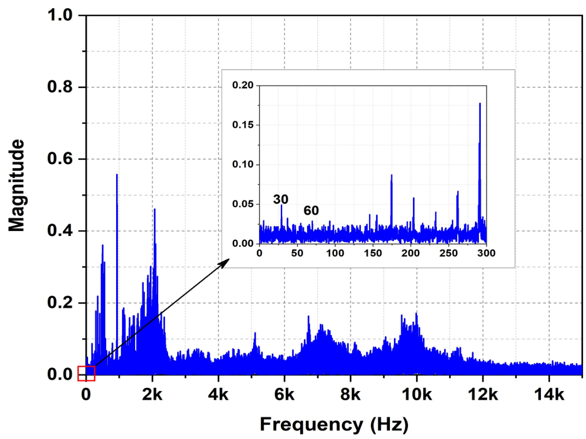


FIGURE 13. The faulty signal: Spectrum.

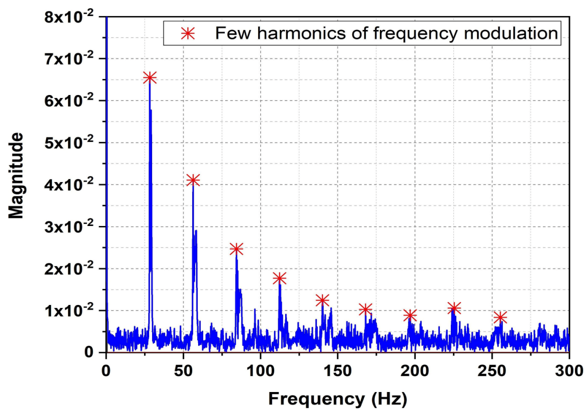
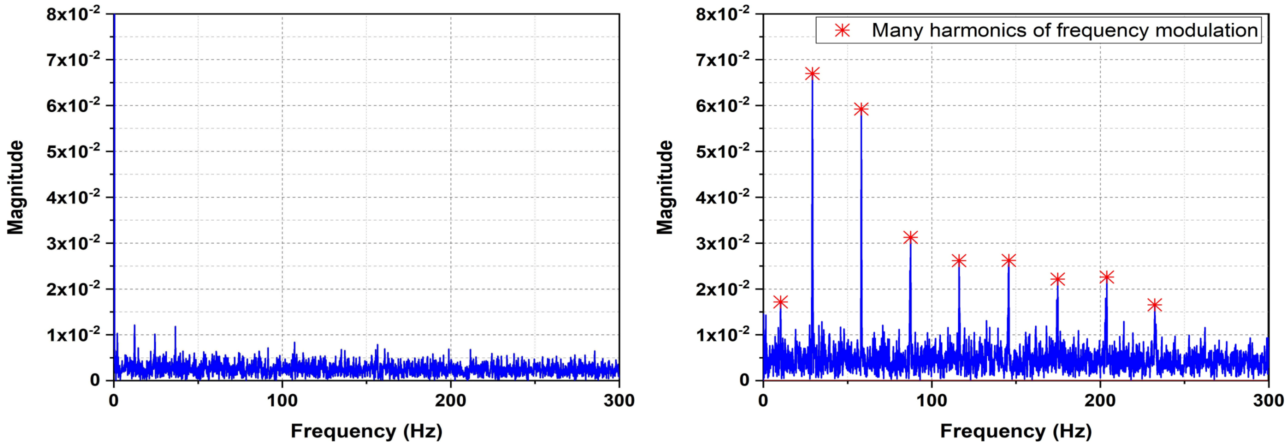


FIGURE 14. The envelope spectra of the faulty signal.



(a). Healthy signal. (b). Faulty signal.

Figure 15. Spectrum of the the EDO results.

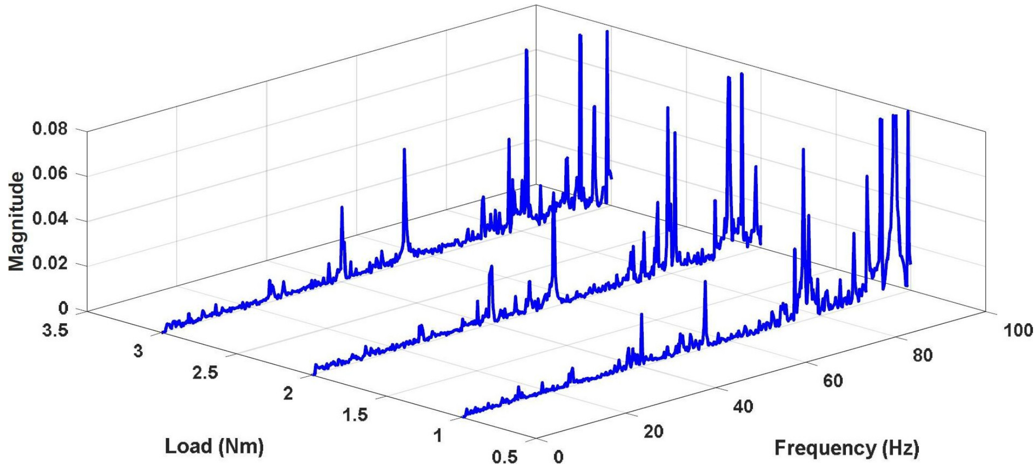


Figure 16. Evolution of the FFT magnitudes of the signals for three load levels.

of the gearbox's health and hold the potential to identify any underlying faults. Additionally, the meshing frequency is approximately 960 Hz, providing an essential reference point for assessing the gearbox performance. It is important to note that the sampling frequency used for data acquisition is set to 97 656 Hz, ensuring that the vibration signals are adequately captured and analysed.

In order to improve our detection approach while dealing with background noise, we use the EDO method to transform the signal. The transformed spectra for both the healthy and defective gear conditions are visually represented in Figure 15.

A notable observation is the presence of multiple harmonics corresponding to the characteristic defect frequency. These harmonics are clearly discernible at frequencies such as 30 Hz, 60 Hz, 90 Hz, 120 Hz, 150 Hz, 180 Hz, 210 Hz, and 240 Hz. These distinct peaks provide critical information for pinpointing the location of the deteriorated tooth within the gearbox. This information becomes particularly evident when examining the rotational frequency of the defective driven wheel.

Conversely, in the case of a healthy gear (as shown in Figure 15a), there is a notable absence of significant peaks or harmonics. This absence underlines the effectiveness of the EDO method in reducing the influence of background noise and substantially improving the precision of defect detection.

In essence, the EDO method proves to be a valuable tool in the context of gear fault detection, allowing us to isolate and identify key spectral components associated with defects, even in the presence of background noise, thus enhancing the reliability and accuracy of our diagnostic process.

4.2. Detection of gearbox faults at different load conditions

This research involved measurements from an accelerometer mounted on the top of the gearbox. and The position of the accelerometer is shown in Figure 8 under three different load conditions of 25, 50, and 60 Nm, and with a rotating frequency of 3 Hz. Therefore, three sets of measurements have been taken to investigate the impact of load on gear fault signals. The vibration signals were recorded for a total of 585 936 samples at a sampling frequency of 24 kHz. Figures 16 and 17 show, the variation of the signal

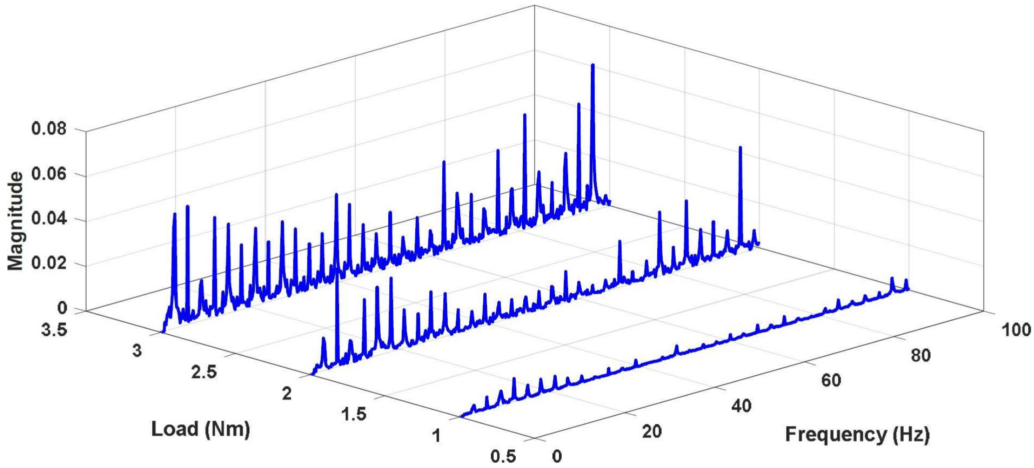


Figure 17. Evolution of the EDO magnitudes of the signals for three load levels.

spectrum measured with the values of the loads using spectral analysis and the spectrum of the same signal demodulated by the EDO method, respectively.

It is evident that the proposed approach reveals an increase in the amplitudes corresponding to the demodulation frequencies created by the gear defect, following the increase in the values of applied loads. The characteristic frequency of the fault seems to be more sensitive to load variation. The impact of the defective tooth on the teeth of the other wheel increases in amplitude, so the frequency content of the signal is influenced by the appearance of several characteristic frequencies of the defect.

5. Conclusion

This paper presents a new approach for identifying gearbox defects by extracting useful features from vibration signals, which can contain background noise and other interferences. The aim of this technique is to improve the early detection of gearbox defects in practical applications. Spectral and envelope analyses have been investigated using both simulated and experimental signals. The Hilbert Transform and Energy Operator Method were compared. The latter has proven to be effective in detecting gearbox defects, as it is sensitive to noise and small defects, which is crucial in preventing the spread of damage spread in the gearbox. In addition, the Envelope Derivative Operator (EDO) is computationally efficient, as it does not require pre-filtering and can be implemented in real time. This makes it suitable for use in online monitoring systems. Overall, the EDO demonstrated superior performance and efficiency in detecting defects over classical techniques, making it a valuable tool for ensuring reliable operation and preventing costly failures.

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