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DETECTION OF DEFECTS IN A BEARING BY ANALYSIS OF VIBRATION SIGNALS

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Abstract

This work presents the analysis of vibration signals by an approach consists of several mathematical tools more elaborate such as the Hilbert transform, kurtogram, which allows the detection of vibration defects in a simple and accurate way. The steps or methods inserted in the process one complementary to the other as scalar indicators generally used in monitoring to follow the evolution of the functioning of a machine when an abnormal functioning it must make a diagnosis to detect the failing element through the use of a process. The determination of the defective organs at an optimal time is a very important operation in the industrial maintenance, which keeps the equipment in a good condition and ensures the assiduity of work. To see the effectiveness of fault detection by the proposed approach by analyzing the real vibration signals of a bearing type 6025-SKF available on the Case Western Reserve University platform.

Keywords: vibration signal, Hilbert transform, bearing, kurtogram, detection.

List of Symbols/Acronyms

A – Angle of contact;
CEEMDAN–Complete ensemble empirical mode decomposition with adaptive noise;
CWRU – Case western reserve university;
D – Diameter of rolling element;
Dm – Pitch diameter;
EMD – Empirical mode decomposition;
E_j– Operator;
FFT – Fast Fourier Transform;
F_{be} – Fault frequency of outer race;
F_{bi} – Fault frequency of inner race;
F_{ca} – Fault frequency of cage;
F_{er} – Fault frequency of rolling element;
Fr – Rotational speed;
FD– Fault frequencies;
IMF – Intrinsic mode function;
N – Sample size;
$n^i(t)$ –White noise;
$Peak$– Peak value;
R– Real party;
u_k– Modal functions;
VMD – Varational mode decomposition;
ω_k– Center frequency;
$x(t)$ – Vibration signal;
x_i– Samples;
$\bar{x}$– Mean;
z – Number of rolling elements;
$\delta(t)$ – Dirac distribution;
*– Convolution;
∝– Quadratic penalty factor;
λ– Lagrange multiplier;
τ– Time shift parameter;
ε_i– SNR (Signal to Noise Ratio);

1. INTRODUCTION

Conditional maintenance consists of several techniques applied to the industrial environment, but the vibration signal analysis is a better technique for diagnosing bearings, gears, and other components of rotating machines [1]. Bearing a critical component used to support the load and responsible for 40 to 45% of machine failures, bearing defects are characterized as inner ring defects, outer ring defect, defect of the rolling element and defect of the cage [2]. Each defect creates a pulse in the vibratory signal spectrum, the pulse produced in the bearing at a specific frequency called the default frequency depends on the rotation speed and geometric parameters of the bearing [2].

The vibration produced when the bearing subjected to internal forces [3]. And the vibration magnitude signal measured with a measuring chain consisting of a sensor, a data system, for the distinguished sensors three types: the accelerometer that measures acceleration is used in case of high operating speed, speed sensor used when average operating speed, motion sensor worn in case of low speed [4].

The vibration signal often processed in the time domain, frequency domain, and time-frequency domain, the temporal analysis performed by the calculation of scalar indicators such as RMS, kurtosis, and Crest factor [5]. And the frequency analysis made by the Fourier transform which allows to see the variation of a signal according to the frequency also the time-frequency analysis examined the variation of the frequency according to the time is accomplished by transformations such as the transform of Hilbert Huang, the transform of Fourier to short term [6].

Monitoring and detecting faults in a bearing requires the acquisition and processing of signals through mathematical tools [7] such as signal decomposition by CEEMDAN or VMD, methods that analyse the non-stationary and non-linear signal [8]. Envelope analysis is a more efficient method to demodulate vibratory signals, and is composed by Hilbert transform and band pass filtering, demodulation of signals intended for the elimination of high frequency components [9].

In this study, we proposed a new approach to the treatment of vibratory signals, the integrated approach of several methods organized in the form of stages each complementary to the other which finally ensure the determination of the frequency of defects of the bearing components. The methods of signal processing are known, but the organization of the methods to achieve an effective diagnostic result must be tested and differently for each author.

2. METHODS AND MATERIALS

The proposed approach to represent in the flowchart (Fig 1) and consist of four steps.

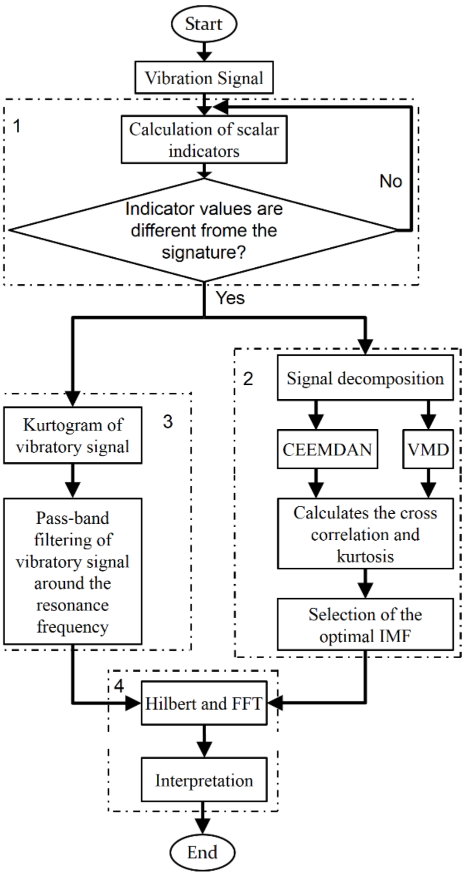

Fig. 1. Proposed approach

The vibration signal is an input parameter to the proposed approach, the signals measured by a measurement chain that allows the storage of vibration data in the form of MATLAB files.

- **Step 1**: calculation of scalar indicators when the values differ from the values of the healthy state (vibration signature) deduces the exceeding danger thresholds, using a set of indicators represented as follows [10]:
  - Root Mean Square :
$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \quad (1)$$
  - Kurtosis :
$$Ku = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^4}{(\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2)^2} \quad (2)$$
  - Crest factor :
$$Fc = \frac{Peak}{RMS} \quad (3)$$
- **Step 2**: signal decomposition by two methods variational mode decomposition (VMD) and Complete ensemble empirical mode decomposition with adaptive noise CEEMDAN, there are several methods, but we will choose two algorithms the first CEEMDAN and an improvement of the EMD algorithm illustrated as follows [8]:

1. Decomposes $x(t) + \varepsilon_o n^i(t)$ by EMD in (i=1, 2,...., m) realization to get the first mode : $\overline{IMF_1(t)} = \frac{1}{m}\sum_{i=1}^{m} IMF_1^i(t)$
2. Calculate the first residual for k=1 as in the equation : $r_1(t) = x(t) - \overline{IMF_1(t)}$
3. The second mode obtained by decomposition of $r_1(t) + \varepsilon_1 . E_1(n^i(t))$
$$\overline{IMF_2(t)} = \frac{1}{m}\sum_{i=1}^{m} E_1(r_1(t) + \varepsilon_1 . E_1(n^i(t)))$$
4. For k=1, 2,..., K : $r_k(t) + \varepsilon_k . E_k(n^i(t))$
$$\overline{IMF_{k+1}(t)} = \frac{1}{m}\sum_{i=1}^{m} E_1(r_k(t) + \varepsilon_k . E_k(n^i(t)))$$

The components obtained after the decomposition of the signal called intrinsic mode function (IMF), for empirical mode decomposition (EMD) method, each function (IMF) must satisfy the following two conditions [11]:

- All maxima are positive, and all minima are negative.
- The local average is approximately equal to zero.

The second VMD algorithm processes the signal decomposition in variational model and translates it into a solution with the constraint that the sum of the IMF be equal to the input signal [12]:

- The variational model is expressed by the following equation:
$$min_{\{u_k\}\{\omega_k\}} = \{\sum_{k=1}^{K} \|\partial_t[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)]e^{-j\omega_k t}\|_2^2\} \quad (4)$$
- The saddle point of the Lagrange function $L(\{u_k\},\{\omega_k\},\lambda)$ is found as the optimal solution of the variational model :
$$L(\{u_k\},\{\omega_k\},\lambda) =\propto \sum_{k=1}^{K} \|\partial_t\left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right]e^{-j\omega_k t}\|_2^2 + \|x(t) - \sum_{k=1}^{K} u_k(t)\|_2^2 + < \lambda(t), x(t) - \sum_{k=1}^{K} u_k(t) > \quad (5)$$

After the decomposition of the vibratory signal realizes the selection of the optimal intrinsic mode function, defining two criteria for the selection the first is the value of cross correlation between the original signal and the IMF, the second criterion is the value of kurtosis.

The optimal IMF indicates a maximum cross-correlation value as well as a kurtosis value greater than 3.

The kurtosis used to define the impulsiveness of a signal when the value of kurtosis superior to three, signals it of impulse form and in the case the kurtosis inferior to three signals, it almost sinusoidal to the causes all IMF of kurtosis inferior to three are eliminated [13].

The cross correlation function between two signals (x, IMF) defined by the following equation [14]:

$$R_{x,IMF}(\tau) = \int_{-\infty}^{+\infty} x(t) \times IMF(t-\tau)dt \quad (6)$$

- **Step 3**: calculate the kurtogram of the vibratory signal for defining the resonance frequency that will used in the band pass filtering.

The kurtogram is a graphical representation of spectral kurtosis values as a function of frequency f and bandwidth (Δf) [15].

The spectral kurtosis $K_x(f)$ of a non-stationary signal $x(t)$ defined as the fourth-order normalized spectral momentum [15]:

$$x(t) = \int_{\frac{-1}{2}}^{\frac{1}{2}} H(t,f) \times e^{j2\pi ft}\, dZ_x(f) \quad (7)$$

$$K_x(f) = \frac{< |H(t,f)|^4 >}{< |H(t,f)|^2 >^2} - 2 \quad (8)$$

$dZ_x(f)$: Orthogonal spectral increment.
$H(t,f)$: It is the complex envelope of $x(t)$ at frequency (f), can estimated by the short term Fourier transform [15].
The initial and final value of the interval with maximum spectral kurtosis values in the kurtogram is the filter pass frequency.

- **Step 4**: determining the envelope spectrum of the selected IMF and filtered signal, Hilbert transform and Fourier transform define the envelope spectrum of a signal $x(t)$.

The Hilbert transform defined by the formula follows [16]:

$$H[x(t)] = x(t) * \frac{j}{\pi t} \quad (9)$$

This transform is a convolution between $x(t)$ and the signal $\frac{j}{\pi t}$ [16].

The analytical signal associated with $x(t)$ noted [16]:

$$z(t) = x(t) + jH[x(t)] \quad (10)$$

$$z(t) = b(t) \times (\cos(\theta(t)) + j\sin(\theta(t)) \quad (11)$$

$$z(t) = b(t) \times e^{j\theta(t)} \quad (12)$$

Therefore:

$$x(t) = R\{z(t)\} \quad (13)$$

$$x(t) = b(t)\cos(\theta(t)) \quad (14)$$

The absolute value $|b(t)|$ is the envelope $E(t)$ of the signal $x(t)$ and $\theta(t)$ is the phase modulation [16]:

$$E(t) = |b(t)| = |x(t) + jH[x(t)]| \quad (15)$$

The Fourier transform identifies the spectrum of the envelope $E(t)$:

$$E(f) = \int_{-\infty}^{+\infty} E(t) \times e^{-j2\pi ft}dt \quad (16)$$

According to the proposed approach in obtaining three envelope spectra, one of the filtered signal is the other of the optimal IMF obtained by the CEEMDAN algorithm and the last one of the IMF obtained by VMD. In interpreting the envelope spectra, the relationship between the peak frequency and the defect frequency of the bearing components is sought.

The Case Western Reserve University (CWRU) platform consists of a test on the of ball bearing type 6025-SKF supports the shaft of a rotating electric motor and subjected to different speeds and loads as well as the actual signals for the bearing available in the form of MATLAB files.

Taking the signals of the healthy state and the inner race defects when the bearing is rotating at a speed of 1750 rpm and subjected to a load of 1491.4 watt, the defect size is 0.1778 mm [17].

Frequencies of defects of bearing components defined by mathematical formulas depend on geometrical parameters [10]

Table 1. The frequencies of defects

Components	Formulas
Inner race	$F_{bi} = \frac{z \times Fr}{2}(1 + \frac{D}{Dm}\cos(A))$
Outer race	$F_{be} = \frac{z \times Fr}{2}(1 - \frac{D}{Dm}\cos(A))$
Cage	$F_{ca} = \frac{Fr}{2}(1 - \frac{D}{Dm}\cos(A))$
Rolling element	$F_{er} = \frac{Dm \times Fr}{2D}(1 - \frac{D^2}{Dm^2}cos^2(A))$

In CWRU, the fault frequencies (FD) of the bearing 6025-SKF components is the multiple of the operating speed (Fr=1750 rpm) in Hz with the coefficients represented in the table 2 [17]:

Table 2. The values of the frequencies

Components	Coefficient	$FD(Hz)$
Inner race	5.4152	$F_{bi} = 157.943$
Outer race	3.5848	$F_{be} = 104.556$
Cage	0.39828	$F_{ca} = 11.616$
Rolling element	4.7135	$F_{er} = 137.477$

Finally, on applying the proposed approach on the selected signals to see the efficiency of the fault detection.

3. RESULTS AND DISCUSSIONS

Vibratory signals measured by accelerometers placed at the level of the electric motor, have distinguished two bearings, the first replaces next to the motor driver and the other next to the fan, we'll take the bearing signals next to the trainer and the sampling frequency 12 kHz [17].

The CWRU bearing data set is long, varied and complex [18].

The signals inserted in the MATLAB code are:

- 99. mat: healthy state to identify the signature.
- 107. mat: defect of the inner race of size 0.1778 mm.

3.1. Vibration signature

The three scalar indicators used indicate the following values:

- Root Mean Square : RMS=0.0644
- Kurtosis: Ku=2.925
- Crest factor: Fc=3.484

The time signal and the spectrum of the healthy state represented on Fig 2.

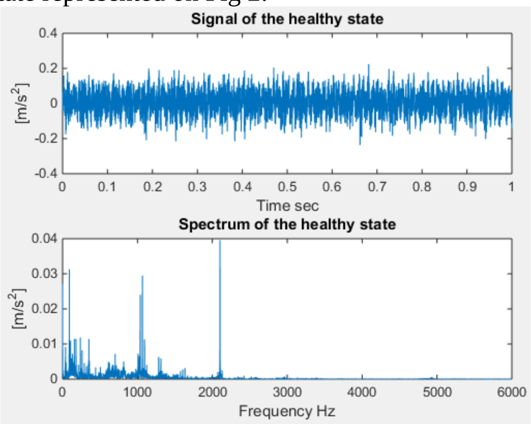

Fig. 2. Signal and spectrum of the healthy state

When applying steps 2, 3 and 4 of the proposed approach on the signal of the healthy state (99.mat), have obtained the following results:

- The kurtogram indicates a maximum value of spectral kurtosis ($K_{max} = 0.1$) has the centered frequency ($fc = 1500\ Hz$) and width $B_\omega = 3000\ Hz$, so the two pass-band filter frequencies $F_p1 = 1\ Hz, F_p2 = 3000\ Hz$.
- The CEEMDAN algorithm gives 14 IMF, and the optimal function number six shows a maximum value of cross-correlation (6.28) and kurtosis (3.56).
- In the VMD algorithm defines the number of IMF=5 and the parameter $\propto = 2000$, based on the decomposition of the signal, the function of number five is optimal since illustrates a maximum value of cross-correlation (0.05) and kurtosis (3.20).

The envelope spectra do not have peaks as shown in Figs 3, 4 and 5.

The information of the healthy state of the bearing called the vibration signature and all the vibratory defects modify this signature.

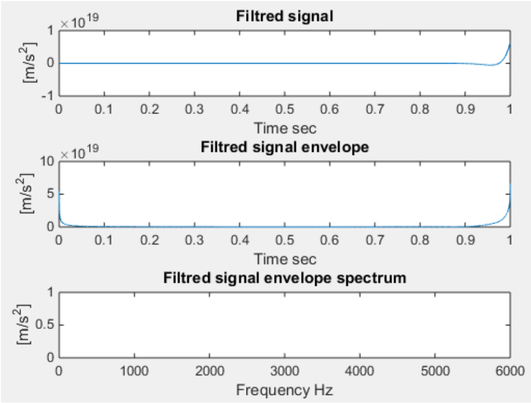

Fig. 3. Filtered vibratory signal

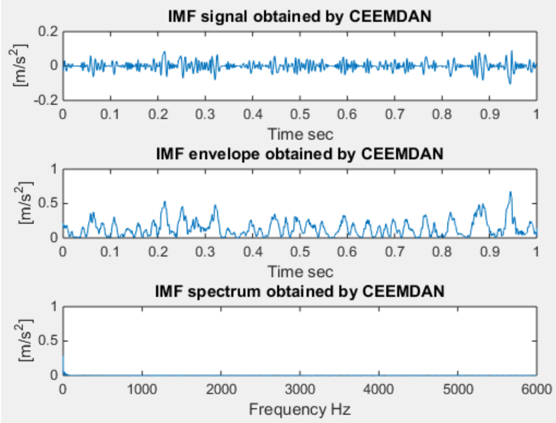

Fig. 4. Optimal IMF of CEEMDAN

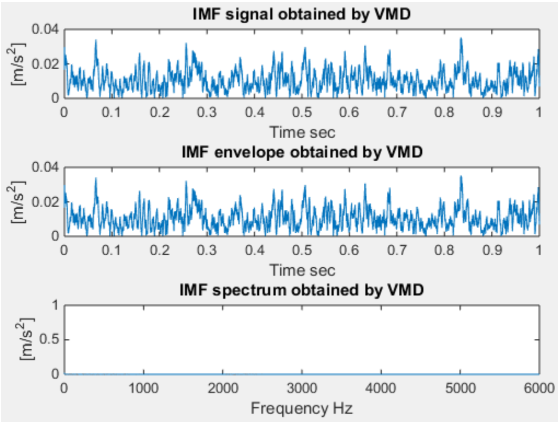

Fig. 5. Optimal IMF of VMD

3.2. Signal of the faulty state

The values of the scalar indicators different at the signature that reflects the exceeding of the danger threshold:

- $RMS = 0.298$
- Kurtosis : $Ku = 5.536$
- Crest factor : $Fc = 5.131$

The spectrum is very rich with the information, but the form complicates it is difficult to interpret grace to this cause applying another technique.

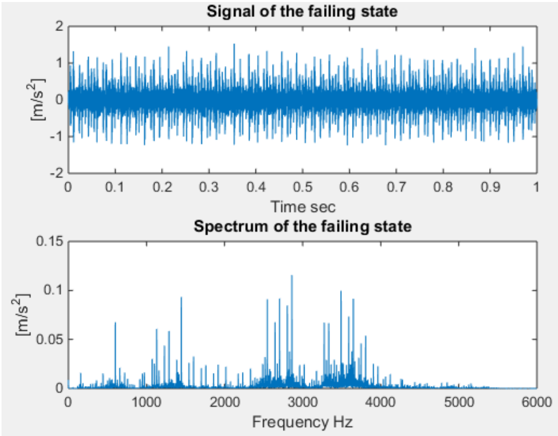

Fig. 6. Signal of the failing state

3.2.1. Kurtogram of the defaulting state

The kurtogram of the failed signal shows a maximum value of spectral kurtosis $K_{max} = 0.4$, at level $(k = 2)$ at the centered frequency $f_c = 3750\ Hz$ and width $B_\omega = 1500\ Hz$, as shown in Fig 7.

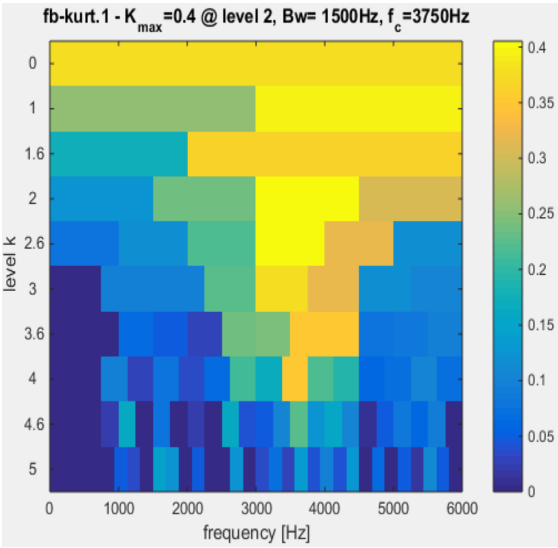

Fig. 7. Kurtogram of the defaulting state

Consider the frequency fc as a resonance frequency.

From the resonance frequency and width determined by the kurtogram on defining the two pass frequencies (F_p) of the Buttrworth type band pass filter:$F_p1 = 3000\ Hz$, $F_p2 = 4500\ Hz$, the filtered vibratory signal is represented in the Fig. 8.

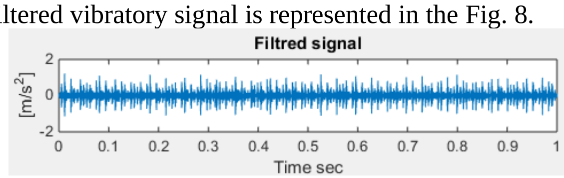

Fig. 8. Band-pass filtering of vibration signal

3.2.2. Signal decomposition

Decomposition by VMD: By defining the number of intrinsic mode functions IMF=5 and the parameter $\propto= 2000$.

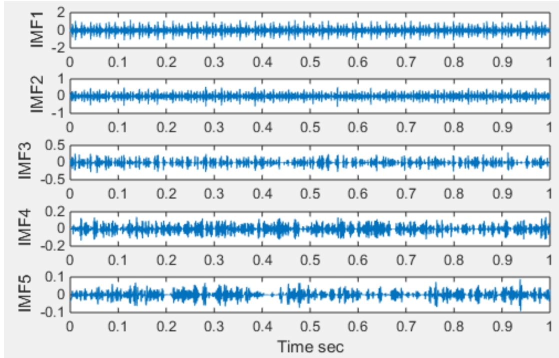

Fig. 9. The IMF obtained by VMD

Decomposition by CEEMDAN: the CEEMDAN algorithm gives 14 intrinsic mode functions (IMF=14):

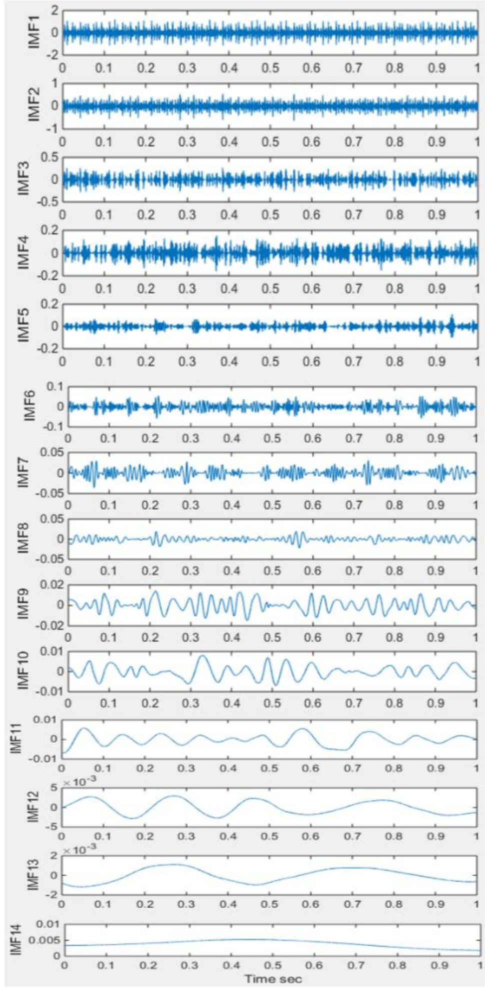

Fig. 10. The IMF obtained by CEEMDAN

3.2.3. Selection of optimal IMF

Optimal IMF obtained by CEEMDAN: the first function (IMF=1) is optimal since it consists of a maximum cross-correlation value (911.3) and the kurtosis $Ku = 5.31 > 3$.

Optimal IMF obtained by VMD: third function (IMF=3) is optimal since it consists of a maximum cross-correlation value (271.51) and the kurtosis $Ku = 3.7 > 3$.

Table 3. Kurtosis and correlation values

IMF	Correlation	Kurtosis
1	911.3	5.31
2	104.6	4.63
3	6.57	6.34
4	29.9	4.65
5	8.52	5.57
6	2.8	4.35
7	0.7	4.66
8	0.2	3.5
9	0.08	4
10	0.03	3.24
11	0.06	3.06
12	0.02	2.92
13	0.01	2.14
14	0.03	1.4

Table 4. Cross-correlation and kurtosis values

IMF	Correlation	Kurtosis
1	49.37	2.16
2	116.38	2.49
3	271.51	3.7
4	155.09	3.68
5	244.88	3.77

3.2.4. Spectrum of envelope

Finally obtained three envelope spectra represented in Figs 11, 12 and 13, the envelope spectra show the same peak amplitude at frequency $f = 157.5\ Hz$, this value very close to the fault frequency of the inner race $F_{bi} = 157.9\ Hz$.

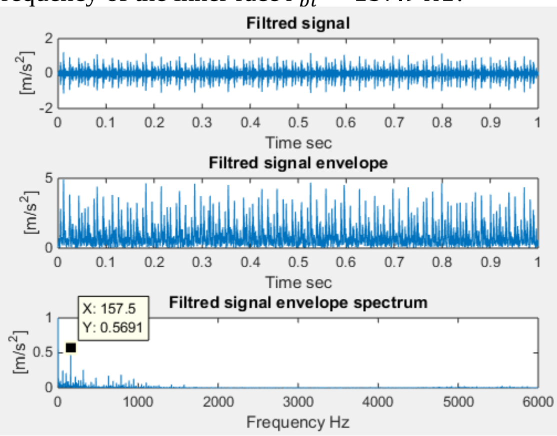

Fig. 11. Envelope spectrum of the filtered signal

4. CONCLUSION

In this paper, by proposing a set of methods organized in the form of processing steps of vibration signals to detect the defects of the bearing, we analyzed the signal of the bearing in a healthy state and in faulty state.

The Hilbert and Fourier transform is very important in the diagnosis of the bearing, which allows the simplicity of the form of the vibration signal.

Signal decomposition is a very significant step that allows the division of a signal into several functions, and the selection of useful functions according to criteria such as cross-correlation ensures the removal of undesirable functions and finally improves the quality of the useful signal.

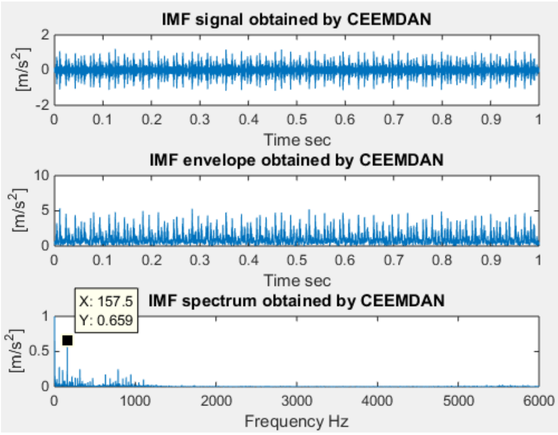

Fig. 12. Envelope spectrum of the optimal IMF obtained by CEEMDAN

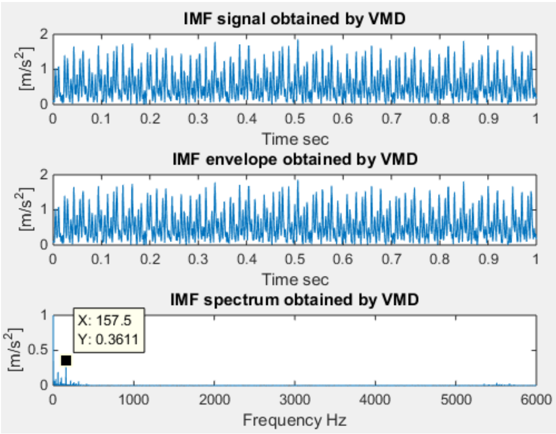

Fig. 13. Envelope spectrum of the optimal IMF obtained by VMD

The healthy state information is a reference value used for fault detection and all vibratory faults change the healthy state data.

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Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

REFERENCES

1. Mohd Ghazali MH, Rahiman W. Vibration Analysis for Machine Monitoring and Diagnosis: A Systematic review. Shock and Vibration. 2021; 2021:9469318. https://doi.org/10.1155/2021/9469318.
2. Gundewar SK, Kane PV. Condition monitoring and fault diagnosis of induction motor. Journal of Vibration Engineering & Technologies. 2021;9(4):

643-674. https://doi.org/10.1007/s42417-020-00253-y.
3. Ramadhan S, Susanto H. Analisa kerusakan conveyor pada pt mifa bersaudara dengan metode reability centered maintenance. Jurnal Mahasiswa Mesin. 2022; 1(2): 10-17.
4. Randall RB. State of the Art in Monitoring Rotating Machinery - Part 1. Sound & Vibration. 2004; 38(3): 14-21.
5. Avoci Ugwiri M, Carratù M, Lay-Ekuakille A, Paciello V, Pietrosanto A. Cascade based methods in detecting rotating faults using vibration measurements. 2021 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). IEEE. 2021:1-5. https://doi.org/10.1109/I2MTC50364.2021.9460107.
6. Lin H-C, Ye Y-C, Huang B-J, Su J-L. Bearing vibration detection and analysis using enhanced fast Fourier transform algorithm. Advances in Mechanical Engineering. 2016; 8(10): 1687814016675080. https://doi.org/10.1177/1687814016675080.
7. Amanuel T, Ghirmay A, Ghebremeskel H, Ghebrehiwet R, Bahlibi W. Comparative Analysis of Signal Processing Techniques for Fault Detection in Three Phase Induction Motor. Journal of Electronics. 2021; 3(1):61-76. https://doi.org/10.36548/jei.2021.1.006.
8. Torres ME, Colominas MA, Schlotthauer G, Flandrin P. A complete ensemble empirical mode decomposition with adaptive noise. 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2011: 4144-4147. https://doi.org/10.1109/ICASSP.2011.5947265.
9. Hoseinzadeh MS, Khadem SE, Sadooghi MS. Quantitative diagnosis for bearing faults by improving ensemble empirical mode decomposition. ISA Transactions. 2018;83:261-275. https://doi.org/10.1016/j.isatra.2018.09.008.
10. Jain PH, Bhosle SP. Study of effects of radial load on vibration of bearing using time-Domain statistical parameters. IOP Conference Series: Materials Science and Engineering. 2021; 1070(2021): 012130. http://doi.org/10.1088/1757-899X/1070/1/012130.
11. Chaudhari H, Nalbalwar SL, Sheth R. A review on intrensic mode function of EMD. 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT). 2016: 2349-2352. http://doi.org/10.1109/ICEEOT.2016.7755114
12. Xiaozhou D, Qi X, Haiyang G, Zihong Z. A Method of On-line Monitoring for Vibration Table Bearings Based on VMD. IOP Conference Series: Materials Science and Engineering. 2020; 751(2020): 012017. https://doi.org/10.1088/1757-899X/751/1/012017.
13. Mahgoun H, Bekka RE, and FELKAOUI, Ahmed. Gearbox fault diagnosis using ensemble empirical mode decomposition (EEMD) and residual signal. Mechanics & Industry. 2012; 13(1): 33-44. https://doi.org/10.1051/meca/2011150.
14. Al-Dabag MLA, Al Rikabi H, Al-Nima RRO. Anticipating Atrial Fibrillation Signal Using Efficient Algorithm. International Association of Online Engineering. 2023. https://www.learntechlib.org/p/218994.
15. Antoni J. Fast computation of the kurtogram for the detection of transient faults. Mechanical Systems and Signal Processing. 2007; 21(1): 108-124. https://doi.org/10.1016/j.ymssp.2005.12.002.
16. Jiménez GA, Muñoz AO, Duarte-Mermoud MA. Fault detection in induction motors using Hilbert and Wavelet transforms. Electrical Engineering. 2007; 89(3): 205-220. https://doi.org/10.1007/s00202-005-0339-6.
17. Database Case Western Reserve University, https://engineering.case.edu/bearingdatacenter/download-data-file.
18. Neupane D, Seok J. Bearing fault detection and diagnosis using case western reserve university dataset with deep learning approaches: A review. IEEE Access. 2020; 8: 93155-93178.

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