FAULT IDENTIFY OF BEARING USING ENHANCED HILBERT-HUANG TRANSFORM

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ABSTRACT

Today the maintenance and repair based on condition monitoring techniques of rotating equipment is one of the most important tools to prevent stopping of production and reduce the cost of maintenance and repair and the vibration analysis according to the width of identifiable defects scope has a specific importance. In this paper, we discuss about rolling bearings defects detection with using of normalized Hilbert huang approach.

KEYWORDS

Hilbert huang transform, fault detection, rolling bearing

1. INTRODUCTION

Rotary equipments are one of the key components of any industrial plant, and any forms of occurrence or stopping them can cause the continued operation of any industrial unit with serious problems. In this regard, the establishment of an effective maintenance system is important and today, monitoring techniques are at the heart of every modern maintenance system and extensive research is being carried out on various monitoring techniques, including analysis Vibration has been widely used due to the extent of defects that can be identified with this technique. So far, several techniques have been used to diagnose roller bearings, such as Fourier analysis, envelope analysis, bcu, and so on, each of this techniques Have benefits, limitations and disadvantages.

In recent research, time-frequency methods such as wavelet transformation and Hilbert transformation are considered because signal time signal frequency information are simultaneously presented. One of the important benefits of time-frequency domain methods in contrast of the FFT[1] fast Fourier transform which only produces frequency content results, by means of time-frequency domain methods we can also observe the time of occurrence of this signal in addition to the frequency content of a signal. For example, if the force is applied alternately, in time-frequency response, we find that force in the time interval and we know its frequency and alternate content of that alternating signal at the same time. Among all the different methods, the wavelet transform method is one of the most widely used and known methods for working in the time-frequency domain. Using a wavelet transform to identify defects not only allows us to identify the defect, but also determines its frequency. Although this method has a

[1] Fast Fourier Transform

DOI : 10.14810/ijmech.2017.6401

great deal of use, it nevertheless has some weakness in defect detection [1], which are interlacing phrases, distortion in the amplitudes, energy leakage leading to The turmoil existence in the results, complexity and prevents easy defect identification. Also, because the frequency accuracy of the wavelet transform method is low for low frequencies, this method it's not suitable to use to identify defects in roller bearings, which usually have a low defect characteristic frequency. Also, the computational volume in the wavelet transform method is high and so it is difficult to use it online. In recent years, a new method of time-frequency domain methods, called Hilbert-Huang's [2-4] transformation, has been gaining a lot of attention.

The main part of this approach is to use a method called empirical mode decomposition (EMD) that is time-consuming and comparative. The EMD converts a signal into a number of signals that are perpendicular to each other, and the sum of them generates the original signal. By applying Hilbert's conversion to each of these signals, the energy content of the signals is obtained. One of the important advantages of the HHT[2] method is its low computational volume, which can also be applied to large signals. It seems that gradually the HHT method is used as one of the most important methods in the field of monitoring and defect identification. However, the HHT has problems that emerge from EMD. The first is to create inappropriate components at low frequencies. The other is that the first signal covers a large frequency range, and sometimes it cannot display components at low frequencies. In this way, the researchers have tried to eliminate these bugs. Su and his colleagues [5] examined and identified defective bearing roller faults using the first method to eliminate intrusive and additional signals using a cross-pass filter, whose coefficients were determined based on the Morellet wavelet transform method, Filtered the signal. The other way of eliminating noise and highlighting intermittent bell signals is to use self-correlation. The important thing about their method was that they could be done somewhat automatically. By using their method on the measured and simulated signals, they transformed the Morellet wavelet with self-correlation. They used the hybrid method to determine the defect in the early stages of the creation of these two methods simultaneously and they were sure of effectively of their own method. Nicolao and Anthonyadis [6] found a method for demodulation of the signal of a defective roller bearing or using a Morellet wavelet transform whose coefficients were determined by the minimum entropy method to obtain the optimal envelope coefficient. For these optimal coefficients to determine the Morelt wavelet transform, Qui et al. [7] used the minimal Shannon entropy. However, the complexity of their method is considered to be the disadvantages of their work.

He. et al. [8] used two methods for converting Morelt wavelet and SCS to detect faults in the measurace signal from faulty roller bearings. First, Moretl filter coefficients are optimized using DE gradual evolution method to eliminate vibration interactions. The SCS method, soft-thresholding method, was used to improve detection of shock absorbing roller bearings. This method is based on MLE. Lin and Qu [9] presented a new method for dual-modification based on Morel transform method, which is a more advanced method of soft-thresholding and evaluated its use for identifying defects in roller bearings. Huang et al. [10] first introduced the method of decomposition of experimental modes. At the 2005 conference, he introduced the Hilbert-Huang transformation that was developed using the EMD method to explain and use it. Lee et al. [11] reviewed the empirical analysis and its use in defect identification in rotating devices. dou and Yang [12] devoted a research on improving the EMD method and its application in identifying defects. One of the advantages of their optimal method is to reduce the time required for calculations. They showed that the EMD method, unlike the envelope method, has the potential to

[2] Hilbert huang transform

decompose signals into signals with frequency bands. They showed that the EMD method is a very powerful method for identifying defects in roller bearings. Yang and Gau [13] used the Hilbert-Huang HHT transformation method to identify defects in roller bearings, and concluded that the HHT method is a valuable method in detecting and monitoring the position of roller bearings and devices. In particular, the HHT method, as a time-frequency domain-based method, can clearly show what is happening transiently. Yang et al. [14,15] sought to reduce some of the disadvantages of the envelope method by using the IMF method and reducing the result in defect identification and status monitoring. One of the main disadvantages of the envelope method was the determination of the central frequency during filtering, which requires the use of information and experience. They showed how the problem could be solved by combining the IMF. The purpose of this paper is to troubleshoot roller bearings based on Hilbert Huang's transformation, which is itself a Hilbert transformation method and has been used in numerous branches of basic and engineering sciences to describe and analyse phenomena of nonlinear or transient nature. Its ability has been proven, and due to the fact that the defects of roller bearings also have this feature, this study tried to evaluate their capability.

2. COMPUTATIONAL THEORY

2.1. The basics of Hilbert's transformation theory

In the Hilbert-Huang transform, a nonlinear and non-stable signal must be decomposed into perpendicular signals, the sum of which is the defect characteristic of the main signal, while each signal is called the intrinsic function that have essential Conditions for using Hilbert conversion. To derive the intrinsic functions used of empirical separation method. This method has no theoretical foundation and it is an algorithm that finds inherent functions based on the repetition and satisfaction of the necessary conditions. The EMD algorithm actually isolates the signals, each of which delivers a specific band function of the fundamental frequency band of the original signal. In order to obtain the content of the frequency and the amplitude of the raw signal, we must take any of Hilbert's intrinsic functions and consider their sum as the Hilbert transform of the total signal. he HHT method is widely used in analysing non-stable signals and analysing data in the analysis of signal structures, earthquakes, bridges and buildings. The HHT method generally consists of two parts, namely, the application of EMD, and in the next step, Hilbert transformation is applied to the inherent functions. Each of the inherent functions must satisfy the following requirements.

A. The number of extremes and the number of times that the curves disconnect the horizontal axis should be equal or, maximum; one number may differ in the entire range of data.

B. The mean value of the connecting curve and the mean points and the connecting curve of the maximal points must be averaging zero.

Displays the sifting method used in this method to extract the inherent functions. The following step-by-step method must be implemented to obtain all inherent functions one after the other.

1. All extremes including minima and maxima are extracted locally. Using the cubic spline method, two curves are drawn, one connecting the maximum points and the other with

respect to the minimum points. The first curve with the name x_U and the other by the name x_L. These two curves enclose the entire signal.

2. We obtain the mean value of these two curves by equation (1)

$$\mu_{11}(t) = (x_U(t) + x_l(t))/2 \tag{1}$$

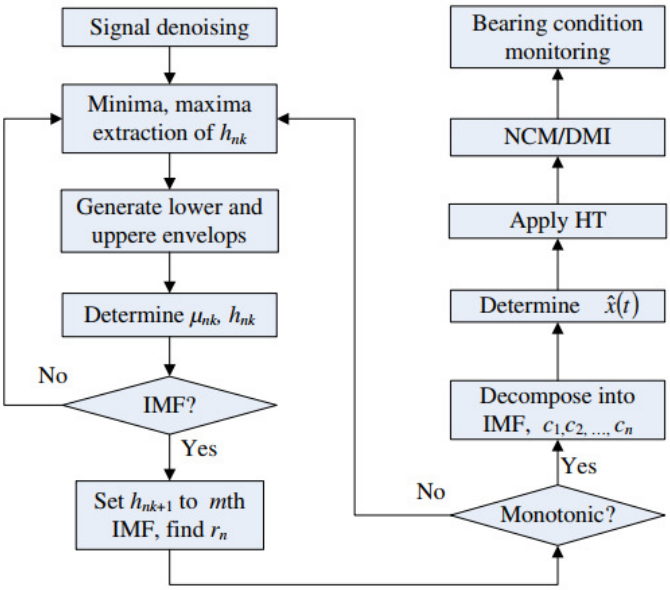


Figure 1. Hilbert-Huang conversion flowchart and use it for troubleshooting

We get the difference between the initial signal and the mean signal:

$$h_1(\mathrm{t}) = \mathrm{x}(\mathrm{t}) - \mu_{11}(t) \tag{2}$$

3. Now, the signal obtained in relation (8) examines the two conditions of intrinsic functions to determine whether this curve is an intrinsic function. If the resulting curve does not meet the requirements, we will consider the function as the main signal and repeat steps 1 and 2 on this signal.

$$h_{11}(t) = h_1(t) - \mu_{11}(t) \tag{3}$$

This algorithm is repeated several times in order to eventually satisfy the constraints inherent in the K repetition of the curve. They call this screening process. When we get the first inherent function, we call it the name of c_1.

$$c_1(t) = h_1(t) \tag{4}$$

4. Get the first remaining signal $r_1(t)$ as follows(5).

$$r_1(t) = r_0(t) - c_1(t) \tag{5}$$

Which is in the first state $r_0(t) = 0$ and the remained is considered as a new signal.

5. The steps 1 through 4 are repeated to n times, so that n function is the intrinsic function and the remaining signal amount is n.

$$r_n(t) = r_{n-1}(t) - c_n(t), \quad n = 2,3,4,... \tag{6}$$

6. The screening method will end if the nth remaining signal is uniform, and the other inherent function will no longer be extracted, and the original signal will be approximately equal to

$$\bar{x}(t) = \sum_{m=1}^{n} c_m + r_n(t) \tag{7}$$

We perform Hilbert transformation on any of the intrinsic functions to obtain instantaneous frequencies.

Consider the $\hat{x}(t)$ signal as the real part of the following function.

$$\hat{x}(t) = \mathrm{Re}\,al\left(\sum_{m=1}^{n} a_m(t)\, e^{j\int \omega_m(t)\,dt}\right) \tag{8}$$

Where the value of the instant domain is called a_m as follows (9):

$$a_m(t) = \sqrt{c_m(t)^2 + (HT[c_m(t)])^2} \tag{9}$$

Where HT (*) is the same as Hilbert transformation.

The instantaneous frequency function can be obtained by having an angular momentum value

$$\theta = \tan^{-1}\left(\frac{c_m(t)}{HT[c_m(t)]}\right) \tag{10}$$

and derived from it(11).

$$\omega_m(t) = \frac{d(\theta(t))}{dt} \tag{11}$$

The instantaneous frequencies and amplitudes obtained from the inherent functions in the range represent the frequency of the original signal.

2.2. Enhanced Hilbert-Huang transformation method

In this method, another way has been used for this weighting, which is based on the calculation of linear and nonlinear dependencies between the intrinsic functions and the raw signal y.

There are many methods to measure the linear dependence of the two signals, such as the correlation method and the explanation, and we look at the method of comparing MI data.

Assume that there are two informational spaces for two variables (the same signals), F_1 and F_2, $H(F_1)$ and $H(F_2)$ the entropy of information, and the amount of $H(F_1,F_2)$ entropy is composite. The value of F_1 and F_2, respectively, represents the original signal and the response of Hilbert is an intrinsic function. In this case, the MI value is defined as follows(12).

$$I(F_1, F_2) = H(F_1) + (F_2) - H(F_1, F_2) \tag{12}$$

In which H entropy is considered by the following equation(13).

$$H(X) = E[I(X)] = E[-\ln(P(X))] \tag{13}$$

Where probabilistic distribution $P(X)$ is a probabilistic variable X and is E an operator of hope. the amount of $H(F_1,F_2)$ entropy of the signal is composed of F_1 and F_2.

The weighting method for each of the inherent functions in the eHHT method is as follows.

1. Normalized correlation size of NCM

This section is inherent in the calculation of the correlation of the original signal with each Hilbert response.

$$NCM = \sum_{i=1}^{N} \| R(y, \hat{x}) \| / L_N \tag{14}$$

Where $R(y,\hat{x}) = E(y - E(y))(\hat{x} - E(\hat{x})) / (\sigma_y \sigma_{\hat{x}})$ is the correlation between the original signal and the demodulated signal $\hat{x}$. $L_N = 2N - 1$ That N is the number of samples in the signal. $E(*)$ The operator is the mathematical hope $\sigma_{\hat{x}}$ and σ_y the standard deviation for the original signal and demodulated signal is each of the inherent functions.

2. DMI mutual information fraction

This coefficient represents the nonlinear correlation between two signals as defined below.

$$DMI = \frac{\| \hat{I} \|}{\sqrt{\log_{10}(N)}} \tag{15}$$

Where $\hat{I} = \hat{I}(F_1, F_2) = \frac{H(F_1) + H(F_2)}{H(F_1, F_2)}$ mutual information is normalized.

Each of the NCM and DMI coefficients represents a degree of correlation between the original signal and the inherent functions. In general, it is possible to combine both of these coefficients with arbitrary coefficients and, according to them, weigh the inherent functions defined as follows.

$$NCM \ / \ DMI = a_n(NCM) + b_n(DMI) \quad (16)$$

Which a_n , b_n are coefficients and two arbitrary coefficients that are more effective by increasing each corresponding NCM or DMI, and n the index is inherent. The value can represent the signal that has the most information needed to identify the characteristic frequency of the defective bearings.

2.3. Detection of roller bearing defects

Under laboratory conditions. Equipped with data from laboratory vibration signals used in this study. Data from accelerometer sensors on a damper chamber and a free electric horsepower electromotor it is measured at the bearing data centre of CASE Western Reserve UNIVERSITY, which is accessible to the public on its website. The laboratory system includes a motor with two horsepower, a power measuring sensor and an encoder for measuring speed, dynamometer, and eventually a speed control circuit. A defect in the roller bearing is created at a specific location, such as a ball, internal or outer race with a specific size and placed in the laboratory system. After the engine is turned on using accelerometer sensors, the amount of vibration is measured. The speed of the axis of rotation along with the sampling rate should be mentioned in order to calculate and process the signal to verify the model's accuracy.

The roller bearings used in all tests are from the famous SKF company's products. The fault depth created in the laboratory in different parts of the roller bearing is 0.011 inches. Bearing name is 6205-2RS JEM SKF, deep. The dimensions of these bearings are shown in Table 1.

Table 1 Dimensions of roller bearing 6205-2RS JEM SKF in mm

Screw Diameter	Ball Diameter	Thickness	Outer Diameter	Inner Diameter
38.42	7.81	14.76	51.18	24.6

The shape of the measured time signal shows the defective bearing in the inner race. In order to obtain fault frequencies, it is best to use SKF's website to specify the bearing type, motor speed and the type of software flaw automatically calculates this frequency and gives us the information.

2.4. Investigation of the bearing with defective outer race using the eHHT method

The eHHT method was evaluated on the defect in the outer race. The rotation frequency of the shaft in this test is 1721 Hz. The characteristic frequency for the outer race is 102.8 Hz that was calculated by bearing frequency calculator skf software and shown in fig.2

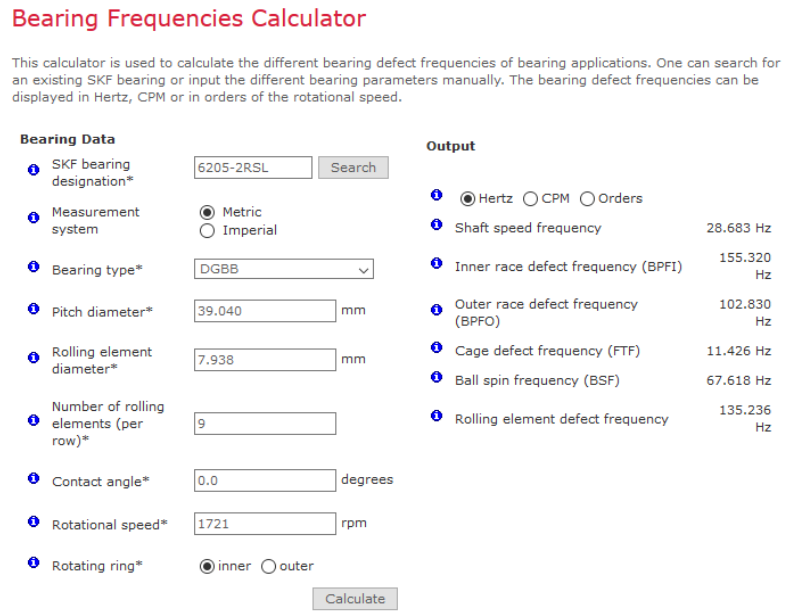


Figure 2 shows characteristic frequencies with a shaft speed of 1721 rpm [16]

3. RESULTS AND DISCUSSION

The time signal measured for this bearing is shown in Fig. 3 Fig. 4 is also displayed to give a clearer signal over a period of zero to one second. It's quite obvious how much difference there is between the time responses for each of the defects in the bearings. However, it is not easy to use this type of difference to identify the defect, and these signals must first be taken to the frequency domain.

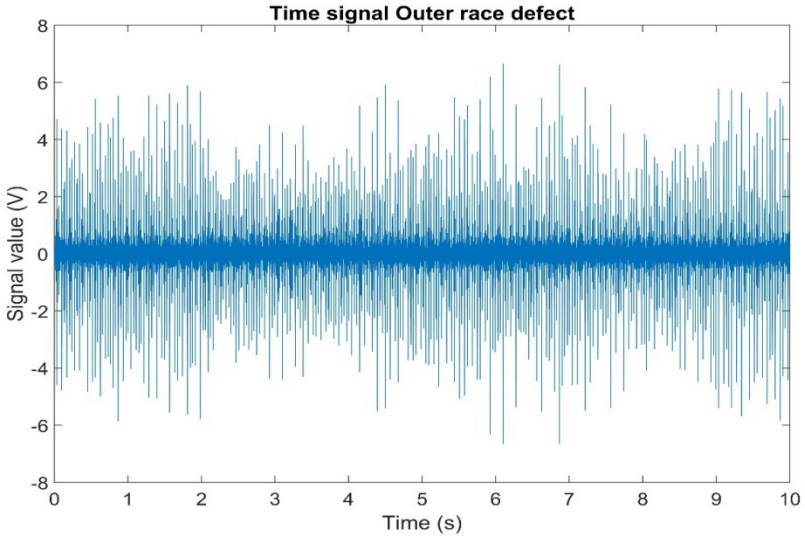


Figure. 3. Time signal for a bearing with a defective outer race

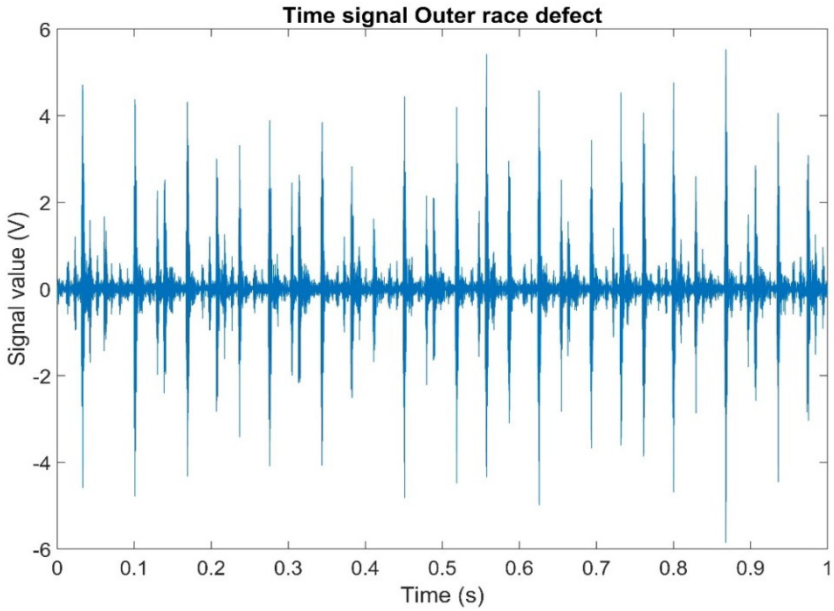
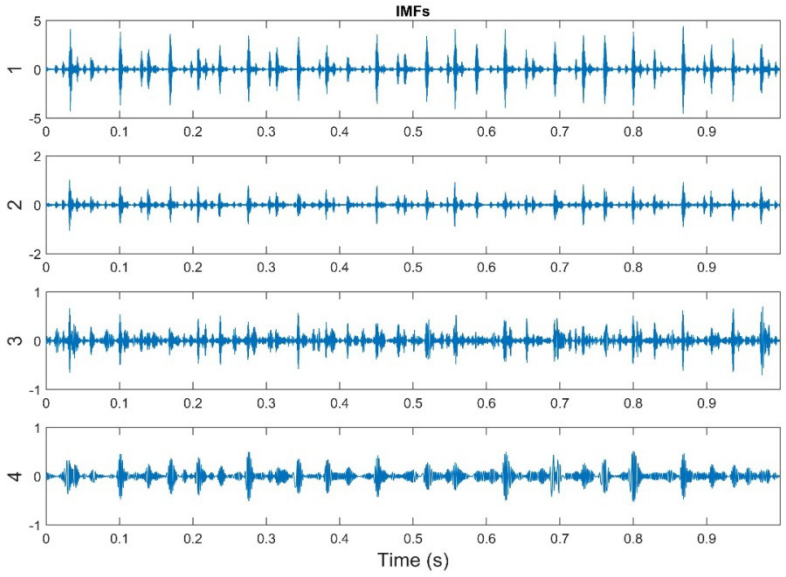


Figure. 4 The measured response time in the range of zero to one second

First, the EMD method is used to obtain the functionality. Figure 5 shows the intrinsic functions corresponding to this signal.



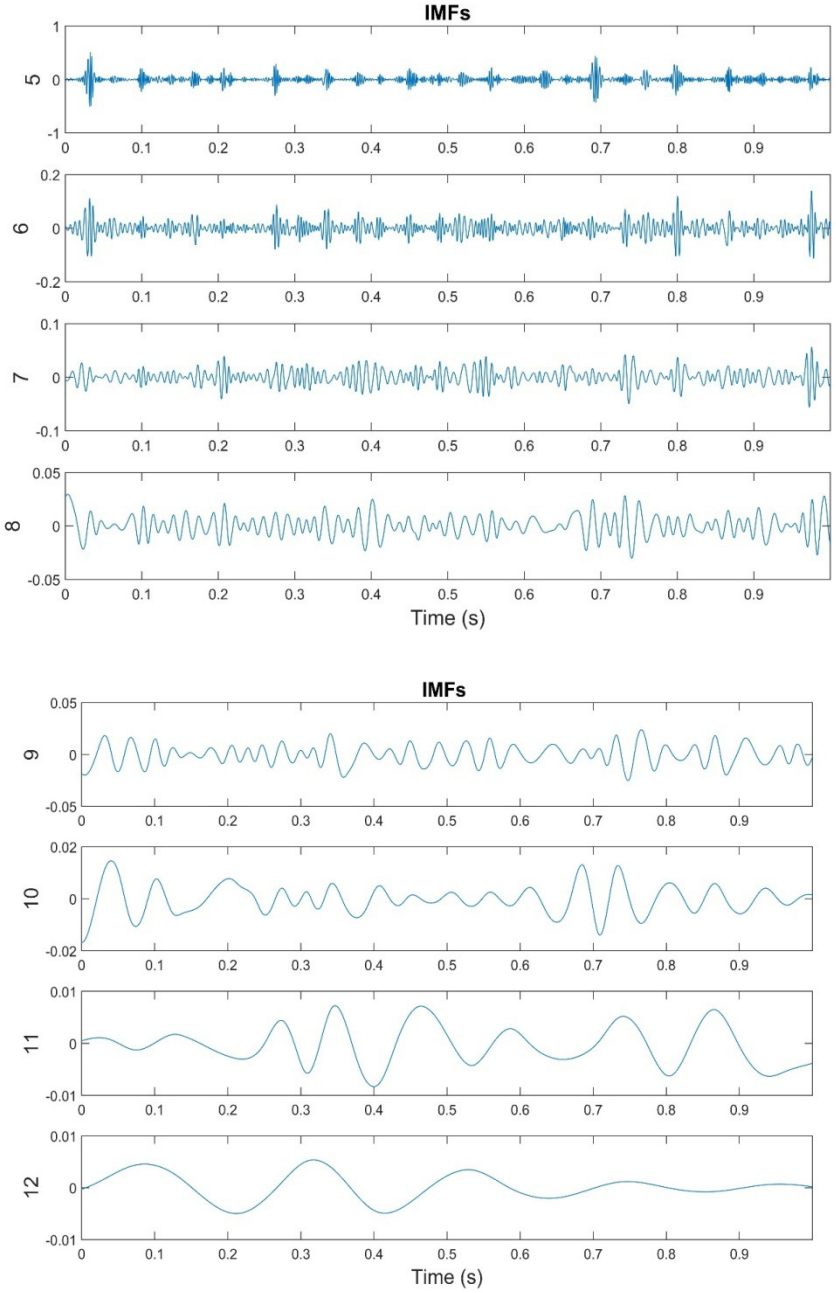


Figure. 5 Functional Functions Obtained using the EMD method

The eHHT method is used to identify the defect frequency in the outer race. By executing the eHHT code, the NCM and DMI and NCM / DMI coefficients corresponding to each of the inherent functions are obtained. The results are shown in Figure 6.

Figure. 7 shows the response frequency of the eHHT method. As seen in this figure, the peak of the largest frequency range is 103 Hz, which is equal to the result of the nHHT method, and is

also very close to the calculated frequency. Thus, the eHHT method, with great accuracy and efficiency, produces a defect frequency corresponding to a faulty outer race.

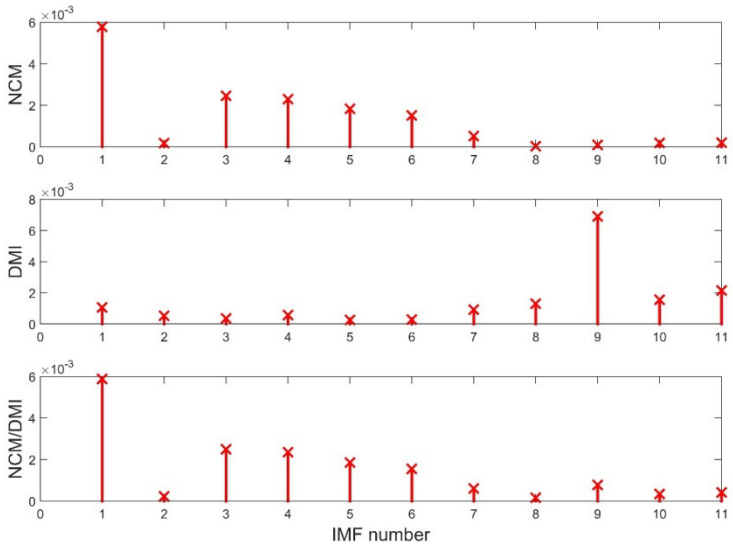


Figure 6: NCM and DMI and NCM / DMI coefficients for a signal with an outer race

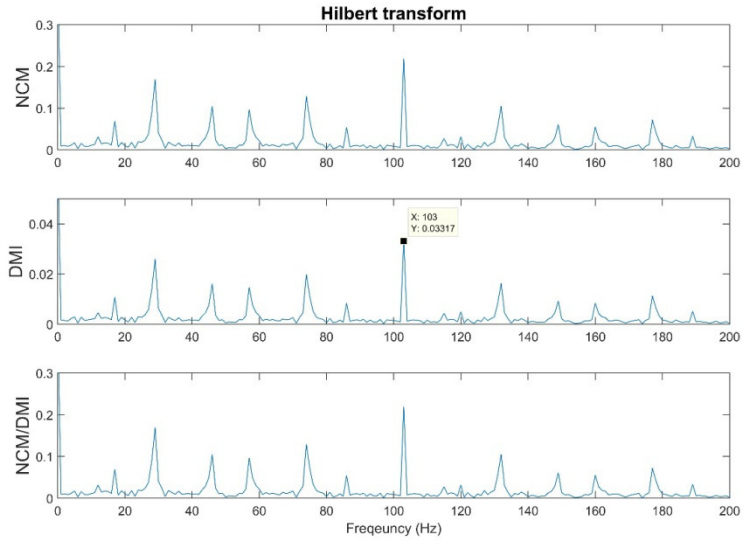


Figure 7. Frequency response using the eHHT method

4. CONCLUSIONS

In this study, the Enhanced Hilbert Huang transformation technique was used to identify the defect of the outer race of roller bearings, and the proper accuracy of this defect was identified and the efficiency of these methods was proved. On the other hand, due to much less computation, Hilbert Huang's conversion method was compared with Other time-frequency domain-frequency transforms, such as wavelet transformation, can be used online as well.

ACKNOWLEDGEMENTS

The authors would like to thank National Iranian South Oil company (NISOC) for their financial supports.

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