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Improved Mechanical Fault Identification of an Induction Motor Using Teager-Kaiser Energy Operator

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Abstract – Induction motors are a workhorse for the industry. The condition monitoring and fault analysis are the main concern for the engineers. The bearing is one of the vital segment of the induction machine and the condition of the whole machine is decided based on the condition of the bearing. In the present paper, the vibration signal of the bearing has been used for the analysis. The first line of action is to perform a statistical analysis of the vibration signal which gives trends in signal. To get the location of a fault in the bearing the second action is to develop an index based on Wavelet Packet Transform node energy named as Bearing Damage Index (BDI). Further, Teager-Kaiser Energy Operator (TKEO) has been calculated from higher index value to get the envelope and finally Power Spectral Density (PSD) has been applied to identify the fault frequencies. A performance index has also been developed to compare the usefulness of the proposed method with other existing methods. The result shows that the strong amplitude of fault characteristics and its side bands help to decide the type of fault present in the recorded signal obtained from the bearing.

Keywords: Bearing Damage Index (BDI); Kurtosis; Power Spectral Density(PSD); Skewness; Teager-Kaiser Energy Operator (TKEO)

1. Introduction

The induction motor is one of the most popular rotating machines used in industry and performs duty heavily. The induction motor health monitoring condition may be related with the production of the industry. The catastrophic failure of these machines leads to a huge loss in production [1-2]. Hence, It is required to keep the machine working condition intact. The condition monitoring and fault diagnosis analysis may increase the life span of the machine [3]. To know the present status of the machine, acquiring of various parameter i.e. current signal, vibration signal, temperature, and flux is necessary. The Vibration signal is the mostly used signal for the condition monitoring, since it is nondestructive by nature [4]. It has been observed that the occurrence of a fault in the bearing segment is more due to its rotating nature and loading effect. Hence, in this paper vibration signal has been chosen for the fault diagnosis and condition monitoring of the bearing.

The instrument used for the vibration signal recording is an accelerometer [5]. The recorded signal generally masked in noise due to the environmental effect of the machine. Due to noise in the signal, it is very difficult to confirm the presence of the fault or exact condition of the machine.

The first line of action is to carry out the statistical analysis of the signal. The statistical parameters show some trends if it is calculated from recording vibration at regular interval [6]. The statistical analysis is rich in content but poor in information and may lead to the wrong interpretation of the recorded data. The other option is to transform the time domain content to the frequency domain and search the frequency corresponding to the fault. The Fast Fourier Transform (FFT) is the method which is widely used for the transformation of the time domain signal to the frequency domain [7]. The simple FFT does not help more because along with fault frequencies many other frequencies are present due to noise and that is why it is difficult to find the exact fault frequencies. The other modified version of FFT known as Power Spectral Density (PSD) has been used to minimize the amplitude of frequencies due the noise.

A Hilbert Transform (HT) and FFT in combination have also been used to detect the fault frequencies [8]. The purpose of Hilbert Transform is to calculate the envelope and FFT is to transform the envelope into the frequency domain. The problem with this method is the poor identification of sidebands which is present along with fault frequencies. Due to lack of sidebands confirmation, one cannot guarantee the presence of faults in the bearing of machine. Short-Time Fourier Transform (STFT), Wigner-Vile distribution and Wavelet Packet Transform (WPT) are also other fault detection methods which comes under the time-frequency domain and have been used to improve the detection of fault frequencies [9, 10].

In this paper, an improved method has been presented to identify the fault frequencies due to bearing fault in the machine. This includes WPT, Teager-Kaiser Energy

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Operator (TKEO) and PSD for the analysis of bearing vibration signal. The paper is organized as follows. Section 2 describes theoretical background along with the used data description and its statistical analysis. Section 3, describes the proposed methodology along with Teager-Kaiser energy operator and power spectral density. Section 4, deals with discussions on the results obtained from vibration signal after applying the proposed methodology. The conclusion of this paper is given in Section 5.

2. Theoretical Background

2.1. Data description

For the mechanical fault diagnosis, vibration signal has been used from Case Western Reserve Lab data center [11]. The bearing used in induction machine is 6205 SKF deep-groove and this is used to support shaft at the drive and non-drive end of a 2 HP motor. The recording has been performed by the accelerometer sensor which was mounted at drive end and non-drive end side of the induction machine. The sampling frequency of the recording has been chosen as 12,000 samples per second for each of 16 channels digital audio tape (DAT) recorder. The speed of the machine varies from 1797 rpm to 1752 rpm while loading the machine from 0 HP to 3 HP load [12]. The details of the bearing used in the experiment are shown in Table 1.

To create the single point fault in bearing Electro-Discharge Machining (EDM) has been used. The seeded fault size are 0.007 inches and 0.021 inches in diameter with the depth of 0.011 inches in the bearing has been taken in to account for this paper. The frequencies associated with the bearing are calculated using the physical parameter as per equation no (1) to (4). These theoretical frequencies which are calculated will be present if the bearing is defective and generate impulses in the signal when rolling ball pass from the defective area [13, 14]. The bearing along with the defect has been depicted in Fig. 1.

Table 1. Ball bearing specification

Specification	Value
Rolling Element, N	9
Diameter of Rolling Element, B_d	7.940 mm
Pitch Diameter, P_d	39.039 mm
Contact Angle, θ	0 degree

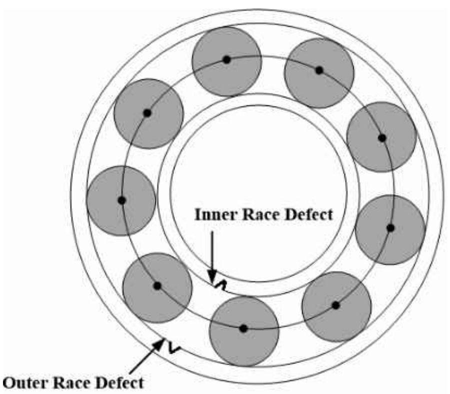


Fig. 1. Defect in inner race way and outer race way of the bearing

Fundamental Train Frequency,

$$FTF = \frac{f_r}{2}\left[1-\left(\frac{B_d}{P_d}\right)cos\theta\right] \tag{1}$$

Ball Spin Frequency,

$$BSF = \frac{f_r}{2}\left(\frac{P_d}{B_d}\right)\left[1-\left(\frac{B_d}{P_d}\right)^2 cos\theta\right] \tag{2}$$

Outer Raceway Frequency,

$$ORF = N\times\left(FTF\right) \tag{3}$$

Inner Raceway Frequency,

$$IRF = N\times\left(f_r-(FTF)\right) \tag{4}$$

Where, f_r, B_d, P_d , θ are speed of inner race way in Hz, ball diameter in mm, pitch diameter in mm and contact angle in degree respectively. These defective frequencies often provided by the manufacturing company in the form of bearing data sheet. The calculated defective frequencies from the equations (1) to (4) are shown in the Table 2.

2.2 Statistical analysis

Before going to identify the fault frequency, it is essential to confirm the presence of the fault. The statistical analysis is one of the methods through which the trend of the fault using calculated value may be observed. In this paper, the Skewness and Kurtosis have been calculated for the different fault size on the bearing. The fault has been seeded on the inner surface and outer surface known as inner race fault (IRF) and outer race fault (ORF). The chosen statistical parameter Skewness (S_k) and Kurtosis (K_v) has been calculated as per equation no. (5) and (6). [15]:

Table 2. The theoretical characteristics frequencies

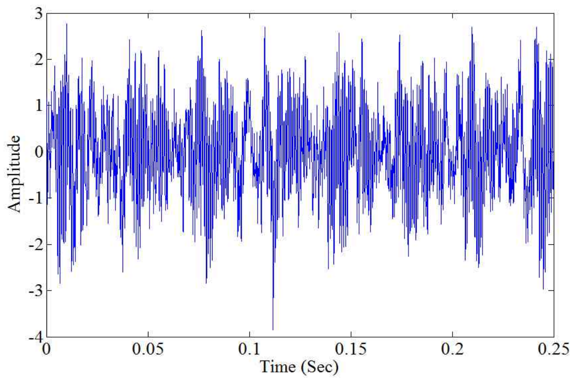
Characteristics Frequency	Value (Hz)
Running Speed Frequency, (f_r)	**29.23 Hz**
Fundamental Train Frequency, (FTF)	11.64 Hz
Ball Spin Frequency, (BSF)	68.89 Hz
Outer Race Fault Frequency, (ORF)	104.76 Hz
Inner Race Fault Frequency, (IRF)	158.6 Hz

$$S_k = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3}{\sigma^3} \tag{5}$$

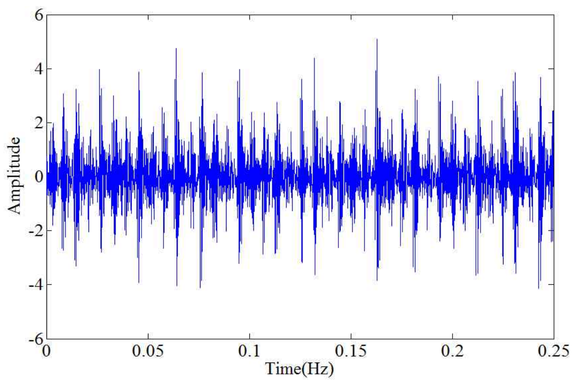
$$K_v = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\sigma^4} - 3 \tag{6}$$

where, x_i is the sample, $\bar{x}$ is the mean of sample and σ is the standard deviation of the recorded signal.

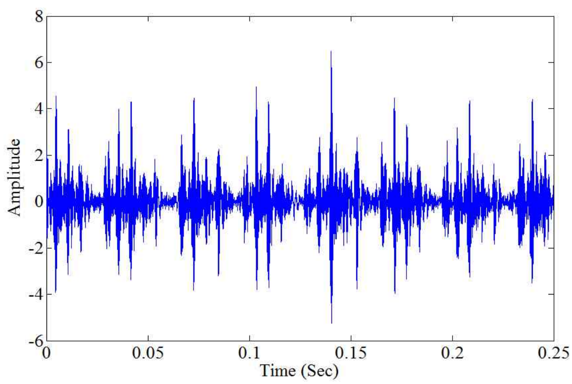
Skewness is the parameter which is generally used for the symmetry measurement of the data. A perfect distribution is symmetric when it equally covers the area from center to left and right of the Gaussian distribution. A left skewed data gives negative value and a positive value when data is skewed in right. For a perfectly normal distribution, Skewness is equal to 0. The Kurtosis gives the information about the flatness of the data and it indicates the standard deviation. It is measure about the data is “peaked” or “flat” relative to the normal distribution. High value of kurtosis indicates a “peaked” distribution or more impulse in the data and low kurtosis value indicates a "flat" distribution. From0 the literature, it has been observed that the kurtosis value equal to three belongs to healthy bearing and it increases with certain level of fault. Kurtosis with a value greater than three is considered as a defective bearing condition. These statistical parameters have been calculated for healthy and faulty bearing with fault size of 0.007 inches and 0.021 inches for the inner race and outer race of the bearing. From the Fig. 2 it has been concluded that the there is significant changes in the skewness and kurtosis value when severity of the fault increases. The lower value has been observed for the healthy condition of the bearing. Similarly, Fig. 3 shows the calculated statistical parameters for outer race fault and it has been found that the kurtosis value for 0.021 inches



(a) Healthy K_v=2.84, S_k=-0.057

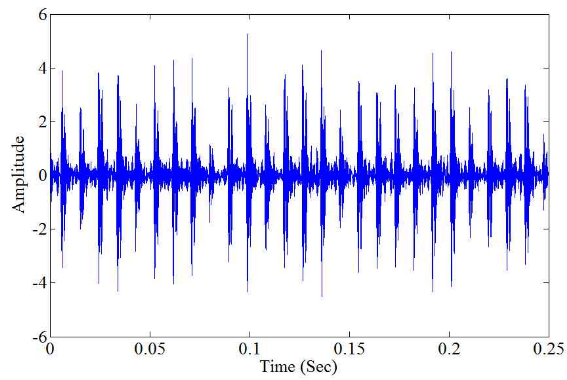


(b) Innerrace Defectat 0.007 inch (K_v=5.531, S_k=0.123)

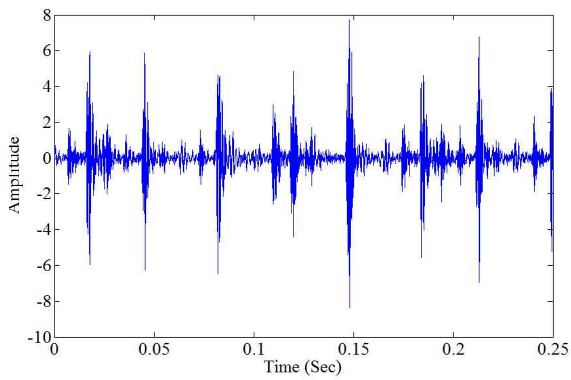


(c) Innerrace Defectat 0.021 inch (K_v=7.253, S_k=0.330)

Fig. 2. Skewness and Kurtosis value for healthy and inner race defect



(a) Outerrace Defectat 0.007 inch (K_v=7.602, S_k=0.125)



(b) Outerrace Defectat 0.021 inch (K_v=18.348, S_k=-0.117)

Fig. 3. Skewness and Kurtosis value for healthy and outer race defect

fault is 18.348 and for 0.007 inches fault it is 7.602. These values are greater than healthy bearing and observed increasing pattern. Hence, increasing trend in statistical parameter may indicate the severity of the bearing.

3. Methodology

The goal of this paper is to identify the fault seeded in the bearing. In section 2 it has already been discussed about the vibration signals which has been taken into consideration for the analysis and validate the proposed method. Fig. 4 shows the proposed method flow chart in which the signal is normalized using pre-processed. Further, the pre-processed signal used for Wavelet Packet Decomposition (WPT) which deals with a richer range of possibilities for the data analysis. In WPT analysis, a data has been offered a successive time localization for frequency sub bands. These sub bands generated by a tree of low pass filter and high pass filter operation. Each sub-band consists of spectral information of original signal and it is easy to identify the high frequency region. This property of WPT makes it an attractive tool for detecting and differentiating transient components with high frequency characteristics. An extensively study on WPT and envelope analysis for bearing fault diagnosis has been done by Wang and Zhang [16].

To explore fault feature information, a WPT-based method has been proposed for developing an index based on sub band energy to explore the node which is rich in information. Eq. (7) has been used to calculate the energy of each sub bands. The goal is to calculate the energy of each sub band for healthy and defective case of the bearing and compared both. These steps are carried out to know the maximum change of energy in the node from a healthy state to defective state.

$$E = \sum_{n=1}^{N} |s(n)|^2 \tag{7}$$

Where, N is the total number of sample in the signal and E is the energy of the sub band.

In the present work, the wavelet decomposition and reconstruction has been performed up to three levels and obtained eight sub bands as shown in Fig. 5. The Daubechies family db10 is used as a mother wavelet for the decomposition. Fig. 5 shows the index value named as Bearing Damage Index (BDI) calculated as Eq. (8) for all eight nodes and it has been observed that the maximum change in energy from healthy to damage state is at node 7 and minimum energy belongs to node 4. This information helps to choose the wavelet coefficient of node 7 only to identify the fault frequencies related to fault as given Table 2. To identify the fault characteristics of the signal, TKEO and PSD has been applied and its theoretical background is given in section 3.1 and 3.2 respectively.

$$BDI\% = \frac{E_{Normal} - E_{Defected}}{E_{Normal}} \times 100 \tag{8}$$

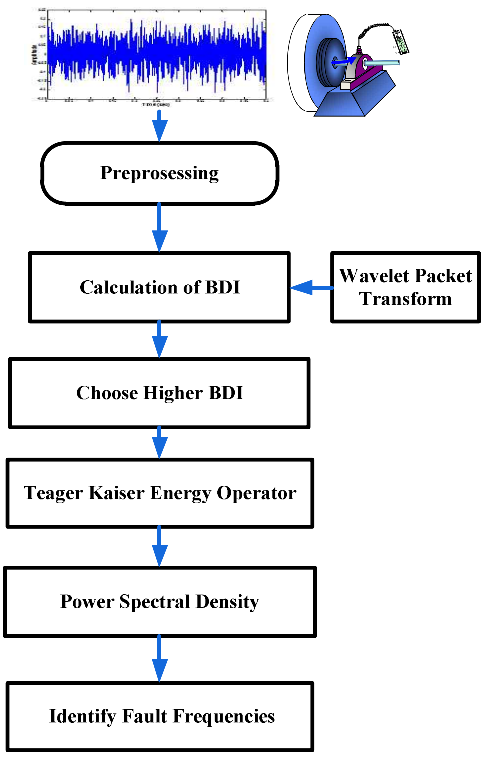


Fig. 4. Proposed method for fault detection

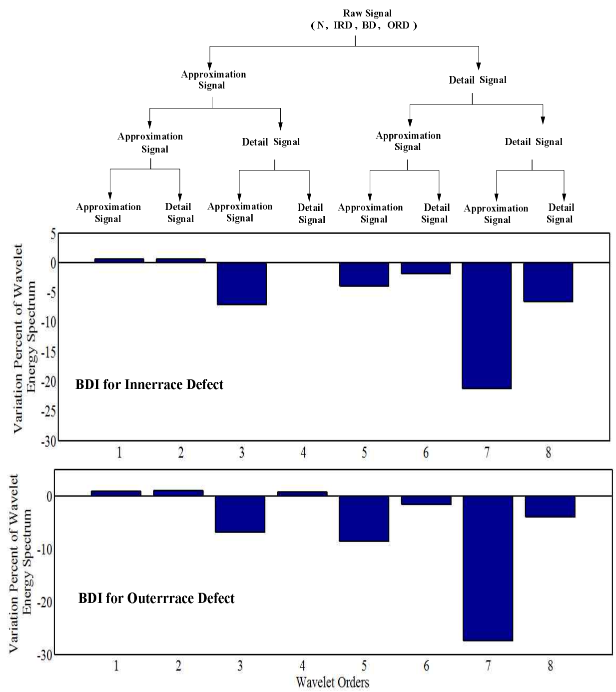


Fig. 5. Wavelet Packet Decomposition and Calculation of Bearing Damage Index

3.1 Teager–Kaiser Energy Operator (TKEO)

The TKEO applied to a real-valued signal $s(t)$ of induction motor bearing vibration signal and is given by Eq. 9. [17-18]

$$\psi_c[s(t)] = \dot{s}(t)^2 - \ddot{s}(t)s(t) \tag{9}$$

Where, $\dot{s}(t)$ and $\ddot{s}(t)$ are the first and the second-time derivatives of $s(t)$. $\psi_c[s(t)]$ is known as the Teager energy of the signal. Its discrete form is given by Eq. (10).

$$\psi_c[s(t)] = s(n)^2 - s(n+1)s(n-1) \tag{10}$$

TKEO shows instantaneous behavior due to only three samples which are essential for the energy calculation at each time of instant. P. Margo et al., develops an algorithm to separate $s(n)$ into amplitude envelope $|a(n)|$ and IF signal $f(t)$ to achieve mono-component AM-FM signal demodulation [19]:

$$f(t) \approx \frac{1}{2\pi}\sqrt{\frac{\psi[\dot{s}(n)]}{\psi[s(n)]}} \tag{11}$$

$$|a(n)| = \frac{\psi[s(n)]}{\psi[\dot{s}(n)]} \tag{12}$$

The energy parting algorithm is very simple demodulation technique for AM-FM demodulation. The best part of TKEO is to its simplicity to implement efficiently. It has better time resolution than the conventional method like Hilbert transform due to less computational complexity. Sensitivity is the major concern of this operator when it is applied to noisy signal. [20].

3.2 Power Spectral Density (PSD)

Spectral analysis is also called Fourier Transform. Fourier transform gives information of frequency from time domain data. Spectral analysis gives alternative representation for the analysis of the signal since in time domain information are hidden and consist of certain features which belongs to the behaviors of the system. Spectral analysis changes the delta basis function in the time domain to infinitely long sinusoidal basis functions in the frequency domain. [21, 22].

The Fourier Transform $S(f)$ of a time series $s(t)$ is given by:

$$S(f) = \int_{-\infty}^{\infty} s(t)e^{-i2\pi ft}dt \tag{13}$$

And its inverse relationship is given by

$$s(t) = \int_{-\infty}^{\infty} S(f)e^{i2\pi ft}df \tag{14}$$

where, $s(t)$ is the signal.

Power spectral density function (PSD) illustrates the variation of the frequency in terms of strong and weak. PSD is an important technique to know the information about the frequency and its amplitude of oscillatory signal of any time series data in to frequency domain. The unit of PSD is energy (*variance*) per frequency (width) and energy obtained within a specific frequency range by integrating PSD within that frequency range.

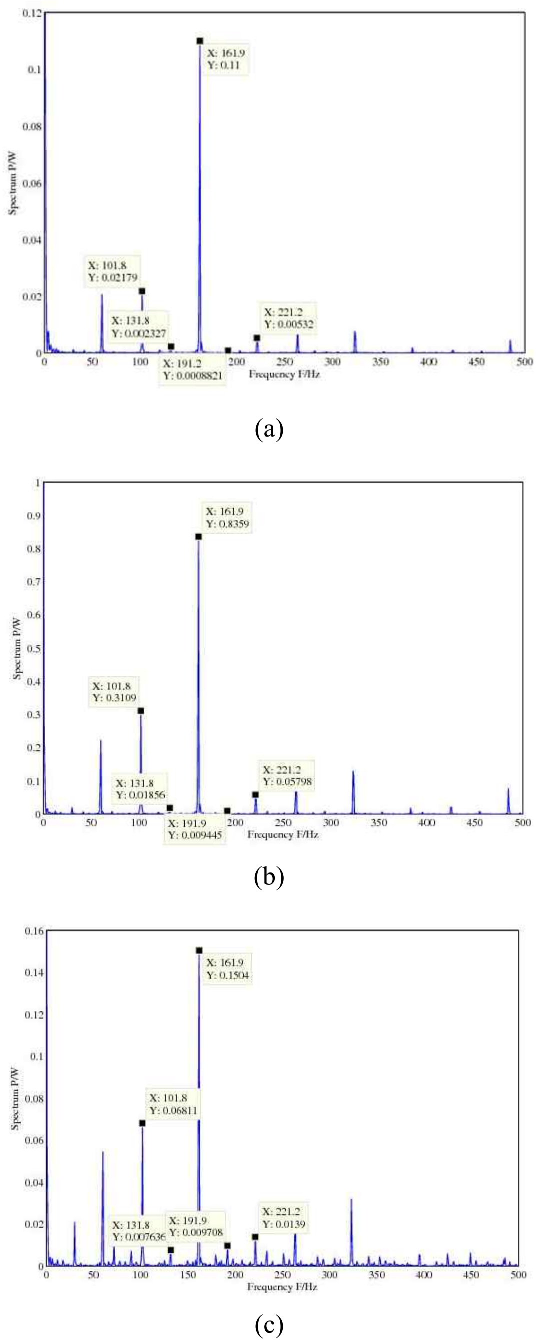
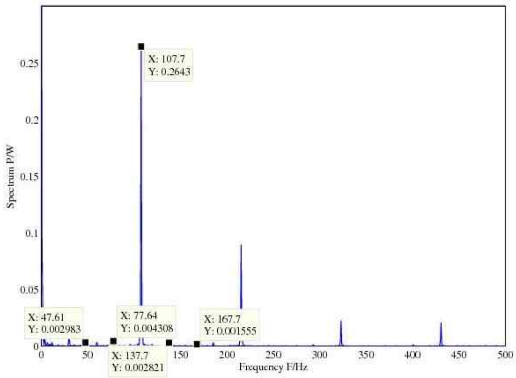


Fig. 6. Power Spectral density of Inner Race Way Defect Using (a) Hilbert Transform (b) Teager Kaiser and (c) WPT+TKEO

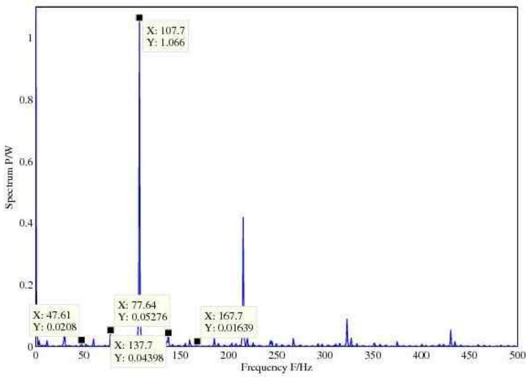
4. Results and Discussions

In this paper, the three different approaches have been applied on Case Western Reserve University bearing data for healthy and defective cases recorded at no load. In the proposed method, a combination of TKEO and WPT are used and compared with the traditional Hilbert Transform method. In the present work, healthy, inner race way and outer race way defective cases has been taken into consideration for the validation of proposed method. The spectrum of defective bearing has been shown in Fig. 6 and Fig. 7 using (a) Hilbert Transform (b) TKEO and (c) proposed method TKEO and WPT for inner race way and outer race way defects. From Fig. 6 it is identified that a frequency of 161.9 Hz is having highest amplitude which belongs to innerrace defect which is clearly visible. The main fault frequencies also can be calculated from the physical dimension of the bearing. The theoretically calculated frequencies are shown in Table 1. The observed frequencies matched with the calculated frequencies and ensure the presence of fault but it fails to confirm about the severity of fault. It has been also observed that there is presence of sidebands on the both side of fault frequency and it has poor visibility. The presence of side bands is the indication of severity of the fault. The first side band can be calculated as $f_1 \pm f_r$ and second side band can be calculated as $f_1 \pm 2f_r$. Where, f_1 is the main fault frequency due to defect in race way and the f_r is the rotational frequency. Similarly, for outer race defect it is observed that in Fig. 7, frequency of 107.7 Hz is having highest amplitude and clearly visible but its sideband visibility is poor.

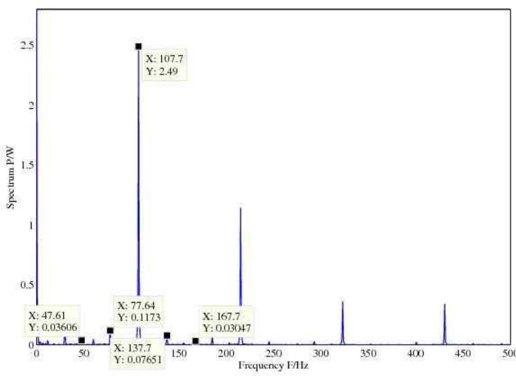
To evaluate the proposed method a performance index, based on the amplitude of frequency have been developed and calculated using Eq. (15) which is depicted in Fig. 8.



(a)



(b)



(c)

Fig. 7. Power Spectral density of Outer Race Way Defect Using (a) Hilbert Transform (b) Teager Kaiser and (c) WPT+TKEO

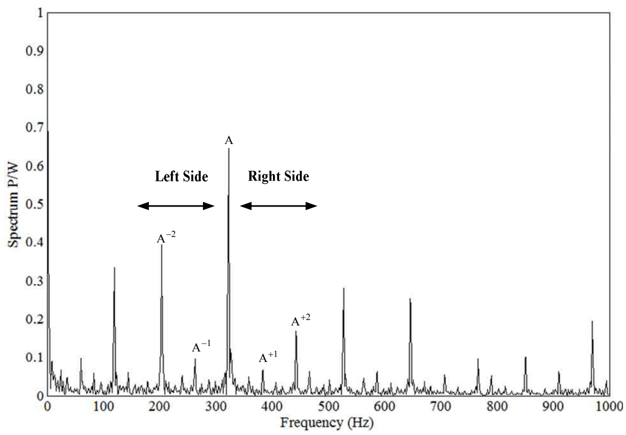


Fig. 8. Spectrum of defected bearing with its side band

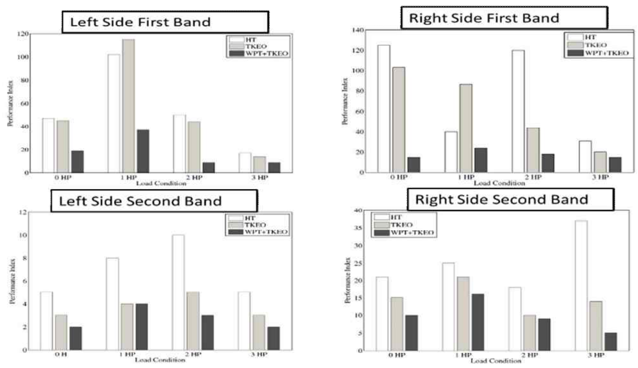


Fig. 9. Performance index for inner race way defect

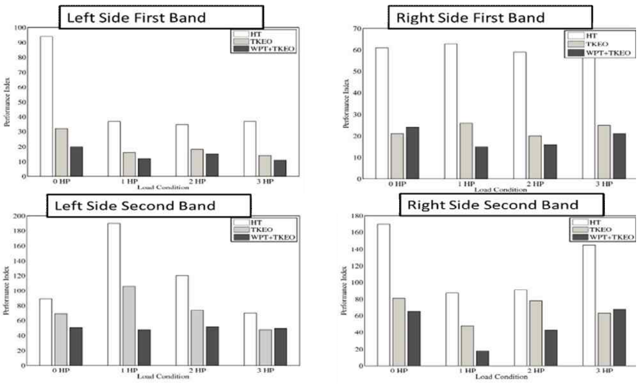


Fig. 10. Performance index for outer race way defect

The Amplitude of main fault frequency indicated by A and left side band, right side band frequency amplitude is represented by A^{-1}, A^{+1} respectively.

Left Side Right Side

$$Performance\ Index = \frac{A}{A^{-1}} \quad Performance\ Index = \frac{A}{A^{+1}} \tag{15}$$

$$Performance\ Index = \frac{A}{A^{-2}} \quad Performance\ Index = \frac{A}{A^{+2}}$$

Where A the amplitude of the main fault frequency is, A^{-1} is the left first side band, A^{-2} is the left second side band. A^{+1} is the right first side band, and A^{+2} is the right second side band.

Lower index value indicates the higher amplitude of the sidebands which helps to identify the side bands. Fig. 9 shows the calculated performance index of left and right side bands for inner race defect and Fig. 10 shows the performance index of left and right side bands for outer race defect. These performance index have been calculated for the spectrum by using Hilbert Transform, TKEO and the proposed method which is combination of wavelet packet transform and TKEO. From the Fig. 9 and Fig. 10 it has been observed that lower index value obtained by the proposed method for both left and right side band as compared to the traditional technique used for the identification of the fault detection which clearly exhibit the effectiveness of the proposed method in which the visibility of sideband improved and can declare the fault is severe.

5. Conclusions

In the present work, fault frequency has been identified using Teager-Kaiser Energy Operator (TKEO) and wavelet Packet Transform (WPT). The output of the proposed method has been compared with the Hilbert Transform (HT) using developed performance index and it has been observed that proposed method gives better resolution which reflects that the proposed method has better fault identification quality and improved identification of its side bands.

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