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Selection of Mother Wavelet for Fault detection of cylindrical bearing

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Abstract

Bearings are a very essential part of any of the machine and their reliability affects the performance. Continuous monitoring of the machine includes the monitoring of the bearing for its failure. This paper aims to detect a fault in cylindrical bearing with the use of signal processing when it is in use. Experimental data for healthy as well as for defective bearings are collected for investigation. Wavelet analysis provides time-frequency domain study together and for that finding out best suitable wavelet is most important. By use of relative energy concept and maximum energy to Shannon entropy ratio, it is identified that out of selected wavelets, symlet 2 gives the best result in terms of mother wavelet as a selection. Further to verify the results FFT diagram is generated for without symlet 2 wavelet and with symlet 2 wavelet and compared for the investigation regarding bearing fault.

Keywords: *Mother Wavelet; Signal Processing; Bearing; Fault Diagnosis.*

1. Introduction

Cylindrical bearings are widely used in industries. So better working of bearing with respect to time is very important. In industries, Failure of bearing can lead to failure of the whole machinery. So, detection of failure and finding out various defects like defects of races (inner and outer both), roller, cage, or combine are prior need in the research of bearing. A perfect bearing may generate vibration due to varying compliance or due to various forces that are acting on faces of it. By studying that vibration, identification of the defects in the recent trend. A. Choudhury (1998) discovered that due to defects in bearing, Vibration response changes with respect to time. Defects of bearings can be classified as localized or distributed. Pits, spalls, and cracks occurred by fatigue are considered as localized defects. Where distributed defects include misaligned races and off-size rolling elements.

For any bearing, the radial clearance can't be changed once it is manufactured. Clearance of bearing and heat generation during application lead to vibration and nature of the vibration usually found nonlinear. Hence Analysis of the nonlinear vibration signal of the bearing is the key factor.

There is no need to stop the machine for the maintenance or fault diagnosis through vibration signals. There are three domains in the field of signal processing in the terms of bearing and that are time domain, frequency domain, and time-frequency domain. The time-domain signal is very useful when signal amplitude changes concerning time. But the disadvantage of this domain is, it cannot give the information about the early-stage failure. This problem can be solved by using frequency-domain a method, as it is using the various characteristic frequency of bearing and

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all components of the bearing, has its natural frequency. Defects in the bearing can be identified by applying Fourier Transformation (FT) on the collected signals from the machine. FT is useful for non-stationary signals, only to identify whether spectral components exist in the signal or not, but it fails to give the location of it. That's why FT is not the right solution to analyze the non-stationary signals. So, moving towards other techniques is required for the defect study in the bearing. Recently many authors have suggested the time-frequency domain like Wavelet Transform (WT) for weak signals.

Many methods are applied to analyses the response of the vibration signal for rolling bearings with defects. There are majorly two types of defects: localized and distributed. Tandon and Choudhury [1] classified Vibration measurement as time, frequency, and time-frequency domains. Out of these three-frequency domains, techniques can find the location of the defect. But sometimes the direct vibration spectrum of the defective bearing may fail in detecting the defect at the initial stage. So that signal processing techniques are used. The higher frequency resonance method is best among these and so many researchers also applied the same and got successful results. In the past few years, the WT (wavelet transform) the method is suggested to extract some weak signals for which FT (Fourier transform) becomes inadequate. In the time-frequency domain, vibration analysis can be done by parameters such as RMS level, crest factor, kurtosis, etc. Among these, kurtosis is the most adequate.

2. Mother Wavelet Selection

A wavelet is a small signal having wave-like oscillation. The amplitude of wavelet is started from zero then it increases and at last decreases back to zero. Wavelet is used as a mathematical tool to take out information from many different signals. A representation of the function by different wavelet is called wavelet transform. Translated and Scales wavelets are often known as daughter wavelets which are for limited length. If they are represented as oscillating waveform then it is said Mother Wavelet. Wavelet Transforms is better than FT for the representation of discontinuing of signal.

The wavelet transform is the time-frequency representation. It is noted that Vibration signals generated from the defective bearings are showing non-stationary behavior and that non-stationary behavior of signals are effectively analyzed by WT technique, which is well known under the time-frequency technique.

The wavelet transform is almost like the Fourier transform but it has different merit function as written below.

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\psi^{*}_{(a,b)}(x)dx \tag{1}$$

Wavelet analysis is represented by the above function and it is used to divide data into different frequency components and study every component individually with a resolution matched to its scaling. WT is also capable to process stationary and non-stationary signals in both time and frequency domains. It is for feature extraction. After analyzing all research works, it is found that the selection of the mother wavelet function, which is a significant topic in signal analysis, is open to question.

According to Rafiee et al. [2], WT can be mainly divided into discrete and continuous forms. So many different types of mother wavelets are there which can be used for wavelet analysis. Different types of mother wavelets used to analyze any particular signal will generate different results. Ngui et al. [3] classified Mother Wavelets by their properties such as compact support, orthogonally of signal, symmetrical properties, and vanishing moment. Based on the past study, the properties of any mother wavelet are taken in the study for selecting a mother wavelet. However, some wavelet with same properties often exists and to overcome this problem, the similarity between signal and mother wavelet is taken in the study for selecting proper mother wavelet.

Antoni [4] said that a spectral kurtosis is a statistical tool that indicate the presence of a series of transients and their locations in the frequency domain. It is also helpful to supplements the classical power spectral density, which is well known by completely eradicates non-stationary information. Again Antoni and Randall [5] explained that SK provides the best way of detecting hidden faults even in high noisy signals. SK also offers a unique way of creating optimal filters for bifurcating the mechanical signature of faults. Also, the concept of Kurtogram has introduced her and explained. Direct analysis of a vibration signal by use of SK is most valuable in detecting the presence of incipient faults.

According to Jerome Antoni [6], The Kurtogram is a 4th order spectral analysis tool which is recently introduced to detect and bifurcate non-stationary signals. The Kurtogram is a very powerful analysis tool for the non-stationary signals. The ability of it to detect transients buried in the availability of strong background noise opened up so many new directions. Kankar et al. [7] in his research stratified that at the time of applying wavelet transform to ball-bearing signals, if the Shannon Entropy measure of a given scale is minimum then it can be concluded that a major defect frequency component exists in that scale. Complex Morlet wavelet is selected as the best base wavelet from all other wavelets considered by the proposed methodology.

For the selection of the mother wavelet, below two criteria, is implemented in this research work.

1. Maximum Energy to Shannon Entropy

2. Maximum relative wavelet energy

Maximum Energy to Shannon Entropy (MESE) Ratio Criterion: The energy content in signal is a measurement of the unique character of the signal and it may be considered for selection of base wavelet. The amount of energy contained in any signal x (t) is given by

$$E_{x(t)} = \int |x(t)|^2 dt \tag{2}$$

Shannon entropy of the signal is given by

$$E_{entropy}(s) = -\sum_{i=1}^{N} p_i \log_2 p_i \tag{3}$$

Where pi is the energy probability distribution of the wavelet coefficients and is given by

$$p_i = \frac{|wt(s,i)|^2}{E_{energy}(s)} \tag{4}$$

To find out best base wavelet, the ratio of energy and Shannon entropy is calculated by the below equation, $R(s) = \dfrac{E_{energy}(s)}{E_{entropy}(s)}$ (5)

Max Energy-to-Shannon Entropy Ratio Measure. R Yan (2009) discovered that the base wavelet that has produced the max energy-to-Shannon entropy ratio is selected as the most appropriate wavelet for defecting any induced transient vibration extraction.

Relative wavelet energy (RWE): It is chosen as time-level density which can be used to detect any specific phenomenon in frequency and time planes. It is shown that the signification of RWE in continuous WT is very high. RWE can give information about relative energy with associated frequency and its sub-bands and it can also detect the degree of similarity between various segments of a particular signal. The energy at each sub frequency band is given by

$$E_{X_j^m(t)} = \int | x_j^m(t) |^2 dt \tag{6}$$

Kulkarni [8] have explained the importance of mother wavelet selection by saying, mother wavelet helps in the perfect reconstruction of any signal in time and frequency domain. The coefficients of the wavelet transform are the best way for deciding how good the signal is for analyzing using selected base wavelet.

Based on literature it is noted that inner race defect is non-stationary in nature while outer race defects are stationary. So many works for detecting outer race defects (a stationary type of defect) is done but very less work on effective fault diagnosis of the non-stationary defect. Peng-Yi Weng, Meng-Kun Liu [9] noted that the traditional Fourier analysis accepts sinusoidal basis functions to generate the time domain signal to its frequency complement. Sinusoidal based signals are those functions that follow Fourier-based methods but they can’t return the original characteristics of the non-stationary signal. Mother wavelets are used as local transformation supported by Continues wavelet transforms. This mother wavelet is very useful in achieving the time-frequency analysis. The biggest benefit of Continues wavelet transformation is the best frequency resolution for the low-frequency component and at the same time also the best time resolution for the high-frequency component.

After analyzing all the research papers, it is also clear that many types of research had done their work for fault diagnosis of roller bearing using signal processing techniques and some machine learning also. But very less work has been done for cylindrical bearings. So here NTN NJ 305CN is taken for study.

3. Experimental Setup

The experimental setup is used for the study shown in Figure 1. The experimental setup of this research consists of a shaft that is supported on cylindrical bearings and driven by a DC motor. The flexible coupling is used for avoiding any misalignment in the system. The test bearing, NTN NJ 305CN has been taken for the study. The experiment is done on the various bearings out of which one is healthy and other bearings have localized defects like inner race, outer race, rolling element. Data acquisition is done by the COCO analyzer. All the sensors and vibration analyzers are installed on the set-up fabricated. Vibration responses are acquired and analyzed by analyzer with 2 input channels and a sampling rate of 20.480 kHz. Geometrical dimensions of Bearing are: Outer diameter 63mm, Inner diameter 25 mm, Thickness 17mm, Radial Clearance 20-45 microns, and no of rollers 10. Various Trials are taken between 0 to 5000 rpm for all conditions for bearings at an interval of 500 rpm. For this experiment purpose, bearings have been prepared with inner race defect, outer race defect, and roller defect. These defects are created on a laser cutting machine and the size of the defect is around 1 mm.

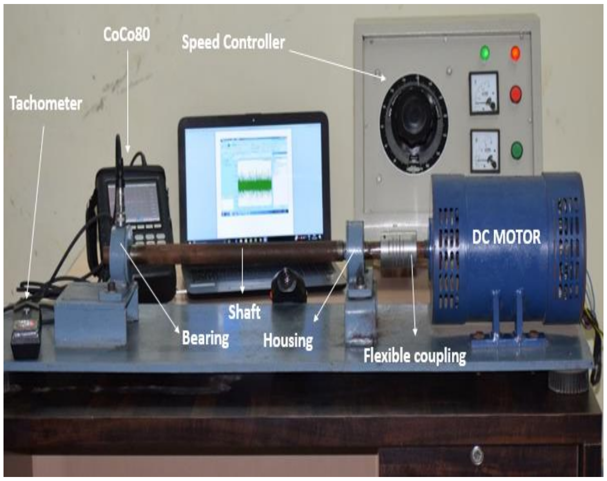

Figure 1. Experimental Setup.

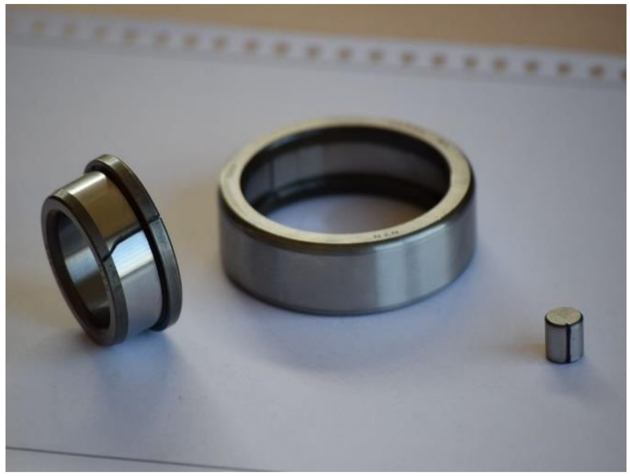

Figure 2. Defective Bearing Components.

For these defective bearing, readings have been taken and analyzed further on the basis of vibration frequency using signal processing techniques.

4. Methodology

Vibration signals are decomposed at suitable level based on sampling frequency fs and frequency component fd to be identified in the signal, as expressed in Eq.

$$\frac{f_s}{2^{j+1}} \leq f_d \leq \frac{f_s}{2^j} \tag{7}$$

As the sampling frequency is 20,480 kHz, so therange of frequency component according to the above equation is shown in the Table 1.

Table 1. Range of Frequency for particular level.

Level of Decomposition(j)	Frequency component Range (f_d)
1	5120 – 10240
2	2560 - 5120
3	1280 – 2560
4	640 – 1280
5	320 – 640
6	160 – 320
7	80 – 160

These level of decomposition is used for wavelet analysis hence selecting the right level becomes more essential and For deciding the appropriate level of decomposition, first of all, different frequencies like ball pass frequency for the inner race (BPFI), ball pass the frequency for the outer race (BPFO), ball spin frequency (BSF), Fundamental train frequency (FTF) are calculated for 500, 1000; 1500 and 2000 RPM in table below. These values are calculated by standard equations for selected bearing.

From the above table, it is noted that for the speed range of 500 to 2000 RPM all the frequencies are lying between 0 to 200 Hz and according to table 1, level 5, 6, and 7 are most suitable for decomposition.

Table 2. Frequency values for different conditions of bearing

SPPED (RPM)	Shaft Frequency (Hz)	BPFO (Hz)	BPFI (Hz)	BSF (Hz)	FTF (Hz)
500.00	8.33	33.06	50.28	19.30	3.31
1000.00	16.67	66.11	100.56	38.60	6.61
1500.00	25.00	99.17	150.83	57.90	9.92
2000.00	33.33	132.22	201.11	77.20	13.22

In this Research, Bearing Preparation is done at the initial stage with inner race, outer race, and roller defect. Four different conditions of bearing (one healthy and three defectives) have been selected for the work. On the Setup, reading has been taken at various speeds. The minimum Speed of motor is 500 rpm and the maximum it goes to 2000 RPM for the research. Readings are taken at an interval of 500 RPM.

Steps followed in this research:

1. Bearing Preparation as Healthy bearing. Bearing with inner race defect, with outer race defect, and with roller defect.
2. Vibration Signal Acquisition at selected rotor speed (500, 1000, 1500, 2000 RPM).
3. Select Level of Decomposition using the concept of spectral kurtosis.
4. Calculate energy and entropy at the selected level for all selected wavelets.
5. Find relative wavelet energy and Shannon entropy.
6. Calculate Avg. Max. Relative Energy and Avg. Max. Energy to Shannon Entropy ratio.
7. Select wavelet with Avg of Avg. Max. Relative Energy and Avg of Avg. Max. Energy to Shannon Entropy ratio criteria.

The kurtosis of the signal has usually considered in the signal-processing technique to get the answer to the unknown problems: for example, identification of fault can be done by kurtosis maximization, random separation of all signals by particular maximized kurtosis, etc. Jerome Antoni and R.B. Randall [5] used spectral kurtosis for blindly identify detection filter.

According to Antoni [4], The spectral kurtosis, or K(f), of a signal x(t), can be computed based on the short-time Fourier transform (STFT) of the signal, S(t,f):

$$S(t,f)=\int_{-\infty}^{+\infty} x(t)w(t-\tau)e^{-2\pi ft}dt \tag{8}$$

where w(t) is the window function used in STFT. K(f) is calculated as

$$K(f)=\frac{\left\langle \left|S(t,f)\right|^{4}\right\rangle}{\left\langle \left|S(t,f)\right|^{2}\right\rangle^{2}}-2,\ f\neq 0. \tag{9}$$

where, $\langle . \rangle$ is the time-average operator.

Based on the above Equation for level 5, 6 and 7 value of kurtosis is found for the entire range of the frequency and their plot on the graph. Here using the concept of spectral kurtosis, the Best Level of decomposition is identified and for that level's wavelet transformation is applied. According to Nader Sawalhi and Robert B. Randall [10] and also explained above, the calculated SK does depend on the selected level of decomposition. This also describes the different lengths of the time window, which aims to give a balance between the separation of characteristics and detail coefficient data within the window. Figure 3 is explaining faulty cylindrical bearing's SK which are calculated for window lengths of 32, 64, and 128 samples. It is evident that 32 gives insufficient frequency resolution, while 64 are 128 increases the values of SK, so in this research either 64 and 128 are chosen.

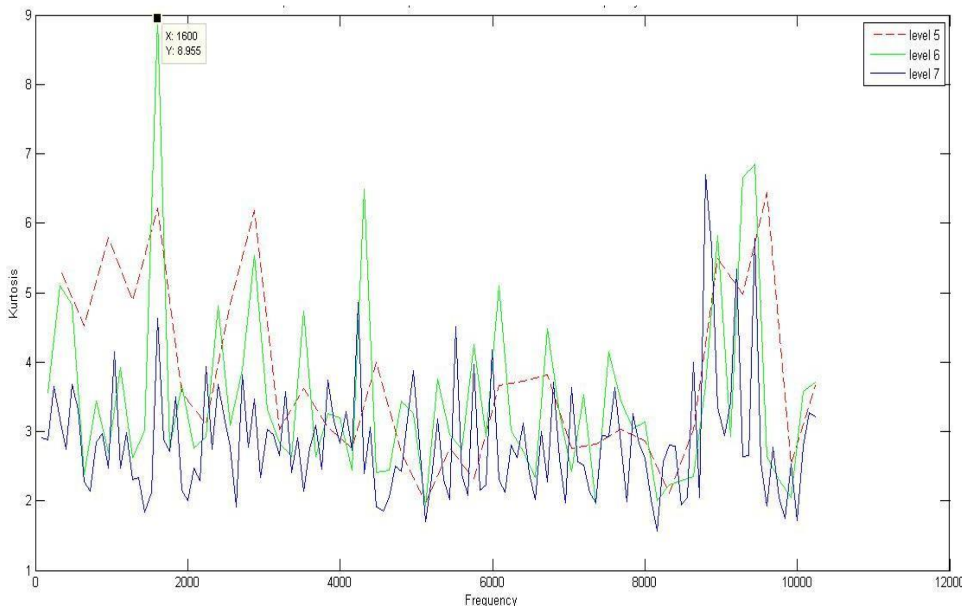

Figure 3. Spectral Kurtosis value for level 5, 6 and 7.

Here in this research Max Energy to Shannon entropy ratio is calculated and an average of it for all conditions is considered for concluding results. By these mathematical parameters of signal, finding of mother wavelet for the current system is done.

5. Result and Discussion

Generally cylindrical bearings are used in heavy machinery hence it is always subjected to high radial load and high impact load also. These machines are usually run at low speed. So here only up to 2000 RPM, the result is analyzed and concluded.

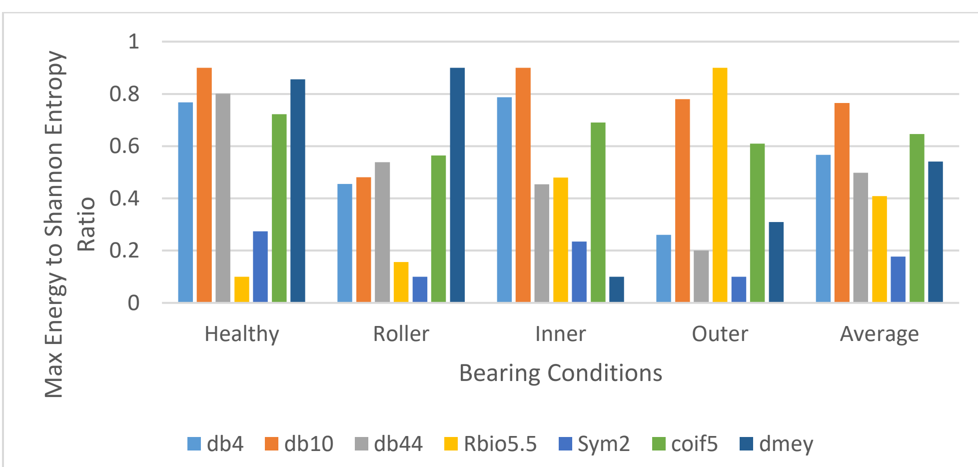

Figure 4. At Level 6, Max Energy to Shannon entropy ratio for 500 RPM for seven different wavelets.

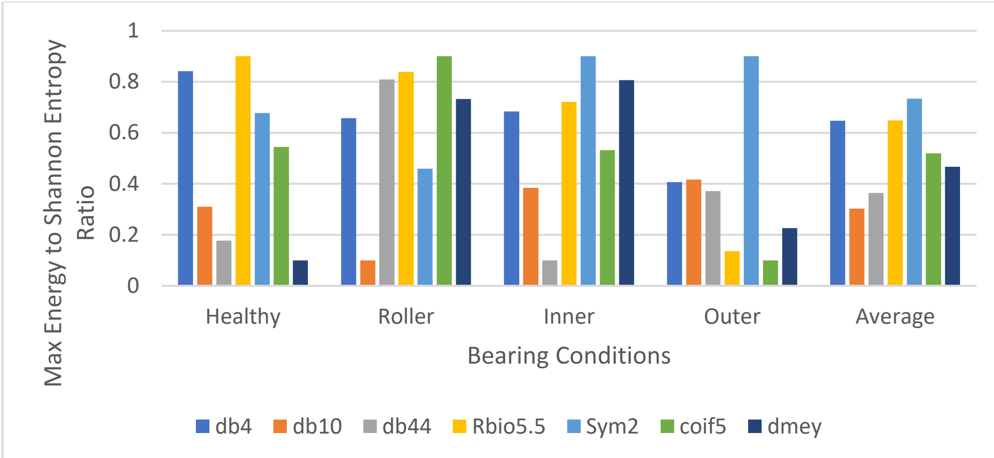

Figure 5. At Level 6, Max Energy to Shannon entropy ratio for 1000 RPM for seven different wavelets.

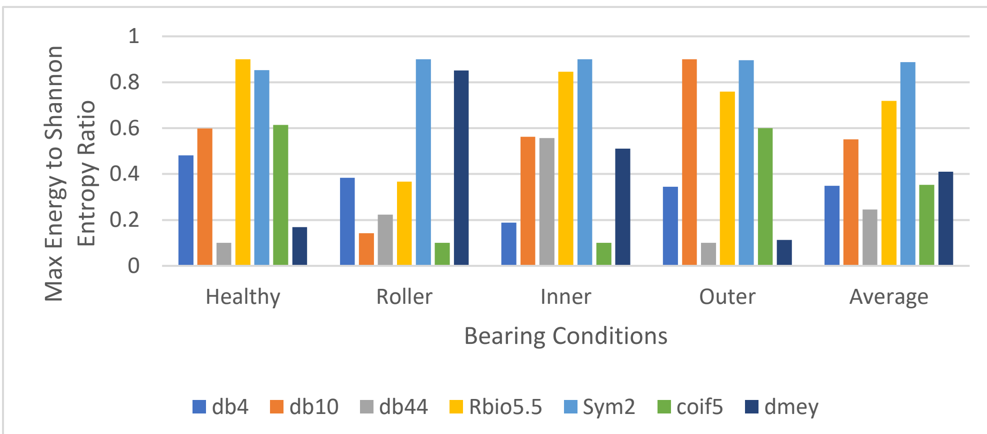

Figure 6. At Level 6, Max Energy to Shannon entropy ratio for 1500 RPM for seven different wavelets.

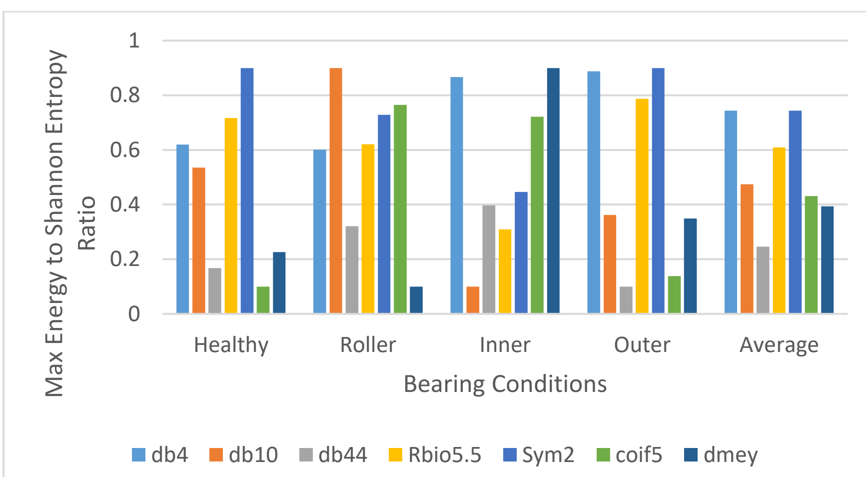

Figure 7. At Level 6, Max Energy to Shannon entropy ratio for 2000 RPM for seven different wavelets

At level 6, for seven different wavelets – db4, db10, db44, rbio5.5, sym2, coif5, and dmey, here in Figures 4 -7, max energy to Shannon entropy ratio is been calculated and shown. For healthy bearing, bearing with inner, outer and roller defects is plotted. For concluding the result, the average of all is considered in the last columns. For 500 rpm it is noted that the db10 wavelet showing highest ratio while in 1000, 1500 and 2000 rpm readings Sym2 is showing the best results.

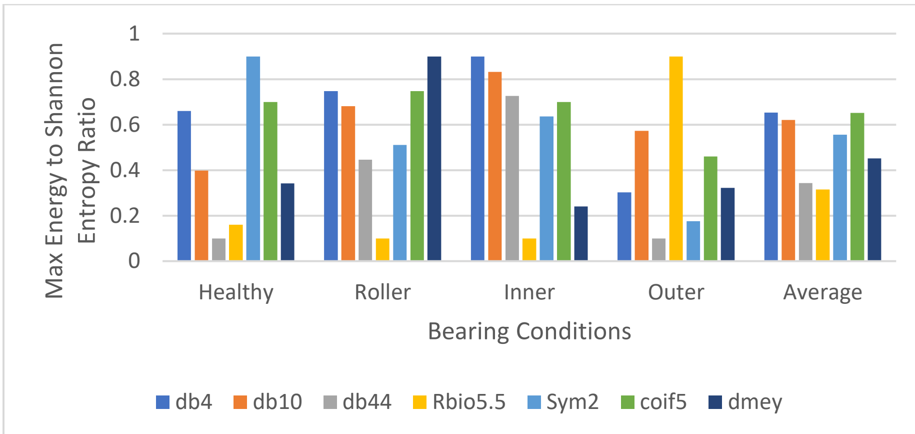

Figure 8. At Level 7, Max Energy to Shannon entropy ratio for 500 RPM for seven different wavelets.

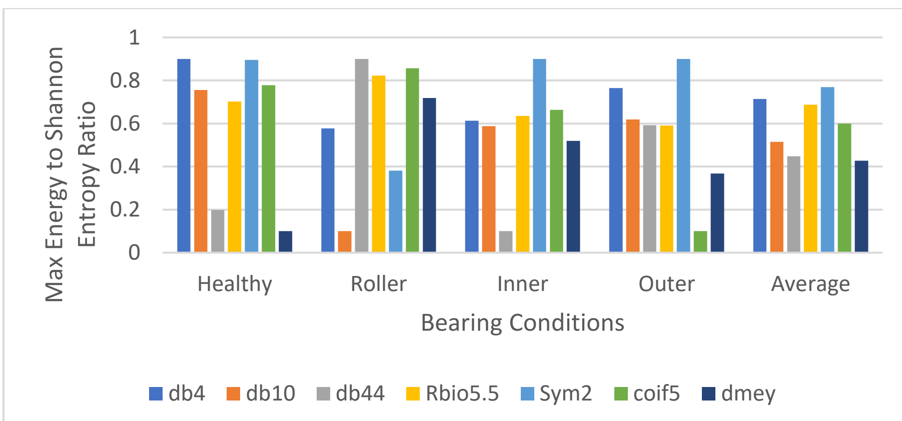

Figure 9. At Level 7, Max Energy to Shannon entropy ratio for 1000 RPM for seven different wavelets.

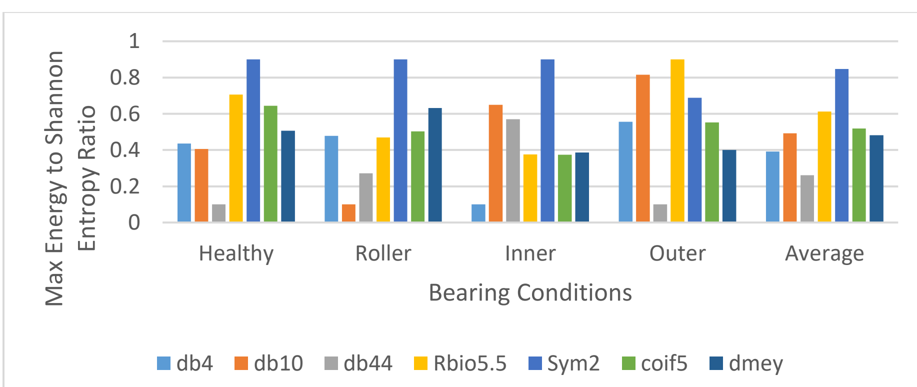

Figure 10. At Level 7, Max Energy to Shannon entropy ratio for 1500 RPM for seven different wavelets.

Here in Figures 8-11, Max energy to Shannon entropy ratio for level 7 is plotted. These readings are for different conditions of the bearing at 500, 1000, 1500, and 2000 RPM. Here for 500 rpm db4 is showing the highest ratio but for 1000, 1500, and 2000 RPM same as level 6, Sym2 is showing best results.

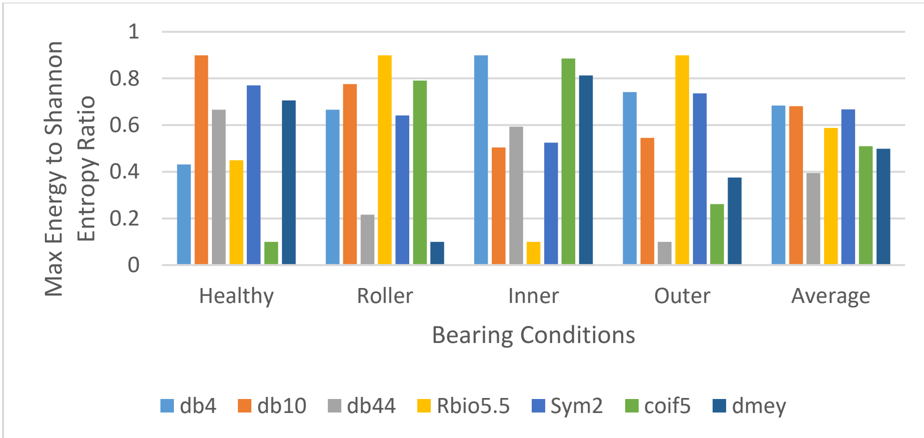

Figure 11. At Level 7, Max Energy to Shannon entropy ratio for 2000 RPM for seven different wavelets.

The maximum relative energy and maximum energy to Shannon entropy criterion are calculated with average of average at all speeds are taken for the selection of statistical number for wavelet. Final output in terms of statistics at speeds 500, 1000, 1500 and 2,000 calculated and presented in Table 3.

Table 3. For lever 6 and 7 Avg of Avg for max energy to Shannon entropy ratio.

Wavelet	Average of Average for Max Energy to Shannon Entropy Ratio	
	Level 6	Level 7
db4	0.57688	0.61075
db10	0.5233	0.57763
db44	0.33868	0.36127
Rbio5.5	0.59614	0.55056
Sym2	**0.63559**	**0.70987**
coif5	0.48764	0.56988
Dmey	0.45303	0.46454

Here, both the criteria are applied for finding the best mother wavelet for further processing and results are plotted. In the first criteria for all the conditions max energy to Shannon entropy ratio is found and the average of it calculated. And the second criteria is based on wavelet energy. A concussion is made on the basis of both the criteria.

Here reordering of the frequency band at the level 5, 6 and 7 is done using the MATLAB. For this research work after having sym2 wavelet as the best wavelet, it is applied to all signals and a fast Fourier transform (FFT) diagram is generated. Without applying wavelet as noise reduction FFT is generated and after applying also FFT is generated and both are compared for getting a conclusion. For this comparison, all the conditions of the selected bearing are considered.

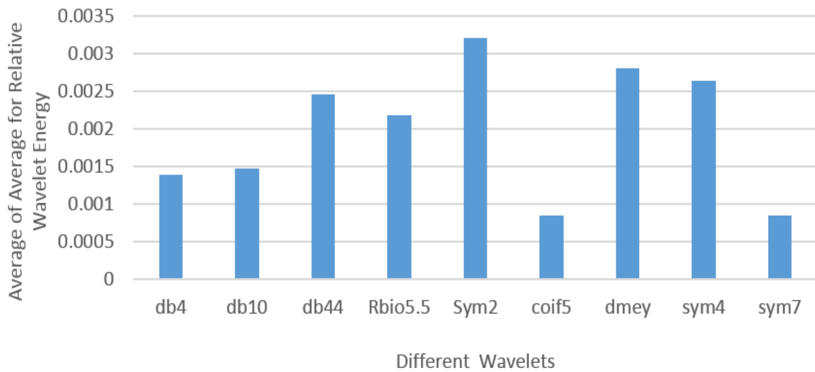

Figure 12. Average of average for relative wavelet energy for nine different wavelets.

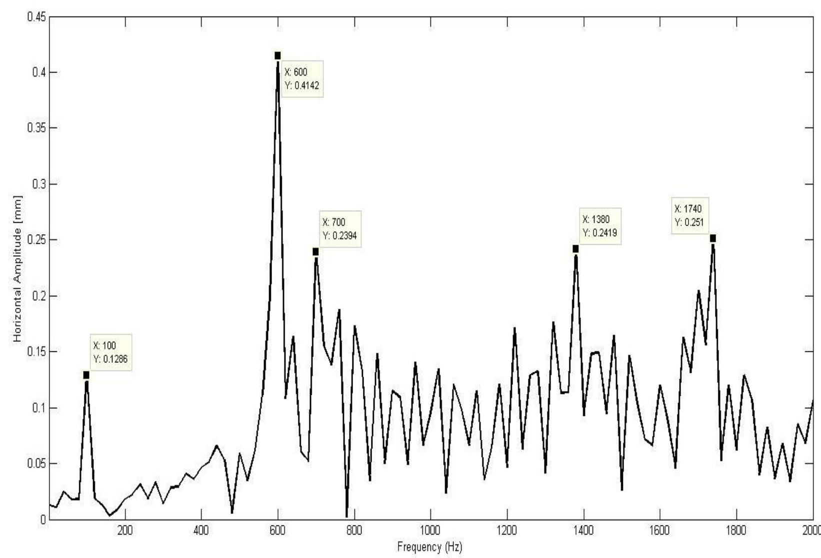

Figure 13. Fast Fourier Transform (FFT) at 500 RPM for inner race defect before applying wavelet.

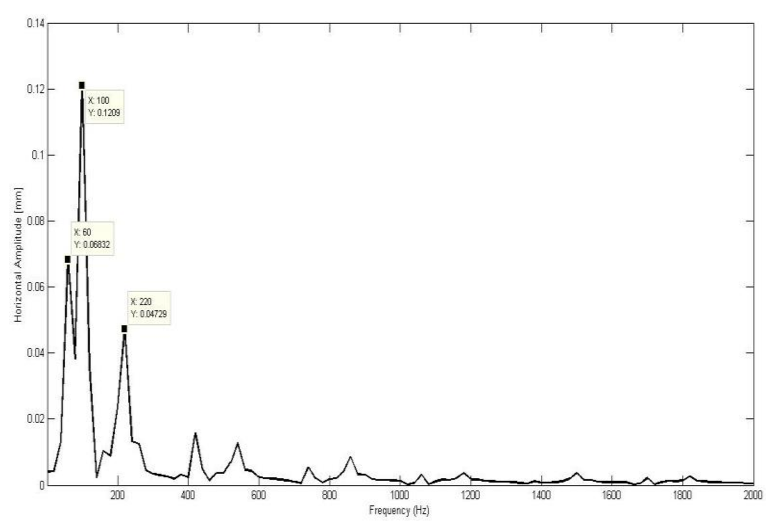

Figure 14. Fast Fourier Transform (FFT) at 500 RPM for inner race defect after applying wavelet.

Figure 13 Shows the FFT diagram of the bearing having inner race defect in which wavelet is not introduced as denoising of signal and the diagram shows multiple pick values on the interval of 100 Hz. It is also noted that these peak values are in the higher frequency range. So from that diagram is it very difficult to decide which kind of defects in the bearing. But when in fig 14, wavelet is introduced as denoising of original signal then peak values are found in the low range and also, peak values are showing at the twice of ball pass frequency of inner race which helps in the identification of defects as well.

Many researchers concluded that mother wavelet selection based on the similarity between signals and mother wavelets is not the perfect method for all wavelet-based techniques. But it is best for detecting few defects like outer race defects which comes under the stationary type of singles, but defects like inner race defects having cyclostationary nature are difficult to analyze. So that here inner race identification is shown with the use of symlet 2 wavelet. For that analysis here we found that Symlet family can give better result compare to others.

6. Conclusions

Selected Cylindrical bearings with different speed range and with different defects are analyzed using two criteria. The conclusion which is derived from it is as below:

- Mother wavelet selection based on the similarity between signals and mother wavelets is not a perfect method for all wavelet-based techniques. But it is best for detecting a few defects likes outer race defects.
- MESE criteria for level 6 and level 7 for seven different wavelets is showing that Sym2 is giving maximum value in terms of the average of average.
- After applying RWE criteria. It is also found that out of nine selected wavelets sym2 is giving the best result.
- For cylindrical bearing, it is concluded that sym2 is the best mother wavelet for denoising of ball bearing signals.
- Application of symlet 2 wavelet for detection of bearing condition especially inner race defects has significant output using FFT diagram.

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