Condition Monitoring and Fault Diagnosis

Submitted by

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CERTIFICATE

This is to certify that the thesis entitled, "Condition Monitoring and Fault Diagnosis" submitted by Mylarapu Shiva Sai (2014230) in partial fulfilment of the requirements for the award of degree of Bachelor of Technology at PDPM Indian Institute of Information Technology, Design and Manufacturing, Jabalpur is a record of genuine work carried by him under my supervision. To the best of my knowledge, the material embodied in this thesis has not been submitted elsewhere to any other university/institute for the award of any degree.

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At last but not the least, I would like to extend my sincere thanks to my family members for their valuable support which has been a source of encouragement and inspiration throughout the duration of my work.

Sincerely,

Mylarapu Shiva Sai

15 November, 2017

ABSTRACT

Right from the beginning of invention there has always been a need for the machines of higher efficiency. Rotating machine elements such as bearings, gears, wheels etc. form the crucial parts of machinery. The efficient working of these elements will be crucial in deciding the life and efficiency of machines. Bearings are the important machine elements used to support axial/radial loads in rotating machinery. Bearings undergo tribological failures under scuffing, pitting, mild wear and spalling due to increase in load and higher speeds. The failure of these elements eventually leads to the decrease in efficiency and unexpected shutdowns of the rotating machines. So the need to monitor the online working of these elements is highly important. Condition monitoring of rolling element bearings has received considerable attention in the last four decades, the use of vibration and acoustic signals is quite common in the field of condition monitoring of rotating machinery. This thesis presents the applications of the wavelet transforms (WT) to process the vibration signals acquired from the roller bearing setup. A roller bearing test rig was fabricated to conduct bearing fatigue tests under controlled conditions. Results obtained from the experiments highlighted the suitability of wavelet transform to detect the surface fatigue wear developed on the roller bearing contact surfaces.

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CHAPTER 1

INTRODUCTION

1.1 Machine and its elements

Machine is any device that transmits a force or directs the application of the force. From a simple sharp stone to the most advanced Computer Numerical Control (CNC) machines there has been a tremendous increase on the dependency of machines by mankind. So machines of higher efficiency has always been a major concern. However, the currently available machines are not 100% efficient due to various conditions.

Machines elements are broadly divided into two categorizations namely, rotating machine elements and non-rotating machine elements. Rotating machine elements are the elements which have rotatory motion during the course of their action. This includes gears, bearings, wheels, shafts etc. Non-rotating machine elements are the machine elements that does not have any rotating motion which includes all other elements such as fastener, switches, sensors etc. Roller/ball bearings are frequently encountered machine elements in the rotating machinery due to their load carrying capacity and friction characteristics. Due to the heavy forces acting and adverse operating conditions surface fatigue wear occurs on bearing contact surfaces. Detection of such faults in the initial stages would be highly beneficial for the efficient operation of high speed rotating machinery. Taking preventive measures during the initial stages of fault occurrence can lead to decrease in machine down time and also avoid unexpected shutdown of machinery. [1]

1.2 Condition Monitoring

Condition monitoring is the process of monitoring a parameter of condition in machinery in order to identify a significant change which is indicative of a developing fault. The use of condition monitoring allows maintenance to be scheduled, or other actions to be taken to prevent failure and avoid its consequences. These techniques are normally used on rotating equipment and other machinery. This includes various types of monitoring such as [2]

- ✓ Vibration analysis & diagnosis.
- ✓ Lubricant analysis.
- ✓ Acoustic emission.

- ✓ Infrared Thermography.
- ✓ Ultrasound testing.
- ✓ Motor condition monitoring & motor current signature analysis (MCSA).
- ✓ Model based voltage & current systems (MBVI).

In the last few decades, many methods have been proposed to monitor bearing faults, however vibration analysis is considered the most important method and widely used in the condition monitoring of rotating machinery and engineering structures. Vibration analysis is particularly suited for the early detection of bearing failure. Every part of the machine vibrates in its natural frequency which makes the vibration analysis to localize the faults and find the cause of the failure. [3]

1.3 Literature Review

Peter *et al*. [4] carried out experimentation to detect bearing faults using vibration signal analysis techniques. Results showed that both Fast Fourier transformation (FFT), Wavelet transform (WT) and empirical mode decomposition (EMD) methods are effective in finding the bearing outer race fault however WT is handier in diagnosing the inner race and roller fault due to the better frequency resolution provided by wavelet analysis at the low frequency region. Amarnath et al. [5] employed WT to detect fault in helical gear mounted in two stage helical gear box. The authors have concluded that continuous wavelet transform (CWT) technique appears to be a promising tool to detect simulated faults in helical gears. On the other hand, cross correlation wavelet plots reveal better diagnostic information on fault growth in helical geared system. Muralidharan and Sugumaran [6] conducted experiments to detect local faults in bearings of the mono-block centrifugal pump using wavelet analysis for five different failure conditions. The authors concluded that features extracted using CWT possess the capability of discriminating the faults and therefore wavelet features were recommended for fault diagnosis of mono-block centrifugal pump. Amarnath *et al.* [7] studied the gear box operating conditions under partial and boundary lubrication conditions. In this work time–frequency analysis of vibration signals using Morlet wavelet transform provided better results in detection and diagnosis of gear tooth wear severity. Morlet wavelet transform showed a good pictorial representation of the changing features of transient vibration signals of a spur gear pair subjected to accelerated test conditions. Awrejcewicz *et al.* [8] studied the behavior of Timoshenko-type beams. It has been mainly shown that a spectral-temporal signal representation given by wavelet transform analysis using Morlet wavelet is more suitable for analysis of chaotic vibrations of complex dynamical systems than the classical Fourier based signal analysis. Brian *et al*. [9] developed customized wavelets for detecting localized defects in bearings. The authors showed that customized wavelet has provided a more descriptive decomposition of the features contained within the bearing signal than a standard wavelet. The developed wavelet was computationally efficient as that of Daubechies (db4) wavelets. Smith *et al.* [10] conducted experiments to analyze characteristics of vibration signals acquired from the aircraft body structure. The vibration signals were analyzed using three different mother wavelets viz. Haar, Daubechies and Morlet Wavelet. Authors have highlighted the suitability of Daubechies wavelet family to obtain the greatest degree of flexibility for parametric modifications involved in signal analysis. Post processing the signal it has been determined that Daubechies-16 provided least amount of error while maintaining most of the signal energy.

1.4 Objective of the study

The objective of the work is to determine the most reliable wavelet for the detection of naturally occurring fatigue faults on the surface of bearings. This thesis describes the results of experimental investigation carried out to detect faults developed on inner race of roller bearing due to surface fatigue failure. The vibration signals acquired from the bearing setup were post processed using three WTs. Daubechies wavelet provided better result to detect surface fatigue failure in comparison to Morlet and Gaussian wavelets.

1.5 Organization of the thesis

Chapter 1 gives an introduction to the machines and importance of condition monitoring in the rotating machinery, previous works done on bearing condition monitoring and the objective of the study. Chapter 2 explains the relative concepts and techniques implemented in the thesis. Chapter 3 demonstrates the experimental setup used for the bearing failure analysis and various parameters of the experimentation. In chapter 4, the various analysis made on the vibration signal has been shown and the results has been explained. Chapter 5 summarizes and concludes the analysis made in the chapter 4.

CHAPTER 2

CONCEPTS AND TECHNIQUES

2.1 Introduction

The vibration signals acquired from the experimental setup does not show any visual information. To visualize the information and to analyze the signal the acquired signal is plotted on graphs in time domains or frequency domains.

Time domain analysis – The analysis of a vibration signal with respect to the time axis as shown in fig. 2.1 (a). In this analysis the signal is varied with respect to time on one axis and another parameter on other axis. This analysis shows how a signal varies with time. It does not provide the crucial diagnostic information hidden in the machinery vibration signal.

Frequency domain analysis – The analysis of a vibration signal with respect to the frequency axis as shown in fig. 2.1 (b). In this analysis the signal is varied with respect to frequency on one axis and another parameter on other axis. Unlike time domain, this analysis shows how much of the signal lies within each given frequency band over a range of frequencies.

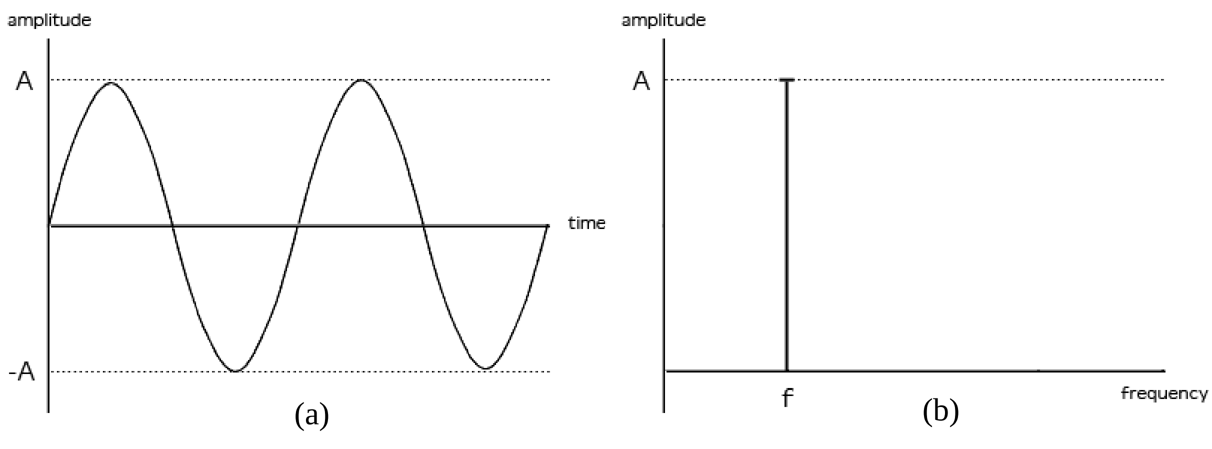


Fig. 2.1 (a) Time domain plot, (b) Frequency domain plot.

2.2 Fourier Transform

Fourier transform is used to convert a signal from its original domain to frequency domain and vice versa. The Fourier transformation decomposes the signal into sines and cosines. It is also called the frequency domain representation of the signal. The Fourier transform of a signal is given by equation 2.1 [11]

$$\widetilde{f(\omega)} = \int_{-\infty}^{\infty} f(t)e^{-i\omega t}.dt \qquad \text{(Eq. 2.1)}$$

Where *t* represents time and ω represents frequency in Hz.

Time domain solely represents the variation of signal with time whereas Fourier transform represents the spectral information of signal. In order to obtain reliable fault diagnostic information of rotating machinery, it is required to consider both time and frequency information in one plot. The time-frequency representation is ideal for signals that vary in amplitude of frequencies with time. Hence, a variant of Fourier transform known as Short-time Fourier Transform (STFT) has been introduced to analyze machinery vibration signals. In STFT, the entire signal is divided into small intervals of time and the Fourier transform is applied on these intervals and then plot of the changing spectrum as a function of time is obtained. In Continuous STFT, the function is multiplied by a window function $\varphi(t)$. The continuous STFT of a signal *f(t)* is given by equation (2.2) [12]

$$\mathbf{STFT}\{f(t)\}(\tau,\omega) \equiv X(\tau,\omega) = \int_{-\infty}^{\infty} f(t).\varphi(t-\tau).e^{-j\omega t}.dt \qquad \text{(Eq. 2.2)}$$

However in STFT the plots consists of fixed window function i.e. same time interval for both higher and lower frequencies as shown in Fig. 2.2

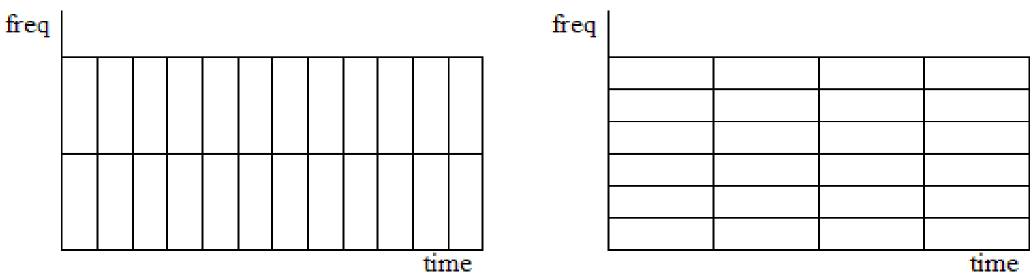


Fig. 2.2 Fixed window plot in STFT [12]

2.3 Wavelet Transform

To overcome the drawback of fixed window function, a new methodology has been proposed called wavelet transform. . In a wavelet transform, the signal is multiplied by a windowed function, generally a small wave called wavelet. The function by which the signal is multiplied is called a mother wavelet. The wavelet transform is of 2 types, namely continuous wavelet transform (CWT) and discrete wavelet transform (DWT). In CWT, the signal is compared with the scaled and shifted versions of the mother wavelet whereas in DWT, the wavelets are sampled discretely. The time-frequency plot obtained through this transformation is a variable window function is shown in Fig. 2.3, which provides a good time resolution for low frequency region and good frequency resolution for high frequency regions.

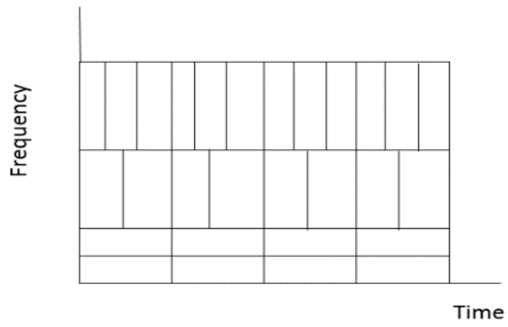


Fig. 2.3 Variable window plot in WT

Wavelets have the ability to separate the very fine details of a vibration signal which offers simultaneous localization in both time and frequency domains. Wavelet transform has the ability to decompose the signal into very small components based on the mother wavelet being used. Wavelets have the benefit of examining specific frequencies over Fourier transform, the variable windowed property of wavelets provides high time resolution in the low frequency region and high frequency resolution in the higher frequency region.

CWT of a signal is given by the equation (2.3) [13]

$$CWT(f(t), \psi, a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t).\psi^{*}.\frac{(t-b)}{a}.dt \qquad \text{(Eq. 2.3)}$$

Where ψ is the mother wavelet function and ψ^* is the complementary function, a is the scale and b is the translational value. In this thesis three mother wavelets viz. Morlet wavelet, Daubechies wavelet and Gaussian wavelet have been used to analyze the machinery vibration signal.

2.3.1 Morlet Wavelet

A Morlet wavelet is a simple sine function multiplied by a Gaussian window. The wavelet tends to 0 at both the extremities. The Morlet transform is given by the following equation (2.4)

$$\psi = e^{-i\omega_0 t}.e^{(-t^2/2\sigma^2)} \qquad \text{(Eq. 2.4)}$$

The window function of the Morlet wavelet transform is shown in fig. 2.4 [14]

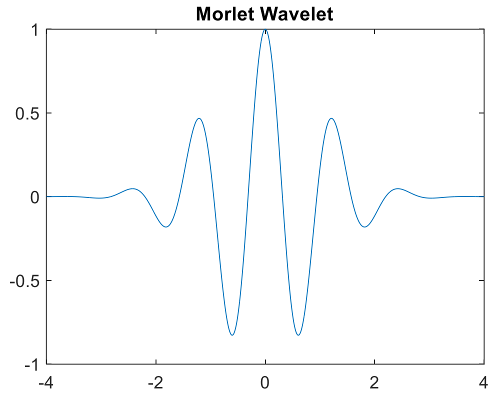


Fig. 2.4 Morlet mother wavelet [14]

2.3.2 Daubechies Wavelet

Daubechies wavelets are employed to extract better fault related features from the signal which consists of a smoother scaling functions produced using longer filters. Daubechies wavelets are an extension of Haar wavelets. These wavelets produce different plots depending on the number of vanishing moments and compresses the regular patterns of the vibration signal. There are two naming schemes for Daubechies wavelets, *DN* and *dbA*. In *DN*, N refers to the number of coefficients and in *dbA*, A refers to the number of vanishing moments. A transformation of N coefficients consists of N/2 vanishing moments, i.e. A.

For Daubechies wavelet transform, a pair of linear filters with quadrature mirror filter property is used. A quadrature filter is generally used to split a signal into two bands, high pass and low pass. In Daubechies transform, low pass filter coefficients sum to unity and high pass filter coefficients sum to zero. Some of the different levels of Daubechies mother wavelet are shown in fig. 2.5

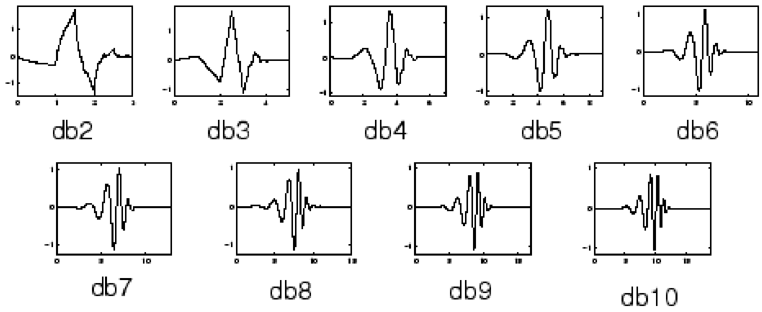


Fig. 2.5 Daubechies mother wavelet with different orders [14]

2.3.3 Gaussian Wavelet

The Gaussian wavelet of order n is the n[th] order derivative of the Gaussian function given by equation (2.5)

$$f(x) = a.e^{-\frac{(x-b)^2}{2c^2}} \qquad \text{(Eq. 2.5)}$$

Where *a* is the curve height, *b* is the position of center of peak and *c* is the standard deviation, this function is windowed with the given signal to obtain the wavelet plot. The Gaussian mother wavelet of order 4 is shown in fig. 2.6

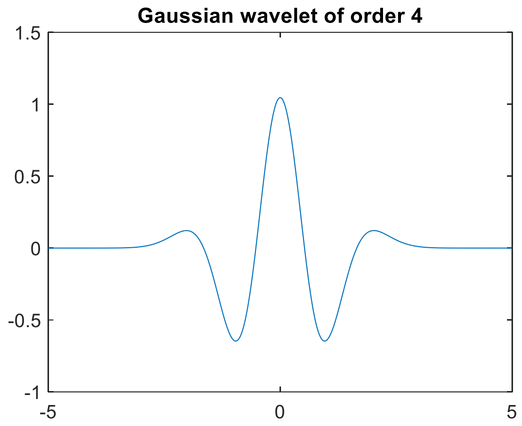


Fig. 2.6 Gaussian mother wavelet of order 4 [14]

2.4 Advantages of wavelet

Wavelets have the ability to separate the very fine details of a signal which offers simultaneous localization in both time and frequency domains. Wavelet transform has the ability to decompose the signal into very small components based on the mother wavelet being used. Wavelets have the benefit of examining specific frequencies over Fourier transform. The variable windowed property of wavelets enables for the high time resolution in the low frequency region and high frequency resolution in the higher frequency region.

CHAPTER 3

EXPERIMENTAL SETUP

3.1 Specifications of the test rig

The main objective of the experiment was to assess surface fatigue wear on rolling contact surfaces of grease lubricated roller bearing. The experimental setup is shown in Fig 3.1 it consists of a 5 HP three phase induction motor (1) which drives a shaft through belt and pulley arrangement. The bearing shaft was operated at a constant speed of 800 rpm using variable frequency drive. The shaft is mounted on two bearings i.e. support bearing (2) and test bearings (3), the detailed specifications of the bearing and grease are given in Table 3.1. A radial load (4) of 1kN is applied to the test bearing, which is off center towards the test bearing as shown in Fig. 3.1. Lithium based mineral oil grease NLGI 3 is used to lubricate the bearing.

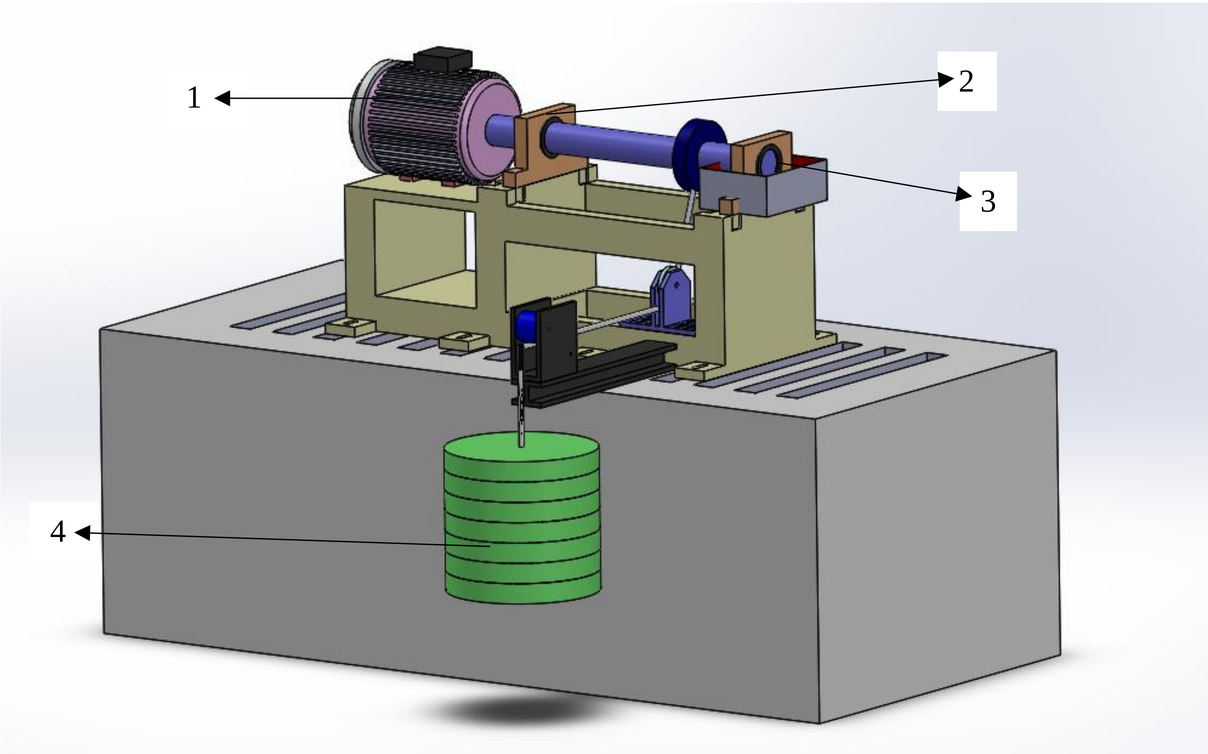


Fig. 3.1 CAD Model of the experimental setup used for the analysis of the bearing failure

A detailed working of the test rig can be explained in fig. 3.2. As explained above, the shaft is mounted on two bearings support bearing (1) and test bearings (2) shown in fig. 3.2. A radial load (3) of 1 KN is applied using a rope and pulley arrangement on the load bearing (4). The vibration signals are captured using a data acquisition system (DAS) connected to a PC.

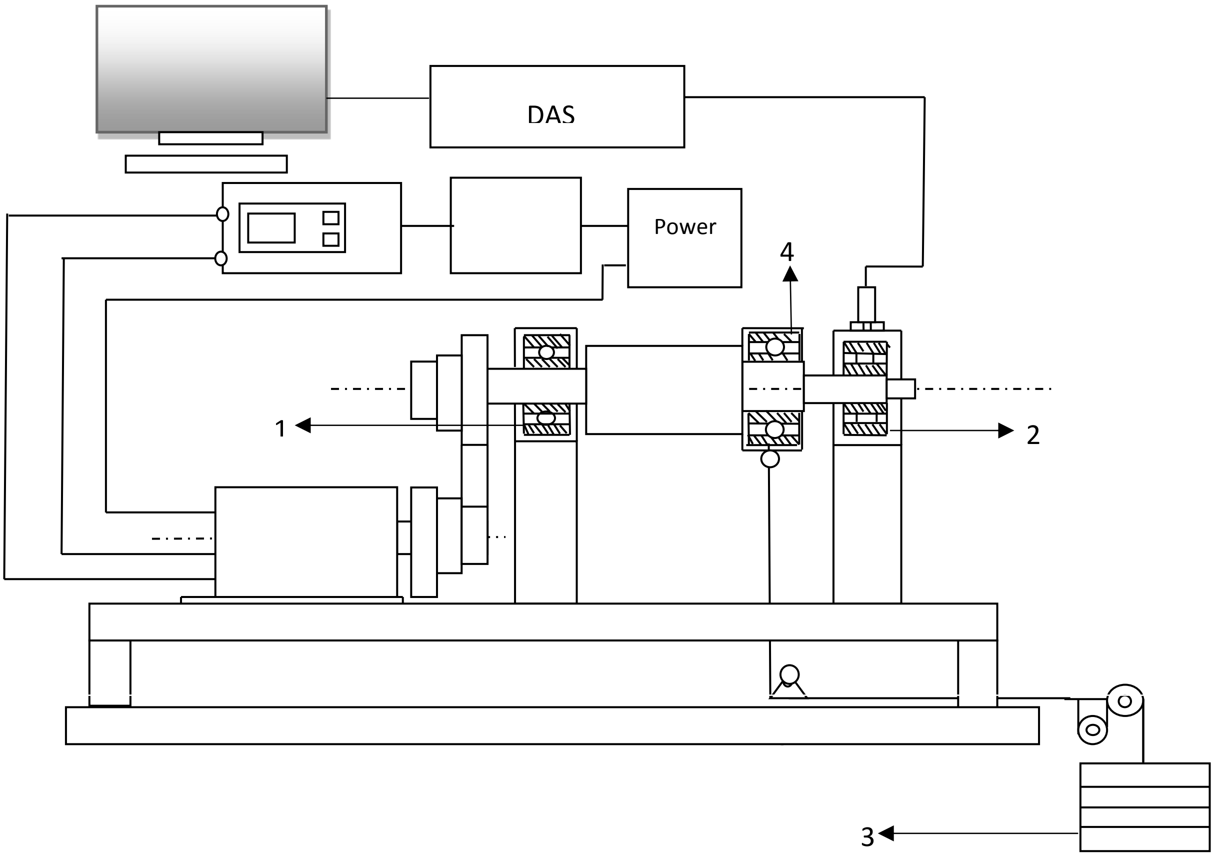


Fig. 3.2 Schematic diagram of bearing test rig

Table 3.1 Specification of test bearing used for the analysis

Parameter	*Specification*
Bearing No.	NJ 307E
Category	Cylindrical roller
Inner race diameter (mm)	35
Outer race diameter (mm)	72
Width (mm)	15
Roller diameter (mm)	12
Bearing material	AISI 52100 steel
Grease	Li soap / mineral oil grease
Base Oil	Mineral oil (naphthalene)
Kinematic viscosity (mm^2/s) (40^0 C / 100^0 C)	120 – 130 / 12
Atmospheric density (g/cm^3)	0.890

CHAPTER 4

RESULTS AND DISCUSSIONS

The vibration signals of bearing acquired for analysis are first analyzed by using temporal plots. The fig. 4.1 (a)-(d) shows the temporal plots obtained at an interval of 450 hours starting from a healthy bearing (a) to worn out bearing (d). Due to gradual wear of the bearing, an increase in the amplitude of the signal can be observed.

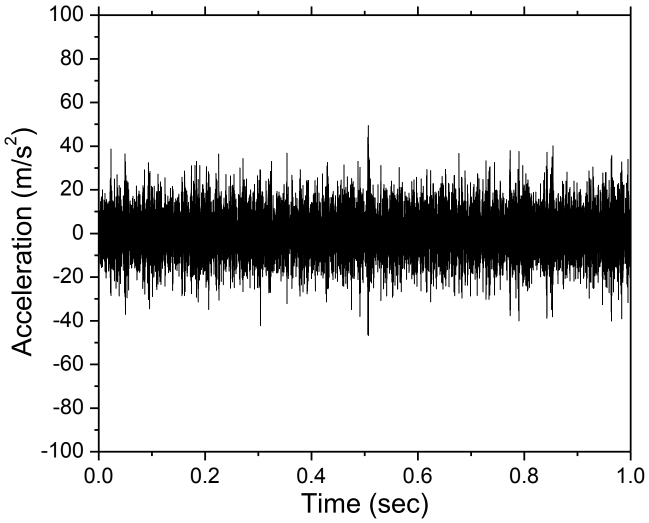


Fig. 4.1 (a) Temporal plot for a healthy bearing

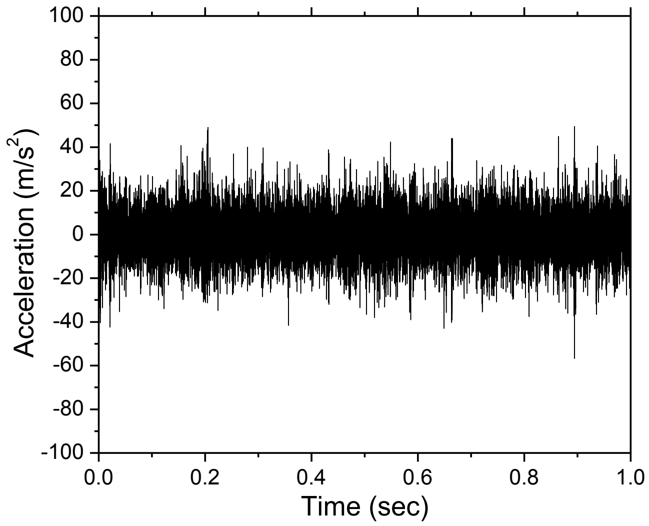


Fig. 4.1 (b) Temporal plot after running the machine for 450 hours

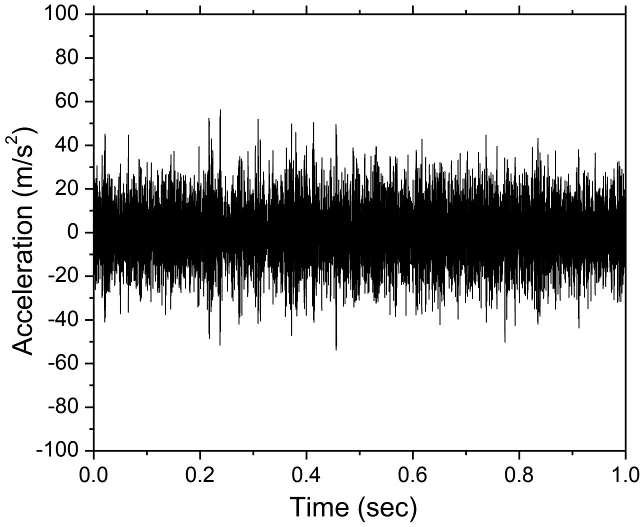


Fig. 4.1 (c) Temporal plot after running the machine for 900 hours

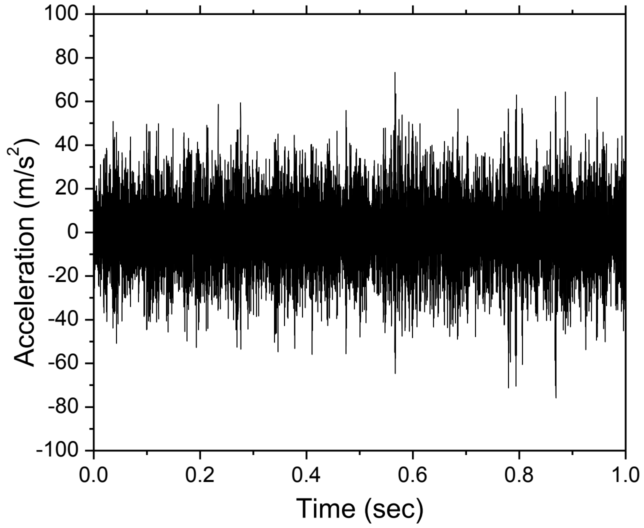
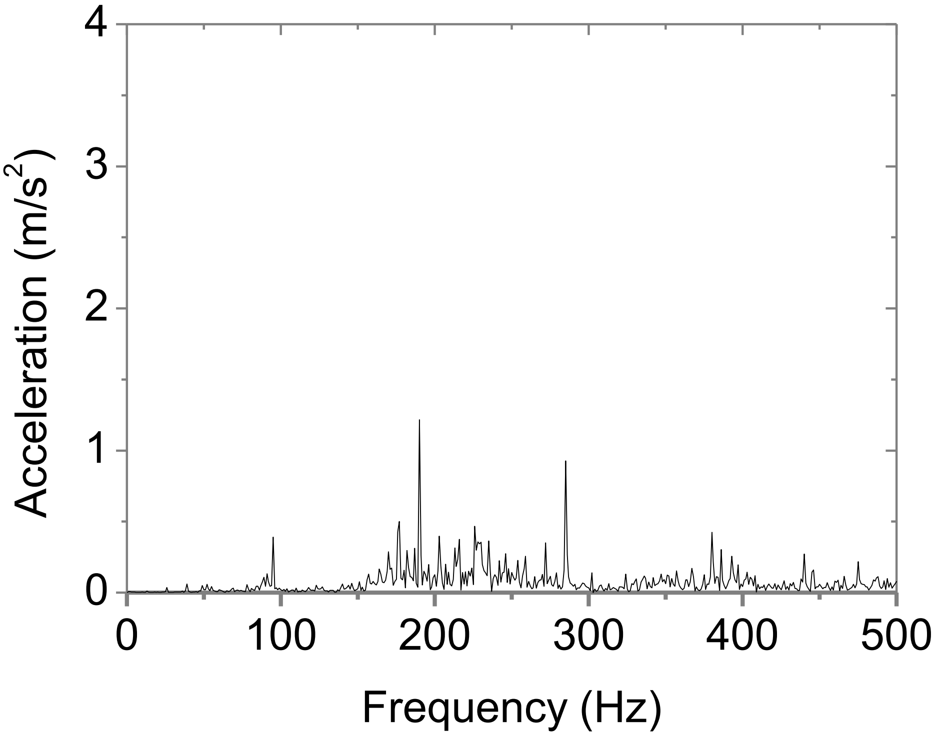
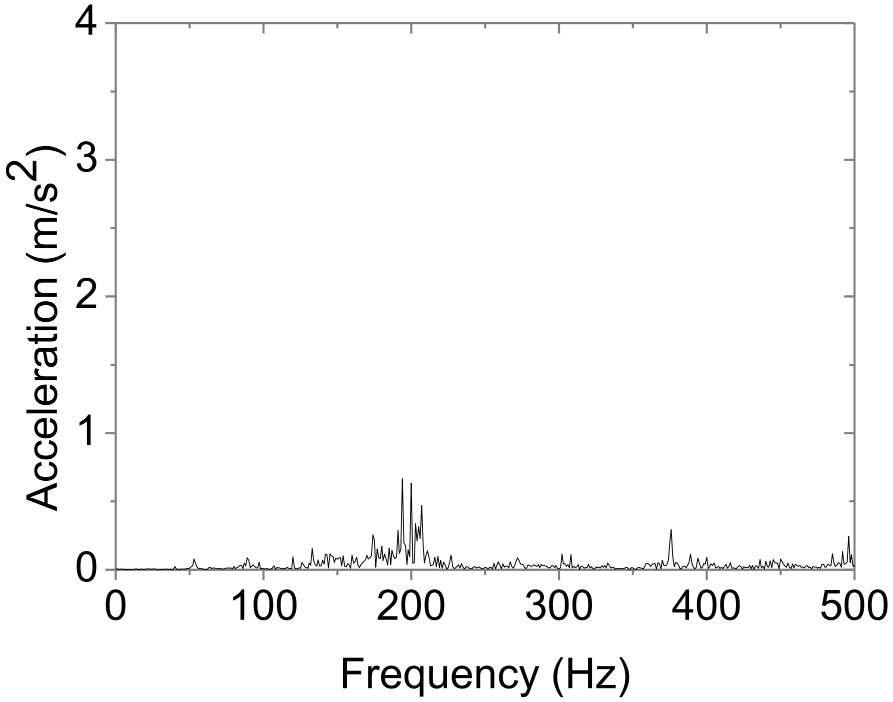


Fig. 4.1 (d) Temporal plot after running the machine for 1350 hours

As mentioned in section 2.1, the temporal plots does not provide any information regarding the bearing. The plot just shows the variation of the signal with respect to time. So we need to acquire the frequency plots to know the spectrum of the vibration signal. Hence Fourier transform (FFT) is employed to analyze the behavior of the vibration signals. The vibration signals encompass with the frequency components of various machine elements. As every component vibrates in its own natural frequency, vibration analysis enables for the localization of faults. Hence, the characteristic frequencies of bearing components viz. inner race, outer race and roller are calculated and found to be 100 Hz, 61 Hz and 54 Hz respectively. Fig. 4.2 (a) – (d) depicts frequency domain plot obtained from the roller bearing under healthy and worn conditions at a regular interval of 450 hours. From the fig. 4.2 it can be observed that frequency amplitude of inner race fault and its higher harmonics show an overall increase in trend which indicates wear propagation on inner race of the test bearing. The other bearing components does not show any increase in the trend of the amplitude. So it can be concluded that fatigue failure of inner race plays a dominant role in the life of bearing.

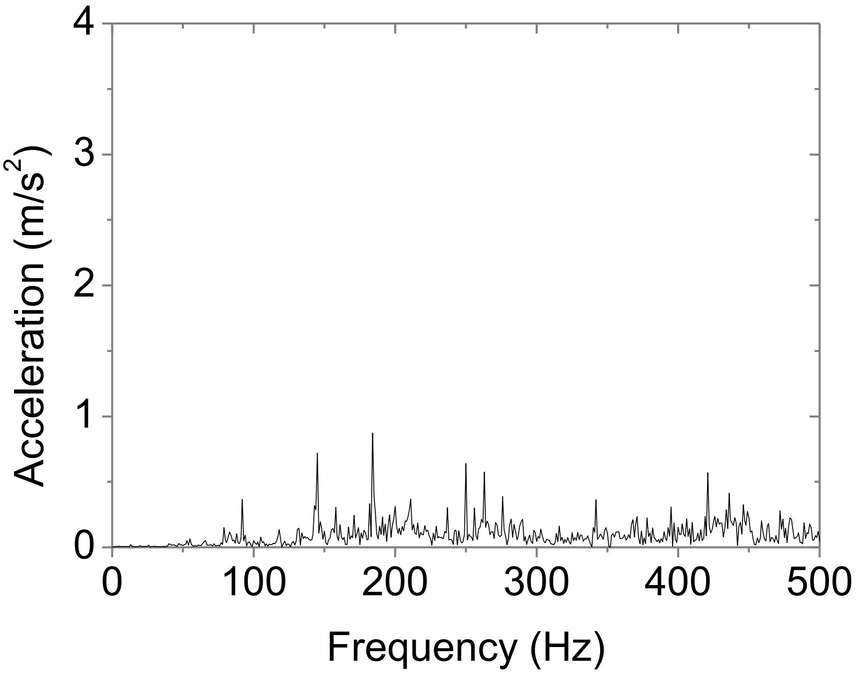


(a)



4
3
2
1
0
Acceleration (m/s^2)
0
100
200
300
400
500
Frequency (Hz)

(b)



4
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Acceleration (m/s^2)
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Frequency (Hz)

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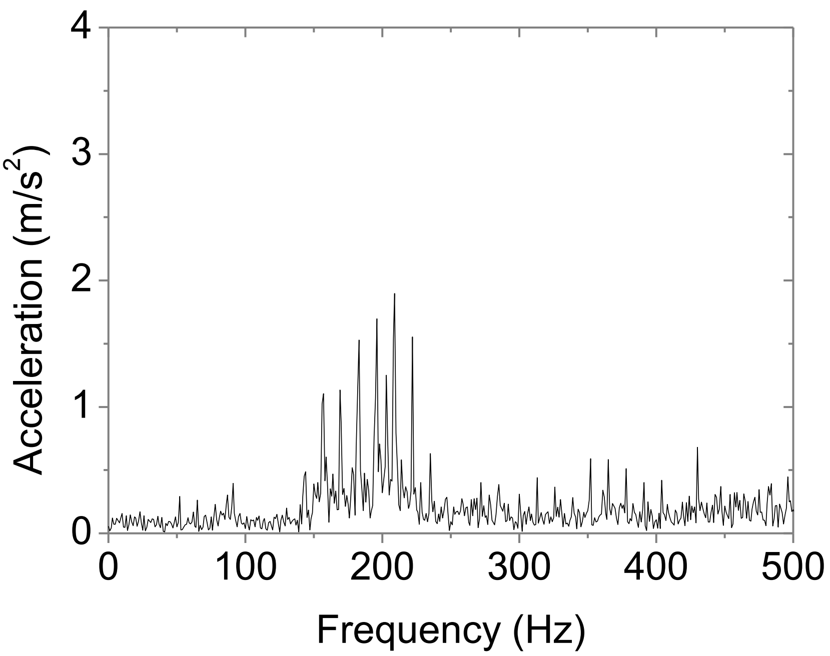


(d)

Fig. 4.2 Frequency vs. Amplitude plots of signal (a) FFT plot of healthy bearing, (b) FFT plot after 450 hours, (c) FFT plot after 900 hours, (d) FFT plot after 1350 hours

However the fixed window property of the Fourier transform does not enable it to analyze the signal over specific frequencies. Hence to overcome this problem, the use of wavelet function is needed. As discussed earlier in section 2.4, wavelets have the benefit of examining specific frequencies over Fourier transform and the variable windowed property of wavelets enables for the high time resolution in the low frequency region and high frequency resolution in the higher frequency region. The machinery vibration signal is analyzed using three different mother wavelets viz. Morlet, Daubechies and Gaussian. A comparative analysis has been made to extract the best wavelet reliable for the early detection of the fatigue failure of the bearing.

Firstly the signal has been analyzed using the Morlet wavelet as the mother wavelet function. Fig. 4.3 shows the 2-D time-frequency plot of the vibration signal after 1350 hours of operation analyzed using Morlet wavelet. The arrows shown in the fig. indicate the high energy of the signal corresponding to the inner race fault frequency 100 Hz (f=1/t, 0.01s) and its harmonics 200 Hz, 300 Hz and 400 Hz (0.005 s, 0.003 s, 0.0025 s).

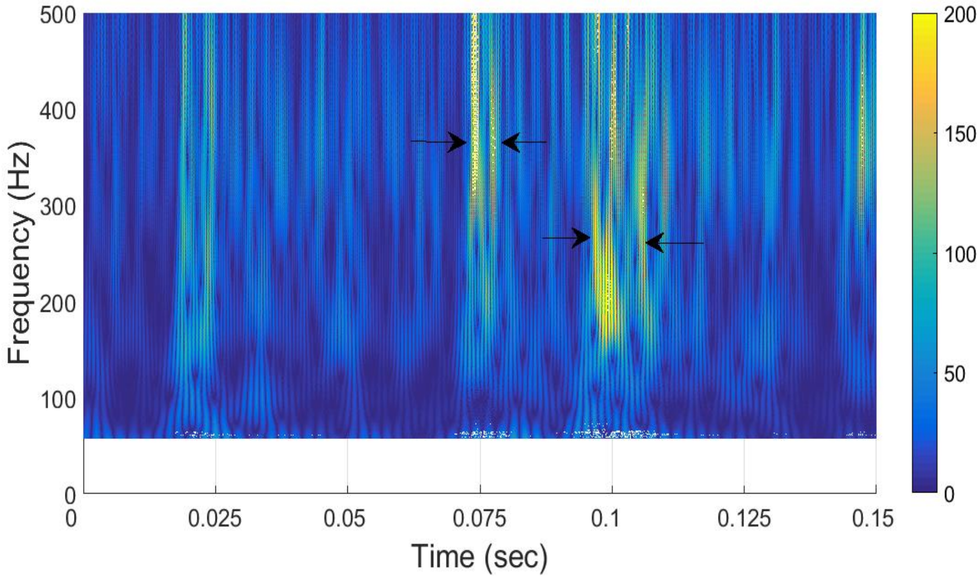
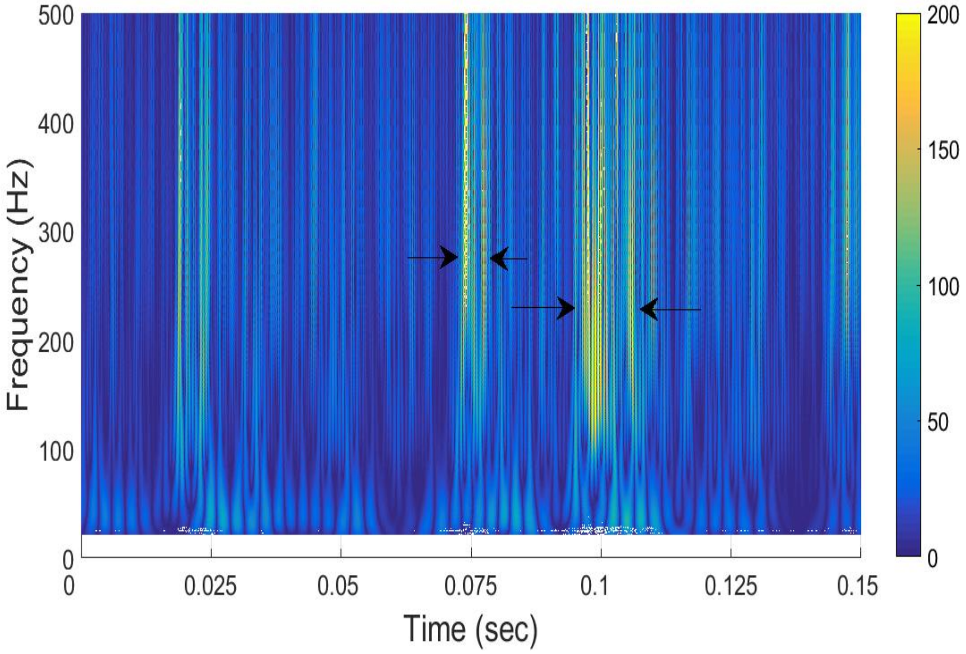
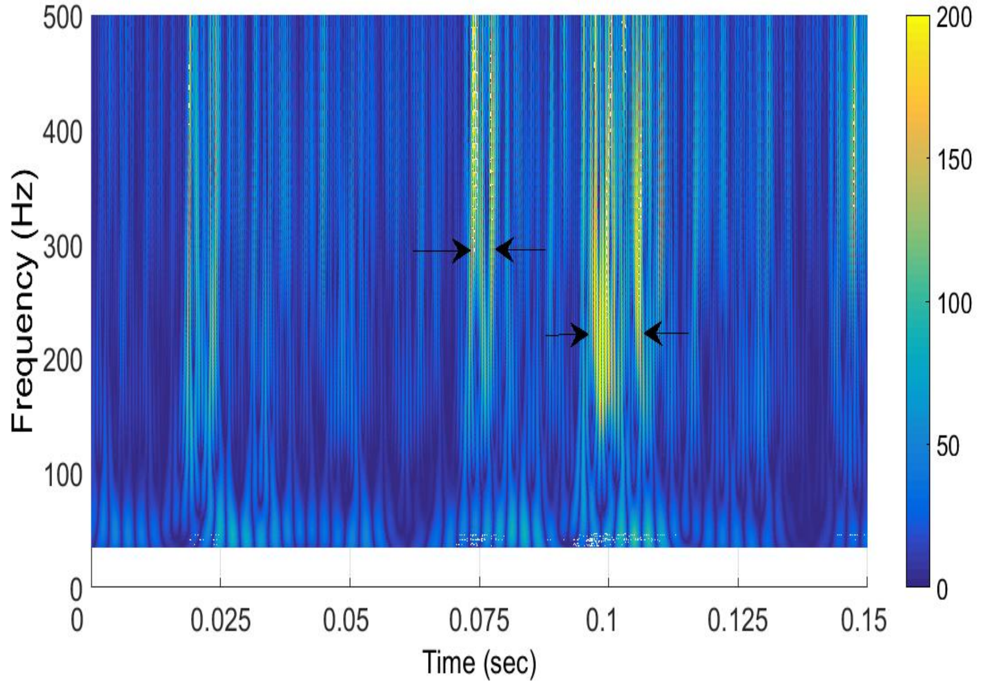


Fig. 4.3 Morlet wavelet plot after 1350 hours of operation

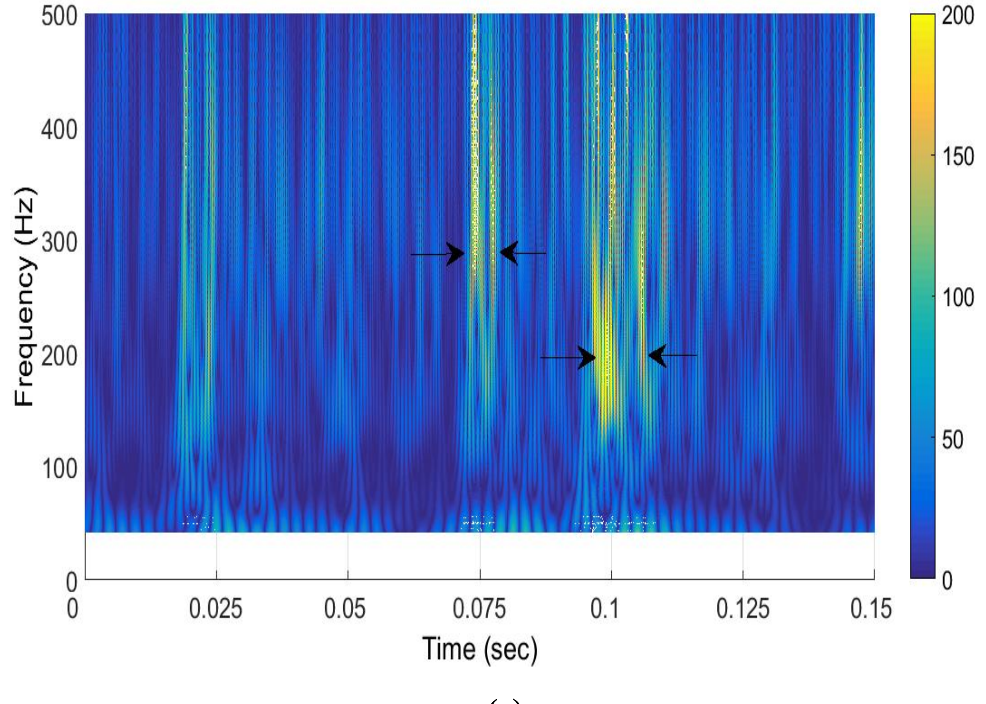
Secondly, the signal has been processed by using the Gaussian wavelet as the mother wavelet. As mentioned earlier, the Gaussian wavelets have different orders. In this thesis, order 2, 4 and 8 have been employed to process the signal. Fig. 4.4 (a) – (c) shows the gaus2, gaus4 and gaus8 wavelet plots respectively.



(a)



(b)



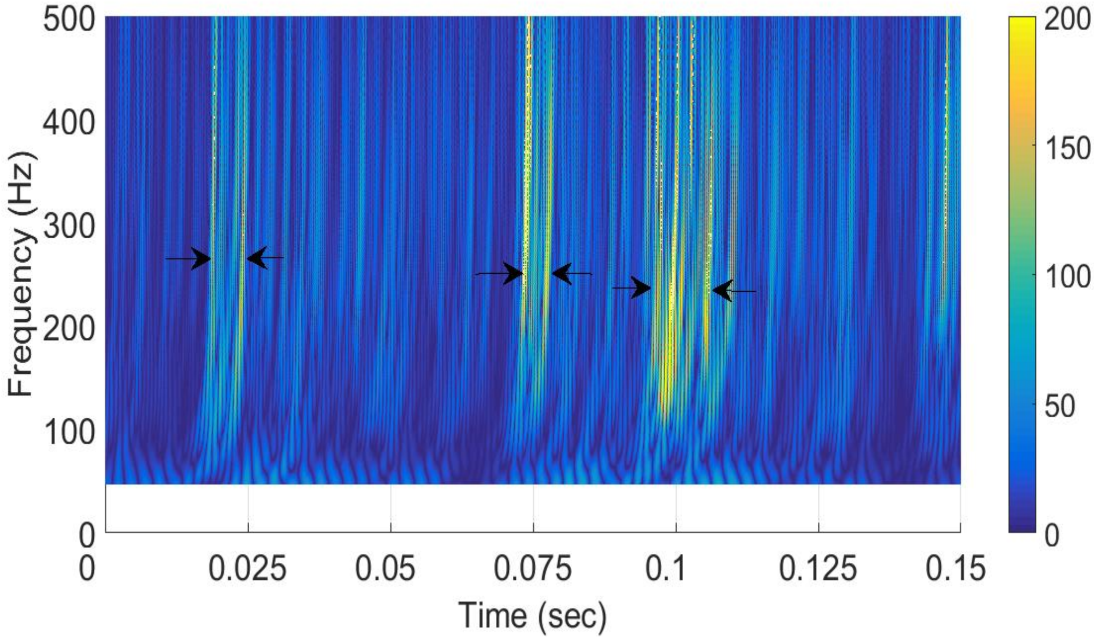
(c)

Fig. 4.4 Gaussian wavelet plot of the vibration signal after 1350 hours of operation by using (a) order 2, (b) order 4 and (c) order 8

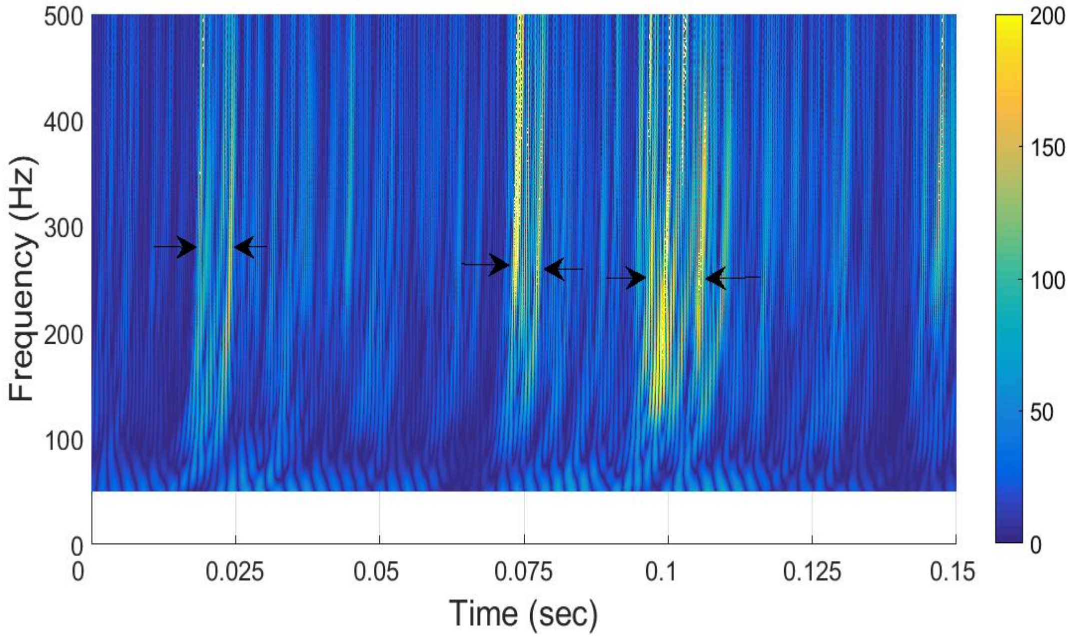
From fig. 4.4 (a), it can be observed that high energy amplitudes of the signal can be observed in the frequency region of inner race i.e. 100 Hz. In the other two figures, the high energy signals cannot be observed. However, the frequency harmonics can be observed in all the plots.

So it can be concluded that among these three orders of the Gaussian wavelet, order 2 can be considered as the reliable wavelet for the early detection of bearing fault.

Now the vibration signal is analyzed by using different levels of Daubechies wavelet as the mother wavelet. Fig. 4.5 shows different level Daubechies plots used for the analysis of the vibration signal. Daubechies level 8 plot is shown in fig. 4.5 (a), level 9 in fig. 4.5 (b), level 10 plot in fig. 4.5 (c) and level 12 plot in fig. 4.5 (d).



(a)



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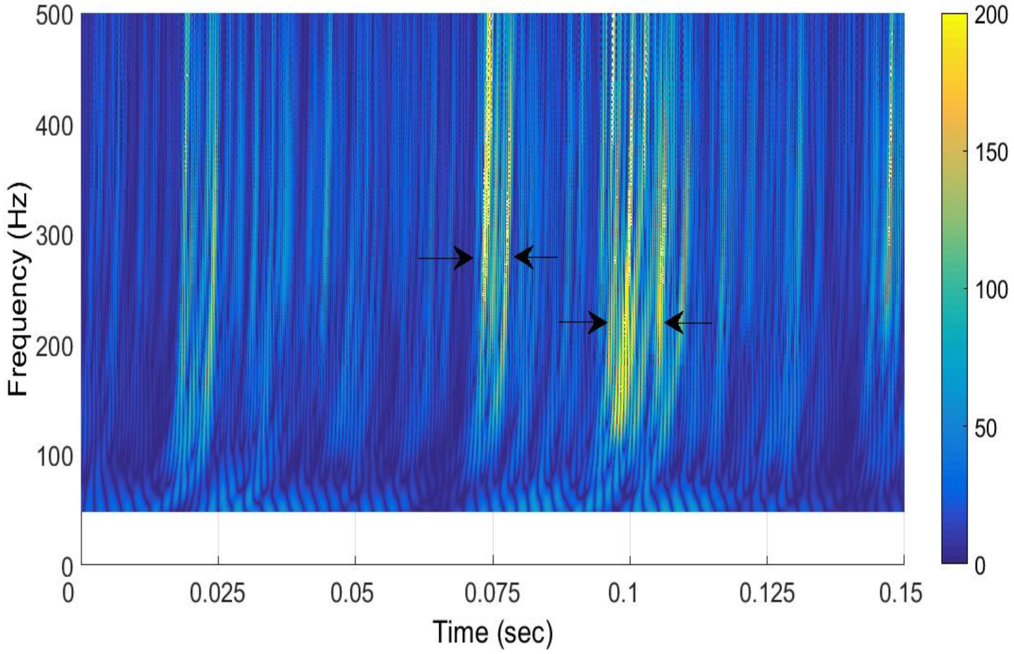
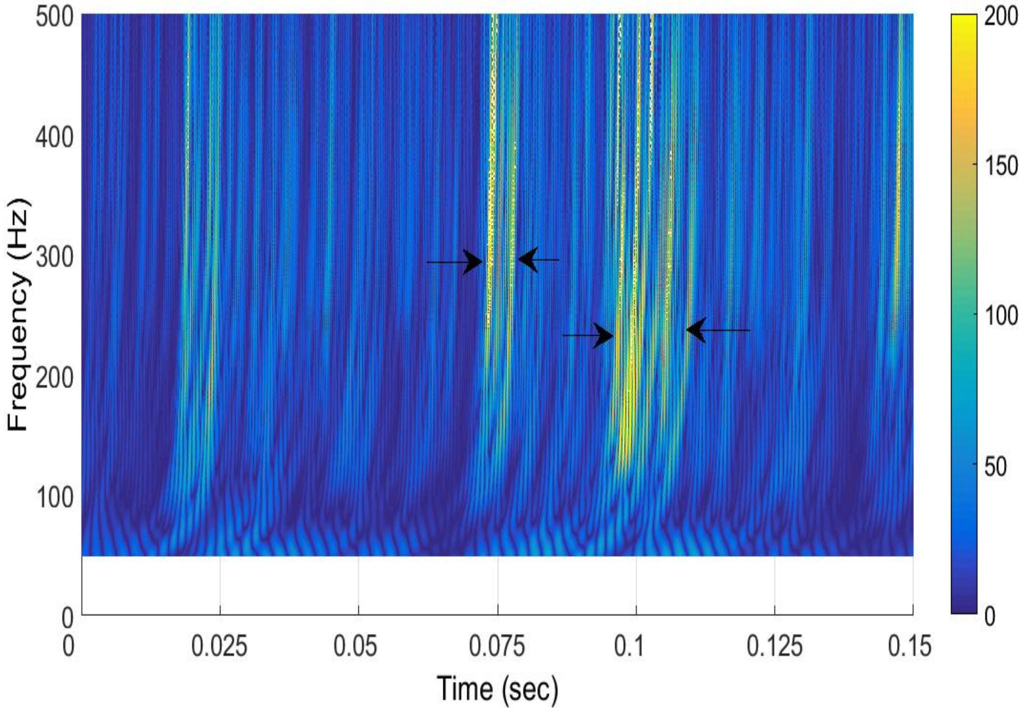


(c)

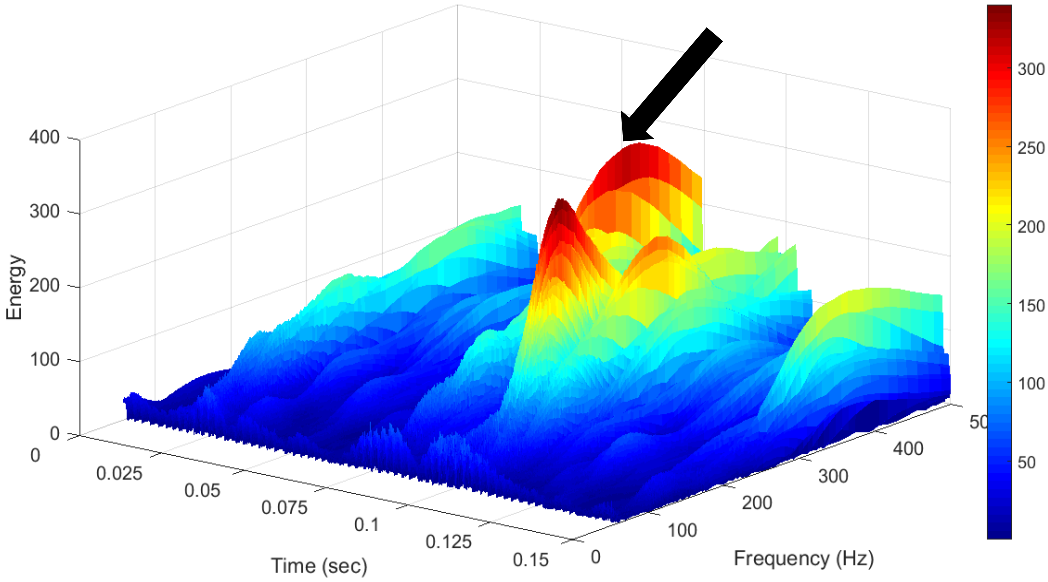


(d)

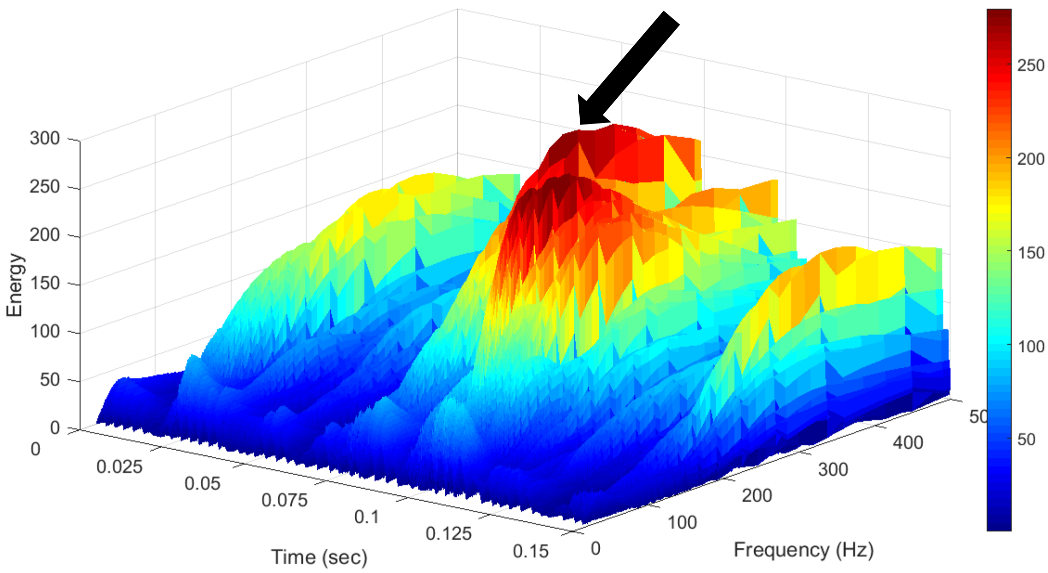
Fig. 4.5 Different levels of Daubechies plots after 1350 hours (a) db8, (b) db9, (c) db10, (d) db12

From fig. 4.5 (b), it can be observed that the high energy signals can be observed for the inner race fault frequency. Also the energy of the harmonics of the inner race fault frequency is better visualized in fig. 4.5 (b). In the other 3 plots the energy of the signal shown by the plots is comparatively lower than the level 9 plot. From these observations, Daubechies level 9 (db9) can be considered for a reliable early fault detection of the bearing.

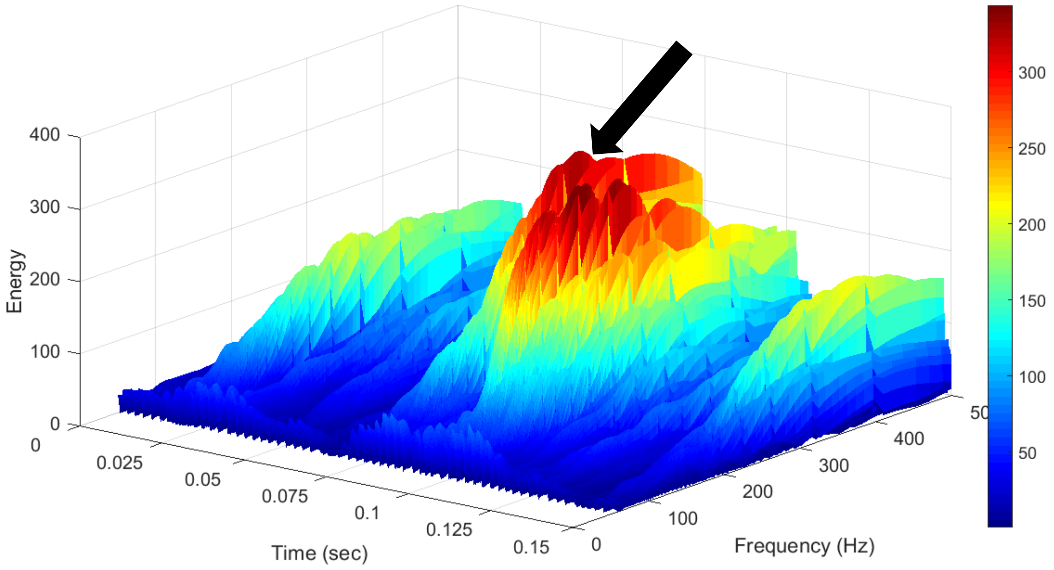
Now a comparative analysis has been made among the Morlet, Gaussian (gaus4) and Daubechies (db9) wavelet transformations. Fig. 4.6 (a) – (c) shows the 3d plot of the vibration signal processed by wavelet transformation using Morlet, Gaussian and Daubechies wavelets respectively. The three axes represents the time, frequency and energy of the signal.



(a)



(b)



(c)

Fig. 4.6 Wavelet transform plots of the vibration signal by using (a) Morlet wavelet (morl), (b) Gaussian wavelet (gaus2), and (c) Daubechies wavelet (db9)

The arrow in fig. 4.6 (a), (b) and (c) shows the maximum energy of the vibration signal of the bearing for the inner race fault frequency. The energy of the signal is high in db9 plot as compared to morl and gaus2 plot. From fig. 4.6 (b), gaus2 plot is found to be processing the signal for the lower frequency regions i.e. the components of lower natural frequency. However in the interest of bearings, db9 is found to be more reliable as compared to gaus4 and morl plots for the detection of natural failures of the bearings occurred due to fatigue load cycles.

CHAPTER 5
SUMMARY AND CONCLUSIONS

Experiments have been conducted to detect surface fatigue wear in cylindrical roller bearings using wavelet analysis. The various characteristic frequencies of the bearing components have been calculated and found to be 100 Hz for inner race, 61 Hz for outer race and 54 Hz for rollers. By using Fourier transform of the signal, it has been concluded that inner race characteristic fault frequency and its higher harmonics has a considerable increase in the amplitudes of the energy indicating a wear on the inner race. From this observation it has been observed that inner race plays a dominant role in the life of a cylindrical bearing for fatigue cycle loads.

Further the vibration signal has been analyzed using wavelet transform by using 3 different mother wavelets Morlet, Gaussian and Daubechies wavelets. Among the different orders of Gaussian wavelets, gaus2 (order 2) is found to be more informative. Similarly among the different levels of Daubechies, db9 (level 9) is found to be analyzing the signal better as compared to the other levels. Finally, a comparative analysis among the Morlet, Gaussian (gaus2) and Daubechies (db9), db9 showed better diagnostic information of surface fatigue wear occurred on inner race of roller bearing as compared to morl and gaus2. From this it has been concluded that db9 can be used as a reliable tool for the early detection of the surface fatigue failure in bearings.

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