B. TECH. PROJECT REPORT

On

DIAGNOSIS OF FAULT IN ROLLING ELEMENT BEARING

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DISCIPLINE OF MECHANICAL ENGINEERING

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DIAGNOSIS OF FAULT IN ROLLING ELEMENT BEARING

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Submitted in partial fulfillment of the

requirements for the award of the degrees

Of

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In

MECHANICAL ENGINEERING

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INDIAN INSTITUTE OF TECHNOLOGY INDORE

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CANDIDATE'S DECLARATION

We hereby declare that the project entitled **"DIAGNOSIS OF FAULT IN ROLLING ELELMENT BEARING"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'MECHANICAL ENGINEERING' completed under the supervision of **Dr. ANAND PAREY (associate prof.) MEACHINACAL ENGINEERING,** IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Signature and name of the student(s) with date

CERTIFICATE by BTP Guide(s)

It is certified that the above statement made by the student is correct to the best of my knowledge.

Signature of BTP Guide(s) with dates and their designation

Preface

This report on “DIAGNOSIS OF FAULT IN ROLLING ELEMENT BEARING" is prepared under the guidance of Dr. ANAND PAREY.

Through this report I have tried to develop a wavelet-packet based signal denoising approach for vibration signals from rotating mechanical equipment.

I have tried to the best of my ability and knowledge to explain the content in a lucid manner. I have also added graphs and figures to make it more illustrative.

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Acknowledgements

I wish to thank Dr. Anand Parey for his kind support and valuable guidance.It is their help and support, due to which I became able to complete the design and technical report.Without his support this report would not have been possible.

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Abstract

Condition monitoring and fault diagnosis of rolling element bearings (REBs) are very important to ensure the steadiness of industrial and domestic machinery. Failures occurring during production operation, lead to serious negative implications like such as increase in machine downtime, low productivity and sometimes can even cause safety risks. Therefore, method to detect machinery faults has evolved from preventive maintenance to condition based maintenance (CBM) in order to make sure that the production operation can reach maximum capacity.

Detection of incipient degradation requires extraction of sensitive features accurately when signal-to-noise ratio (SNR) is very poor, which appears in most rotating mechanical equipment. Vibration signals of REBs are widely used for bearing fault diagnosis. In this BTP report I present denoising and extraction of weak signature technique based on wavelet packet transform (WPT), and this technique is very useful in detecting early stage outer race fault. Minimal Shannon entropy is used to optimize the Daubechies wavelets shape factor, and 3 level wavelet decomposition is used to achieve satisfactory results.

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CHAPTER 1

INTRODUCTION

Rolling element bearings are used in many classes of rotating machinery where compact, high-load-capacity rotor support systems are required. They have low starting and high running friction. There is a frequency barrier which seriously limits the use of REBs in high speed application.

Rolling element bearing are of paramount importance to almost all forms of rotating machinery and are among the most common machine elements. Bearing failure is one of the foremost causes of breakdowns in rotating machinery and such failure can be catastrophic, resulting in costly downtime. In order to prevent these kinds of failures from happening, various bearing condition monitoring techniques have been developed. Among them, vibration analysis has been used extensively due to its intrinsic advantage of revealing bearing failure.

Traditional concepts of preventive and corrective maintenance are gradually supplemented by diagnosis form. The main objective of this maintenance type is to ensure the dependability of industrial systems and increase their availability with lower cost. However, fault diagnosis is not an easy task; itis essentially a problem of pattern recognition.

The signature of a damaged bearing consists of exponentially decaying ringing that occurs periodically at the characteristic frequency. The vibration signal of a defective bearing usually considers being amplitude modulated at the characteristic defect frequency. Matching the measured vibration spectrum with the defect characteristic frequency enables defect detection and enables diagnosis of the defective area.

As for the vibration signal of rolling element bearing, signal modulation effect and noise are two major barriers in incipient defect detection. Because of the amplitude-modulated effect, the spectrum of defect signals consists of a harmonic series of frequency components present at the bearing defect frequency with the highest amplitude around the resonance frequency.

Most of the time vibration signals are collected with a vibration sensor installed on the bearing housing. The sensors are subject to collecting vibration responses from other mechanical components and noise sources. The inherent deficiency of the measuring mechanism introduces a great amount of noise to the signal. The signature of a defective bearing is spread across a wide frequency band and hence can easily become masked by noise and low frequency effects. The weak signature, at the early stage of defect development, is even more difficult to detect. A signal enhancing method is needed to provide more evident information for incipient defect detection of rolling element bearings.

The problem of signal de-noising has a strong connection to roller element bearing prognostics. De-noising and extraction of the weak signature are crucial to fault prognostics in which case features are often very weak and masked by noise. Prognostics is achieved by detecting the defect at its initial stage and alerting maintenance personnel before it develops into a catastrophic failure.

The wavelet transform has been widely used in signal de-noising due to its extraordinary time-frequency representation capability, which is discussed in detail later in this report. The performance of wavelet decomposition-based de-noising on signals from mechanical defects reveal that it is suitable and reliable to detect weak and impulse-like signatures of mechanical defect signals.

Minimal Shannon entropy is used as a criterion to optimize the shape factor of a Daubechies wavelets.

CHAPTER 2

MOTIVATION

Rolling element bearings (REBs) are widely used in rotating machines. One of the fundamental problems currently faced a wide range of industries is how to identify a bearing fault before it reaches a critical level and even its catastrophic failure. REB is one of the important parts of rotating machinery and their failure is one of the most frequent reasons for machine breakdown. Approximately 45% of the failures are due to the bearing faults. A failure survey by the Electric Power Research Institute (EPRI) indicates that bearing-related faults are about 40% among the most frequent faults in induction motors.

The maneuver of rotating machinery is entirely dependent upon the health state of the REBs, which accounts for almost 45–55% of these equipment failures. The presence of bearing faults such as galling, spalling, peeling, subcase fatigue or failure of the bearings due to misalignment, shaft slope, surface roughness, high extent of waive-ness and inclusions, etc. causes a catastrophic collapse of the system thereby reducing the reliability and availability of the plant. This in turn increases the production downtime causing a massive financial loss to the organization and may every so often prove dangerous to the safety of the workers.

Thus, it becomes very important to implement and expand effective maintenance strategies to minimize the impact of failures due to malfunctioning of the rolling element bearings.

If we can identify a problem before a catastrophic failure occurs, then we can schedule a cost-effective maintenance.

CHAPTER 3

DESCRIPTION OF PROPOSED METHOD

3.1 Rolling Element Bearings

There are two major classes of rolling element bearings:-

1. Spherical ball bearing
2. Cylindrical roller bearing

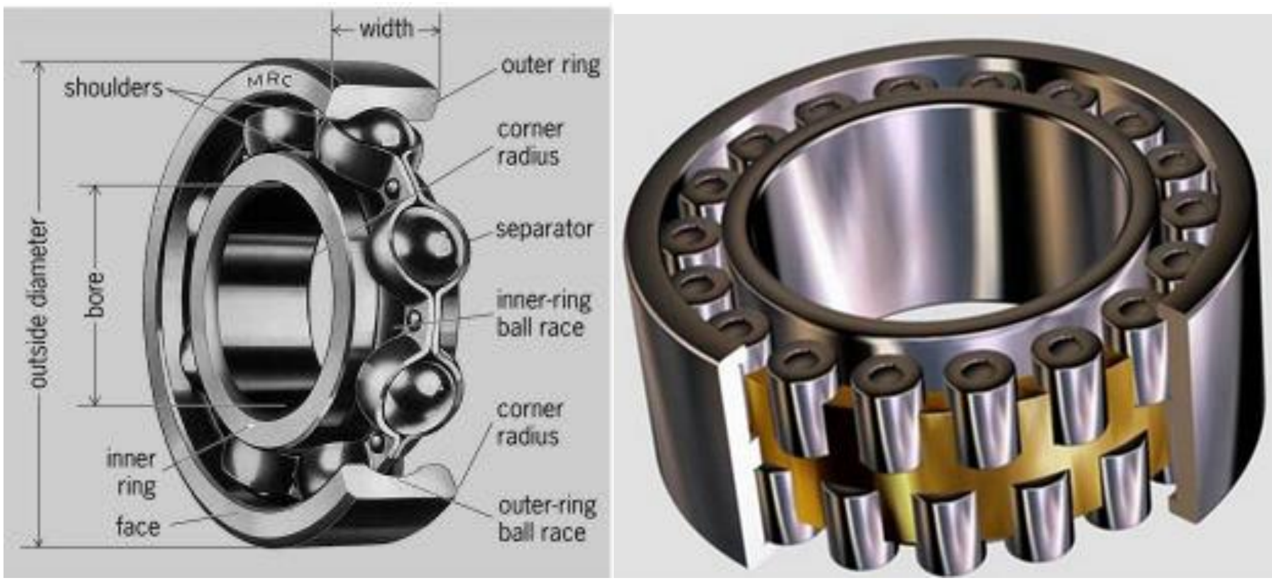


Figure 1: Spherical ball bearing and cylindrical roller bearing

3.2 Vibrations from Faulty Rolling Element Bearings

Since no bearing is perfect, all rolling element bearings will have faults such as irregularities in the surface of the race and in the roundness of the balls. When a bearing spins, these faults create periodic frequencies called fundamental defect frequencies.

There are four fundamental defect frequencies in REBs:

1. FCF – Fundamental Cage Frequency. This is the rotational speed of the bearing cage and ball/roller assembly.
2. BPFI – Ball Pass Frequency of Inner Race. This is the frequency created as all the balls roll across a fault in the inner race.
3. BPFO – Ball Pass Frequency of Outer Race. This is the frequency created as all the balls roll across a fault in the outer race.
4. BSF – Ball/Roller Spin Frequency. This is the circular frequency of each ball/roller as it spins during revolution around the shaft.

Fundamental defect frequencies depend on both the bearing geometry and the shaft speed.

The bearing fault frequencies equations are the following (all in Hz):

$$F_{FCF} = \frac{F_S}{2}\left(1 - \frac{d\cos(\alpha)}{D}\right) \qquad (Hz) \tag{1}$$

$$F_{BPIF} = \frac{N_B F_S}{2}\left(1 + \frac{d\cos(\alpha)}{D}\right) \qquad (Hz) \tag{2}$$

$$F_{BPOF} = \frac{N_B F_S}{2}\left(1 - \frac{d\cos(\alpha)}{D}\right) \qquad (Hz) \tag{3}$$

$$F_B = \frac{DF_S}{2d}\left(1 - \frac{d^2\cos^2(\alpha)}{D^2}\right) \qquad (Hz) \tag{4}$$

Equation 1-4

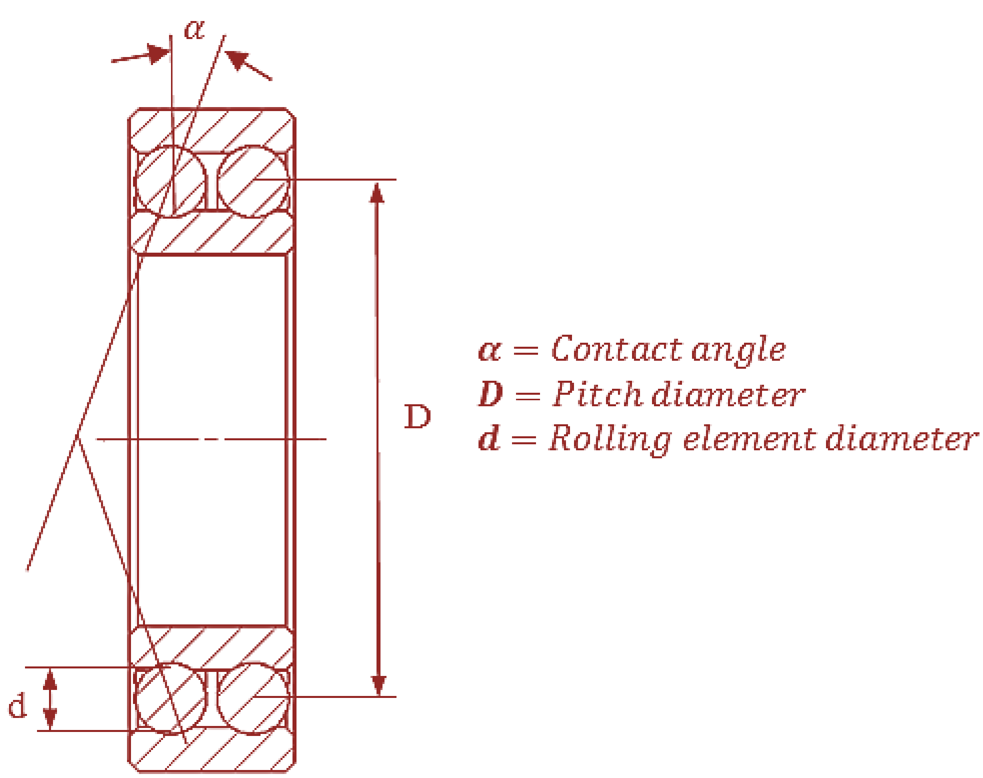


Figure 2 : Bearing geometry

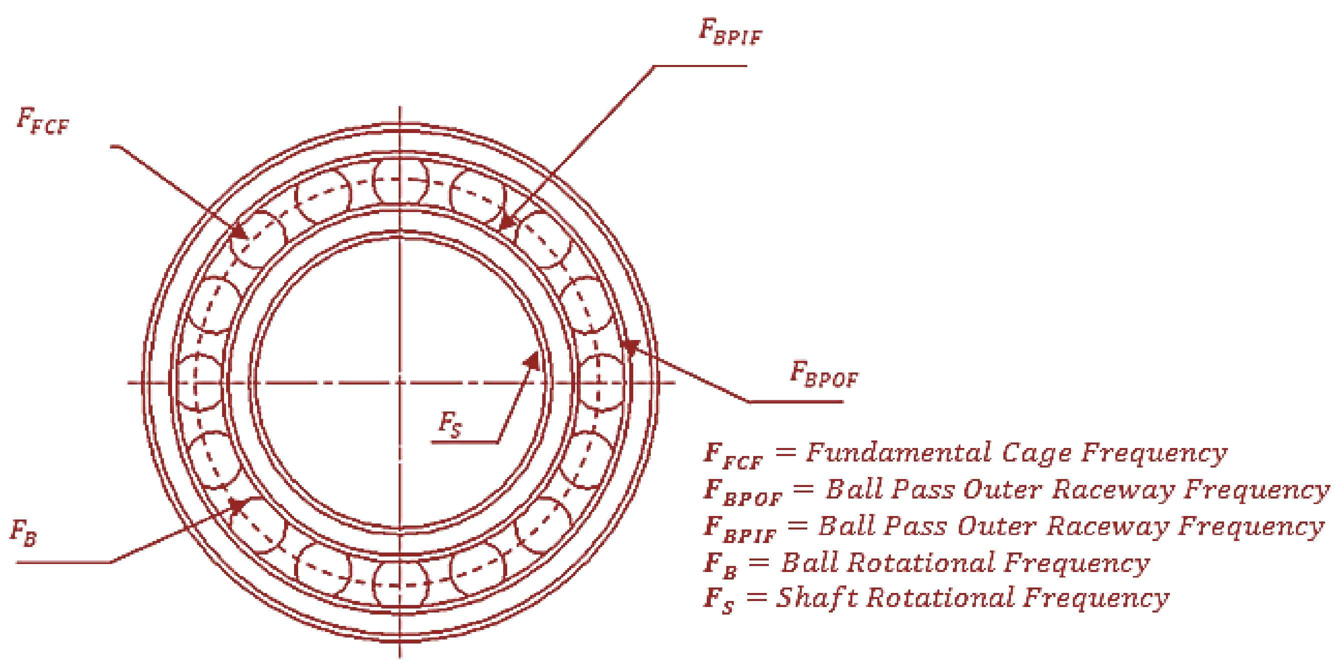


Figure 3: Bearing Fault Frequencies

The amplitude of vibration in REBs depend largely on the extent of bearing fault. All the machines have natural frequencies of vibration and are excited by the impact forces. When the rolling elements of bearing strike a crack or pitted area in its runway, the natural frequency of the bearing, shaft or bearing support may be excited.

3.3 Wavelet Packet Transform (WPT)

Wavelet transform (WT):

The wavelet is obtained from a single function $\psi_{(a,b)}(t)$ by translation and dilation:

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

Where a is the so-called scaling parameter, b is the time localization parameter and $\psi(t)$ is called the ‘‘mother wavelet’’. The parameters of translation $b \in$R and dilation a > 0, may be continuous or discrete.

The wavelet transform of a finite energy signal x(t) with the analysing wavelet ψ(t) is the convolution of x(t) with a scaled and conjugated wavelet:

$$W(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)\mathrm{d}t,$$

Where ψ*(t) stands for the complex conjugation of ψ(t). The wavelet transform W(a,b) can be considered as functions of translation b with each scale a. Above equation indicates that the wavelet analysis is a time-frequency analysis, or a time-scaled analysis. Different from the Short Time Fourier Transform (SFFT), the wavelet transform can be used for multi-scale analysis of a signal through dilation and translation so it can extract time frequency features of a signal effectively.

However, WT does not split the high frequency bands where the modulation information of machine fault always exists. A better representation of signal is extending WT to wavelet packet transform (WPT). WPT further decompose the high-frequency bands and the frequency resolution may be enhanced. A signal can be decomposed into a set of wavelet packet nodes with the form of a full binary tree by the WPT.

WPT is more efficient than continuous wavelet transform (CWT) and discreet wavelet transform (DWT) of the time-scale analysis to describe bearing fault signal in different frequency bands of local information. The proposed method uses the WPT as a powerful tool to do orthogonal decomposition of vibration signals in the whole frequency domain. As a result, WPT can process all frequency bands, especially high frequency bands, more efficiently where bearing characteristic frequencies exist.

3.4 Shannon Entropy

The sparseness of wavelet coefficients is often used as the rule for evaluating the efficiency of wavelet transforms. The wavelet corresponding to the fewest and dominant wavelet transformation coefficients of a signal is ideal. An optimal wavelet transformation should be able to condense the signal into several large coefficients. The simplest definition of sparseness states that in a sparse matrix or vectors, most of the elements are zero.

The sparseness of a series can be evaluated by various criteria. Among them, Shannon entropy is one of the well-adopted sparseness criterion. Shannon entropy was first introduced by Shannon in connection with communication theory in 1948.

Shannon entropy is defined as:

$$H(p) = -\sum_{i=1}^{n} p_i * \log p_i, \qquad \sum_{i=1}^{n} p_i = 1,$$

Where *Pi* is the probability of observing the *i*th possible value of random variable X ∈ [x1; x2; . . . ; xn].

Shannon entropy is the central role of information theory sometimes referred as measure of uncertainty. The entropy of a random variable is defined in terms of its probability distribution and can be shown to be a good measure of randomness and sparseness. Shannon Entropy, thus can be used to evaluate the sparsity of wavelet coefficients. Wavelet transform coefficients with minimal Shannon entropy can be treated as the sparsest result. Therefore, the corresponding shape factor can be adopted as the optimal result.

3.5 Wavelet decomposition-based de-noising

The objective of de-noising is to suppress the noise part of the signal and to recover original signal. Wavelet de-noising is based on the principle of multi-resolution analysis. By multi-level wavelet decomposition the discrete detail coefficient and approximation coefficient can be obtained. Grossmann proved that the variance and amplitude of the details of white noise at various levels decreases regularly as the level increases, whereas the amplitude and variance of the wavelet transform of the available signal are not related to the change of scale. According to this property, noise can be weakened or even removed by adjusting the wavelet coefficients properly.

The general de-noising procedure involves three steps. The basic version of the procedure is as follows:

1. *Signal decomposition*. Choose a wavelet basis, and choose a level N. Compute the wavelet decomposition of the signal at level N.

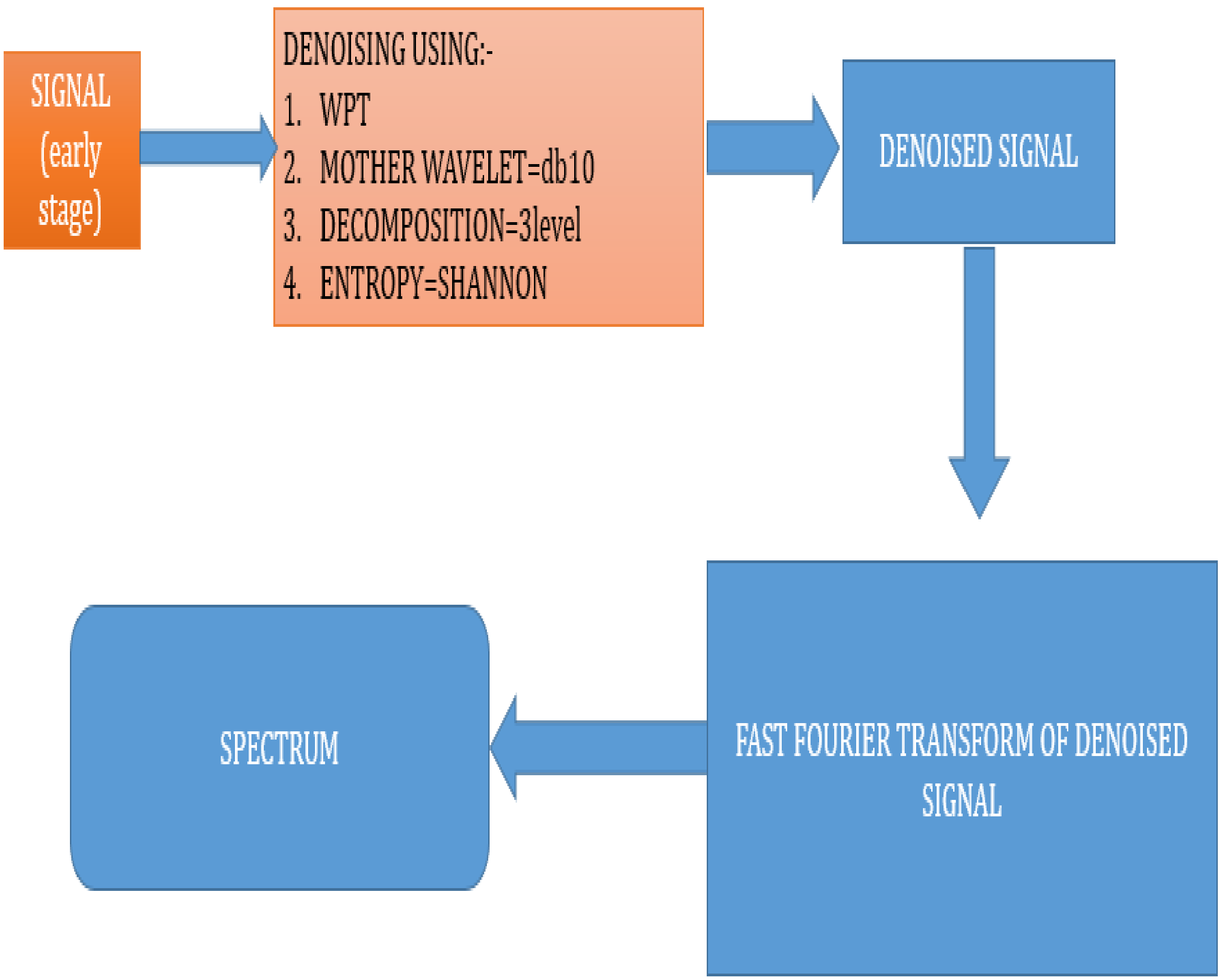
2. *Threshold detail coefficients*. For each level from 1 to N, select a threshold and apply soft thresholding to the detail coefficients.

3. *Signal reconstruction*. Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

In the application of machinery prognostics, what attracts attention in the original noisy signal is the periodicity and relative energy level of the impulse components, which are indicators of impacts due to cracks, spalling, or corrosion, etc. Therefore, the objective of weak signal detection is to detect the target signal, instead of recreating the signal. Specifically, in roller bearing prognostics, I will attempt to detect the hidden periodic impulses.

3.6 Proposed Methodology

Proposed Methodology



CHAPTER 4

EXPERIMENTAL SETUP AND RESULTS

4.1 Experimental setup of run-to-failure test

In order to reflect the real defect propagation processes, bearing run-to-failure tests were performed under normal load conditions on a specially designed test rig. The test rig is shown in *Figure 4*. This test rig hosts four test bearings on one shaft driven by an AC motor and coupled by rub belts. The rotation speed is kept constant at 2000 rpm. A radial load of 6000 *lbs*. is added to the shaft and bearing by a spring mechanism. All the bearings are forced lubricated. An oil circulation system regulates the flow and the temperature of the lubricant. A magnetic plug installed in the oil feedback pipe collects the debris from the oil as an evidence of bearing degradation. The test will automatically stop when the accumulated debris adhered to the magnetic plug exceed a certain level and causes an electrical switch to close.

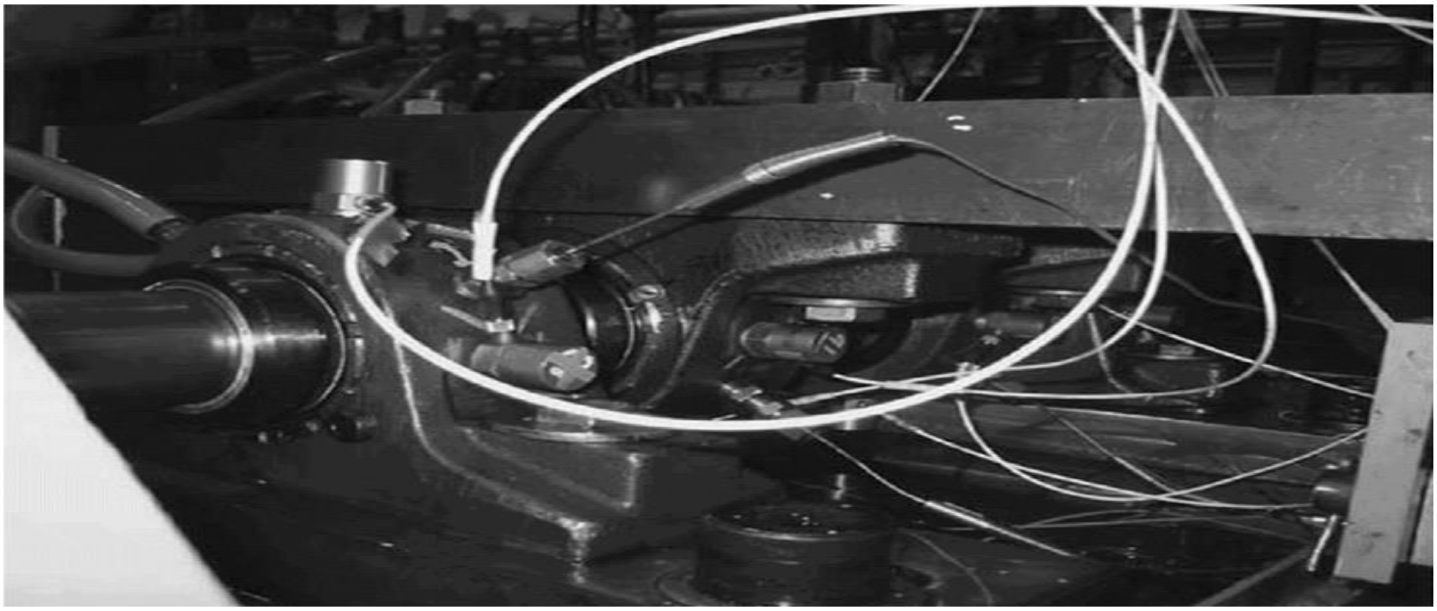


Figure 4: Bearing test Rig

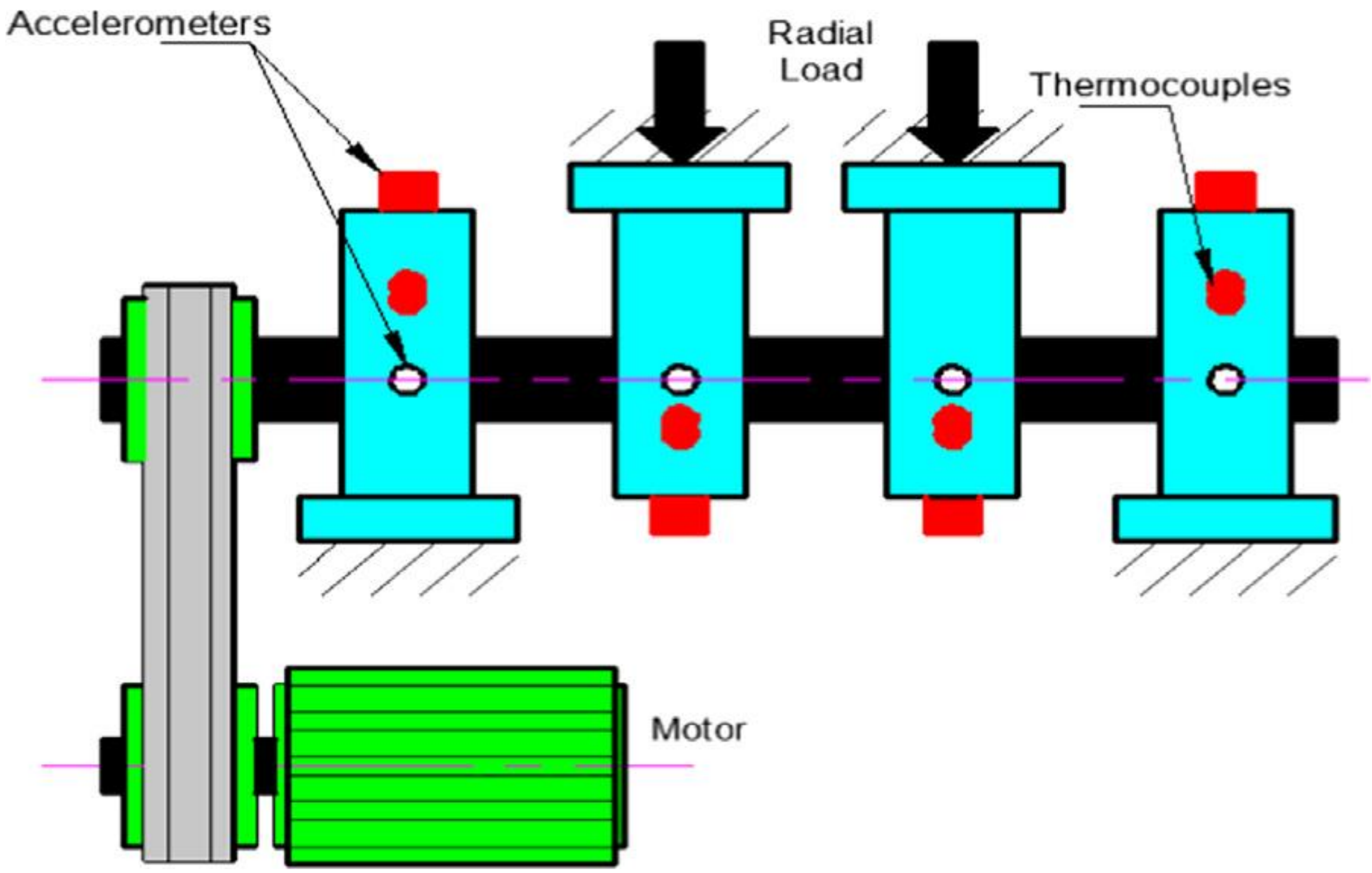


Figure 5: sensor placement illustration

Four Rexnord ZA-2115 double row bearings were installed on one shaft as shown in *Figure 5*. The bearing characteristic frequencies are usually calculated by Eqs below:

$$f_O = \frac{n}{2}\left(1 - \frac{d}{D_p}\cos\theta\right) f_r$$

$$f_I = \frac{n}{2}\left(1 + \frac{d}{D_p}\cos\theta\right) f_r$$

$$f_B = \frac{D_p}{d}\left[1 - \left(\frac{d}{D_p}\cos\theta\right)^2\right] f_r$$

$$f_C = \frac{1}{2}\left(1 - \frac{d}{D_p}\cos\theta\right) f_r$$

$$f_{BS} = \frac{D_p}{2d}\left[1 - \left(\frac{d}{D_p}\cos\theta\right)^2\right] f_r$$

The outer-race fault frequency f_o

The inner-race fault frequency f_I

Rolling element fault frequency f_B

The fundamental cage frequency f_c

The ball spin frequency f_{BS}

Where *n* is the number of balls, *d* is the diameter of the rolling element , D_p is the groove section size, θ is the contact angle, f_r is the shaft frequency. The structural parameters and kinematical parameters of the four experiment bearings are listed in Table 1.

A PCB 353B33 High Sensitivity Quartz ICPs Accelerometer was mounted on the housing of each bearing. For monitoring the lubrication, four thermocouples were attached to the outer race of each bearing to record bearing the temperature. Vibration data of the bearings collected every 10 min by a National Instruments DAQ Card-6062E data acquisition card. The data sampling rate is 20 kHz and the data length is 20480 points. Data collection conducted by a National Instruments LabVIEW program. *Data can be downloaded from Prognostics Centre Excellence (PCoE) through prognostic data repository contributed by Intelligent Maintenance System (IMS), University of Cincinnati.*

Structural parameters and kinematical parameters of the experiment bearing.

Bearing designation	Ball numbers	Groove section size (in.)		Contact angle	Diameter of the rolling element (in.)	
	16	0.331		15.17°	2.815	
ZA-2155 of Rexnord	f_r (Hz)	f_I (Hz)	f_O (Hz)	f_B (Hz)	f_C (Hz)	f_{BS} (Hz)
	33	296.9	236.4	139.9	14.8	70

Table 1

4.2 The analysis of the outer race fault signal

The RMS increased to a certain level, then decreased and rose again. The fluctuating trend in *Figure 7and 8* can be explained by the intrinsic characteristics of the damage propagating process. When the surface defect of the

Outer raceway just initiated, small spall or cracks were formed and later smoothed by the continuous rolling contact. When the damage spread over a wider area, the vibration level rises again.

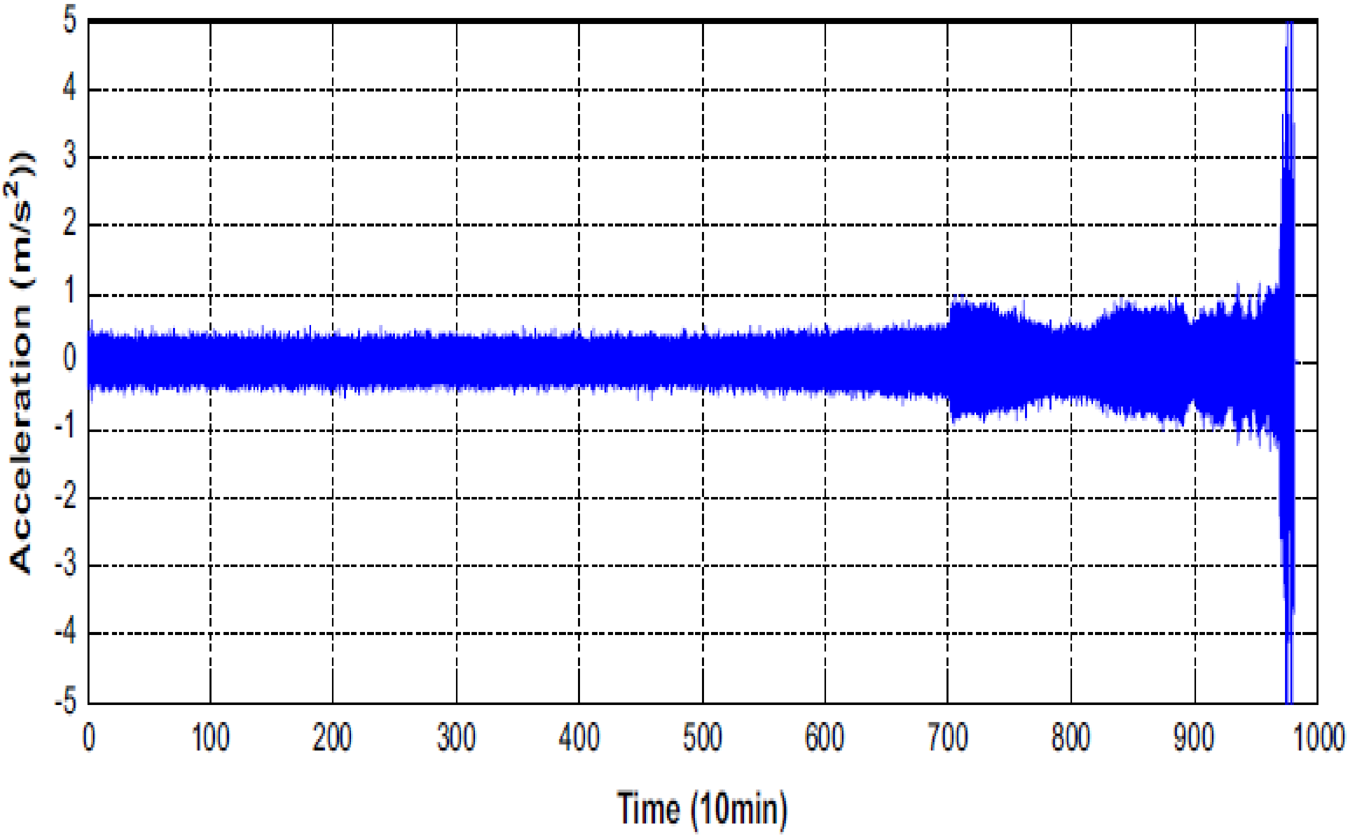


Figure 6: Run-to-failure vibration signal ending with an outer race defect

As it is clearly visible from the *Figure 6&7,* that bearing developed fault after 4.86 days of continuous running. My aim is to detect fault at early stage of failure.

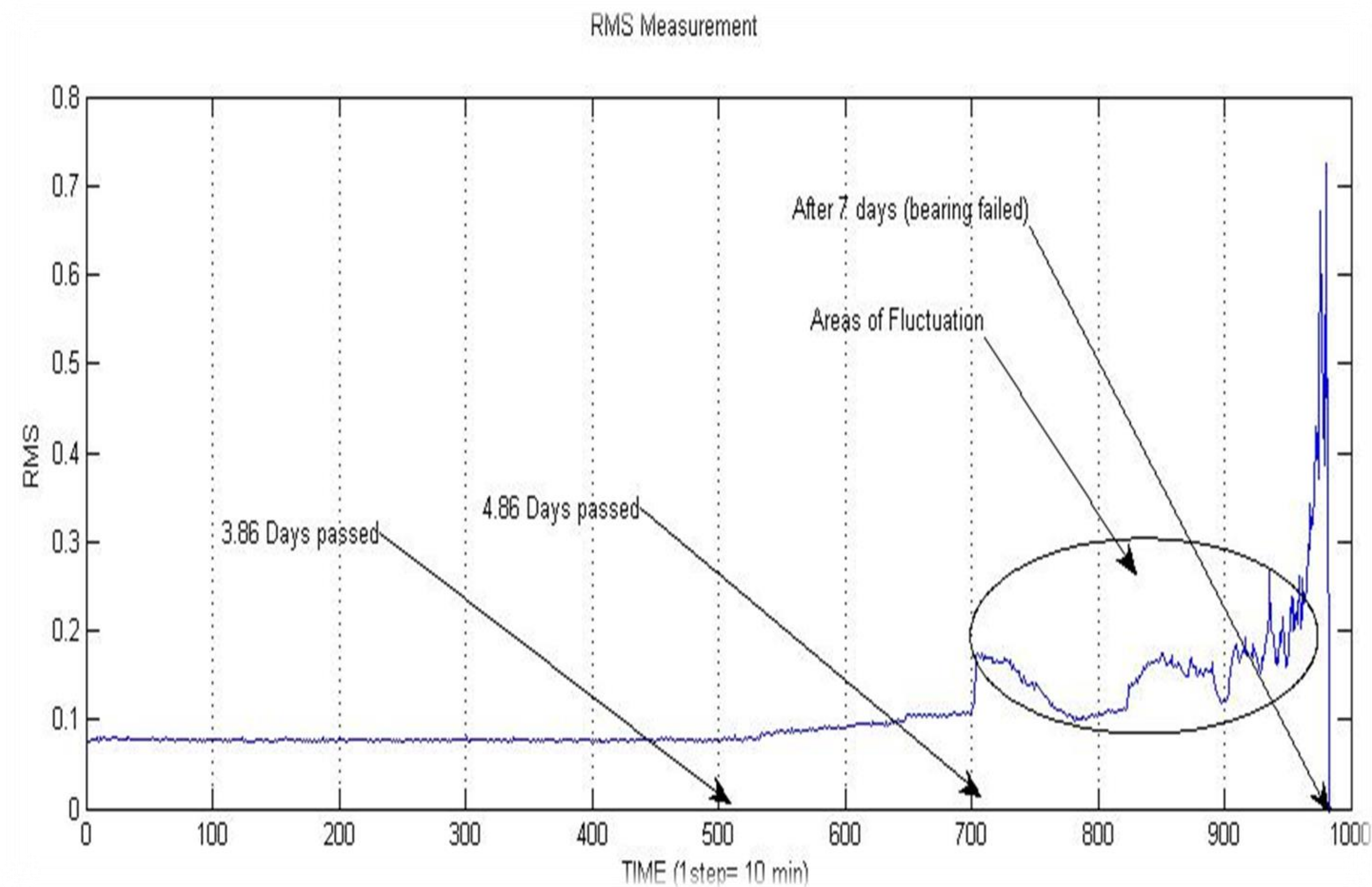


Figure 7: RMS measurement

From *Figure 7&8,* we can say that abrupt change in RMS value after 4.86 days of running is the clear indication of some kind of fault in bearing.

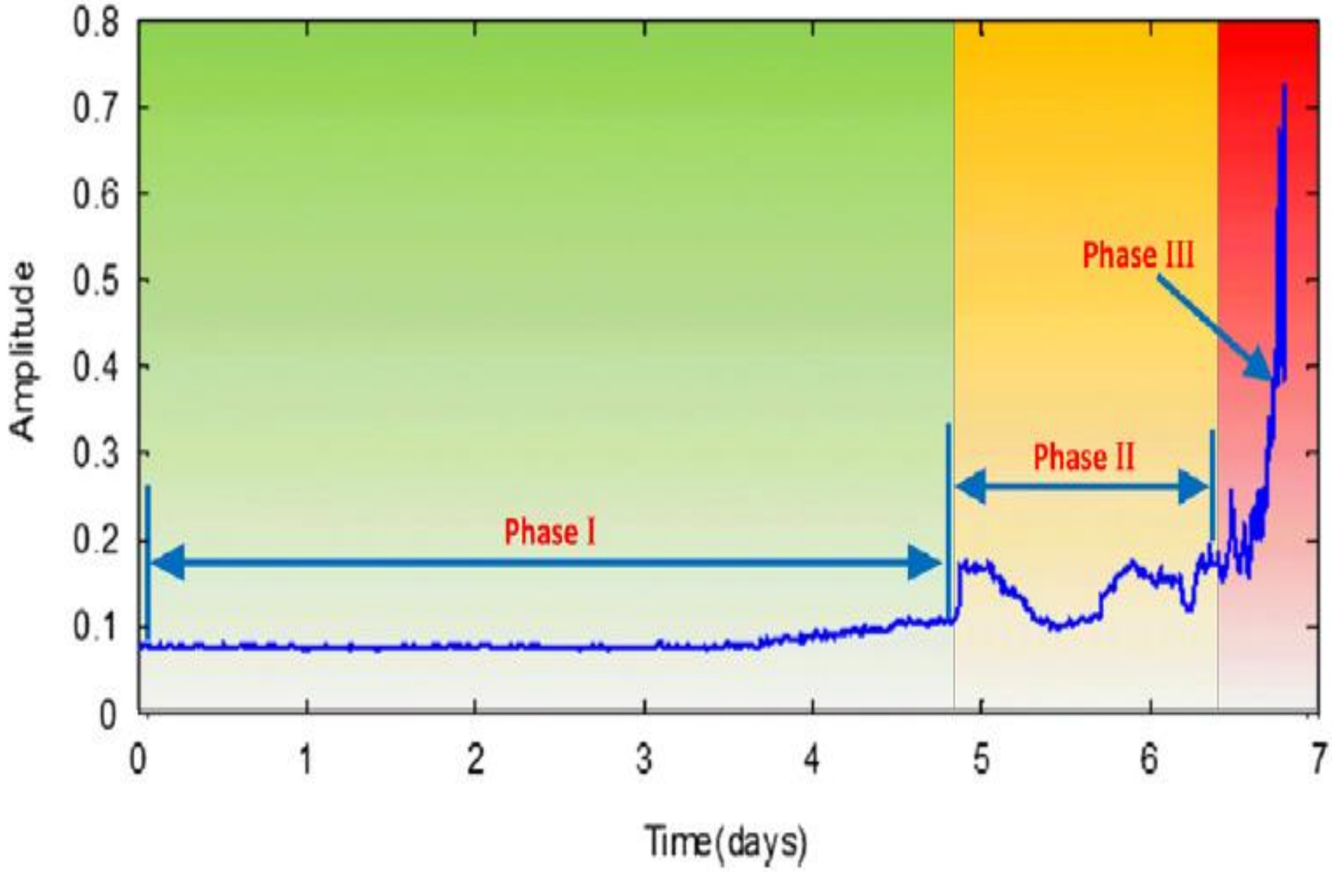


Figure 8: RMS measurement of bearing for whole life cycle

From *Figure 8*, we can conclude in phase 1 region bearing is in healthy state, as time progress it started developing fault i.e in phase 2, and finally as time progress it develops serious defect in phase 3.

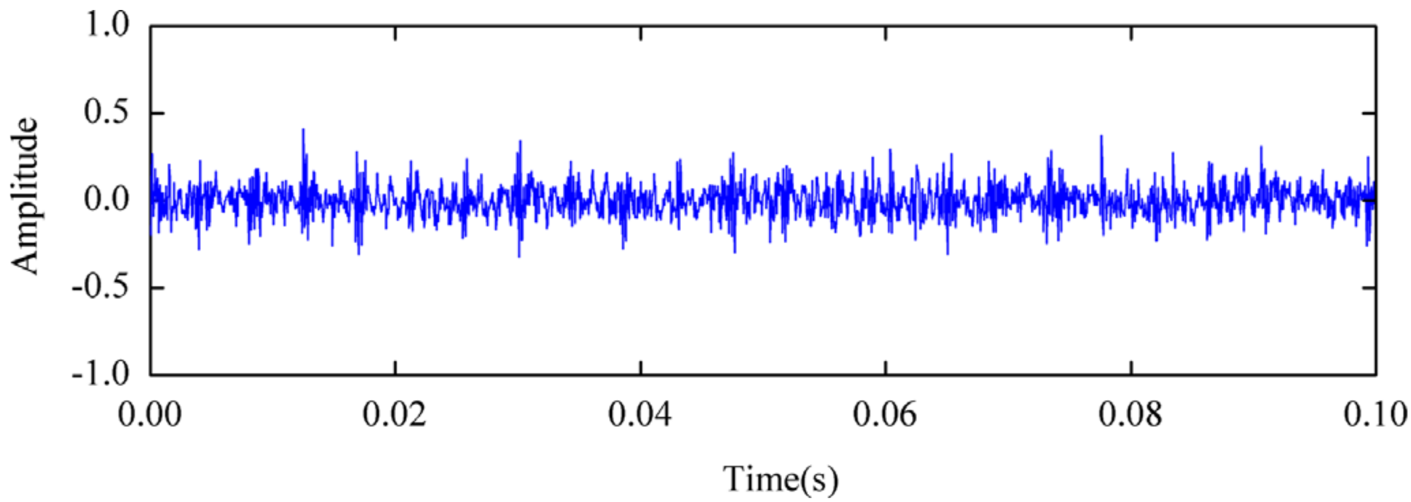


Figure 9: The vibration signal with early stage defect

Figure 9, amplitude of vibration signal is lower as compared to that of vibration signal with serious defect in *Figure 11*.

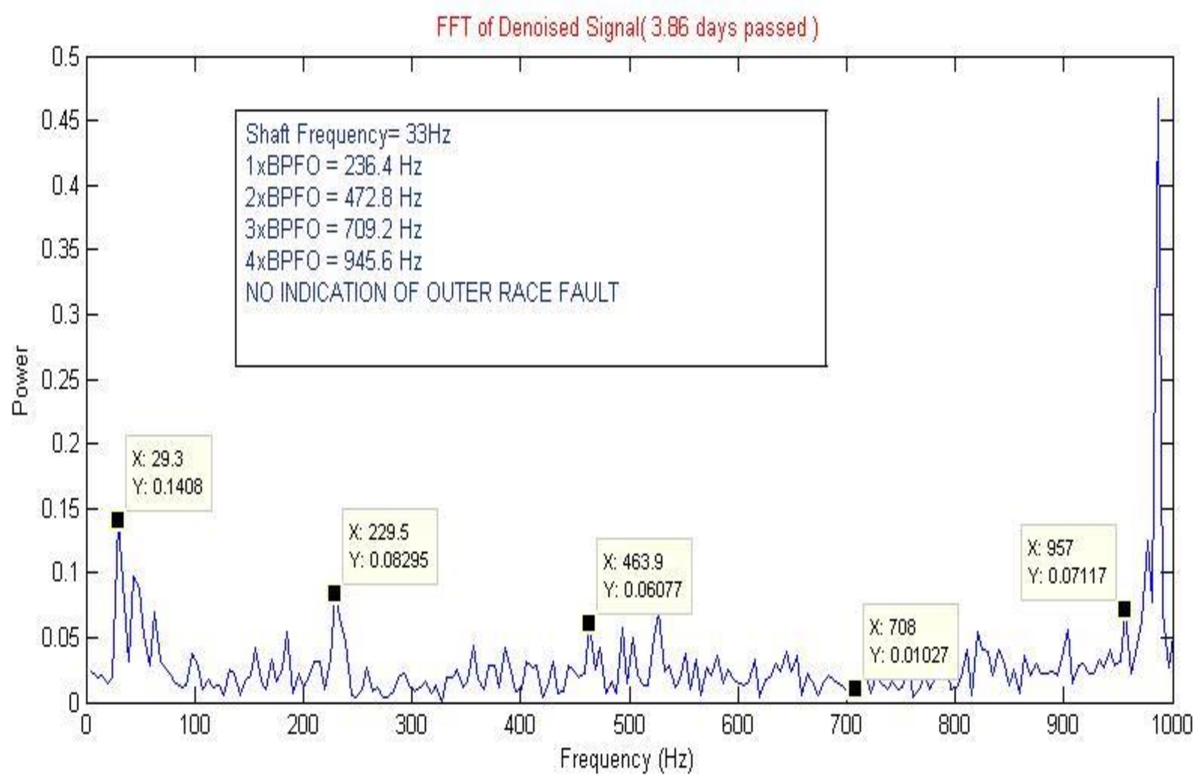


Figure 10: Spectrum of vibration signal with early stage defect

Figure 10, is the power spectrum of de-noised vibration signal, which is of phase 1 region. That is why we are unable to see peaks of higher power at calculated outer race fundamental fault frequencies.

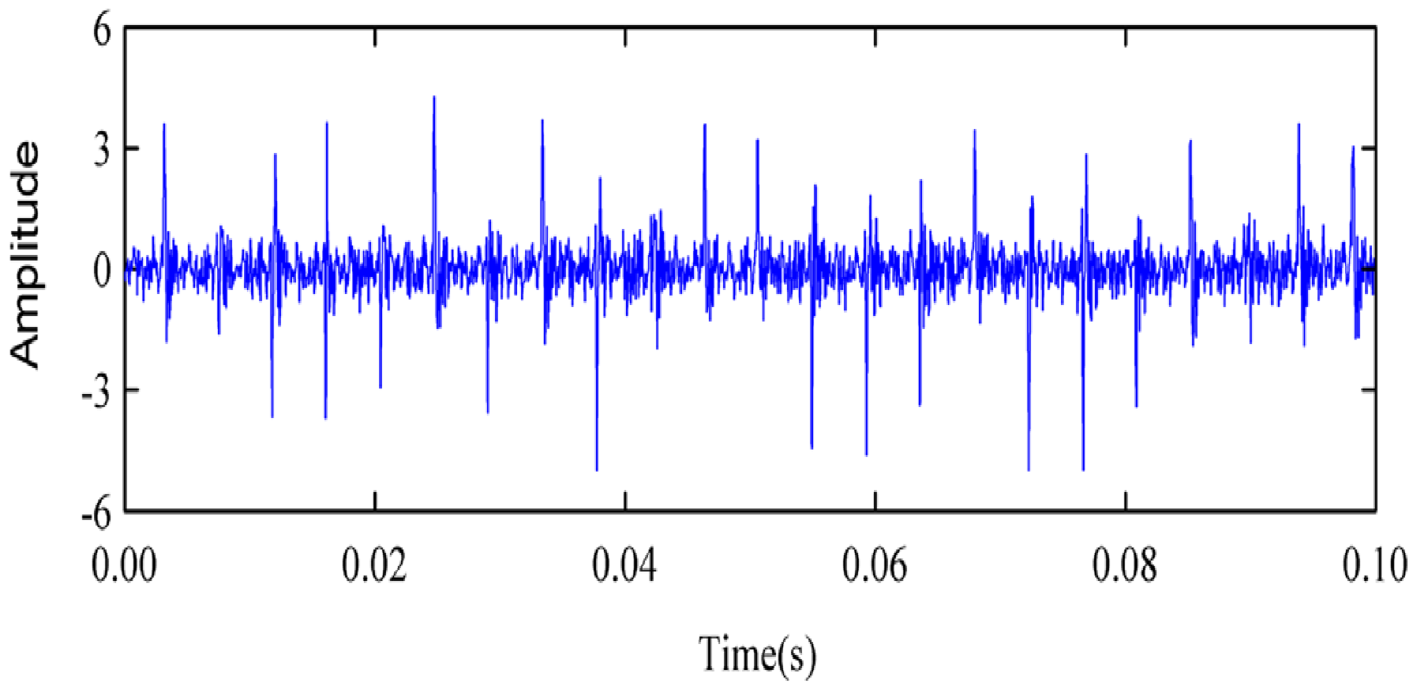


Figure 11: The vibration signal with serious defect

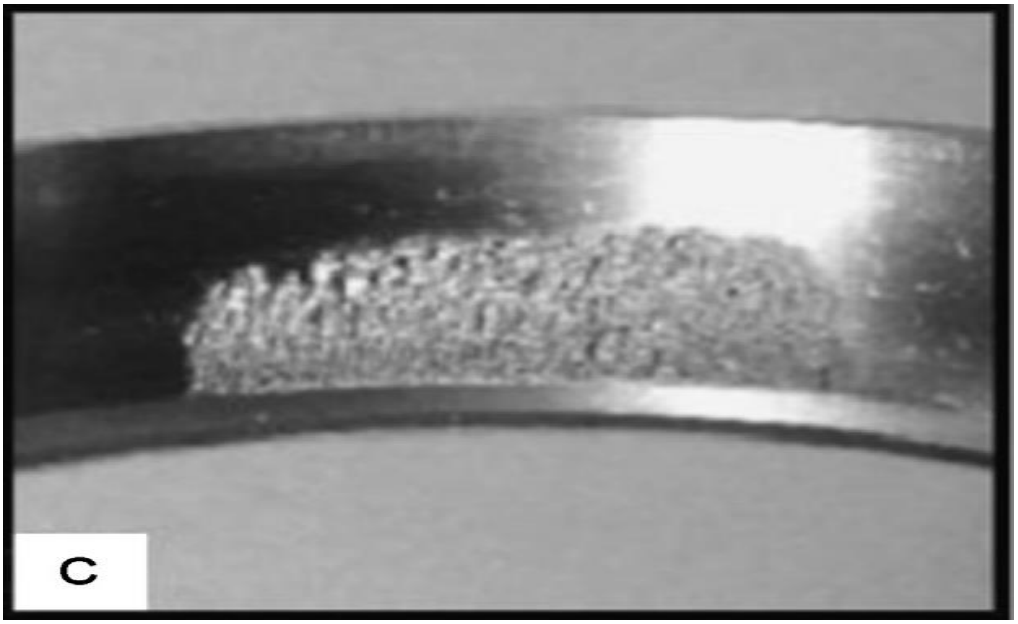


Figure 12: Outer race defect

Figure 12, indicate outer race fault developed after 7 days of run-to-failure test.

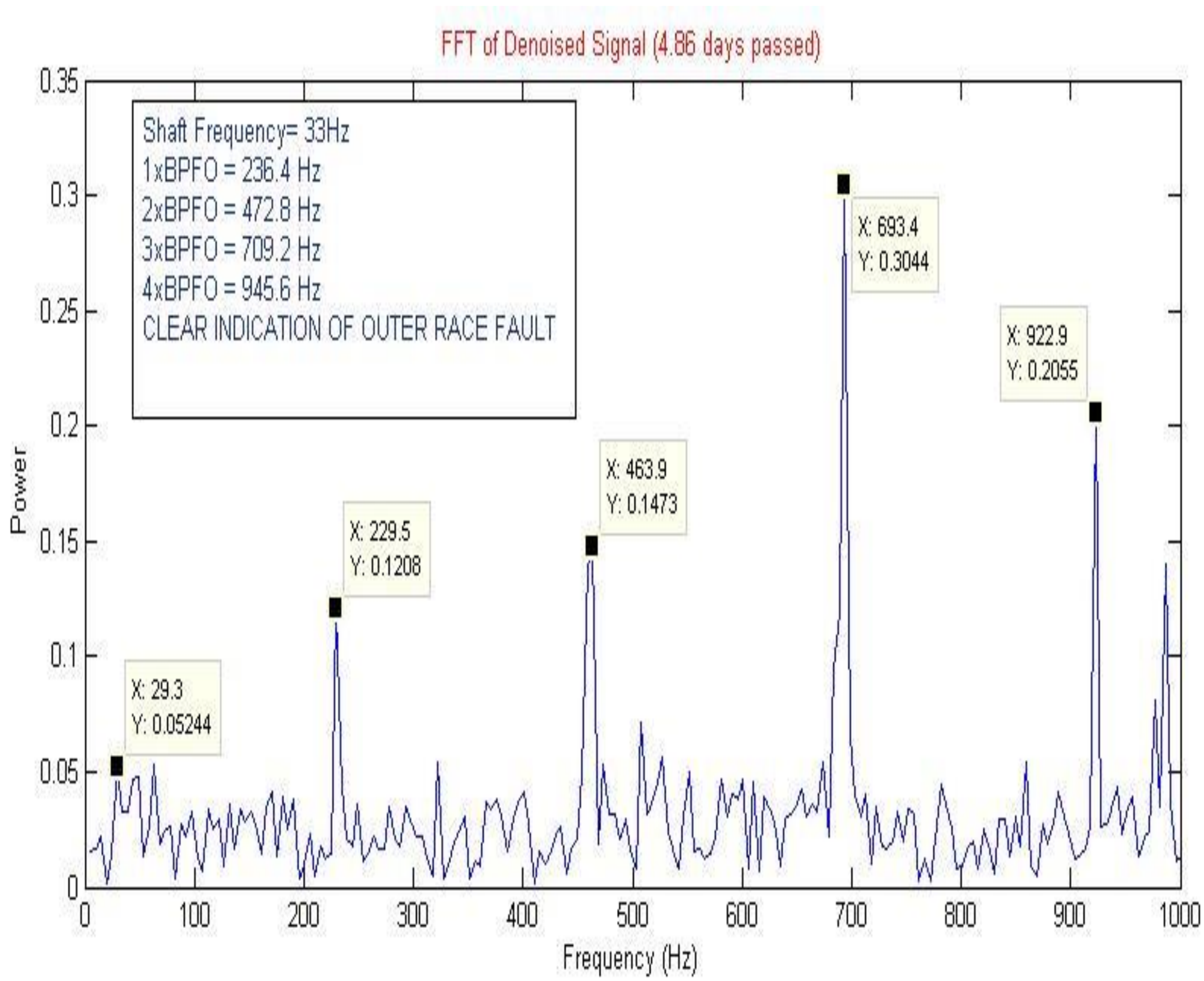


Figure 13: Spectrum of vibration signal with outer race defect

Figure 13, We can clearly see the peaks at calculated outer race fault frequencies, it indicates that outer race fault started developing in bearing after 4.86 days of running.

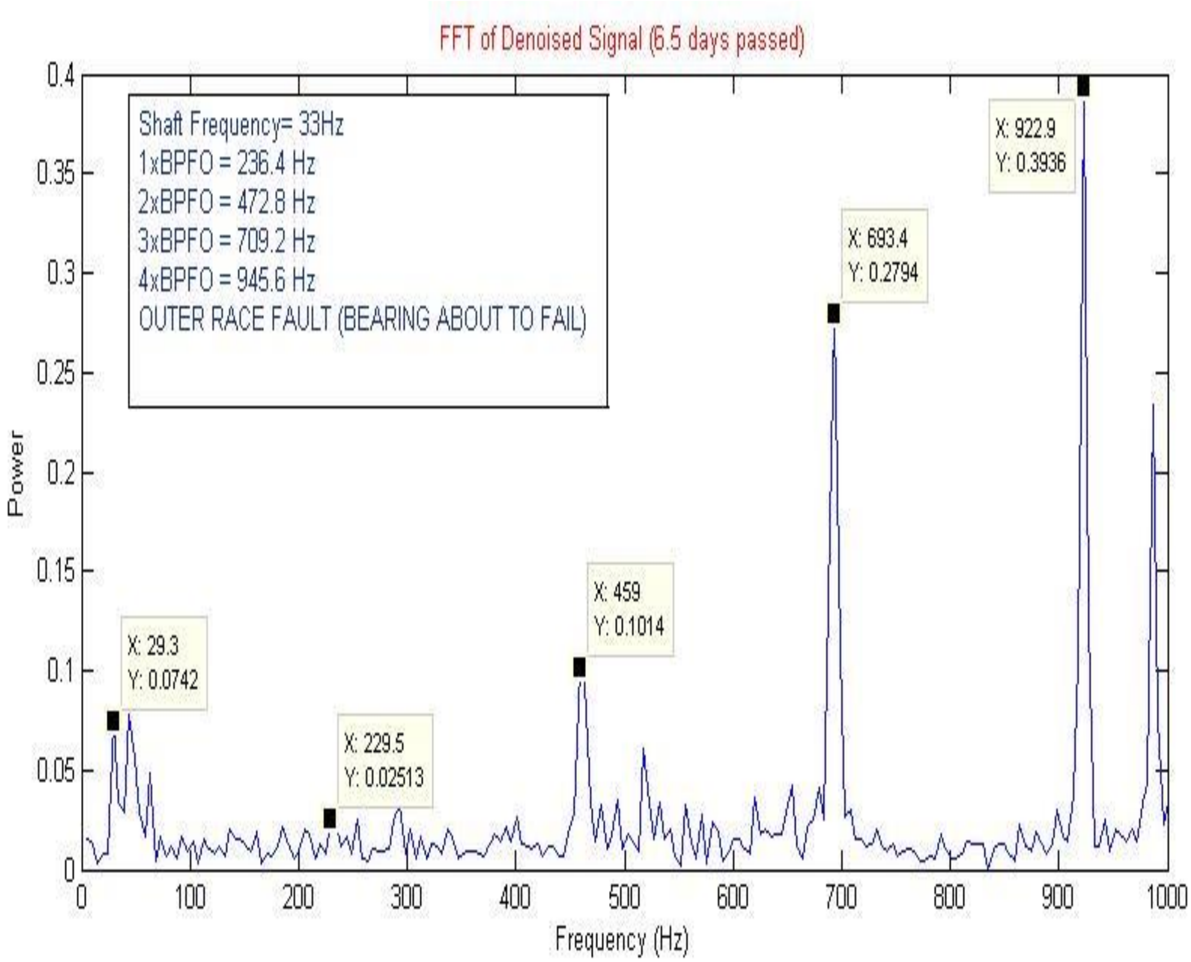


Figure 14: Spectrum of vibration signal with serious outer race defect

Figure 14, Power Spectrum of vibration signal after 6.5 days. Peaks at outer race fault frequencies are clearly visible which indicates the outer race fault is fully developed and its power is higher than the previous one (*fig 13*).

CHAPTER 5

CONCLUSION AND SCOPE OF FUTURE WORK

De-noising and extraction of the weak signature from the noisy signal are crucial to fault prognostics, in which case features are often very weak and masked by the background noise. Prognostics is achieved by detecting the defect at its initial stage and alerting the operator or maintenance personnel before the defect develops into a catastrophic failure.

The performance of traditional wavelet decomposition-based de-noising methods is greatly impacted by relative energy levels of signal coefficients and white noise coefficients. When dealing with smooth signals, satisfactory results can generally be achieved by manipulating the threshold. The underlying reason is because with smooth signals, a small number of large coefficients can characterize the original signal. However, it is much more challenging to de-noise impulse series signals where wavelet coefficients are not so concentrated.

The experimental results verify the effectiveness of the proposed method. The weak periodic impulse signature is successfully revealed and enhanced. Detection of the degradation signature at its early stage gives more time for maintenance reaction and business decision-making and also provides proof for prognostics.

The results validate the proposed method is able to extract fault signatures from weak signals and can be regarded as an effective and reliable method for rolling element bearing faults diagnosis at an early stage.

This method can be extended to measure the remaining useful life of bearing in future.

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