Fault Diagnosis of Rolling Element Bearing with Advance Signal Processing Techniques

[1]A. A. Darji,[2]Dr.P. H. Darji,[3]Dr.D. H. Pandya
[1]Research Scholar,[2]Professor and Dean-C U Shah University,[3]Head of Mechanical Dept. LDRP-ITR
[1]Mechanical Engineering Department,
[1]C U Shah University, Wadhwan,Surendranagar, India

Abstract: This Diagnosis of rolling bearing based on vibration signature analysis in Time-frequency domain. Its signal analysis techniques, centered on spectral approaches such as the FFT are powerful in diagnosing a selection of vibration related problems in rotational machinery. While these techniques provide powerful diagnostic tools in stationary conditions, they fail to do so in numerous practical cases concerning non-stationary data. Recent development in signal processing approaches make available new methods in time-frequency representation, which major information regarding the time happening of the fault. In this research paper delivers a comparative learning between traditional signal processing methods, like periodograms, Welch Periodogram, Spectrogram and the Scalogram. Presentations of these techniques are evaluated through experimentations and compared for single point defects on IR, OR and ball fault, including balanced condition of rotor bearing system.

***Keywords* - Bearing Diagnostics, Time-frequency domain, Spectogram, Welch Periodogram**

I. INTRODUCTION

The process of a failure in a rolling bearing starts with microscopic cracks, when the balls make contact with a crack it produces a low energy signal similar to an impact, detecting these impacts out of the machine vibration acceleration signal is the way to monitor and control the condition of its rolling bearings. The drawback behind enveloping is that it is not really designed for processing signals characterized by impulses, it causes averaging out of important data because of the multiple FFT's used; instead, this technique is expected to work better with periodic signals. Furthermore, it is necessary to concentrate the application of enveloping in a band with around the natural frequencies of the machine frame because these are excited when the bearing balls produce impacts; thus the design of a band pass filter is required with its boundaries set between the machine natural frequencies, this process requires the good experience of the vibration technician, or if more precision is desired, a modal analysis shall be performed.

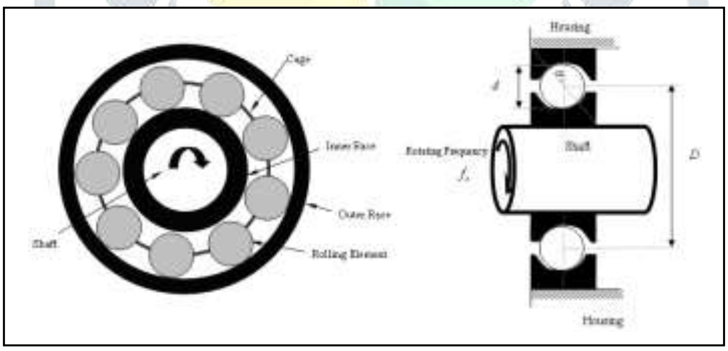


Figure.1 Ball bearing geometry for Characteristic Defect frequency,
Where, D = Diameter of ball bearing as measure to the center of rolling element, d = Diameter of rolling element , α = contact angle of ball with outer race, N =Number of rolling element

II. DEFECTS IN BEARING

One important issue in rotor bearing application is the reduction of noise and vibration originating from the ball bearings. The rolling element bearing is composed of the rolling elements, IR, OR and cages. One possible source of bearing vibration is the defects in its various components. Rolling elements bearings defects classified as local defects and distributed defects. The vibrations are made by geometrical limitations on the individual rolling elements bearing components and these imperfections are produced by irregularities through the manufacturing process as well as wear and tear. And the several distributed defects were surface roughness, waviness, misaligned races, and off-size rolling elements. The local defects embrace cracks, corrosion pitting, brinnelling and spalls on the rolling elements surfaces. The dynamic responses of the rotating bearing elements as they encounter the various modes of failure determine the resulting vibration [1].

2.1 Localized defects:

In the Localized defects embrace cracks, pits and spalls on the rolling elements surfaces. The mode of failure of rolling element bearings is spalling of the races or the rolling elements.

2.2 Distributed defects:

Distributed defects embrace surface roughness, waviness, misaligned races and off-size rolling element bearings. If the surface feature of the wavelength of the bearing is lesser than the hertzian contact width of the rolling element raceway contact, then it is known as roughness. If the feature of the wavelength of the rolling bearing is longer than the Hertzian contact width of the rolling element raceway contact, then is known as waviness. There are global sinusoidal designed limitations on the outer surface of the bearing constituents. The distinguishing wavelengths of the imperfections are much larger than the dimensions of the Hertzian contact areas among the balls and the guiding rings. The number of waves per boundary is denoted by the wave number.

Fig.2. Seeded Localized defect on elements of ball bearing

The roller bearing frequency calculations deliver a theoretical estimation of the frequencies to be expected, when numerous defects occur on the rolling bearing elements. These frequencies are intended based upon the assumption that an ideal instinct is generated whenever a rolling bearing element encounters the defect. Haughty no slip and seeing outer race to be stationary, the general forms of the bearing distinguishing defect frequency calculations are given as [2].

IR defect frequency $$f_{bpfi} = \frac{N_b f_{inner}\left(1+\frac{d}{D}\cos(\alpha)\right)}{2} \qquad [1]$$

OR defect frequency $$f_{bpfo} = \frac{N_b f_{inner}\left(1-\frac{d}{D}\cos(\alpha)\right)}{2} \qquad [2]$$

Cage rotational frequency $$f_{cage} = \frac{f_{inner}\left(1-\frac{d}{D}\cos(\alpha)\right)}{2} \qquad [3]$$

Ball spin frequency $$f_{bsf} = \frac{f_{inner}}{2}\frac{D}{d}\left(1-\left(\frac{d}{D}\cos(\alpha)\right)^2\right) \qquad [4]$$

III. ADVANCE SIGNAL PROCESSING TECHNIQUES

This research paper presents different signal processing techniques which can be working to extract frequency content of a discrete signal, the current will be denoted by the discrete signal$x[n]$,which is found by sampling the continuous time current every T_s= 1/$F_s$seconds.

3.1Periodogram

The periodogram, (f), estimations of the Power Spectral Density (PSD) of a signal $[n]$:

$$P_x(f) = \frac{|X(f)|^2}{N}$$

Where (f) is the Discrete Fourier Transform $[n]$ i.e.

$$X(f) = \sum_{n=0}^{N-1} x[n]e^{-2j\pi fn/F_s}$$

Where, Fs is the sampling frequency, X(f), is calculated a Fast Fourier Transform (FFT) [3], which reduces number of computations to O(Nlog(N)) operations. One would note, the periodogram is not a consistent estimator of the PSD since it has a non-zero bias and its variance does not tend to zero as the data length Ntends to infinity. In spite of this drawback, the periodogram have been used widely for failure detection in the literature survey.

3.2 Welch Periodogram

As related to classical periodogram, Welch periodogram is a better-quality estimator of the PSD that reduces both the variance and the biais. The Welch technique divides $[n]$ into segments, calculates a modified periodogram of each segment and then averages the result [3]. The Welch periodogram, (f),will be conveyed into a mathematical form as

$$P_w(f) = \frac{1}{L}\sum_{k=1}^{k=L} P_{xw}^k(f)$$

where :

$$P_{xw}^k(f) = \frac{|X_{xw}^k(f)|^2}{NU}$$

Where, is a normalization factor. Additionally,(k) (f) corresponds to the DFT of the windowed signal $[n][n-\tau k]$, where w[.] is a time-window (hanging, hamming, Kaiser) and where $\tau k$is a time lag.

3.3 Spectrogram

To find the evolution of the frequency satisfied over time, Fourier transforms can be computed for dissimilar time segments and then prescribed one next to the other over the time axis. This technique is known as the Short Time Fourier Transform (STFT). For discrete signals, the STFT is given by [4].

$$STFT[f,\tau] = \sum_{n=0}^{N-1} x[n]w[n-\tau]e^{-2j\pi fn/F_e}$$

Where, w[.] is a time window. The spectrogram is distinct as the square modulus of the STFT i.e. |[f, τ]|2. The time and frequency determination is limited by the Heisenberg-Gabor inequality [4]. In the situation of the spectrogram, this resolution is the same for all time-frequency bins. One would note that the spectrogram previously in [5], [6] for diagnosis purpose in time-varying condition

3.4 Scalogram

Wavelet Transform (WT) delivers a time-scale (or time frequency) demonstration of a signal. Though STFT gives constant time-frequency resolution, WT is a multi-resolution method which analyses frequencies with dissimilar resolutions. The WT stretches a good time resolution and poor frequency resolution at high frequencies, and delivers good frequency resolution and poor time resolution at low frequencies [7]. The Wavelet Transform at frequency scale $l$is specified by:

$$W(a^l,\tau) = \sum_{n=0}^{N-1} x[n]\psi_l^*[n-\tau]$$

where

$$\psi_l[n] = \frac{1}{\sqrt{a^l}}\psi\left(\frac{n}{a^l}\right)$$

Where, ψ(.) is the mother wavelet which contents a number of conditions. The scalogram is distinct as the square modulus of the WT i.e. |(al, τ)|2. One would note that the Wavelet Transform must been used previously in [8]–[10] for failure detection.

IV. Experimental Set up

Experimentation is carried out on a rotor test rig. This contains of a shaft reinforced on rolling element bearings & driven by a DC motor of 3HP. The SKF 6205 bearings have been taken for the study. The localized defect of spall seeded on outer race of bearing and experimental data acquire with unbalance rotor bearing classification. Vibration responses at 4000 rpm were analyzed by vibration analyzer with 4 input channels at sampling rate of 2.04 kHz. To obtain and analyse the data, CoCo-80 was used. It is a handheld data recorder, dynamic signal analyser and vibration data collector. The CoCo-80 hardware supports two different platform software occupied modes: dynamic signal analyser (DSA) and vibration data collector (VDC). It consumes 24-bit A/D converters, digital technology and unique hardware intended to offers more than 130 dB dynamic ranges. Therefore data may be swapped with other data formats like as UFF, BUFF, NI-TDM, ASCII, MATLAB or Excel.

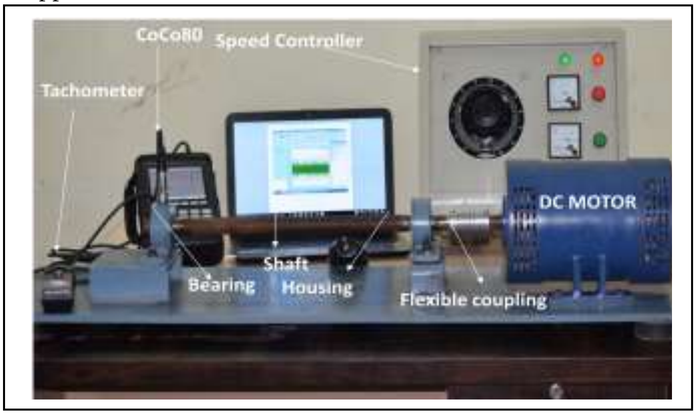


Fig.3. Experimental Set up

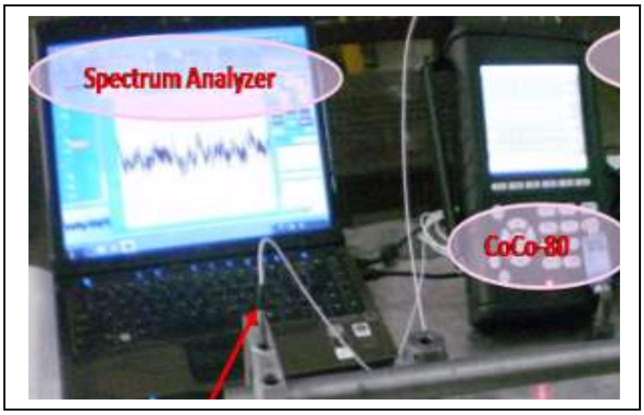
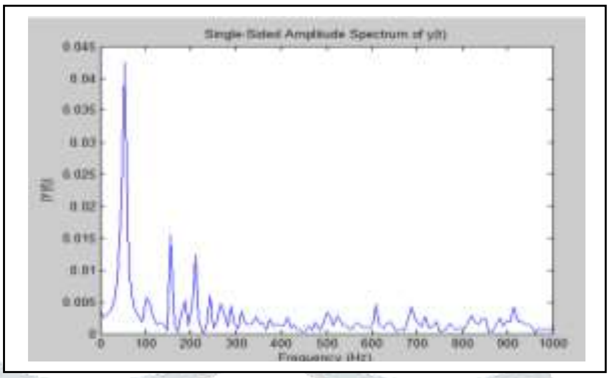


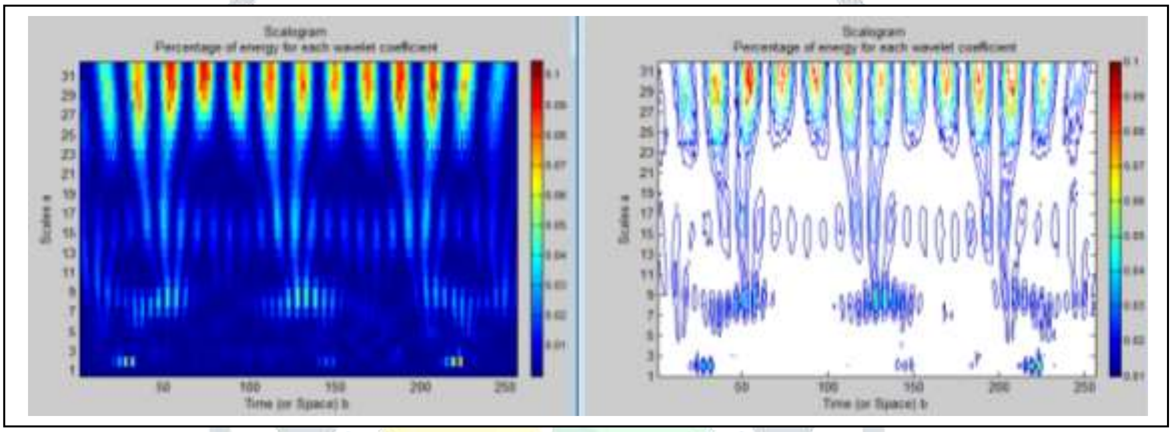
Fig.4. CoCo-80dynamic signal analyzer

V. RESULT AND DISCUSSION

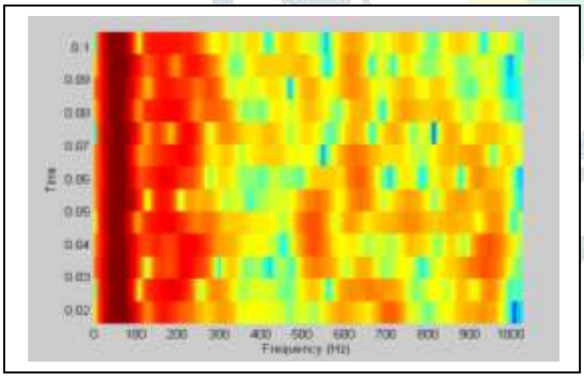
Present experiment carried out at 4000 rpm with unbalanced rotor dynamic bearing condition. Figure.5(a) represent fast Fourier transformation of raw signal indicate the highest pick at 66.67 Hz which is at 1X fundamental frequency. Figure.5 (b) scalogram shows multi resolution presentation in time scale domain. As shown in figure.5(c) maximum percentage of energy highlighted in 2^{nd} slab with scale number 5-7 and 7-9. The frequency level for these scales are ranging between 256-512 Hz and characteristic defect frequency are 354 (VC), 239(f_{bpfo}) and 361 (f_{bpfi})



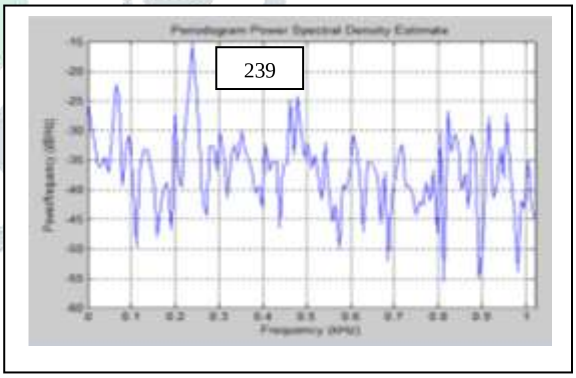
(a) FFT



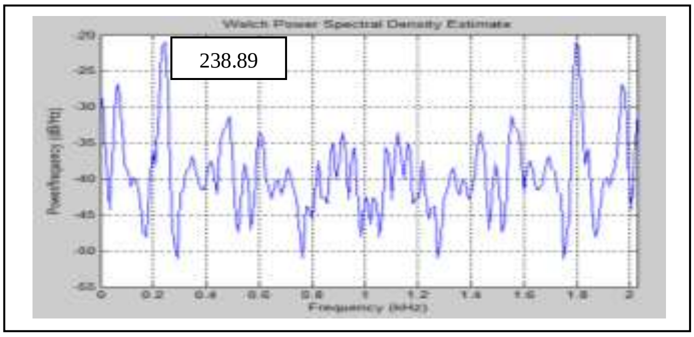
(b) Scalogram (c) Contour scalogram



(d) Spectrogram



(e) Periodogram



(f) Welch Periodogram

Figure.5. Unbalanced Rotor Bearing system with Outer Race fault at 4000 rpm, (a) FFT (b) Scalogram (c) contour scalogram(d) Spectrogram (e) Periodogram (f) Welch Periodogram

VI. CONCLUSION

This research paper obtainable a evaluation between four signal processing approaches for fault detection in the case of deep grove ball bearing for OR defect. Investigational simulations must show that the classical and Welch Periodogram have very close presentations. Though for noisy data, the Welch periodogram shows a better signal to noise ratio. One more significant conclusion tinted from this research work is that as compared to Periodogram and Welch Periodogram, the spectrogram and the scalogram, which are time-frequency representations, bring up more information concerning the time occurrence of the fault.

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