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Early detection of bearing faults by using vibration signal analysis

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Abstract: Bearings are the important machine elements used to support axial/radial loads in rotating machinery. Bearings undergo tribological failures such as scuffing, pitting, mild wear and spalling due to increase in load and speeds, these faults eventually lead to the decrease in efficiency and unexpected shutdowns of the rotating machines. Condition monitoring of roller 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 paper 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 operating 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.

Keywords: Bearing, vibrations, fatigue, wavelet.

1. Introduction

Roller/ball bearings are frequently encountered machine elements in the rotating machinery due to their load carrying capacity and friction characteristics. The heavy forces acting and adverse operating conditions result in surface fatigue wear 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 lead to decrease in machine down time and also avoid unexpected shutdown of machinery [1]. In the last few decades, many condition monitoring methods have been proposed to monitor bearing faults, however the vibration signal analysis is considered as the most important method and widely used in the condition monitoring of rotating machinery and engineering structures. 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 [2].

Peter *et al*. [3] carried out experimental investigations to detect bearing faults using vibration signal analysis techniques. Results showed that Fast Fourier transformation (FFT), Wavelet transform (WT) and empirical mode decomposition (EMD) methods are effective in finding the fault simulated on outer race, however WT analysis is handier in diagnosing the inner race and roller faults due to the better frequency obtained at the low frequency region. Amarnath et al. [4] 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 in helical geared system. Muralidharan and Sugumaran [5] conducted experiments to detect local faults in bearings of the mono-block centrifugal pump using wavelet analysis. 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.* [6] carried out experimental investigation to detect surface fatigue wear on gear tooth surfaces spur gear mounted on back-to -back power recirculation type spur gear box. In this work time–frequency analysis of vibration signals using Morlet wavelet transform was used to find wear severity on gear tooth surface. 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.* [7] studied the behavior of Timoshenko-type beams. Results obtained from the experimental investigations conclude that a spectral-temporal signal representation given by Morlet wavelet transform is more suitable to analyze the chaotic vibrations of complex dynamical systems than the classical Fourier based signal analysis. Brian *et al*. [8] developed the customized wavelets for detecting localized defects in bearings. The authors have highlighted the importance of customized wavelet to obtain 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.* [9] conducted experiments to analyze characteristics of vibration signals acquired from the aircraft body structure. The vibration signals were processed using three different mother wavelets viz. Haar, Daubechies and Morlet wavelets. Authors have highlighted the suitability of Daubechies wavelet family to obtain the highest degree of flexibility for parametric modifications involved in vibration signal analysis. Post processing the signal it has been determined that Daubechies-16 provided least amount of error thereby maintaining most of the signal energy.

This paper 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 wavelets. Daubechies wavelet provided better result to detect surface fatigue failure as compared to Morlet and Gaussian wavelets.

Wavelet analysis in machinery health monitoring

Time series representation of the data reveals how the signal is varying with time. It does not provide the crucial diagnostic information hidden in the machinery vibration signal. The statistical features can be extracted from the signal which provide the physical insight of the rotating machinery. Unlike time domain, frequency domain graph shows how much of the signal lies in the given range, Fourier transformation is

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used to convert a signal from its original time 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 the signal *f(x)* is given by equation (1) [10].

$$\widetilde{f(\omega)} = \int_{-\infty}^{\infty} f(t)e^{-i\omega t}.dt \qquad (1)$$

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 time intervals to obtain time-frequency plot. In Continuous STFT, the function is multiplied by a window function $\omega(t)$. The continuous STFT of a signal *f(t)* is given by equation (2) [11].

$$\textbf{STFT}\{f(t)\}(\tau,\omega) \equiv X(\tau,\omega) = \int_{-\infty}^{\infty} f(t).\omega(t-\tau).e^{-j\omega t}.dt \qquad (2)$$

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. 1.

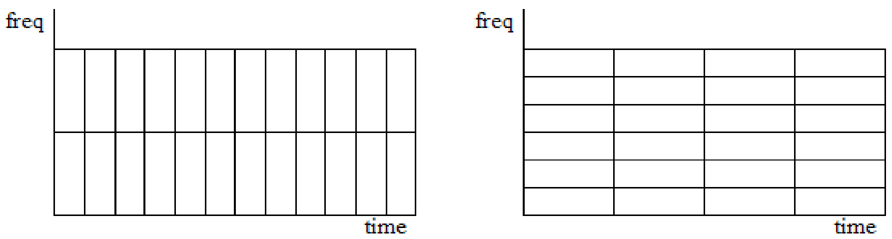

Fig. 1 Fixed window plot in STFT [11]

Hence in order to overcome this drawback, a new method called Wavelet transform has been proposed. 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 two 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 WT is a variable window function as shown in Fig. 2.

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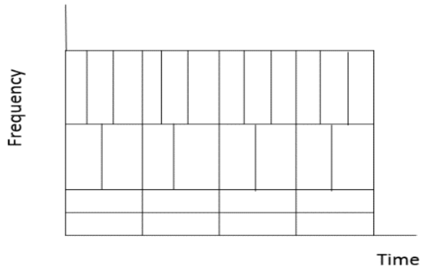

Fig. 2 Variable window plot in WT

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. In this paper CWT is used to analyze of the vibration signals acquired from the roller bearing subjected to fatigue load cycles over a period of 1350 hours. CWT of a signal is given by the equation (3) [12].

$$CWT(f(t), \psi, a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) . \psi^* . \frac{(t-b)}{a} . dt \qquad (3)$$

Three mother wavelets viz. Morlet, Daubechies and Gaussian wavelets have been employed to study the behavior of the machinery vibration signals. 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 (4) [13].

$$\psi = e^{-i\omega_0 t} . e^{(-t^2/2\sigma^2)} \qquad (4)$$

Further Daubechies wavelets are employed to extract better fault related features from the signal which consists of smoother scaling functions produced using longer filters. Daubechies wavelets are an extension of Haar wavelet which produce 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 represents the number of coefficients and in *dbA*, A is 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.

The Gaussian wavelet of order n is the nth order derivative of the Gaussian function given by equation (5) [13].

$$f(x) = a.e^{-\frac{(x-b)^2}{2c^2}} \quad (5)$$

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.

2. Experimental Setup

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, it consists of a 5 HP three phase induction motor 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 and test bearings. A radial load of 1 kN was applied to the test bearing, which is off center towards the test bearing as shown in Fig. 3. Lithium based mineral oil grease NLGI 3 was used to lubricate the bearing.

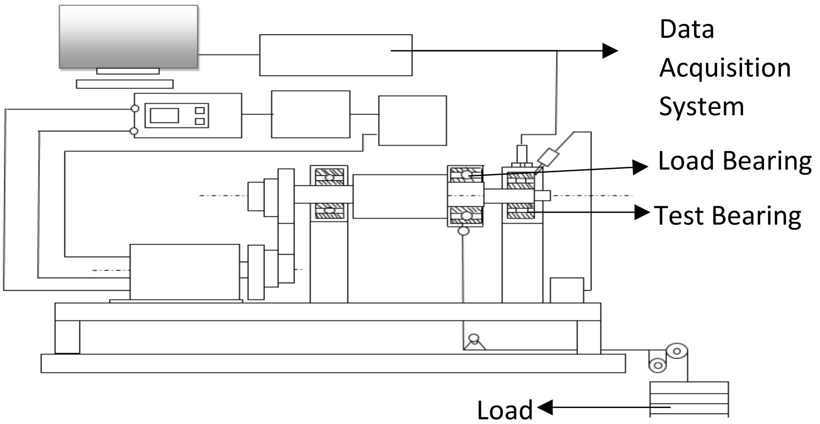

Fig. 3 Bearing test rig setup

3. Results and Discussions

The test bearing was allowed for run-in wear over a period of 40 hours. After running-in wear, the test bearing was dismantled to remove grease, further fresh grease was applied on the bearing components and mounted on the test rig to conduct fatigue tests. Experiments were carried out over a period of 1350 hours under a load of 1 kN, the bearing was operated at a constant speed of 800 rpm. Vibration signals were acquired at regular intervals of 450 hours. Fig. 4 (a)-(b) show vibration signals acquired from the bearing housing. Increase in fatigue load cycles on bearing surfaces resulted in surface fatigue wear, hence vibration signals acquired after 1350 hours showed increase in amplitudes in the temporal plot, which can be clearly observed in Fig. 4 (b).

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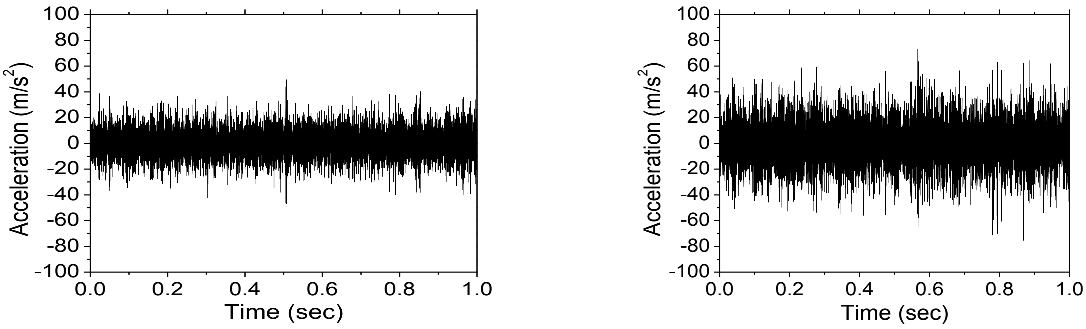
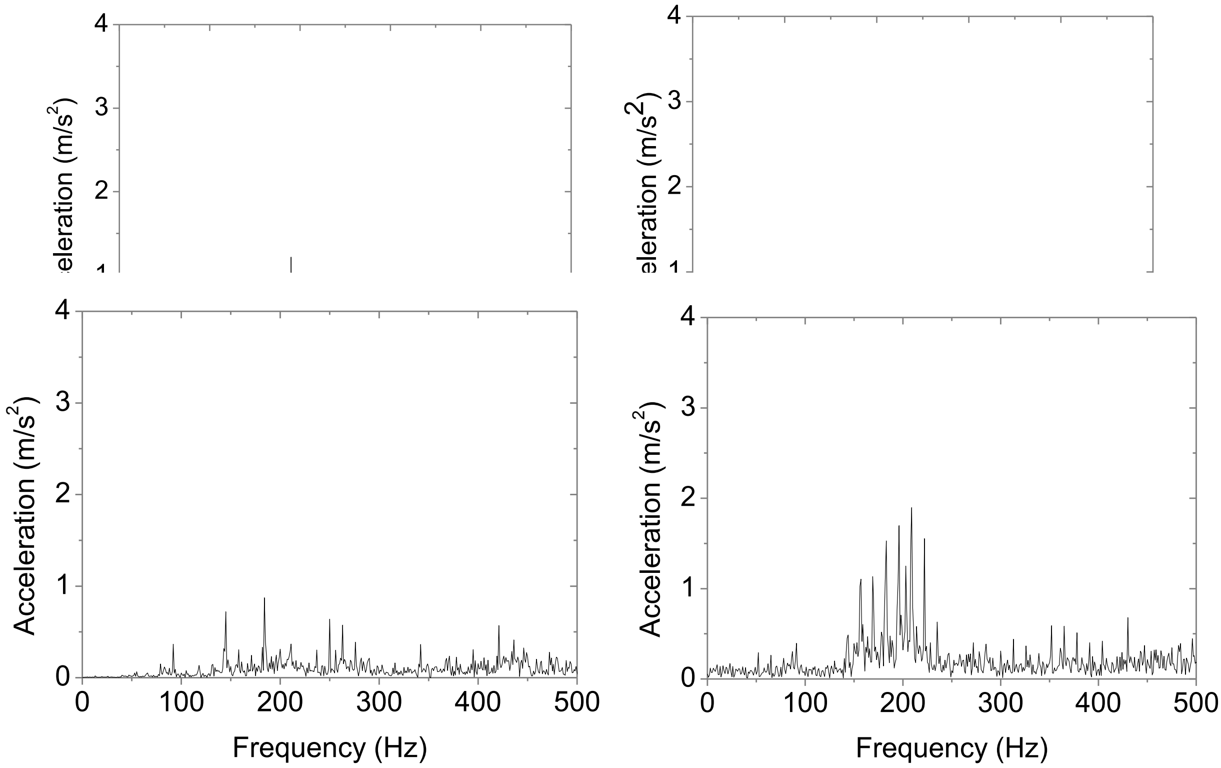


(a) (b)

Fig. 4 Temporal plots of the vibration signals acquired (a) Healthy bearing (b) after 1350 hours

Over a period of time, the gradual increase of wear on rolling contact surfaces results increase in vibration signal amplitude. The vibration signals encompass with the frequency components of various machine elements. As every component vibrates in its own natural frequency, vibration analysis facilitates in detection of localized 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. 5 (a) – (d) depicts frequency domain plot obtained from the roller bearing under healthy and worn conditions at a regular interval of 450 hours, 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.



(c) (d)

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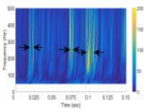
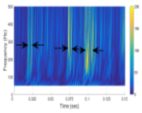
Fig. 5 Frequency vs. Amplitude plots of signal (a) FFT plot of healthy bearing, (b) FFT plot after 450 hours, (c) FFT plot after 900 hours, (d) FFT plot after 1350 hours

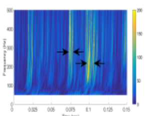
To obtain better diagnostic information, the machinery vibration signal are further analyzed by using Morlet, Gaussian and Daubechies wavelet transformation. However Daubechies wavelet shows better fault related features on time-frequency plots. Fig. 6 (a)-(d) show different levels of Daubechies plots considered for bearing fault assessment, y-axes show the frequency range of 0-500 Hz which highlight various fault characteristic frequencies. In all the plots the energy levels are more or less the same. However, the energy level of the inner race fault characteristic frequency harmonics is better visualized in level 9 Daubechies wavelet (db9). Hence in comparison to Morlet and Gaussian wavelets, db9 has been considered as suitable wavelet transform to detect bearing faults occurred due to fatigue load cycles.



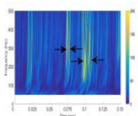
(a)



(b)



(c)



(d)

Fig. 6 Different levels of Daubechies plots after 1350 hours (a) db8, (b) db9, (c) db10, (d) db12

4. Summary and Conclusions

Experiments have been conducted to detect surface fatigue wear in cylindrical roller bearings using wavelet analysis. Fatigue test experiments were carried out over a period of 1350 hours, vibration signals were acquired at a regular time intervals and the vibration signal data was processed using different wavelets viz. Daubechies, Gaussian and Morlet wavelets. Among the different levels of the Daubechies wavelets, db9 (level 9) showed better diagnostic information of surface fatigue wear occurred on inner race of roller bearing.

Acknowledgements

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