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Wavelet based Vibration Signal Analysis of Rotary Machines in a Foundry

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ABSTRACT: For the early detection of faults to maximize the productivity by minimizing the downtime a tool called Condition Monitoring (CM) is commonly employed. In this paper, some rotating machineries in a foundry running at real operating conditions were selected. Vibration readings have been taken at regular intervals of time and have been analysed suitably in time and frequency domains. A time-frequency domain technique namely wavelet transform (WT) has been used. Two techniques based on features extracted from the wavelet coefficients namely multiscale slope feature and kurtosis has been applied to the vibration signals extracted from these machines. These techniques have been found to be effective in identifying the presence of faulty condition in these machines.

KEYWORDS: Vibration Signal Analysis, Fault Diagnosis, Rotating Machinery, Wavelet Transform, Multiscale Slope Feature, Kurtosis Value.

I. INTRODUCTION

A need to increase the reliability and to decrease the possible loss in production due to the breakdown of the machine is being felt by industries. Accordingly condition monitoring is attaining much importance in every industry [1]. To monitor the operating condition of the machine by utilising the predictive maintenance technique leads to reduce maintenance cost and downtime [2]. Vibration analysis involves vibration measurement and its interpretation. Vibration signals are collected first by vibration analyser (VIBSCANNER) in time domain and frequency domain using in-built Fast Fourier Transform (FFT) analyser and information obtained from the vibration signals have been used to predict machine failure. Common techniques used in vibration signal analysis includes time, frequency and time-frequency domain analyses. Many frequency analysis methods have been used for fault diagnostics, but these are not suitable for nonstationary signal analysis that are generally related to machinery faults. Non-stationary signals can be analysed by applying time-frequency domain techniques, as they use both time and frequency domain information allowing for the investigation of transient features like impacts [2]. Time-frequency analysis, including the wavelet transform (WT), is one of the powerful tools in the field of biomedical, image processing and vibration signal analysis [3]. Multiscale slope feature extraction method based on wavelet transform has been increasingly used in analysing non stationary signals [4] extracted from bearings and gear boxes. Kurtosis is a statistical parameter and found to be a good criteria to distinguish the healthy and faulty condition of the bearing [5].

In this paper, vibration signals were acquired from the machines running under real operating conditions in a foundry and analysed suitably in time and frequency domain. For these signals multiscale slope feature and kurtosis techniques were applied to identify the presence of faulty condition in these machines.

II. INDUSTRY PROFILE

Lamina Foundries Limited, Nitte, is a medium scale foundry belong to Lamina Group of Companies started in the year 1983 located at Nitte on Padubidri-Karkala state highway. It produces iron castings such as motor bodies, flywheels and valve bodies etc. [6] and exports machined brake drums to Germany. Three machines were considered for



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monitoring, in which two machines namely shot blasting machine and shot blasting blower which had faults have been considered in this work.

III.DATA ACQUISITION

VIBSCANNER® is a handheld portable vibration data collector and analyser for rotary machines. It is capable of FFT analysis, bearing condition measurement, balancing and trending. Regularly recurring measurement tasks are processed in the form of a route [7]. This is created with the OMNITREND PC based software and loaded into the VIBSCANNER. Here, mobile accelerometer (VIB 6.142R) is used as the external transducer to extract the signals from the bearing points of the selected machines. Obtained data from all the three axes have been compared and the dominant data of the respective direction has been used to characterize the health of the machinery.

IV. WAVELET TRANSFORM OF VIBRATION SIGNALS

Wavelet transform allows to detect the short-lived frequency components present in the signals, converts signal in time domain into a series of wavelet coefficients in time- scale domain and indicates sufficient difference between healthy and faulty condition [5]. WT can be categorised as Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT).

The Continuous Wavelet Transform (CWT) of function f (t) is defined as

$$CWT(a,b) = \int_{-\infty}^{+\infty} f(t) \Psi_{a,b}(t) dt$$
 (1)

Here $\Psi_{a,b}(t)$ denotes the mother wavelet. The parameter 'a' denotes the scale, which is reciprocal of the frequency and parameter 'b' represents the time shifting.

A. Discrete wavelet transform

Mathematically, DWT can be formulated as

$$DWT(j,k) = \frac{1}{\sqrt{2^j}} \int x(t) \Psi^*(\frac{t-k2^j}{2^j}) dt \qquad (2)$$

Using the wavelet filters, the signal is decomposed into a set of low and high frequency components as,

$$Ca_{j,k} = \sum_{m} h(2k - m)a_{j-1,m}$$
(3)
$$Cd_{j,k} = \sum_{m} g(2k - m)a_{j-1,m}$$
(4)

Where, $C_{a_{j,R}}$ is the approximation coefficient represents the low-frequency components of the signal and $C_{d_{j,R}}$ is the detail coefficient, corresponds to the high frequency components of the signal [5].

B. Wavelet Packet Transform

The signals detail information in the high frequency region is further decomposed by the WPT. This can be performed on the signal at certain level, the functions in the above equations are unified as [5],

$$u_{2n}(t) = \sqrt{2} \sum_{k} h(k) u_n (2t - k)$$
(5)
$$u_{2n+1}(t) = \sqrt{2} \sum_{k} g(k) u_n (2t - k)$$
(6)

where $u_0(t) = \phi(t)$ and $u_1(t) = \Psi(t)$

Then the signal decomposed correspondingly as,

$$d_{j+1,2n} = \sum_{k} h(m-2k) d_{j,n}$$
(7)
$$d_{j+1,2n+1} = \sum_{k} g(m-2k) d_{j,n}$$
(8)

where $d_{j,m}$ represents a wavelet packet coefficient at level j, sub-band n. $d_{j+1,2m}$ and $d_{j+1,2m+1}$ represents wavelet packet coefficients at level j+1, sub bands 2n and 2n+1 respectively. Wavelet packet coefficient number is denoted by m.



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C. Multiscale slope feature extraction

With high resolution WT can be used to analyse the localized features in time-frequency domain simultaneously, therefore use of multiscale slope analysis based on wavelet transform is increasingly used to analyse the non-stationary signals. The important information in the form of energy obtained from detail coefficients after decomposition of the vibration signals indicates the operating condition of the machine [8]. The principle of this method is mainly based on the vibrational characteristics of the rotating machines. A typical frequency behaviour is produced by the defect frequency and resonant frequency in the presence of defects in the vibrational signal. Power spectra of the vibration signals is divided into two parts, which satisfy the process of 1/f, whose empirical power spectra as shown in equation 9 [8]. A wavelet based multiscale slope feature extraction technique is used to differentiate the healthy and faulty conditions of the machine. WPT can be used to extract the multiscale slope features from the denoised vibration signals.

$$S(\omega) = \frac{\sigma^2}{\omega^{\beta}}$$
(9)

where ω is frequency, σ^2 is the variance of the original signal, β is the slope of the divided power spectra at different frequencies. The logarithm of the divided power spectra gives the linearity to the two divided parts of the power spectra from which the slope β for each part can be obtained by line fitting using least square method [8].

D. Kurtosis

Kurtosis is a compromise measure between the intensive lower moments and other sensitive higher moments. And termed as the fourth moment normalized with respect to the fourth power of standard deviation and useful in fault diagnosis [5]. This is a good criteria to distinguish between the healthy and damaged bearings [5]. In this paper, kurtosis value is used to differentiate the healthy and faulty condition of the machine. Kurtosis is calculated from equation 10 [9].

$$K_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} [\frac{D_{j}(i) - \mu_{j}}{\sigma_{j}}]^{4}$$
(10)

where K_j is the Kurtosis for level j, μ_j is the mean, σ_j is the standard deviation of the detailed coefficients in level j and n is the number of detailed coefficients. Kurtosis value is higher for faulty signals when compared to healthy signals.

V. CASE STUDY-1

Shot blasting is a surface cleaning and finishing process, effectively used in foundry [10]. The spinner hanger shot blast machine uses hangers to alternately send the work piece into the blast chamber, where blast wheel forcibly propels shots against work piece surface to remove rust, welding slag and other contaminant. The machine used in a foundry is named as an Indabrator shot blasting machine and works on wheelblast technique in which electric motor energy is directly converted into kinetic abrasive energy by rotating a turbine wheel.

Drive system of shot blasting machine consists of 15 kW induction motor, pulley and belt drives. The vibration readings were taken between the periods 25-11-2015 till 29-02-2016. Measurement locations at bearing points 3A and 3B are as shown in Figure 1.



Figure 1: Measurement location for Shot blasting machine



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The overall RMS velocity and FFT spectrum of velocity and acceleration for bearings 3A and 3B at the defined measurement locations were obtained regularly using the vibration analyser.

On 27-01-2016 there is an increase in the overall RMS velocity value which indicates some defect in the machine, which is witnessed in the trend plots as shown in Figure 2 and 3. The overall values of RMS velocity in three axes were compared for the bearing 3A. For the bearing 3A, RMS velocity of horizontal (x - axis, 3AX) direction, 8.49 mm/s is greater than axial z - axis, 3AZ direction 5.48 mm/s. According to ISO 2372 chart [11], the RMS values were in the "unacceptable" range (greater than 4.5 mm/s). The rise in the RMS values was mainly due to the unbalance. From the overall RMS velocity trend plots, it can be observed that on 04-12-2015 the measured RMS value is low compared to other measurements. It has been observed from the FFT spectrum as shown in figure 3, there is a trend with significant amplitude at 1xrpm. At 2x, 3x and 4xrpm small peaks were observed. But these amplitudes were small compared to trend at 1xrpm. Maximum amplitude at 1x RPM is because of unbalance and small peaks at 2x, 3x and 4x indicates looseness. Looseness is small compared to unbalance.

Vibration data measured on 04-12-2015 has lower overall RMS velocity value and is considered to be the healthy machine condition and on 27-01-2016 has higher overall RMS velocity value and is considered to be the faulty machine condition as shown in figure 3.



Figure 2: Overall RMS velocity for left bearing [3A] in 3AX and 3AZ direction



Figure 3: A. Overall RMS velocity and velocity spectrum for left bearing [3A] in 3AY direction

A. Multiscale slope feature extraction

The vertical vibration data which is more sensitive to machine condition is considered for vibration signal analysis. Vibration signal with 1600 data samples is divided into 8 bins each containing 200 data samples. A wavelet based denoising technique, principal component analysis [12] is used to denoise the raw signals. The denoised vibration signal is decomposed to 6 levels using Daubechies wavelet of order 8 using WPT, in which turning point is at scale 4 as shown in figure 5.

The denoised vibration signals were decomposed for obtaining the wavelet packet coefficients. A plot of log-variance versus scale and scatter plot obtained by extracted multiscale slope features is shown in figure 5, in this healthy and faulty conditions of the machine has been clearly differentiated.



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Figure 5: Plot of log-variance versus scale and scatter plot for bearing 3A using WPT

B. Feature extraction using Kurtosis

The denoised vibration signal is decomposed to a level of 5 using DWT by selecting Daubechies wavelet of order 8 to obtain the detail coefficients. The kurtosis value is calculated for each level using detailed coefficients. The average kurtosis value for two different conditions has been considered for the analysis. Kurtosis value obtained for healthy condition is 112 and for faulty condition is 121. The kurtosis value which is higher for faulty condition indicates presence of a fault in the machine.

VI. CASE STUDY-II

Shot blasting blower is an auxiliary unit of shot blasting machine [10]. Blower is the component by which dusted air is suck from blasting chamber through dust collector. Drive system of shot blasting blower consists of 15 kW induction motor, pulley and belt drives. Functionally, this drive system unit is more important for working of shot blasting machine. The vibration readings were taken between the periods 25-11-2015 till 29-02-2016. Measurement locations at bearings 4A and 4B are shown in figure 6.



Figure 6: Measurement location for Shot blasting blower

Vibration data is collected only in the vertical direction because mounting of transducer is not possible in other two directions as shown in figure 6. On 21-01-2016 there is an increase in the overall RMS velocity value indicating some defect in the machine, which is witnessed in the trend plots as shown in figure 7.According to ISO 2372 chart [11], the RMS values were in the "unacceptable" range (greater than 4.5 mm/s for class I) and is mainly due to the unbalance. On 02-12-2015 the measured RMS value is low compared to other measurements.



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Figure 7: Overall RMS velocity and velocity spectrum for right bearing [4B] in 4BY direction

From the analysis of the bearing 4B, there is a trend with significant amplitude at 1xrpm and also small peaks were observed at 2x, 3x and 4xrpm as shown in figure 7. Maximum amplitude at 1xrpm is because of unbalance and small peaks were due to looseness. Looseness is small compared to unbalance.

Vibration data measured on 02-12-2015 has lower overall RMS velocity value and is considered to be the healthy condition and on 21-01-2016 has higher overall RMS velocity value is considered to be the faulty condition.

A. Multiscale slope feature extraction using WPT

For WPT a Daubechies wavelet of order 8 is selected as the mother wavelet with level of decomposition as 6 in which turning point is at scale 3 as shown in figure 9.

The vibration signals after denoising were decomposed for obtaining the wavelet packet detail coefficients. A plot of log-variance versus scale and scatter plot obtained by extracted multiscale slope features is shown in figure 9. It has been observed from the figure 9, scatter plots clearly differentiates the healthy and faulty conditions of the machine.



Figure 9: Plot of log-variance versus scale and scatter plot for bearing 4B using WPT

B. Feature extraction using Kurtosis

The signal after denoising has been subjected for decomposition to a level of 5 using DWT by selecting Daubechies wavelet of order 8 to obtain the detail coefficients. The kurtosis value has been calculated for each level using detailed coefficients of healthy and faulty condition of the machine. The average kurtosis value is considered for the analysis. Kurtosis value obtained for healthy condition is 62 and for faulty condition is 84. The kurtosis value is higher for faulty condition and lower for healthy condition.

Observations

The scatter plots obtained using WPT clearly differentiate the two conditions of the machines. The detail coefficients of WPT covers more frequency ranges and there is a less possibility for missing of frequency ranges that contains important information about the conditions of the machine. The energy level of the detail coefficients are different for healthy and faulty conditions of the machine. The feature values are different when the logarithm of variance values are different for all the scales. Kurtosis value is higher for faulty condition of the machine indicating the presence of unbalance in the machine.



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VII. CONCLUSION

In this paper, rotating machinery faults were investigated using vibration monitoring as a predictive maintenance tool in foundry. In both the case studies I and II the fault present is unbalance. Based on the features extracted from the wavelet coefficients, two techniques namely multiscale slope feature and kurtosis has been applied. The scatter plots obtained using WPT clearly differentiate the healthy and faulty condition of the machines. Kurtosis value found to be higher for faulty condition indicates presence of fault in the machines. Both multiscale slope feature and kurtosis value differentiate the healthy and faulty condition of the machine clearly, and are effective for CM of these machines.

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