Application of DWT and PDD for Bearing Fault Diagnosis Using Vibration Signal

A. Raj Kumar Patel, B. Rakesh Thapliyal C. V. K. Giri

Abstract—**Condition monitoring and fault detection of electrical machinery are one of the important issue for commercial enterprises. Incipient fault detection in hardware can spare a large number of rupee in emergency maintenance cost. In present article an efficient real time vibration measurement of an induction motor bearing on full load has been presented. The method used for the analysis and diagnosis of the fault in induction motor bearing are probability density distribution (PDD), Discrete Wavelet Transform (DWT) as a qualitative and, statistical parameters, Fast Fourier Transform (FFT) as a quantitative has been used. The discrete wavelet transform is used to process the accelerometer signals and discrete wavelet coefficient is processed to determine the spectral energy for different frequency bands containing the harmonics due to fault. The higher spectral energy signal from DWT used for the Fourier analysis to get the location of fault. The statistical parameters of detail coefficients are calculated for different levels of wavelet for faulty and healthy bearings. The outcomes got have demonstrated that this methodology is successful for bearing fault detection and analysis.**

***Index Terms*—Bearing Fault, Condition Monitoring, Fast Fourier Transform, probability density distribution, Wavelet Transform,**

I. Introduction

IN the majority of machine, for the fault detection and prognosis, vibration of rotating machine is directly measured by accelerometer. Rotating machine, even new one create some level of vibration. Small level of ambient vibration has been acceptable. However, higher levels and expanding patterns are indications of strange machine execution. Vibration measurement gives an extremely effective method for monitoring the dynamic condition of a machine, for example unbalance, mechanical looseness, structural resonance, bearing fault and shaft bow.

Rolling element is the basic parts of rotating electrical machinery and due to continuous rotation; a regular monitoring has been required. A report on failed components of induction motors has confirm that the most significant contribute to bearing failure is insufficient maintenance [1], and this can, in turn, result in winding failure within the machine [2]. According to the Motor Reliability Working Group and investigation carried by the Electric Power Research Institute (EPRI), the most common failure mode of an induction motor is bearing failure followed by stator winding failure and rotor failures. However, bearings are prone to failure due to many factors such as erroneous design or installation, corrosion, poor lubrication and plastic deformation [3]. Therefore rolling bearing failures are one of the leading causes of failure in induction motor. This requires the development of proper supervising for induction motor bearing condition to avoid capital loss. Condition monitoring based on vibration signal recording can be analyze both in time domain and frequency domain and have been widely used for detection and identification of bearing defects in various parts for 20 years [4]. In time domain analysis mainly use RMS, peak level, crest factor, skewness and kurtosis [5]. Among these, kurtosis is the most effective. Time domain information mostly rich in content, little in information. Fast Fourier Transform (FFT) technique used to transform time domain information to frequency domain, the characteristic of defect frequencies should present corresponding to the bearing defect but sometimes these frequencies components are not present in the spectra because the impulses generated by defects are hidden by noise. To overcome this problem, some signal processing techniques or trending is therefore used [6]–[8].

In the present work, the utilization of vibration signal for monitoring and analysis has been carried out on the induction motor of a power plant. The vibrations of the rotating parts of the machine were observed for a certain period of time. The diagnosing of defects stand up on the bearings of the machineries during selected period was aimed. Bearing vibration signal is analyze in time and time- frequency domain. In time domain qualitative and quantitate analysis has been performed and in time–frequency domain DWT decomposition have been applied to recorded vibration data. The study includes drive end and non-drive end data that were obtained from the machineries, which run under actual operating conditions.

II. WAVELET TRANSFORM

The purpose of signal processing is to signify the signal efficiently with fewer parameters and less computational time. One of the popular signal processing technique is wavelet transform. The nature of wavelet transform can be continuous or discrete. The continuous wavelet transform (CWT) presents

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more details about the signal but its takes more computational time [9].

The continuous wavelet transform of a finite energy signal $x(t)$ with considering wavelet$\psi(t)$which gives the wavelet coefficients by eq, (1)

$$W(a,b) = a^{-\frac{1}{2}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{1}$$

Where, 'a' is the dilation parameter controlling the wavelet frequency, 'b' is the translation parameter localizing the wavelet function in time domain and$\psi^*(t)$ is the complex conjugate of the analyzing wavelet $\psi(t)$.

In DWT, the scale 'a' and the time 'b' are discretized as following: $a = 2^m$ and $b = n * 2^m$where m and n are integers. Thus discrete wavelet $\psi_{m,n}(t) = 2^{-\frac{m}{2}}\psi(2^{-\mathrm{m}}\mathrm{t} - \mathrm{n})$ can be built, which can also found an orthonormal basis. The DWT analysis can be realize by scaling filter h(n), which is low pass filter related to the scaling function Φ(t), and the wavelet filter g(n), which is high pass filter related to the wavelet function ψ(t) [10].

$$h(n) = 2^{-1/2}\langle\phi(t), \psi(2t - n)\rangle \tag{2a}$$

$$g(n) = -1^n h(1 - n) \tag{2b}$$

The step of a fast wavelet algorithm is illustrated in Fig.1 in which signal decomposes and reconstructed.

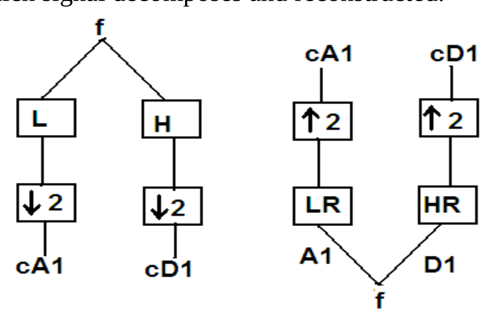

Fig. 1. (a) Decomposition (b) Reconstruction of the signal

In decomposition step, the discrete signal $f(t)$ is convolved with low pass filter L and a high pass filter H, resulting two vector $cA1$ and $cD1$, called approximation and detail coefficient respectively.

In reconstruction step, a pair of low and high pass reconstruction filter LR and HR are convolved with two vector$cA1$, and$cD1$, respectively, important property of this step is $f = A1 + D1$. The two signals after reconstruction $A1$ and $D1$ called approximation and detail. The symbol ↑2 and ↓2 represent up sampling and down sampling.

The procedure of the step can be repeated on the approximation vector $cA1$ and successively on every new approximation vector cA_j with different scales.An approximated signal by DWT can be represented by means of wavelet tree with j levels as shown in Figure 2.

Each of the wavelet scales corresponds to a frequency given by [11].

$$f = \frac{2^{i-j} f_S}{2^j} \tag{3}$$

Where f is higher frequency limit of frequency band represented by decomposition level j, f_s is sampling frequency, 2^i is the number of samples in the signal.

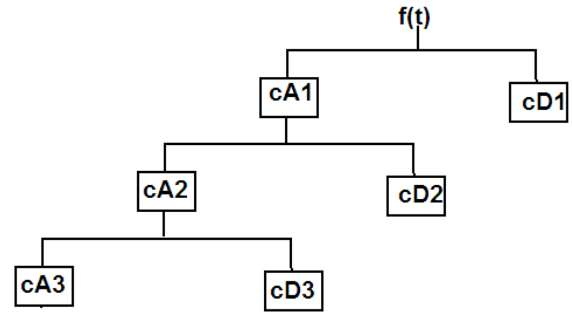

Fig. 2. An example of three – level wavelet tree

The reconstructed signal can be observed and analyze deviation from the original signal due to present of responsible component of fault at each detail level. The frequency bands of the detailed coefficient at different decomposition level are shown in Table. 1 [12].

In the present paper, the vibration of a power plant induction motor bearing type 6309 (SKF) was monitored. The rotation of the motor are 2900 rpm and signal is recorded at 65536 samples/sec, each acquired signal has a length of 8192 points. The measurement of vibration performed in axial, horizontal and vertical directions using accelerometer of bearing. A recorded signal from the vertical direction was influential compared with the other two directions so the vibration signal measured in the vertical direction has been used to describe the health of machinery. Two measurements have been taken from drive end and non-drive end with a time interval of one week.

TABLE I.

FREQUENCY BANDS AT DIFFERENT LEVELS

level	Frequency band (Hz)
cD1	8192-16384
cD2	4096-8192
cD3	2048-4096
cD4	1024-2048
cD5	512-1024
cA5	0-512

III. DATA PROCESSING

For recorded signal $x(t)$, a pre-process is necessary to lighten the influence of random variables before the analysis. This process can be perform as

$$y(t) = \frac{x(t) - \bar{x}}{\sigma} \tag{4}$$

Where,$x(t)$ is the pre-processed signal, $\overline{x}$ is the mean value of $x(t)$ and σ denoted the standard deviation of $x(t)$.

In bearing fault detection, by examining the magnitude of the vibration data under operating conditions with incipient bearing faults, it is possible to distinguish the normal data from faulty data as shown in Fig. 3.Because the early detection and isolation of faults is important for condition based maintenance, a more sophisticated signal processing is necessary. The first approach is to process the recorded data in time domain and second approach in time –frequency domain. In time domain qualitative analysis using PDD and quantitative analysis using statistical parameter has been performed. To better explore fault-related information, in time-frequency domain DWT can be used to divide finer frequency ranges and calculate the energy of each sub- band.

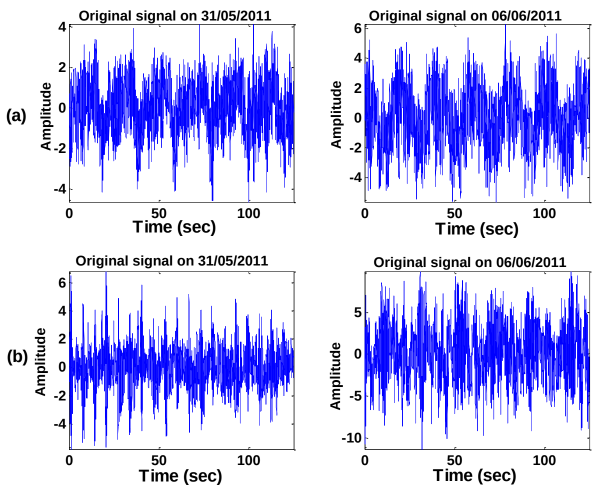

Fig. 3. (a) Non drive end (b) Drive end vibration signal of rolling bearing.

IV. BASIC STATISTICAL PARAMETER FOR DATA ANALYSIS

One of the simpler detection and diagnosis approaches is to analyse the measured vibration signal in the time domain.The simplest, though not the most reliable way to detect faults in machines is to compare their vibration levels with standard criteria for vibration severity. In the time domain analysis, first we use the probability density distribution function $p(x)$ of vibration signal. The probability density of the distribution of data sample is defined as:

$$prob[x \leq x(t) \leq x + dx] = p(x)dx \tag{5}$$

Fig. 4 and Fig. 5 shows PDD of non- drive end and drive end recorded vibration data of an induction motor for a recording time duration of one week. To analyse the vibration signal for a bearing in a good condition, along with the sample, probability density distribution reveals that a bearing in good condition has vibration probability density depicts a roughly Gaussian curve, whereas a deterioation and damaged bearing lead to non-Gaussian distribution withdominant tails because of a relative increase in the number of high levels of acceleration [13], [14]. From figure it is concluded that non-drive end shows perfect gaussian curve for both the recording which indicate that non-drive end is in healthy condition while drive end shows the peeky gaussian curve in later recording, which leads to suspecius damage of the bearing.

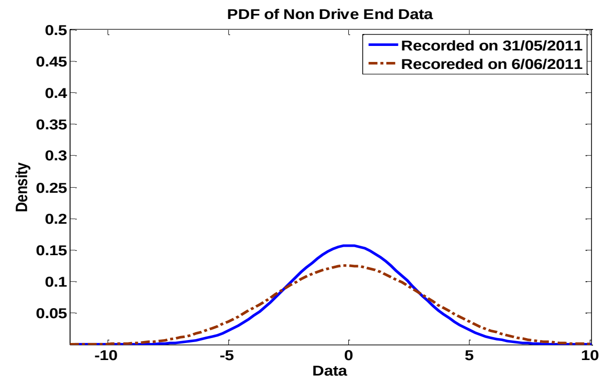

Fig. 4. PDD of non-drive end vibration signal of rolling bearing.

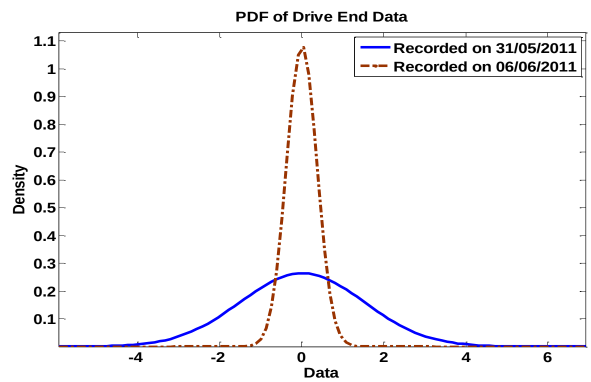

Fig. 5. PDD of Drive end vibration signal of rolling bearing.

The qualitative analysis is not much reliable. Hence, instead of studying the probability density distribution curves, it is often more informative to examine the numerical parameters. Statistical parameters that have been calculated in time domain are generally used to express average properties of recorded signal from rotating machine. The mean value, μ and standard deviation, σ are the two fundamental quantities for a given data set $\{x_i\}$ is used in this paper and these are defined as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i, \tag{6}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}, \tag{7}$$

Where, N is the number of the data points.

For the Gaussian probability distribution, two parameters that reflect the departure from normal distribution are skewness (c) and kurtosis(k). These are calculated as follows:

$$c = \frac{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^3\right]}{\sigma^3}, \tag{8}$$

$$k = \frac{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^4\right]}{\sigma^4}, \tag{9}$$

For a perfect normal distribution, c is equal to zero. Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the centre point. A negative value is due to skewness towards lower values while a positive indicates non symmetry towards high value. For small data sets, one often gets values that different from zero. The kurtosis or flatness k is indicates impulsiveness of the signal and it is very close to unity for normal distribution. Theses statistical parameter may use to perform a quick check of the changes in the statistical behaviour of a signal [15].

V. Result and Discussion

For more reliable damage detection the recorded signals are decompose using DWT and reconstructed. The decomposed signals are set of frequency bands and indicated by D1, D2, D3, D4, D5, and A5 as shown in Figure 6 and 8 for non-drive and drive end recorded signal on difference of one week. In these figures, the approximate (A5) and five levels of details (D1-D5) are chosen for each signal. The non-drive end data has not significant changes in magnitude on both the recording data. However for drive end data; there are significant changes, in both the recording in all the sub-bands of the DWT decompositions. Based on these plots qualitatively fault can be separated from the normal condition. From the figure 8 it can also observed that the maximum changes of magnitude in sub-band D2 which is belong to higher frequency. This hints to focus on D2 sub-band. Further, energy is calculated of each sub–bands as shown in figure 7 and figure 9. When this approach applied to the available data, it is found that, the abnormal change in energy in sub-band D2 of drive end signal. Which confirm that the D2 sub band is rich in information. The change in energy in case of non-drive end signal in all sub-band is insignificant and in a regular pattern. Statistical parameters of sub band D2, also has been calculated and shown in Table II and Table III for both non-drive end and drive end data respectively. The comparison result shows, there is a radical change in peak value and standard deviation of the D2 sub band of drive end signal in comparison with D2 sub band of non-drive end signal. The kurtosis values of the bearing also shows the trend; kurtosis value increases as the bearing defect increases, i.e, kurtosis value recorded on 31/05/2011 is less than the kurtosis value recorded on 06/06/2011.

Only identifying the fault in the bearing is not sufficient [16] [17]. It is also important to know the location of fault in the bearing so that proper replacement can be manage. In order to know the location of fault it is necessary to observe the frequency due to damage of the bearing. It is known that, the different location of fault in the bearing produce different frequencies and it is decided by its structural design.

The challenges are to identify the fault frequency as the recorded data are become noisy during recording and fault frequencies are generally hidden. The fault frequencies corresponding to fault location are provided in Table IV. These frequencies are Fundamental Train Frequency (FTF), Ball Spin Frequency (BSF), Ball Pass Frequency, Outer Race (BPFO), Ball Pass Frequency, Inner Race (BPFI) and have been calculated as follows [6]:

$$FTF = \frac{f_r}{2}\left[1-\left(\frac{B_d}{P_d}\right)cos\theta\right] \quad (10)$$

$$BSF = \frac{f_r}{2}\left(\frac{P_d}{B_d}\right)\left[1-\left(\frac{B_d}{P_d}\right)^2 cos\theta\right] \quad (11)$$

$$BPFO = N*(FTF) \quad (12)$$

$$BPFI = (f_r-(FTF)) \quad (13)$$

Where, f_r, B_d, P_d, θ are the revolution per second of inner race or the shaft, Ball diameter, pitch diameter and contact angle respectively. Manufacturers often provide these fault frequencies in the bearing data sheet.

In order to get the fault location the FFT is perform on D2 signal of drive end data and shown in Figure 10. The obtained frequency is corresponding to the fault on ball of the bearing that is 300 Hz. Hence, on the basis of above analysis, it is concluded that health of drive end side ball bearing is not in good condition in comparison with non-drive end side. It is also confirmed that the fault exist in ball of the bearing.

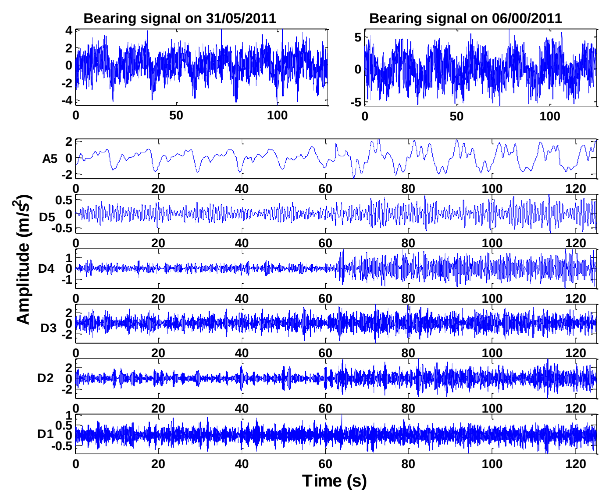

Fig. 6. Details and approximations of vibration signal of non-drive end

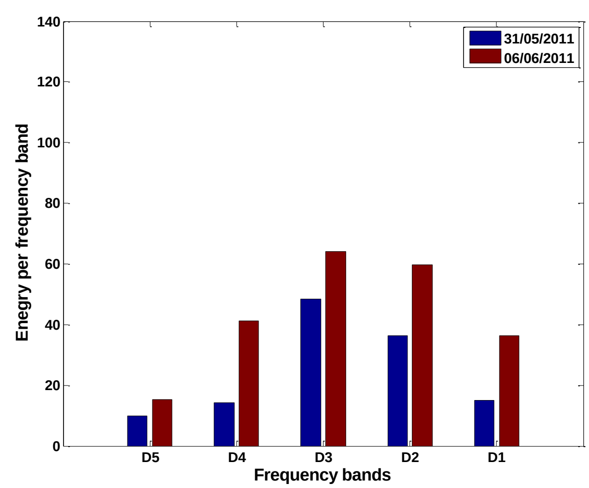

Fig. 7. Average Energy Contained in the Frequency Sub-Bands for Vibration Data for Non-Drive End.

TABLE II. STATISTICAL PARAMETER OF NON-DRIVE END SIGNAL

Date	*Sub-band (D2)*	*Peak*	*Std deviation*	*Skewness*	*Kurtosis*
31/05/ 2011	4096-8192	2.300	0.567	-0.017	4.762
06/06/ 2011	4096-8192	3.698	0.932	0.018	3.659

TABLE III. STATISTICAL PARAMETER OF DRIVE END SIGNAL

Date	*Sub-band (D2)*	*Peak*	*Std deviation*	*Skewness*	*Kurtosis*
03/05/ 2011	4096-8192	1.389	0.347	-0.014	4.216
06/06/ 2011	4096-8192	9.447	2.039	0.016	4.462

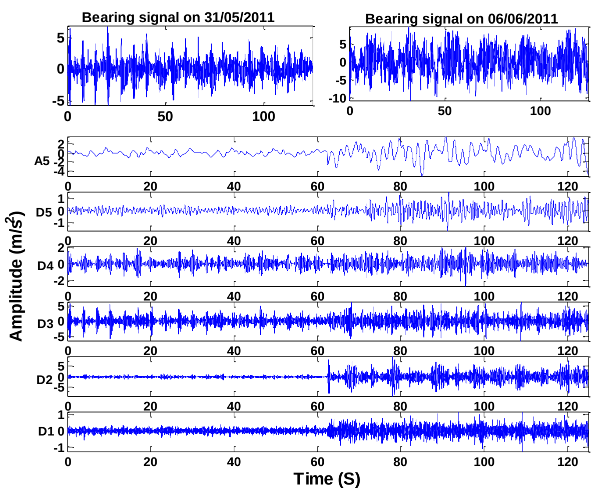

Fig. 8. Details and approximations of vibration signal of drive end.

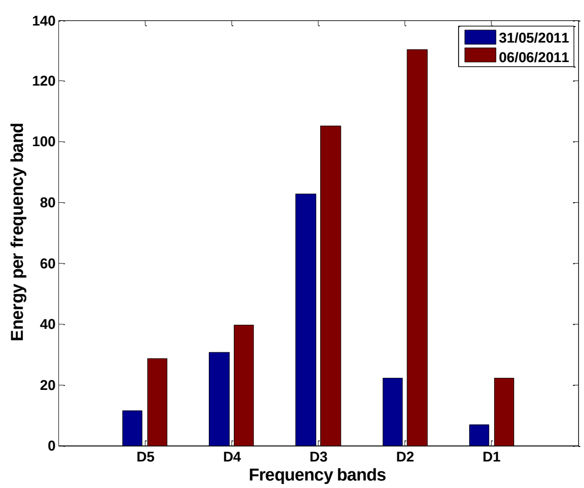

Fig. 9. Average Energy Contained in the Frequency Sub-Bands for Vibration Data for Drive End.

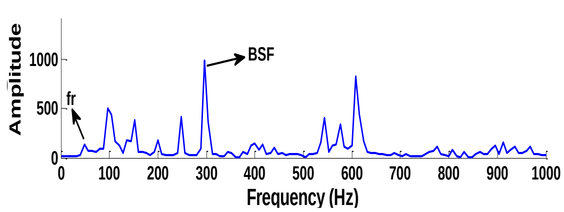

Fig. 10. FFT of Signal D2 Sub-Bands of Drive End Data

TABLE IV. FAULT FREQUENCIES

Machine	BPFI (Hz)	BPFO (Hz)	BSF (Hz)	FTF (Hz)
Frequency	501.94	368.06	302.81	20.45

VI. CONCLUSION

In this study, fault diagnosing techniques of the ball roller element bearing of power plant induction motor have been investigated. All measured data are analyzed and compare using DWT in time-frequency domain and statistical parameter, PDD in time domain. DWT node energy decided the present of faults, as it increases significantly in drive end data. Finally, location of faults also investigated using Fast Fourier Transform method. Vibration monitoring and discrete wavelet transform as a predictive maintenance tool. Ball bearing defect on drive end side were successfully diagnosed.

VII. ACKNOWLEDGEMENT

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