

## **Induction Motor Bearing Fault Diagnosis Using Cascaded EMD and DWT techniques**

**Raj Kumar Patel\* V. K. Giri\*\***

*\*MMMUT, Gorakhpur, 273010, Uttar Pradesh, India,, India,  
E-mail: rajkp007@gmail.com*

*\*\*MMMUT, Gorakhpur, 273010, Uttar Pradesh, India,  
E-mail: girivkmmm@mmm.ut.ac.in*

### **Abstract**

The aim of this paper is to develop a method based on a combination of empirical mode decomposition (EMD) and discrete wavelet transform (DWT) for assessment of damage of the induction motor bearing. A machine in standard condition has certain vibration signatures. These signatures are modulated by a number of high frequency harmonic components resulting from structural response to individual impacts. Fault development changes that signature in such a way that can be related to the faults, and EMD is used to separate these intrinsic modes known as intrinsic mode functions (IMFs). Hilbert Transform (HT) is applied to first four IMFs to get instantaneous amplitude and then applied power spectral density (PSD), to identify the related defect frequencies. Later, DWT has been applied to the IMF, which has higher amplitude and again fault frequencies are obtained from HT and PSD. The work evaluates the detection ability of the applied methods. The obtained results show that the proposed method is superior to the traditional envelope spectrum method of extracting the incipient faults of roller bearings.

**Index Terms:** Empirical Mode Decomposition (EMD), Hilbert Transform (HT), intrinsic mode function (IMF), Power Spectral Density (PSD).

### **1. Introduction**

Nowadays, Induction motors are being widely employed in various industries. Though, spread of induction motor has given many convenient solutions to various industries yet their use poses a significant threat to condition monitoring engineers. In most of the electrical machines for the faults diagnosis and prediction, vibration signals have been found very much useful. These vibration signals have some

significant information or clue which is further utilized in fault diagnosis. These signals in the electrical rotating machine are directly recorded by the accelerometer and provide an efficient way of monitoring the conditions, namely unbalance, mechanical looseness, structural resonance, bearing fault and shaft bow of a machine [1-3]. It has been experienced that the majority of problems in a rotating machine arises from a faulty rolling element. The rolling elements also called bearings are one of the most critical parts of a rotating machine. It has been reported in the literatures that significant cause of bearing failure is inadequate maintenance, which further cause winding failure [4-6]. Therefore, it is needed to cancel the harmful effects posed by them. Mitigation of undesired faults in induction motor bearing needs assessment methods which make correct damage detection.

The basic premise of global damage detection is that; it alters the mass, damping, or stiffness properties of a structure, and finally its dynamic responses[7]. It is required a damage indicator which may assess the presence of damage in a structure by using its responses. Generally, singularity or discontinuity in the response signal of a system, brought on by a sudden change in its dynamic characteristics, can't be recognized by time-analysis. The recorded vibration signal from induction motor bearing are being processed using various digital signal processing techniques (DSP) and finally; features are therefore extracted[8-9]. The extraction of features of recorded signals has been constantly area of interest for condition monitoring engineers. Several studies on signal processing techniques have been reported in the literatures. Among these, the Fourier Transform (FT) technique is commonly used in practice to provide the defect frequencies present in the signal[10]. Although, FFT (Fast Fourier transform) is one of the fast technique but its limited to stationary signal only. Most vibration signatures are non-stationary in nature and therefore, a technique needed, which would not only provide frequency information, but also capture the timing of the events of the defects. As an improvement to FFT technique, the Short-Time FT (STFT) has been reported in the literature [11]. Here, the algorithm employed a stationary window function. However, it has been found that STFT technique needs a significant amount of computation. In the literature [12-14], wavelet transform (WT) has been shown to be suitable for the analysis of non-stationary signals. By allowing variations in time and frequency plane, a multiresolution analysis can be gained. The idea is to offers superior temporal resolution of the high frequency components and scale (frequency) resolution of the low frequency components. This is often beneficial as it allows the low frequency components, which usually give a signal its main characteristics or identity, to be distinguished from one another in terms of their frequency content, while providing an excellent temporal resolution for the high frequency components which add the nuance's to the signals behaviour. The main disadvantage of wavelet transform is its degraded performance under noisy and its basis functions depend on the signal itself thereby making it non adaptive in nature.

As Stated [15], non-stationary signal may not be represented well by sinusoidal components. Since, frequency is defined well for sinusoidal components it loses its effectiveness for nonstationary signal. This has caused notion of Instantaneous Frequency (IF). The instantaneous frequency has mono component signal composing

ora single frequency of a narrow band of frequencies. This motivates to decompose a signal into a number of mono component modes for which IF can be defined. A distorted signal can be conceptualized as superimposition of oscillations of various time scales. This paper thus, puts forward an approach of induction motor bearing assessment based on expanding a distorted signal into its intrinsic mode oscillations. Empirical Mode Decomposition is a time-frequency analysis method developed by Huang et al., [16] which is based on the local characteristic time scale of the signal and decomposes the complicated signals into number of IMFs. These IMFs are mono-component signals and give well behaved Hilbert transform (HT) and thus help in obtaining instantaneous frequencies of nonstationary signals. The characteristic which distinguishes EMD from other techniques is its adaptability from the signal.

This paper develops an assessment of faults by cascading the EMD and the DWT based method. To identify the bearing fault for rotating machinery vibration signal is taken from the induction machine which has been discussed in section 2. Section 3, 4 and 5 gives a brief introduction of EMD, DWT and HT. The results and discussion have been presented in section 6 in which the obtained results have been compared to the traditional methods.

## 2. Vibration Data

The real vibration data of a ball bearing type 22220EAS (FAG) for induction machine have been monitored for the fault diagnosis purpose. The induction machines are installed in a power plant, runs at 2900 rpm and the vibration signal has been recorded at the 65536 samples/sec. Each acquired signal has a length of 8192 points. Table 1 shows the main fault frequencies based on the geometric structure of the bearing used in this work [14]. 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:

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

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

$$BPFO = N * (FTF) \tag{3}$$

$$BPFI = (f_r - (FTF)) \tag{4}$$

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

Vibrations have been measured in axial, horizontal and vertical directions of drive end side at full load. The vertical direction signal is dominant and compared with the other two directions. So the vertical measured vibration signal is used to characterize

the health of machinery. The measurement data have been analysed using, FFT, DWT and statistical parameter in time domain.

**Table 1:** Bearing Characteristic Frequencies

Machine	BPFI(Hz)	BPFO(Hz)	BSF(Hz)	FTF (Hz)
Frequency	501.94	368.06	152	20.45

### 3. Empirical Mode Decomposition (EMD)

EMD is a method of breaking down a signal without leaving the time domain analysis. It can be compared with other analysis methods like Fourier Transforms and wavelet decomposition. It is useful for analysing natural signals, which are most often nonlinear and non-stationary. The real world signals are not purely sinusoidal or stationary. Researchers seeking to analyse the oscillation modes of nonlinear and non-stationary signals and realized that complex signals can be represented as a combination of different sinusoidal component. The representation of these real world signals with sinusoidal component has been just a compromise with the assessment of an event. The sinusoidal signals involve only one oscillatory mode at any given time. These are called “mono component signals” [17]. The requirement suggests a methodology to separate different component of a signal such that for each component EMD, is a signal processing technique that decomposes a complex signal into a set of mono component signals, defined as Intrinsic Mode Functions, via a procedure called “the sifting process”. The decomposed signals have only one extreme between zero crossings, and have a mean value of zero. The shifting process is as follows:

Let  $f(t)$  be the signal to be analysed and decomposed. For a signal  $f(t)$ , let  $m_1$  be the mean of its upper and lower envelopes as determined from a cubic-spline interpolation of local maxima and minima. The locality is determined by an arbitrary parameter; the calculation time and the effectiveness of the EMD depend greatly on such a parameter.

The first component  $imf_1$  is computed as:

$$imf_1 = f(t) - m_1 \quad (5)$$

In the second sifting process,  $imf_1$  is treated as the data, and  $m_1$  is the mean of  $imf_1$  upper and lower envelopes:

$$imf_2 = imf_1 - m_{11} \quad (6)$$

This sifting procedure continues until all the  $imf_s$  have been extracted or the residue has become a monotonic function. Finally, the original signal  $f(t)$  can be expressed as the sum of the  $imf$  components, plus the final residue:

$$f(t) = \sum_{j=1}^{N_e} imf_j(t) + rN_e(t) \tag{7}$$

Where,  $imf_j$  is  $j^{th}$   $imf$  and  $rN_e(t)$  is the final residue. After the EMD, the existed first  $imf$  component has the highest frequency content of the original signal  $f(t)$ , while the final residue represents the component of the lowest frequency in the signal  $f(t)$ . In short, the EMD picks out the high frequency oscillation that remains in  $f(t)$  iteratively.

#### 4. Discrete Wavelet Transform

The wavelet transform is a time-frequency analysis technique. The unique property of the wavelet transform that keeps intact the time and frequency information is very important during transient analysis. It decomposes a signal in both time and frequency in terms of a wavelet, called mother wavelet. The DWT is computed by passing the signal successively through low pass and high pass filters. A signal can be approximated by DWT with different scales [18-19]. Each step of the decomposition of the signal corresponds to a certain resolution. Figure 1 shows the typical two-level wavelet decomposition. Here, HPF and LPF are high pass filter and low pass filter respectively. At each level of scaling and for various positions, the correlation between the signal and the wavelet are called wavelet coefficients [20]. The high pass filter coefficients are termed as detail coefficients (D1, D2...) and the low pass filter coefficients are termed as approximate coefficients (A1, A2...). After decomposition of the signal, one can reconstruct and examine the constituent components of the original signal at each detail level.

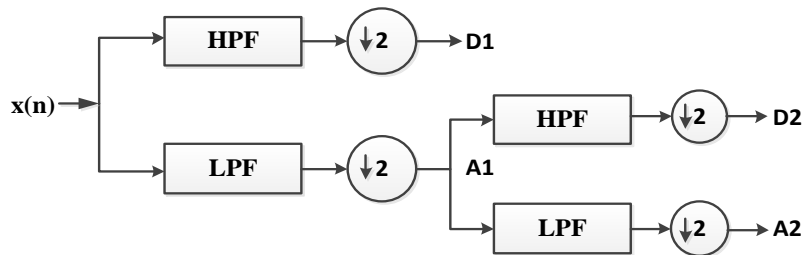


Figure 1: An example of two – level wavelet tree

#### 5. Hilbert Transform

The HT, as a kind of integral transformation, plays a significant role in vibration analysis [16]. It is one of the common ways which may be used as a direct

examination of a vibration instantaneous attribute frequency, phase and amplitude. For one *imf*, we can always have its Hilbert transform as:

$$H[imf(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{imf(\tau)}{t - \tau} d\tau \quad (8)$$

Where,  $t$  and  $\tau$  are the time and transformation parameters respectively.

Because of the possible singularity at, the integral is to be considered as a Cauchy principal value. The Hilbert Transform is equivalent to an interesting kind of filter, in which the amplitudes of the spectral components are left unchanged, but there is phase shifted by.

In machinery fault detection, modulation on caused by local faults is inevitable in collecting signals. In order to identify fault related signatures, demodulation is a necessary step, and it can be accomplished by HT of signal *imf* results in an analytical signal  $Z(t)$  as shown in equation 9.

$$z(t) = imf(t) + iH[imf(t)] = a(t)e^{i\theta(t)} \quad (9)$$

where

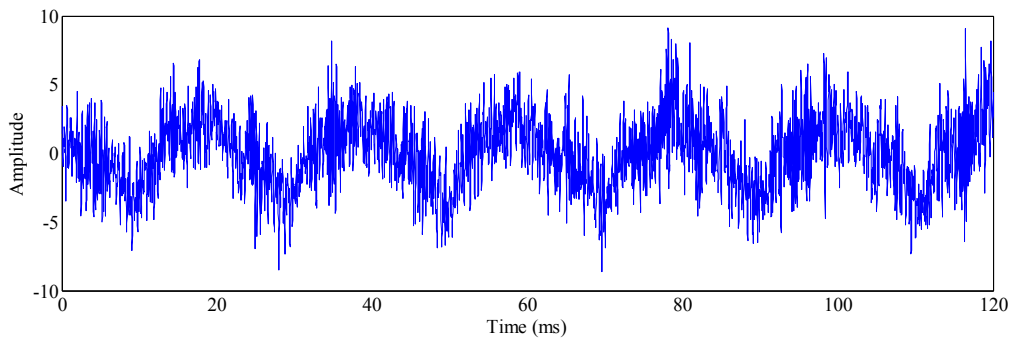
$$a(t) = \sqrt{imf(t)^2 + H[imf(t)]^2};$$

$$\theta(t) = \arctan\left(\frac{H[imf(t)]}{imf(t)}\right)$$

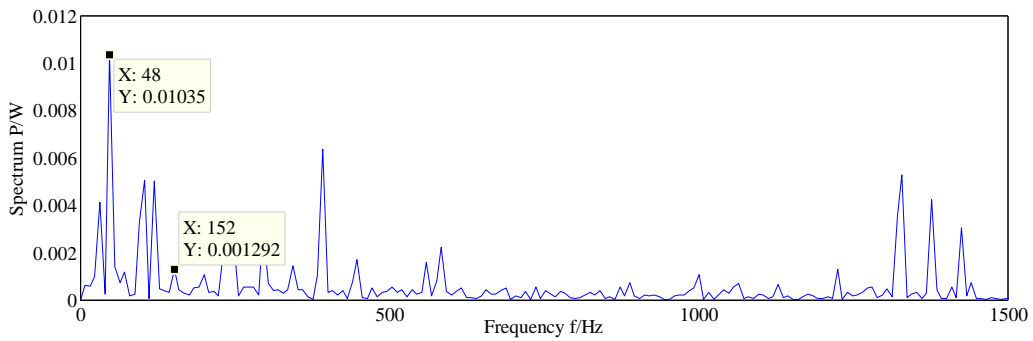
$a(t)$  representation estimate of the modulation in the signal. The Hilbert Transform on each mode of oscillation i.e.  $imf_s$ , which satisfy the condition of local symmetry with respect to zero mean, can give information about instantaneous frequencies (which is given by  $\omega = d\theta / dt$ ) in each mode.

## 6. Results and Discussions

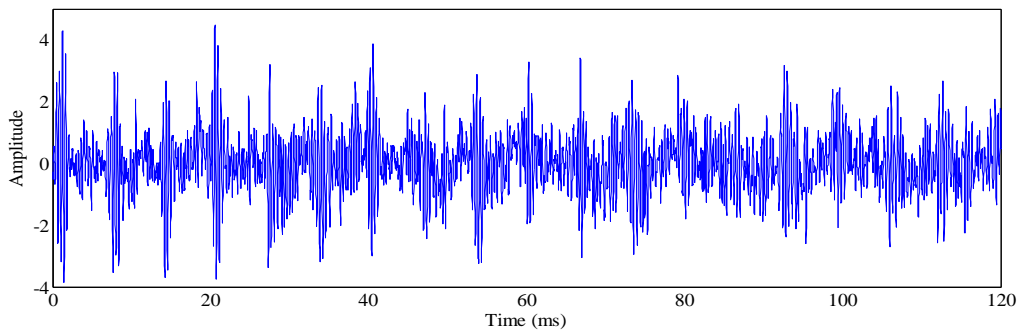
Figure 2 shows the vibration signal which is recorded from a running induction motor to know the condition of rotating parts of the machine i.e. bearing. For the purpose of assessment, the popular method HT is used to find out the envelope of the recorded signal. After getting the envelope, PSD has been used to know the frequency components exist in the recorded signal. Figure 3 shows the PSD of obtaining envelope and it is found that 48 Hz, which is running frequency and small amplitude of 152 Hz. Frequency 152 Hz is a suspect component about the fault. Figure 4 is vibration signal recorded on the same machine after two weeks and Figure 5 is the PSD of same recorded signal. Figure 6 shows the frequency of 152 Hz and its multiple which clearly indicates that the fault exist in the roller of the bearing and match from Table 1. From the above it is concluded that the suspect component of frequency is actually an incipient fault in the roller of the bearing and it is needed to identify the fault at the initial state to stop catastrophic failure.



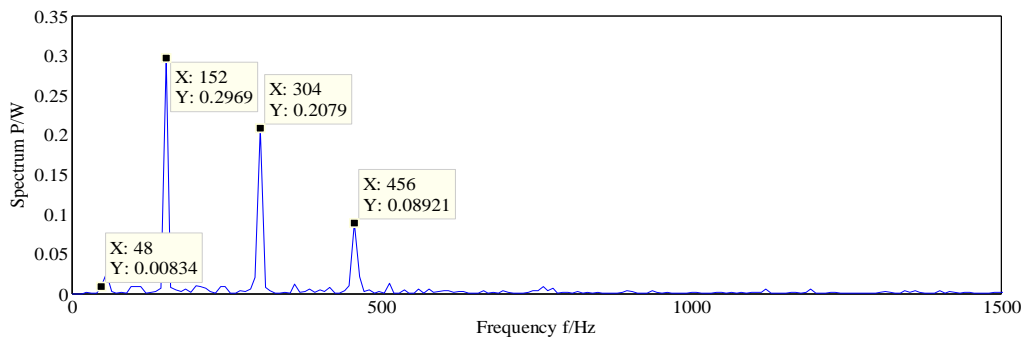
**Figure 2:** Recorded Bearing Vibration Signal for the Assessment



**Figure 3:** PSD of Envelope obtain from Recorded Signal



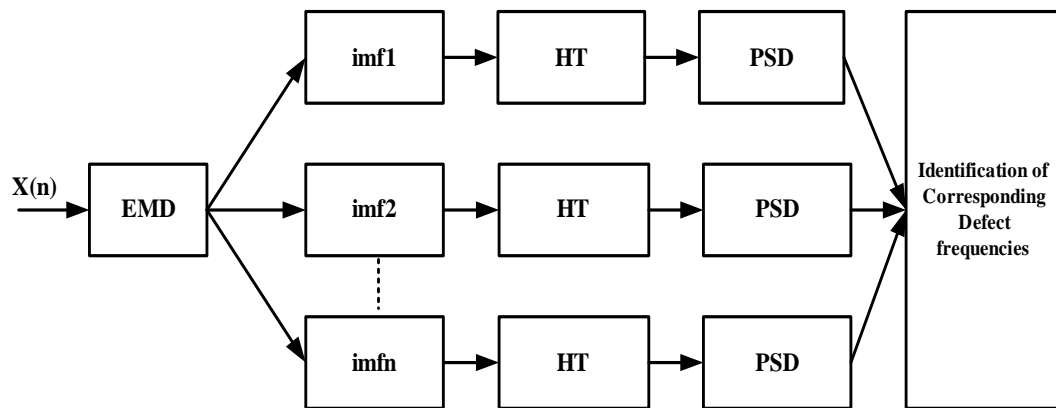
**Figure 4:** Recorded Bearing Vibration Signal after one Month Later



**Figure 5:** PSD of Obtained Envelope from Recorded Vibration Signal

Envelope analysis is used widely, but sometimes it is difficult to decide the central frequency and bandwidth of the band-pass filter. Due to this difficulty envelope detections fails to identify the incipient fault. In order to overcome this problem, in thiswork a combination of EMD and Hilbert Transform is used to identify the defect frequency at an early stage. Figure 6 shows the flow chart of the steps to identify the defect frequencies.

The EMD method can decompose the signal into different frequency bands adaptively. Therefore, in this EMD method is used as a band-pass filter to extract the resonance vibration from the original vibration signal. The central frequency and bandwidth of the filter are not decided any more.



**Figure 6:** Flow hart of Identification of Defect Frequencies Using EMD

The acceleration signal of the bearing with a fault in the roller of the bearing is shown in figure 2 and EMD method has been applied to the signal of defective bearing. The original acceleration signal is decomposed into eleven frequency bands from high to low. Here, first four are represented by  $imf_1$ ,  $imf_2$ ,  $imf_3$ ,  $imf_4$  respectively in figure 7. The amplitude at high frequency ( $imf_1$ ,  $imf_2$ ,  $imf_3$  and  $imf_4$ ) increases. Among first four IMF components, the vibration level increases and the resonant vibrations due to the impulses are found. HT and PSD have been performed on the each IMF of figure 7 and the obtained characteristics are shown in figure 8. In the figure the peak's frequency 152 Hz is similar to the characteristic defect frequency of roller element (BSF) and it has been found that the visibility of BSF is clearer than Figure 3. In order to improve the visibility, further EMD is cascaded with DWT.

Figure 9 shows the flow chart of cascaded EMD and DWT. Figure 10 reveals the decomposed signal of higher amplitude of IMF using DWT. Figure 11 illustrates the envelope spectrum of the discrete wavelet decomposition in the same frequency band. It is found that the defect frequency identification is easier using the propose method.



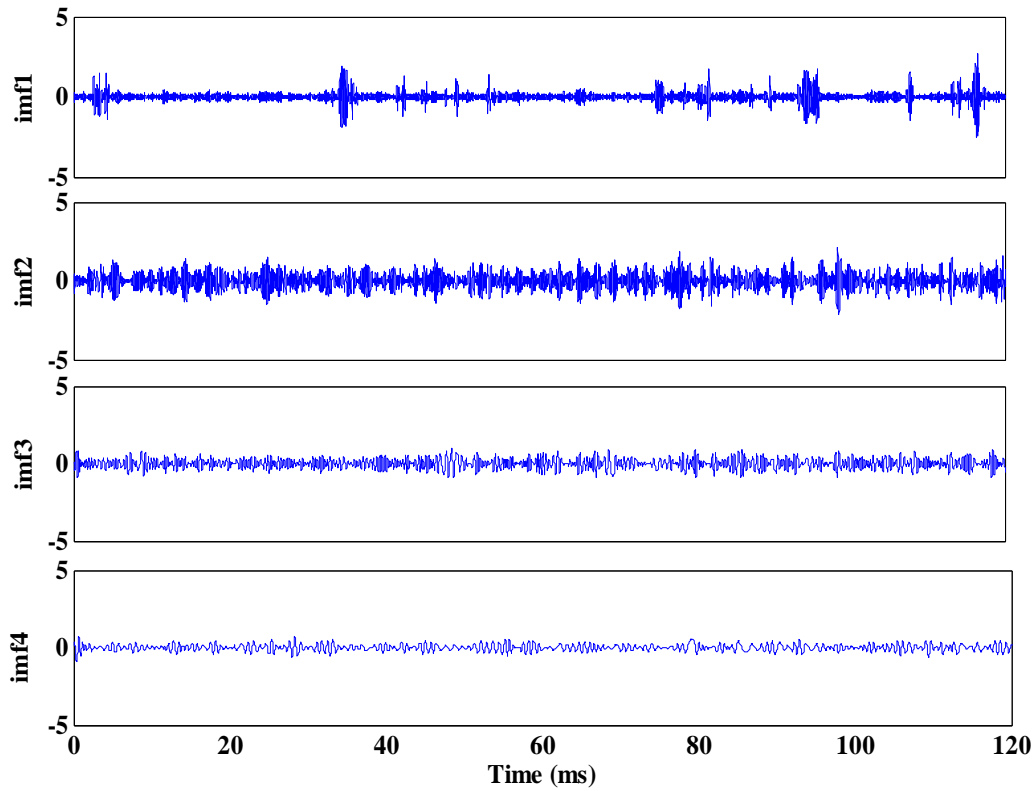


Figure 7:IMFs of Vibration Signal with Incipient Fault

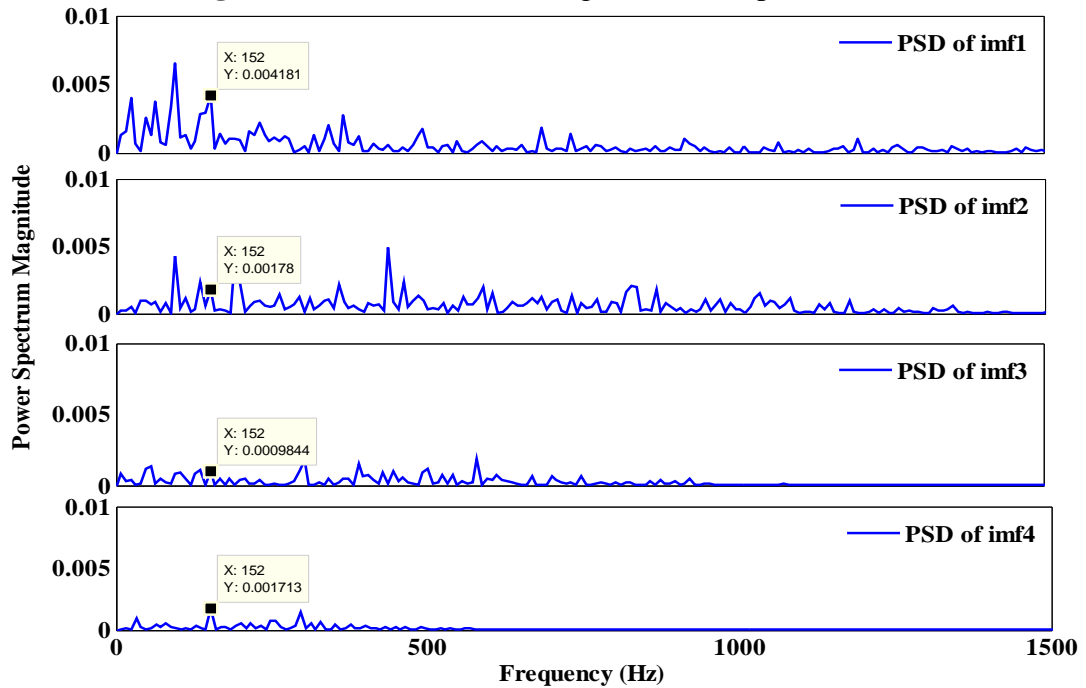
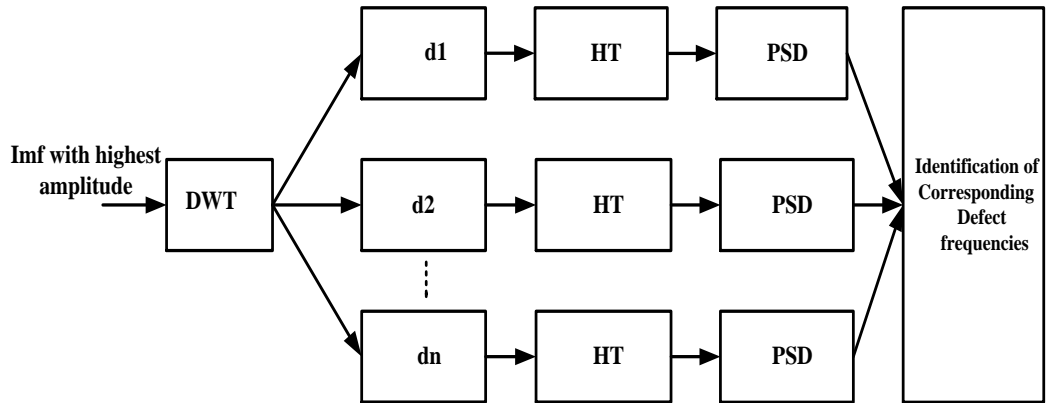
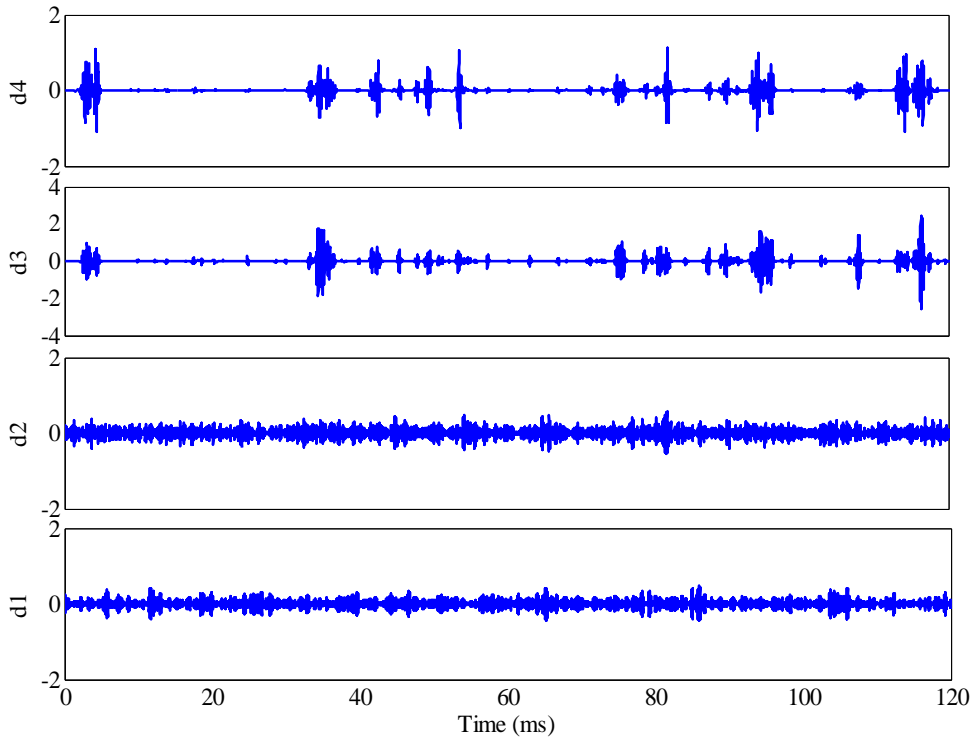


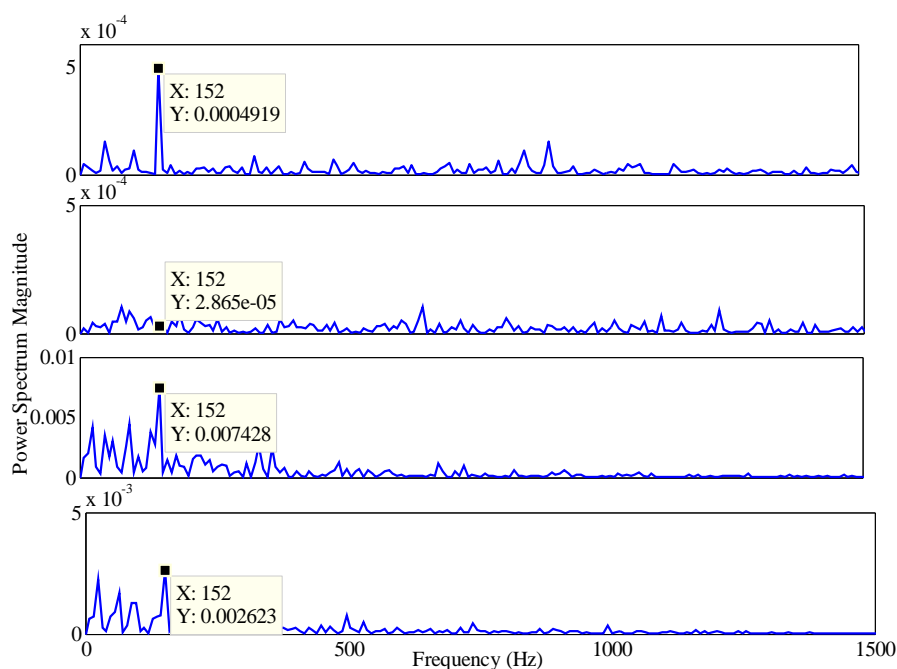
Figure 8:HT and PSD of imf1, imf2, imf3 and imf4 of Vibration Signal with Incipient Fault



**Figure 9:** Flow Chart of Identification of Defect Frequencies using Cascaded EMD and DWT



**Figure 10:** DWT of imf1 of Vibration Signal with Incipient Fault



**Figure 11:** HT and PSD of d1, d2, d3, and d4 of Vibration Signal with Incipient Fault

## 7. Conclusions

The HT and PSD analysis method is a practical approach for the fault diagnosis of roller bearings, whereas the traditional way has its limitations. In order to overcome its limitations, cascaded EMD and DWT are combined with traditional way and applied to the fault diagnosis of roller bearings, and better results are being obtained. In the proposed method, due to its better adaptability, EMD may be used as a powerful tool for fault diagnosis. The vibration signal of a roller bearing with faults is translated into time-scale representation by using the wavelet bases. Hilbert transform is then used to make an envelope analysis of wavelet coefficients of high scales that represent the high-frequency components. By applying PSD, we can obtain the local marginal spectrum from which the faults in a roller bearing can be diagnosed and fault patterns can be identified. The results show that the proposed method is superior to the traditional envelope spectrum method of extracting the fault characteristics of roller bearings.

## Acknowledgements

This work is supported by Technical Education Quality Improvement Program-II (TEQIP- II), at M.M.M. University of Technology, Gorakhpur, a program of the government of India. The authors would like to thank Mr. Vipin Kumar of Aimil Ltd. for providing the bearing data of a power plant Induction motor

## References

- [1] KN Gupta, "Vibration—A tool for machine diagnostics and condition monitoring," *Sadhana*, 1997.
- [2] GG Yen and KC Lin, "Conditional health monitoring using vibration signatures," *Decision and Control*, 1999.
- [3] R. Heng and M. Nor, "Statistical analysis of sound and vibration signals for monitoring rolling element bearing condition," *Applied Acoustics*, 1998.
- [4] HM Monavar, H Ahmadi, and SS Mohtasebi, "Prediction of defects in roller bearings using vibration signal analysis," *World Applied Sciences Journal*, 2008.
- [5] S. Khanam, J. Dutt, and N. Tandon, "Extracting Rolling Element Bearing Faults From Noisy Vibration Signal Using Kalman Filter," *Journal of Vibration and Acoustics*, vol. 136, no. 3, pp. 1–11, 2014.
- [6] C. Liu, G. Wang, Q. Xie, and Y. Zhang, "Vibration Sensor-Based Bearing Fault Diagnosis Using Ellipsoid-ARTMAP and Differential Evolution Algorithms," *Sensors*, vol. 14, no. 6, 2014.
- [7] N Tandon and A Choudhury, "An analytical model for the prediction of the vibration response of rolling element bearings due to a localized defect," vol. 205, no. 3, pp. 275–292, 1997.
- [8] J.-Y. Zhang, L.-L. Cui, G.-Y. Yao, and L.-X. Gao, "Research on the selection of wavelet function for the feature extraction of shock fault in the bearing diagnosis," vol. 4, pp. 1630–1634, 2007.
- [9] G. Bin, J. Gao, X. Li, and B. Dhillon, "Early fault diagnosis of rotating machinery based on wavelet packets—Empirical mode decomposition feature extraction and neural network," *Mechanical Systems and Signal Processing*, vol. 27, pp. 696–711, 2012.
- [10] J. Abellan-Nebot and F. Subirón, "A review of machining monitoring systems based on artificial intelligence process models," *The International Journal of Advanced Manufacturing Technology*, vol. 47, no. 1, pp. 237–257, 2009.
- [11] L. Zhu, H. Ding, and X. Zhu, "Synchronous Averaging of Time-Frequency Distribution With Application to Machine Condition Monitoring," *Journal of Vibration and Acoustics*, vol. 129, no. 4, pp. 441–447, 2007.
- [12] N. Saravanan and K. Ramachandran, "Incipient gear box fault diagnosis using discrete wavelet transform (DWT) for feature extraction and classification using artificial neural network (ANN)," *Expert Systems with Applications*, vol. 37, no. 6, pp. 4168–4181, 2010.

- [13] K. Aharamuthu and E. Ayyasamy, "Application of discrete wavelet transform and Zhao-Atlas-Marks transforms in non stationary gear fault diagnosis," *Journal of Mechanical Science and Technology*, vol. 27, no. 3, pp. 641–647, 2013.
- [14] Y Wang, W Wu, Q Zhu, and G Shen, "Discrete Wavelet Transform for Nonstationary Signal Processing," ... *WAVELET TRANSFORMS* □ ..., 2011.
- [15] B. Boashash, "Estimating and interpreting the instantaneous frequency of a signal. I. Fundamentals," *Proceedings of the IEEE*, vol. 80, no. 4, pp. 520–538, 1992.
- [16] N. Huang, Z. Shen, S. Long, M. Wu, H. Shih, Q. Zheng, N. Yen, C. Tung, and H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 454, no. 1971, pp. 903–995, 1998.
- [17] K. Kappaganthu and C. Nataraj, "Feature Selection for Fault Detection in Rolling Element Bearings Using Mutual Information," *Journal of Vibration and Acoustics*, vol. 133, no. 6, pp. 1–11, 2011.
- [18] S. Prabhakar, A. Mohanty, and A. Sekhar, "Application of discrete wavelet transform for detection of ball bearing race faults," *Tribology International*, vol. 35, no. 12, pp. 793–800, 2002.
- [19] S.-C. Pei and M.-H. Yeh, "Discrete fractional Hilbert transform," *Circuits and Systems II: Analog and Digital Signal Processing, IEEE Transactions on*, vol. 47, no. 11, pp. 1307–1311, 2000.
- [20] Akinci, T. C., Karabeyoglu, S. S., Yilmaz, O., & Seker, S. "Fault detection of washing machine with discrete wavelet methods." *Mechanics* 20.2 (2014): 177-182.



V K Giri obtained his B.E. (Electrical) Degree from REC, Surat (Gujrat) in 1988, M.E. (Measurement and Instrumentation) Hons. degree from University of Roorkee, Roorkee in 1997 and Ph.D. degree from Indian Institute of Technology Roorkee, Roorkee in 2003. He joined the Electrical Engineering Department of M.M.M Engineering College, Gorakhpur, U.P. (presently, M.M.M. University of Technology, Gorakhpur) in 1989 as lecturer. Presently, he holds the position of Professor in the same department since, 2008. He has published more than 81 research papers, guided 19 PG students; and supervising 6 Ph.D. thesis. He has received many awards including the best paper awards of the Institution of Engineers (India) in 23rd Indian Engineering Congress in year 2008. He was elected as Fellow of the Institution of Engineers (I), Institution of Electronics and Telecommunication Engineers, and is a member of many professional bodies such as life member ISTE, member IEE and member CSI. He has also undertaken large number of consultancy, testing & sponsored projects from industries and government departments. His research interests include Digital Signal Processing, Measurement and Instrumentation, Biomedical Instrumentation, ECG Data Compression, Telemedicine and Health Monitoring of Rotating Machines.



Raj Kumar Patel obtained his B. Tech (Electrical and Electronics) degree from Uttar Pradesh Technical University (India) in 2006. M.Tech (Condition Monitoring Control and Protection of Electrical Apparatus) degree from NIT, Hamirpur (India) in 2012, and presently pursuing Ph.D degree from Uttar Pradesh Technical University, Lucknow (India). His research interests include signal processing, condition monitoring and fault diagnosis of rotating machines.