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A Review on Vibration Signal Analysis Techniques Used for Detection of Rolling Element Bearing Defects

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Abstract - *Almost all machines having rotating parts contain rolling element bearings to support the rotating parts during power transmission. Bearing failure is a major cause of the breakdown of machines. Hence it is necessary to identify the defects and their severity in their early stage to avoid breakdown of the machine and catastrophic damages. Defective bearings generation vibrations and various vibration signal analysis techniques have been developed by researchers for bearing condition monitoring. This paper presents an introduction and updated review of vibration signal analysis techniques used for the detection of defects in rolling element bearings. In this paper, vibration signal analysis techniques used for bearing defect detection are reviewed according to their classification viz. time domain, frequency domain, and time-frequency domain. This study will help the researchers to understand recent developments in the detection of defects of bearings from their vibration signals.*

Keywords - *Vibration signal analysis techniques, bearing defects, time-domain, frequency-domain, time-frequency domain*

I. INTRODUCTION

Rolling element bearings (REBs), also known as antifriction bearings, are commonly used in rotating machinery to support the rotating parts and to reduce friction. REBs are usually made up of high carbon chromium steel and consist of four different components, such as inner race, outer race, rollers/balls, and cage, as shown in fig. 1.

The outer race of the bearing is fixed in the casing; the inner race is fixed on the rotating shaft, a group of rolling elements rolls between them, and the cage keeps the rolling elements separated. Any defect produced in the bearing must be correctly detected in time to prevent a shutdown and serious damages to the machinery. Defects in REBs are classified into two broad categories such as localized and distributed defects [1], as shown in fig. 2.

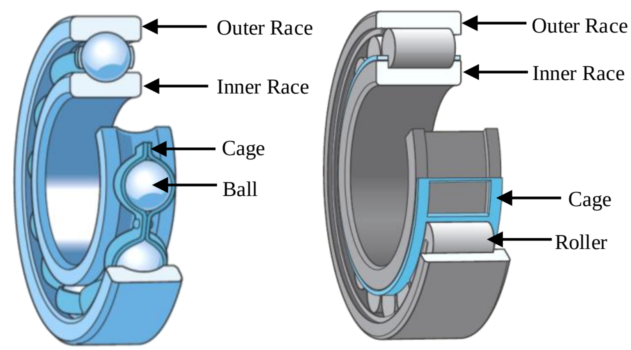


Fig. 1 Components of REB (SKF bearing catalog)

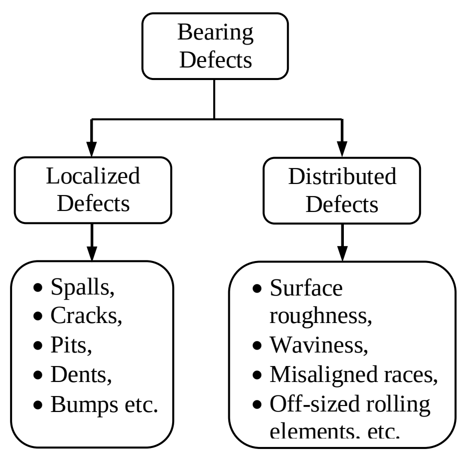


Fig. 2 Various Defects in REBs

Localized defects include spalls, cracks, pits, dents, bumps, etc., on the rolling surfaces. Fatigue, overloading, shock loading, etc., are some of the causes of localized defects. Distributed defects include surface roughness, waviness, misaligned races, off size rolling elements, etc. Some of the causes of these defects are manufacturing error, improper installation, abrasive wear, etc. These defects cause vibrations in the machinery and may cause catastrophic damages if neglected in the early stages. Therefore, condition monitoring (CM) of bearings plays an important role in knowing the severity of these defects before they become critical. A typical CM process involves three steps: data acquisition, feature extraction, and fault classification. Parameters like vibration, acoustic, wear debris, temperature, current, etc., are commonly used for condition monitoring. Different sensors are used for the measurement of this data, like vibration transducers, acoustic emission sensors, oil quality sensors, thermocouples, eddy current sensors, etc. For feature extraction and diagnosis of the bearing defects, different techniques like Vibration Signal Analysis (VSA), Acoustic Emission Analysis (AEA), Wear Debris Analysis (WDA), Temperature Analysis (TA), Current and Voltage Analysis (CVA), etc. are commonly used. For automatic fault classification and decision making, several Machine Learning (ML) techniques like Artificial Neural Network (ANN), Support Vector Machine (SVM), Principal Component Analysis (PCA), k-Nearest Neighbors (k-NN), Deep Learning (DL), etc. are used in recent decades.

Among all feature extraction and diagnosis techniques, VSA is the most widely used and efficient technique because of its reliability and high sensitivity in defect detection. In VSA, vibration signals are usually obtained from the bearings under running conditions by using sensors like accelerometers, and then these signals are processed and analyzed by using different electronic devices or software. Several VSA techniques have been used to analyze and detect the defects in bearings; these techniques are classified into three categories: i) Time domain analysis (TDA), ii) Frequency domain analysis (FDA), and iii) Time-frequency domain analysis (TFDA).

Two approaches are used by the researchers for VSA of bearing defects; the first is the theoretical modeling approach, and the second is the experimental approach. The theoretical modeling approach is used by many researchers, in which dynamic models of bearings are developed to understand their dynamic behavior without and with defects. Recently some researchers, Singh et al. [2], Thalji and Jantunen [3], Sharma et al. [4], Liu and Shao [5], Cao et al. [6], reviewed the theoretical modeling approach. Two experimental approaches are used by the researchers to study the effects of bearing defects on vibration signals. The first is, run the bearing till the development of the defects and then measure the vibration response; and second is, create the defects intentionally in the bearings by scratching, spark erosion, or indentation and then measure the vibration response. Then the vibration signals of defective bearings are compared with that of good bearings. The later experimental approach is preferred by most of the researchers as former approach is quite time-consuming. Many researchers published research work on experimental approaches for detection of defects in REBs using VSA techniques and their research works have been reviewed by the researchers. Howard [7] reviewed the research work done by the researchers 25 years before 1994 on the VSA techniques for defect detection, diagnosis, and prognosis of REBs using experimental approaches. Tandon and Choudhary [8] and Patil et al. [9] reviewed the vibration and acoustic measurement methods for the detection of localized and distributed defects in REBs. In their reviews, they reviewed more papers on experimental approaches than theoretical modeling approaches, and only time domain and frequency domain techniques are covered. Kumar et al. [10] reviewed the application of a VSA technique, i.e., Wavelet Transform (WT) for defect detection of REBs. Patidar and Soni [11], Lin et al. [12], Gupta and Pradhan [13], Malla and Panigrahi [14] presented reviews on the application of VSA techniques for localized defect detection of REBs. In their reviews, they covered time-domain, frequency-domain, and time-frequency domain VSA techniques of defect detection and emphasized on experimental approaches. Patidar and Mandloi [15], Saufi et al. [16] reviewed the research work done on VSA and AE techniques for defect detection of REBs. Rai and Upadhay [17] presented a review on the application of VSA and AE techniques for the defect detection of REBs with their advantages and disadvantages. They reviewed papers on both experimental and theoretical modeling approaches. Prashant Jain and Santosh Bhosle [18] presented review on use of VSA techniques in diagnosis of faults in rotating machineries, which includes pumps, gearboxes, rotor systems, bearings, etc.

In this paper, an attempt has been made to provide an updated review of widely used VSA techniques for the detection of defects in REBs using an experimental approach. This review is categorized according to the types of VSA techniques viz. time domain, frequency domain, and time-frequency domain.

II. TYPES OF VSA TECHNIQUES

A. Time Domain Analysis Techniques

Time Domain Analysis (TDA) technique is the simplest and most commonly used VSA technique for bearing defect detection. Time-domain is the graph of vibration amplitude versus time. Vibration amplitude is measured in terms of displacement (microns or mils), velocity (mm/s or inch/sec) or acceleration (mm/s^2 or g's) [7]. Analog or digital oscilloscope and FFT spectrum analyzer are commonly used instruments for TDA of vibration signals. Fig. 3 shows a typical time waveform of a bearing with an outer race defect. In time waveform, the vibration amplitude level of defective bearing is more than that of a good bearing, which indicates the presence of a defect in the bearing. However, this could not show the exact location of the defect in the bearing [19].

In time waveform analysis, the defects are detected with the help of some statistical parameters like Peak, Peak-to-peak, Root means square (RMS), Crest factor, Skewness, Kurtosis, Clearance factor, Impulse factor, Shape factor, etc. The most commonly used statistical parameters for bearing defect detection are Peak, RMS, Crest factor, Skewness, and Kurtosis. Out of these parameters, the Crest factor and Kurtosis are more effective [20].

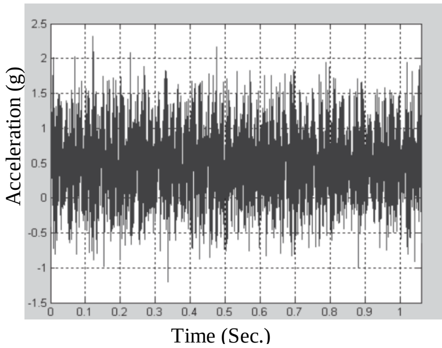


Fig. 3 A Typical Time Waveform [21]

The peak value is the maximum amplitude in the vibration signal. The peak-to-peak value is the difference between the extreme positions of positive and negative peaks of the signal. RMS value is the measure of the overall vibration level of a signal, i.e., it measures the energy of the signal. The crest factor is the ratio of Peak Value to the RMS of the signal. It is the measure of the spikiness or impulsive nature of the signal. Skewness is the measure of the asymmetrical spread of a signal about its mean value. Kurtosis is the measure of the peakedness of the probability density function (PDF) of a time series. Table 1 shows equations of commonly used statistical parameters for the detection of bearing defects.

Table 1 Time-domain statistical parameters

Parameter	**Formula**
Peak	$x_{\max}$
Mean ($\bar{x}$)	$\frac{1}{N}\sum_{i=1}^{N} x_i$
Skewness (S)	$\frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^3}{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2}\right)^3}$
Kurtosis (K)	$\frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^4}{\left(\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2\right)^2}$
Root mean square (RMS)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}$
The crest factor (CF)	Peak/RMS
Shape Factor (SF)	$\mathrm{RMS}/\lvert\bar{x}\rvert$
Impulse Factor (IF)	$\mathrm{Peak}/\lvert\bar{x}\rvert$

where x_i = Instantaneous amplitude of a signal, N = Number of samples taken within the signal

In recent few decades, many researchers worked on the detection of defects in REBs by using TDA techniques. In the year 1978, Dyer and Stewart [22] first used Kurtosis for the detection of bearing defects. They found that for an undamaged (good) bearing, the value of kurtosis is near 3, and this value increases as the defect size increases. However, this value comes down to 3 when the defect is well advanced. Howard [7], in his review, found that for the undamaged bearing, the values of kurtosis and crest factors are approximately 3 and 3.5, respectively. Tandon et al. [23] compared vibration parameters (RMS, peak, crest factor) for the CM of REBs. It is found that this parameter increases with the defect size and the outer race defect (ORD) is not detectable by crest factor. Martin and Honarvar [24] used statistical moments (skewness, kurtosis) for bearing failure detection. They showed that skewness and kurtosis are independent of load and speed, and kurtosis of healthy bearing is 3, and it increases with an increase in defect size. Heng and Nor [25] used crest factor, skewness, and kurtosis to detect defects in REBs for both sound and vibration signals. They concluded that the bearing speed affects these statistical parameters. Tandon and Choudhury [8], in their review, found that kurtosis is most effective among the statistical parameters like overall RMS level, crest factor, probability density, and kurtosis. Almeida et al. [26] showed that skewness is the worst parameter among RMS, Kurtosis, and Skewness. Kurtosis detects only the pit fault at low speed. The results of the RMS value for acceleration signals are better than velocity signals. The detection performance of the RMS increases with the shaft speed. Karacay and Akturk [21] used peak-to-peak value, RMS, crest factor, and kurtosis for ball bearing defect detection. They found that these parameters indicate the presence of defects only but do not identify the location and/or type of the defects. They also observed that the vibration amplitude increases with the defect size. However, it is not possible to obtain the correlation between the defect size and the vibration amplitude. Utpat et al. [27] compared peak-to-peak value, peak value and RMS value bearing defects detection. Their results show that peak-to-peak value gives better defect detectability for ORD, IRD and ball defect.

Some researchers introduced new statistical parameters based on conventional statistical parameters for defect detection. Niu et al. [28] introduced two new normalized statistical moments, namely NM^2a and NM^3a, for bearing defect detection. They showed the effectiveness of these new moments along with skewness and kurtosis. Tao et al. [29] derived a new statistical moment S_α from the viewpoint of Renyi entropy for detection of bearing defects. They performed the comparison of skewness, kurtosis, and this new moment S_α and concluded that the moment has a better overall performance than skewness and kurtosis. Sassi et al. [30] introduced two indicators TALAF and THIKAT, to improve diagnosis capabilities for bearing defect detection. These indicators are designed by combining conventional statistical parameters. Forbearing defect detection Paliwal et al. [31] introduced a new indicator, called CRIS, in combination with conventional statistical parameters for bearing defect detection. They showed that by using CRIS severity of defects can be assessed in the time-domain.

Liu and Mengel [32], Samanta and Al-balushi [33], Sreejith et al. [34], Hariharan and Srinivasan [35] presented localized defect diagnosis of REBs using time-domain statistical parameters as input features and Artificial Neural Network (ANN) as fault classifier. In addition to this work, Patel [36] used SVM also as a fault classifier and showed that SVM gives better results than ANN.

B. Frequency Domain Analysis Techniques

Frequency domain analysis (FDA) or spectral analysis is a widely used method for detecting defects in REBs. FDA techniques include Spectrum Analysis, Envelope Analysis, and Cepstrum Analysis, etc.

a) Spectrum Analysis. In spectrum analysis, the time-domain signal is converted into the frequency-domain signal by using Fourier transform. The frequency spectrum is the graph between vibration amplitude and frequency. Vibration amplitude is measured in terms of displacement, velocity, or acceleration by using an FFT spectrum analyzer. The Fourier transform for frequency f and time t is given by the following equation [37]

$$X(f) = F[x(t)] = \int_{-\infty}^{+\infty} x(t) e^{-j2\pi ft} dt \qquad (1)$$

where $x(t)$ is a vibration signal in the time domain and $X(f)$ is the Fourier Transform of $x(t)$ in the frequency domain.

Spectral analysis of frequencies generated by defective antifriction bearings can used to identify defects on the bearing rolling elements viz. roller/ball, inner and outer raceways. The frequency spectrum not only indicates the severity of the defect in bearing but also indicates the location and nature of the defect. Each element of bearing has a characteristic rotational frequency, which can be calculated from their kinematic analysis. Table 2 shows the formulae of characteristic defect frequencies of bearings [7], [38]. The severity, nature, and location of bearing defects can be detected by comparing the frequency spectrums of defected bearing and a good bearing.

Table 2 Formulae of characteristic bearing defect frequencies

Frequency	Formula
Outer Race Defect Frequency (ORDF)	$\frac{nf_r}{2}\left(1-\frac{D_b}{D_c}\cos\phi\right)$
Inner Race Defect Frequency (IRDF)	$\frac{nf_r}{2}\left(1+\frac{D_b}{D_c}\cos\phi\right)$
Roller Defect Frequency (RDF)	$\frac{D_c}{D_b} f_r\left[1-\left(\frac{D_b}{D_c}\cos\phi\right)^2\right]$
Cage Rotational Frequency (CRF)	$\frac{f_r}{2}\left(1-\frac{D_b}{D_c}\cos\phi\right)$

where n = no. of balls/rollers, f_r = Shaft speed in rpm, D_b = Diameter of ball/roller, D_c = Diameter of cage, ϕ = Contact angle of ball

Fig. 4 shows a typical frequency spectrum of a bearing having outer race defect Shah et al. [39]. In this frequency spectrum, the amplitude spikes at outer race defect frequency and its harmonics indicate that defect is present at the outer race of bearing.

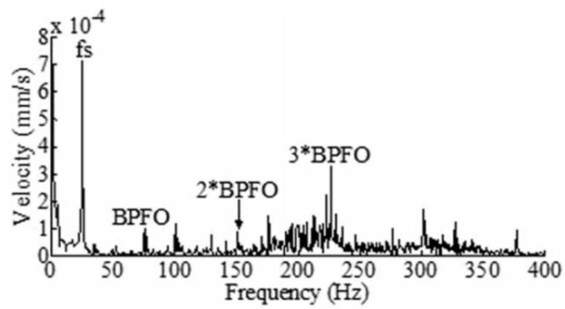


Fig. 4 Typical Frequency Spectrum of a bearing with an outer race defect [39]

Fast Fourier Transform is an effective tool for periodic stationary signals; however, for non-stationary signals, it is not suitable. The important drawback of FFT is the loss of time information when transforming into the frequency domain.

Taylor [40] used a spectrum analysis method for the identification of bearing defects running under low frequencies. They found that spectrum shape, frequency, amplitude, and sum and difference frequencies are useful in the identification of defects and their size. Igarashi and Hamada [41] used an FFT analyzer to detect single dent defects on rolling elements of bearings from vibration and sound signals. Tandon and Kumar [42] used overall vibration RMS velocity levels, frequency spectrums, and shock pulse values for detecting defects in ball bearings at different locations. They showed that the ORDs in the maximum load zone could be easily detected as the vibration levels are high when ORD is in this zone, and it decreases when the ORD has moved away from this zone. They also showed that the vibration levels and shock pulse value decreases with the increase in the angle between two defects. Amarnath et al. [19] employed TDA, FDA, and spike energy analysis to identify different defects in REBs. They showed that the time waveform indicates the severity of the defect in bearing, and the frequency spectrum shows the exact location of the defect in bearing. Liu et al. [43] used the experimental VSA method and finite element analysis (FEA) method to study the effects of localized defect shapes of ball bearing on vibration amplitude. They found that the vibration amplitude produced by localized defects are greatly influenced by the shape of the defect and slightly influenced by the radial load, axial load, and speed. The use of spectrum analysis for bearing defect detection is recently presented by some researchers, viz. Orhan et al. [44], Patel et al. [45], Patel et al. [46], Patel et al. [47], Shah et al. [39], Khadersab and Shivakumar [48].

The power spectrum of a time-domain signal is "the square of the magnitude of the Fourier transform of a signal." The power spectrum of a signal can be written as [49]

$$P(f) = |X(f)|^2 = |F[x(t)]|^2 = \left| \int_{-\infty}^{+\infty} x(t) e^{-j2\pi ft} dt \right|^2 \quad (2)$$

$$P(f) = X(f) X^*(f) \quad (3)$$

where $X(f)$ is the Fourier transform of the signal, and $X^*(f)$ is its complex conjugate?

Tandon [23] compared some vibration parameters along with power spectrum for condition monitoring of bearings. He found that the delectability of overall power is best followed by peak and RMS.

b) Envelope Analysis. Envelope Analysis (EA) is also known as "Amplitude Demodulation," "Demodulated Resonance Analysis," "High-Frequency Resonance Technique (HFRT)," and "Narrow Band Envelope Analysis" [50]. This is another method used to detect bearing defects. Bearing with defects generate repetitive vibration signals of much lower amplitude and higher frequencies than rotational and structural vibration signals. Enveloping removes the low-frequency stationery vibration signals and enhances the repetitive frequency signals occurring in the defect frequency range. Enveloping separates the defect frequencies and the natural frequency of the rotating parts by demodulation. Fig. 5 shows the process of envelope analysis.

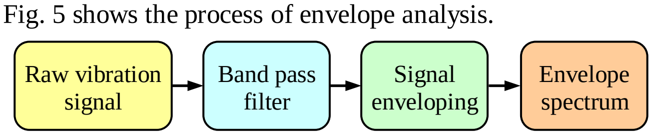


Fig. 5 Process of Envelop Analysis

Hilbert Transform. Hilbert Transform (HT) is an envelope analysis technique in which the phase angle of all components of signal is shifted by ±90°. HT is also useful for the analysis of the demodulated signals and their spectral refining [51]. Hilbert transform of a signal is the transform, in which Hilbert transform $H[x(t)]$ of an original time signal $x(t)$ is defined as

$$H[x(t)] = y(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau = x(t) * \frac{1}{\pi t} \quad (4)$$

HT representation $H[x(t)]$ of the original function is the convolution integral of $x(t)$ with $1/\pi t$. The original signal $x(t)$ and its Hilbert transform $y(t)$ together form a new complex analytic signal

$$z(t) = x(t) + jy(t) \quad (5)$$

The envelope signal $E(t)$ is the absolute value of the analytic signal $z(t)$ and is expressed as

$$E(t) = |z(t)| = |x(t) + jy(t)| = \sqrt{x^2(t) + y^2(t)} \quad (6)$$

The spectral analysis of the enveloped signal is commonly used for the detection of bearing defects. Fig. 6 shows typical signals and envelope signals of a bearing having localized defects in different elements [51].

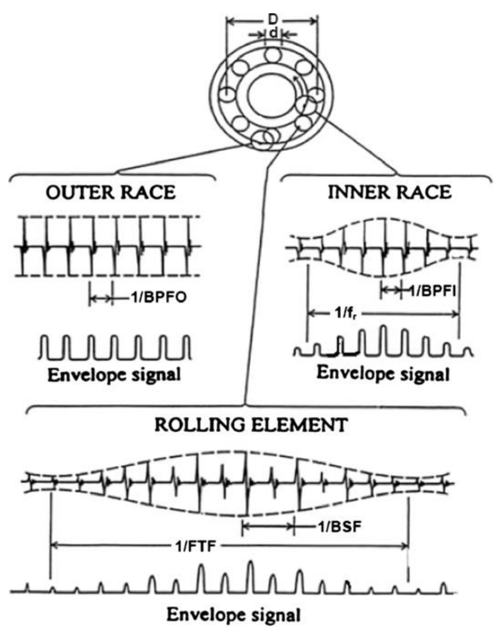


Fig. 6 Typical signals and enveloped signals of defects in a rolling element bearing [51]

Recently, Feng et al. [52], Betea and Dobra [53], Alegranzi et al. [54], Kim et al. [55], Wang and Liu [56] used EA techniques based on HT for defect detection in bearings. Amirat [57] used the HT technique of EA for bearing defect detection and diagnostics in wind turbines. Jimenez-Estevez [58] used this technique for defect detection in bearings of induction motors. Patel et al. [59] compared the HT-based EA with the duffing oscillator technique for identifying localized defects in ball bearings. Authors have concluded that EA enhances the signals of defect frequencies and their harmonics. However, the Duffing oscillator technique shows the existence of the defect frequencies only. Yang et al. [60] used EA and current analysis for the detection of defects in REBs. Their results show the powerful capability of vibration analysis in bearing point defect detection. Jayaswal and Verma [21] used FDA techniques such as FFT and envelope spectrum analysis for bearing defect detection. Their results show that FFT shows the impulses at bearing defect characteristics frequencies and its harmonics. But, in envelop spectrum, other peaks also exist due to the signal modulation effect, and the characteristics frequencies of bearing defects are quite clear.

c) Cepstrum Analysis. Cepstrum is defined as "the inverse Fourier transform of a logarithm of the power spectrum." Thus, cepstrum is defined as [51]

$$c(\tau) = F^{-1}[\log(P(f))] \tag{7}$$

where $P(f)$ is the power spectrum of the signal?

The name 'cepstrum' is given by reversing the first four letters of the term 'spectrum.' Cepstrum Analysis (CA) is also called 'quefrency analysis,' which is revised from 'frequency analysis.' A number of terms are commonly used for the parameters of a Cepstrum, namely 'Quefrency' instead of 'Frequency,' 'Rahmonics' instead of 'Harmonics' and 'Gamnitude' instead of 'Magnitude.' A typical time and quefrency waveforms of a bearing with inner race defect is shown in fig. 7.

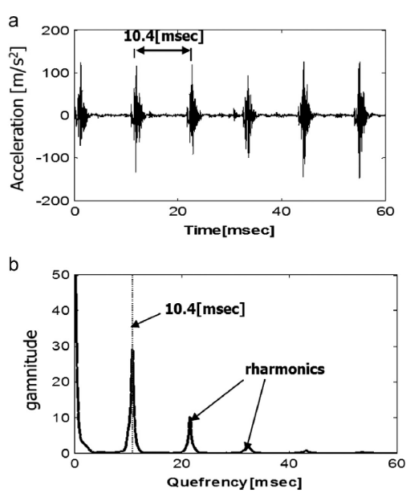


Fig. 7 Typical time and quefrency waveforms of a bearing with inner race defect [61]

Some researchers applied CA for detecting the faults in bearings [61]–[65]. Park et al. [61] introduced Minimum Variance Cepstrum (MVC) for obtaining the periodic impulse signal under noisy conditions for ball bearings in automotive wheels. Their results showed that the MVC is much more efficient in detecting early faults in bearings. Hwang et al. [62] proposed a feature extraction method based on cepstrum for feature extraction from vibration signals of faulty bearing, and they used ANN techniques for the classification of bearing faults. Morsy and Achtenova [63] showed the effectiveness of CA and Autocorrelation analysis in bearing fault diagnosis. Peeters et al. [64] compared automated cepstrum editing procedure (ACEP) and cepstrum pre-whitening for vibration-based bearing fault detection. Sawalhi et al. [65] proposed a cepstrum editing technique to enhance spall-related vibration features in rolling element bearings for the purpose of size quantification and fault prognosis. Bediaga et al. [66] compared the FDA techniques for the detection of ball bearing defects. They concluded that Hilbert transform and amplitude demodulation are the best for bearing defect detection.

C. Time-Frequency Domain Analysis Techniques

Time-Frequency Domain Analysis (TFDA) Techniques (also called spectrogram analysis) are suitable for the analysis of both stationary and non-stationary vibration signals. In TFDA, vibration signal analysis is carried out in both time and frequency domains for capturing the progressive changes in spectrum components [12].

A number of TFDA techniques have been developed by researchers that are capable of detecting and diagnose the bearing problems in rotating machinery, where noise is high, and a large number of frequency components are associated. The most commonly used TFDA techniques are Short Time Fourier Transform (STFT), Wavelet Transform (WT), Wigner-Ville Distribution (WVD), Hilbert Huang Transform (HHT), Local Mean Decomposition, etc. [67]. Among these techniques, WT is the most popular and powerful technique for defect detection and diagnosis [68], [69]. A lot of research has been carried out on the above techniques and used in fault detection in bearings.

Some researchers have published review papers on TFA techniques. Feng et al. [70] reviewed the TFA techniques for fault diagnosis of machinery along with their principles, advantages, disadvantages, and applications. Li H. et al. [71] analyzed and compared some of the TFA techniques along with their theories, properties, physical significance, advantages, disadvantages, and applications. Li S. et al. [72] and Hui et al. [73] summarized the researching status of TFA techniques and fault pattern recognition techniques along with a detailed analysis of their advantages and disadvantages. Lakis [74] presented the theory of STFT, WVD, and WT and their advantages with practical examples.

a) Short Time Fourier Transform (STFT). The STFT is a TFA technique suitable for non-stationary signals. This method was first proposed by Dennis Gabor in 1946. In STFT, the non-stationary signals are broken down into many small-time segments, and then the spectrum of each segment is obtained by the conventional FFT. This technique is also called spectrogram or windowing the signal. The window size is fixed, so it has a fixed time-frequency resolution. The STFT represents the time and frequency representation of a signal. It provides both the time and frequency information of signal, i.e., when and at what frequencies signal amplitudes are changing.

The representation of the STFT using elementary functions as given by Randall [75] is

$$STFT(\tau, f) = \int_{-\infty}^{+\infty} x(t)g(t-\tau)e^{-j2\pi ft}dt \qquad (8)$$

where $x(t)$ is the original time-domain signal, $g(t)$ is a window function, commonly a Gaussian window or Hann window centered around zero, τ is time (slow time; lower resolution than t).

Fig. 8 shows the concept of application of STFT to the signal, showing a sliding window over which the signal is considered as stationary [76].

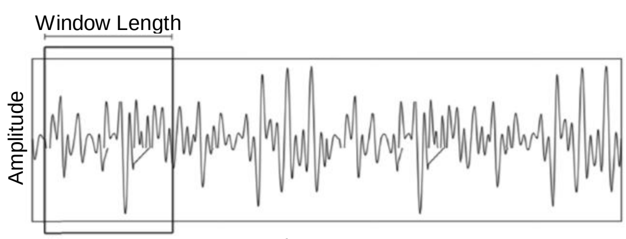


Fig. 8 Short Time Fourier Transform Map [76]

One of the limitations of using STFT is that a large window width provides good resolution in the frequency domain but the poor resolution in the time domain, and vice versa. This limitation is due to the use of a single-window for all defect frequencies. This results in the same resolution at all locations in the time-frequency plane.

Cocconcelli et al. [77] applied STFT defection of defects in ball bearings of varying speed motor. They averaged STFT for each cycle in the time-frequency domain to get enhanced fault features, and then they used the sum of STFT coefficients as simple indicators of bearing damage. Gao et al. [78] used STFT to describe the localized faults in REB and then applied supervised Non-negative Matrix Factorization (NMF) mapping to extract the fault features of bearing. They showed that the drawbacks of FFT analysis for non-stationary signals could be solved using STFT. Liu [79] proposed the use of STFT and stacked sparse auto-encoder for the detection of faults in bearings. They obtained the sound signals using spectrograms, they used STFT and stacked sparse auto-encoder for extracting the fault features automatically. Boudinar et al. [76] proposed time-frequency analysis using the STFT associated with Maxima's Location Algorithm (MLA) for bearing defects detection in induction motor operating at variable speed.

b) Wavelet Transform (WT). The WT is another signal processing tool for the detection of non-stationary vibration signals. WT is applied recently by many researchers for fault diagnosis in rotating machinery because of its strong ability to the analysis of data in the time and frequency domain. In 1984, WT was first introduced by mathematician Morlet. WT describes a signal by using the correlation with translation and dilatation of a function, which is called a mother wavelet. The advantage of WT over the STFT is that it can achieve high-frequency resolutions with sharper time resolutions. The commonly used wavelet algorithms are Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Wavelet Packet Transform (WPT) [80], [81].

CWT decomposes a signal in both time and frequency in terms of a wavelet, called a mother wavelet. Mathematically, CWT of a time-domain signal $x(t)$ [75] is expressed as

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \qquad (9)$$

where $\psi^*(t)$ is the complex conjugate of mother wavelet $\psi(t)$, parameter a represents the scale index, which is a reciprocal of frequency, and parameter b indicates the time-shifting (or translation).

DWT is derived from the discretization of $CWT(a, b)$ by adopting the dyadic scale and translation to reduce the calculation time can be expressed as

$$DWT(j,k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-2^j k}{2^j}\right)dt \qquad (10)$$

where j and k are integers, 2^j and $2^j k$ are the scale and translation parameters.

WPT is a wavelet transform in which the signal is passed through more filters. WPT further decomposes the detailed information of the signal in the high-frequency region, which makes WPT an attractive tool for detecting and differentiating transient components with high-frequency characteristics [82]. Fig. 9 shows a structure chart for a typical three layers decomposition tree of a WPT.

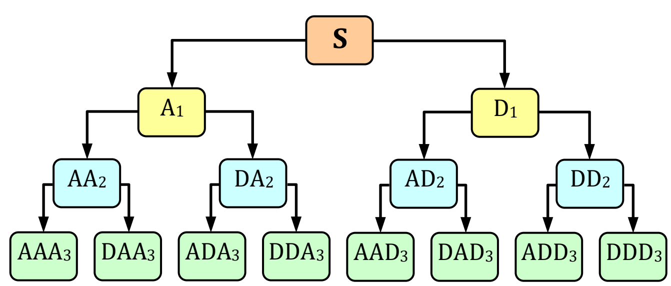


Fig. 9 Structure chart of decomposition tree of WPT

Kumar et al. [10] reviewed the research papers on WT for bearing CM and diagnosis. They concluded that CWT, DWT, and WPT are effective techniques for CM of bearings. Recently, many researchers present the applications of WT to decompose signals for improving the performance of fault detection and diagnosis in bearings [10], [55], [83]–[88].

Kulkarni et al. [93] used a wavelet decomposition technique to analyze the vibration signals acquired from a ball bearing with an extended type of distributed defects. Kankar et al. [84] used a complex morlet wavelet for fault diagnosis of ball bearings having localized defects on various bearing components. Yuan and Zhang [85] combined the wavelet analysis and kurtosis method for detection and diagnosis of the faults based on the unstable vibration signals from the rolling bearings. Prabhakar et al. [86] used DWT for fault diagnosis of ball bearings having single and multiple defects on various bearing components. Mori et al. [87] applied DWT to vibration signals to predict the occurrence of spalling in ball bearings. Kim et al. [55] added DWT in EA to reduce the noise level in acoustic emission signals of faulty inner race bearing. They proved that it was difficult to find the defect frequency in the inner race only by EA, but it was easy after adding DWT. Kumar and Singh [88] used the Symlet wavelet function to perform DWT on the vibration signals of taper roller bearing to measure the outer race defect width. Khanam et al. [89] used DWT to detect different fault sizes in the outer race of a ball bearing. The entry and exit events in the defects were pointed out clearly in the decomposed signal, and a good estimation of the defect size was obtained. Chebil et al. [90] used time-domain, frequency-domain, and time-frequency-domain analysis techniques for bearing defect detection. They found that the DWT, which is based on time-frequency domain analysis, produces the best results. Nikolaou et al. [91] WPT for analyzing the vibration signals resulting from bearing with localized defects. Compared with other methods, WPT has the advantage of the flexibility and efficient computational implementation. Kulkarni and Sahasrabudhe [92] presented a method based on DWT and WPT for the detection of faults in rolling bearings. In this method, mother wavelets from the Daubechies family were adopted for decomposing the vibration signals. Pandya et al. [93] presented localized defect diagnosis of REBs using time-frequency domain and Artificial Neural Network (ANN) as fault classifier. They used two features, kurtosis and energy extracted from wavelet packet coefficient, as input parameters. Nizwan et al. [94] presented a study of VSA for bearing fault detection using DWT. Their findings show that Wavelet decomposition analysis can be used as an effective bearing CM tool.

c) Wigner-Ville Distribution (WVD). The WVD technique, which is another popular time-frequency technique for the detection of non-stationary vibration signals, represents the time, frequency, and magnitude (amplitude) of a signal in one diagram. WVD shows good resolution time-frequency representation of a signal [95]. The WVD is derived by generalizing the relationship between the power spectrum and the autocorrelation function for non-stationary time-variant processes [96]. For a continuous signal $x(t)$, the WVD is defined as

$$WVD(t,f)=\int_{-\infty}^{+\infty} x\left(t+\frac{\tau}{2}\right)x^{*}\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \qquad (11)$$

where x^{*} denotes the conjugate of x.

As compared to the STFT, the WVD shows better time-frequency aggregation in signal processing but produces cross-term interference for multi-component signals Singru [95]. A 3-Dimensional WVD plot for a bearing with ball defect [95] is shown in fig. 10.

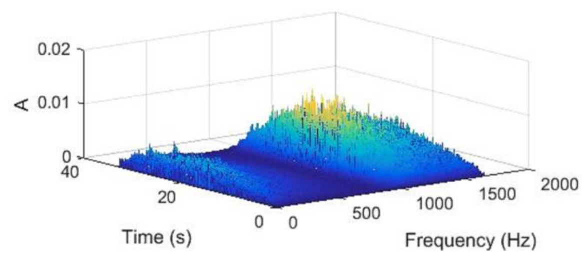


Fig. 10 A Wigner Ville Distribution plot for a bearing with ball defect [95]

Li H. et al. [97] applied WVD based on Empirical Mode Decomposition (EMD) to the fault diagnosis of the inner race of ball bearing. It is shown that WVD based on EMD successfully eliminates the cross-terms and diagnose the faults of bearing. Zhou et al. [98] introduced improved WVD based on the cyclic spectral density to analyze the vibration signals from fault rolling element bearings, including outer and inner race defects. Singru et al. [95] used FFT, modified Poincare mapping, and WVD to detect the bearing failure. But, they found a problem of cross-term interference for multi-component signals.

d) Hilbert-Huang Transform (HHT). The HHT is a data-driven adaptive time-frequency technique for analyzing non-stationary and non-linear time signals. HHT combines the use of Empirical Mode Decomposition (EMD) with the Hilbert Spectral Analysis (HSA). In the HHT technique, first, the EMD method is used to decompose the signal into so-called Intrinsic Mode Functions (IMFs) with a trend, and then HT is used to the IMFs to obtain instantaneous frequency data. Time-frequency representation is then obtained by displaying the time evolution of the instantaneous amplitude and frequency for each IMF. In addition, the marginal spectrum of the signal is also obtained [99]. Fig. 11 shows the methodology of the HHT technique.

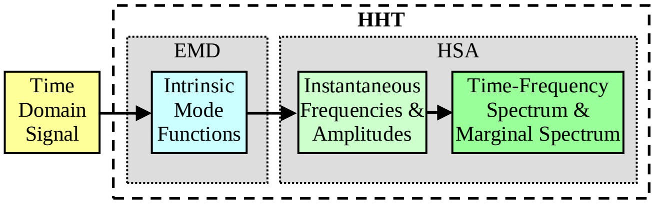


Fig. 11 Methodology of HHT technique

HHT includes two processes, i.e., 1) EMD and 2) HSA. These two processes are described below.

1) Empirical Mode Decomposition (EMD). The EMD is a self-adaptive signal processing method proposed by Huang [100] that is used for processing of both non-linear and non-stationary signals and is widely used to detect and diagnose faults in bearings, gears, rotors, etc. EMD method is based on the local characteristic time scale of the signal and is capable of breaking down (decomposition) the signal into a finite number of the set of complete and almost orthogonal components, which are called Intrinsic Mode Functions (IMFs). This process of decomposition of a number of IMFs from the vibration signal is known as sifting. This decomposition process can be stopped when no IMFs can be extracted from the signal.

A signal $x(t)$ can be reconstructed using IMFs through the EMD process as given by

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{12}$$

where $c_i(t)$ is the i^{th} empirical mode, and $r_n(t)$ is the residue of data $x(t)$ after n number of IMFs are extracted?

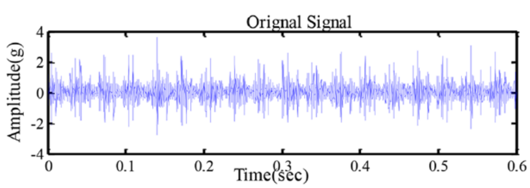


Fig. 12 Time waveform of a bearing with inner race defect [101]

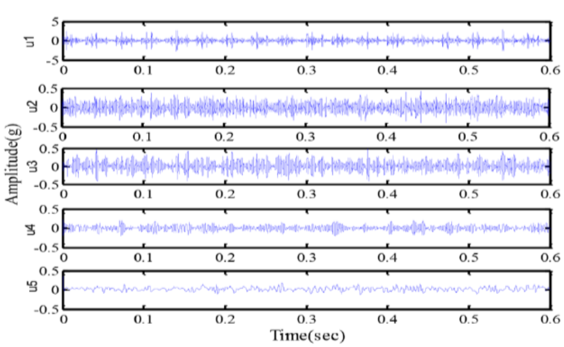


Fig. 13 IMFs of bearing with inner race defect decomposed by EMD [101]

Fig. 12 and 13 shows the original time waveform a bearing with inner race defect and its IMFs decomposed by EMD. IMFs show the intrinsic and real information of the signal, and each IMF is a single component signal. Several methods have been developed by the researchers to select and analyze the IMFs.

After obtaining the IMFs by means of the EMD method, the Hilbert transform (HT) is performed to each IMF component as described below.

2) Hilbert Spectral Analysis (HSA). Hilbert transform $H[x(t)]$ of a real-time signal $x(t)$ is defined as [50]

$$H[x(t)] = y(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{13}$$

The original signal $x(t)$ and its Hilbert transform $H[x(t)]$ together form a new complex analytic signal

$$z(t) = x(t) + jy(t) \tag{14}$$

this equation can be rewritten in a polar coordinate system as

$$z(t) = a(t)e^{j\theta(t)} \tag{15}$$

where $a(t) = \sqrt{x^2(t) + y^2(t)}$ and $\theta(t) = \tan^{-1}\frac{y(t)}{x(t)}$, which represents instantaneous amplitude and instantaneous phase of the signal, respectively. From this instantaneous phase of the signal $\theta(t)$, the instantaneous frequency $\omega(t)$ can be derived as

$$\omega(t) = \frac{d\theta(t)}{dt} \tag{16}$$

Thus the original signal $x(t)$ can be expressed in the following form, which does not contain the residue $r_n(t)$.

$$x(t) = \mathrm{Re}\sum_{i=1}^{n} a(t)^{j\int \omega(t)dt} \tag{17}$$

This equation represents the amplitude of the signal, time, and instantaneous frequency in a 3-D plot, in which the amplitude is the height in the time-frequency plane. This time-frequency distribution is designated as the Hilbert-Huang spectrum $H(\omega,t)$:

$$H(\omega,t) = \mathrm{Re}\sum_{i=1}^{n} a(t)^{j\int \omega(t)dt} \tag{18}$$

With this Hilbert-Huang spectrum, the marginal spectrum $h(\omega)$ can be defined as

$$h(\omega) = \int_{0}^{T} H(\omega,t)dt \tag{19}$$

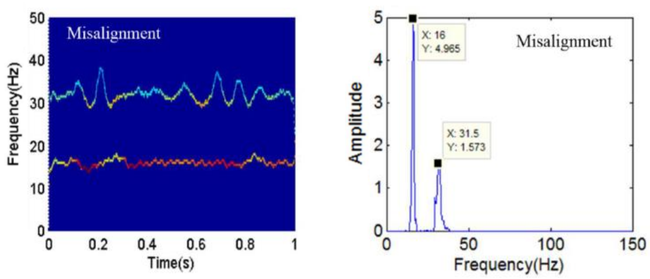
where T represents the signal duration.

The Hilbert-Huang spectrum measures amplitude contribution from each frequency and time, and the marginal spectrum measures the total amplitude contribution (energy) from each frequency.

Therefore, the local marginal spectrum of each IMF component $h_i(\omega)$ can be defined as

$$h_i(\omega) = \int_0^T H_i(\omega,t)dt \tag{20}$$

This local marginal spectrum shows the total amplitude associated with the frequency that we wanted to know. Fig. 14 shows a typical HHT of misalignment fault of a shaft showing the instantaneous frequency of the misalignment running state floats around 16 Hz and 32 Hz.



(a) Hilbert Spectrum (b) Marginal Spectrum

Fig. 14 HHT of Misalignment Fault of a Shaft [99]

A lot of research work has been published on the use of HHT based on EMD for fault detection in bearings as well as other machineries. Yu et al. [102] proposed HHT combining EMD and HT for the fault diagnosis of roller bearings along with wavelet packet for signal decomposition and HT for enveloping of the signal. Rai and Mohanty [103] used the HHT technique for bearing fault diagnosis using FFT of IMFs. The Characteristic Defect Frequencies (CDFs) of bearing faults are determined using time-domain EMD and HT, and then IMFs generated in time-domain are converted to frequency-domain using FFT algorithm. They showed the effectiveness of using the frequency domain approach in HHT. Li H. et al. [104] presented the application of EMD, HHT, and its marginal spectrum in the analysis of vibration signals and fault diagnosis of roller bearings. They used EMD to separate the vibration signals into several IMFs, and then according to the marginal spectrum, the localized fault in REB are detected. Kabla et al. [105] proposed the HHT method combining EMD followed by HT for the fault diagnosis of ball bearings along with SVM as fault classifier. Babu et al. [106] used EMD with HT for fault diagnosis of journal bearing, and it is seen that better results are obtained by the EMD method as compared to FFT and Wavelet Transform methods. Kumar et al. [101] proposed EMD and VMD with subsequent envelope spectrum analysis for diagnosing the inner race and outer race fault in the rolling element bearing. Yan and Gao [107], Chen et al. [108], Elbouchikhi [109] used HHT combining EMD and HT to detect faults in bearing. Peng et al. [110], [111] used the WPT as preprocessors of the HHT and obtained more precise results in fault diagnosis of rolling bearing and fault diagnosis of rubbing in the rotary system, respectively. Osman and Wang [112] proposed an enhanced HHT (eHHT) technique for REB fault detection. They used minimum entropy deconvolution filter to denoise the signals and then used a novel IMF selection method based on analysis of correlation and discrepancy of mutual information (MI) to select the most distinctive IMFs. Osman and Wang [113] proposed a Normalized HHT (NHHT) technique for bearing fault detection. They used a maximum kurtosis deconvolution filter for denoising the signals and then used the NHHT technique based on D'Agostino-Pearson (DP) normality test to select the most distinctive IMPs.

Many researchers published papers on the use of EMD for bearing defect detection with other techniques. Huang et al. [114] combined EMD and Power Spectral Density (PSD) for diagnosing the faults in bearings. First, they used EMD for the decomposition of signals into IMFs and then calculated the PSD of each IMFs. Lei et al. [115] reviewed the applications of EMD in the diagnosis of faults in rotating machinery. In their review, they provided a detailed introduction of the application of EMD in fault detection of bearings, gears, and rotors, etc. Isham et al. [116] reviewed and summarized the mode selection method used to EMD method to select IMF for rotating machinery diagnosis of bearing, gear, rotor, and shaft. Yang et al. [117] used EMD for signal decomposition, calculated the characteristic amplitude ratios of each IMFs, and used them as the input indicators of SVM for fault recognition of roller bearing. Cheng et al.[118] applied EMD to obtain IMFs of signal, the energy operator demodulation is applied to obtain instantaneous frequencies and amplitudes of each IMFs, and then spectrum analysis is applied to obtain envelope spectra from which faults in bearings and gear are is diagnosed. Yan and Gao [119] used EMD and envelope spectrum to detect faults in bearings. Energy measure and correlation measure are used to select the IMF, and the envelope spectrum of the selected IMF is investigated to find the existence and location of the defect in the bearing. Fan and Zuo [69] employed EMD to decompose raw signals into IMFs. The amplitude acceleration energy of IMFs is proposed as an indicator to represent fault characteristics of bearings and gears. Wei and Quan [120] employed EMD for signal decomposition, calculated the energy entropy mean of each IMF and normalization motor speed and used them for constructing the feature vector to train SVM classifiers for ball bearing fault diagnosis in high load-low speed rotary machine. Singh and Harsha [121] used EMD for defect detection in REBs. They used EMD to decompose the vibration signal and then used statistical parameters viz RMS, crest factor, skewness and kustosis for diagnosis of faults. They showed the effectiveness of EMD technique over the VSA of raw signals.

Although the EMD method has been successfully used in the VSA of nonlinear and non-stationary signals in various applications, this method has a number of weaknesses like the problem of mode fixing, end effects, a sifting stop criterion, selection of best IMF, etc. To overcome such problems, there are lots of improved EMD methods developed by the researchers for the detection of faults.

Du and Yang [122] presented an improved EMD method with an average mean method for defect diagnosis of ball bearings. They found that this method able to separate the compliance vibration and the vibration due to surface irregularities in a ball bearing. Dong et al. [123] proposed an improved method to reduce the time of the sifting process of EMD and used with Shock Pulse Method (SPM) to detect the inner race fault of bearings. In this method, only one time of cubic spline fitting is used in each sifting process. Han et al. [124] proposed a signal processing method based on EMD and a different spectrum of singular values for fault diagnosis of bearing. Delprete et al. [125] analyzed and tested orthogonal EMD in the detection of bearing faults in a lean in-service monitoring operation and remote diagnosis.

Ensemble Empirical Mode Decomposition (EEMD). EEMD is another improved EMD method widely used for fault diagnosis of machinery. This is a noise-assisted data analysis method, developed by Wu and Huang in 2009 to overcome the problem of mode mixing in EMD by adding white noise to the investigated signal. Mode mixing is defined as either a single IMF consisting of signals of widely disparate scales or a signal of a similar scale residing in different IMFs [126].

Many researchers have used HHT based on EEMD for the identification of defects in bearings. Some of the recent papers on EEMD methods are reviewed here. Li H. et al. [127] used EEMD and HHT for the diagnosis of outer and inner race faults in a ball bearing. Wu et al. [128] proposed improved post-processing of EEMD with the HHT approach for bearing fault detection. Their results show that this method is capable of extracting the bearing fault features and identifying the types of faults effectively. Also, the vibration level of the bearing fault can be diagnosed by comparing the peak values of the marginal Hilbert spectra. Lu J. et al. [129] used EEMD and instantaneous energy density spectrum for fault diagnosis in the rolling bearing. They demonstrated the effectiveness of this method for vibration signal analysis of a rolling bearing with an inner-race fault. Chang et al. [130] used EEMD, envelop spectrum analysis, and diagnosis of the ball, outer race, and inner race faults in a ball bearing. Qin et al. [131] proposed a method combining Ensemble Empirical Mode Decomposition (EEMD) and Random Forest for diagnosis of faults in roller bearing. Gao et al. [132] proposed an automatic and intelligent fault diagnosis algorithm combined with EEMD, principal component analysis (PCA), and probabilistic neural network (PNN) for fault diagnosis of rolling bearing. Feng Z. et al. [133] used EEMD and Teager Kaiser energy methods to detect the localized faults on ball bearing. Verma et al. [134] used the EMD, EEMD, and Teager Kaiser energy method to detect the localized faults both on the outer and inner race of ball bearing. Xiang and Zhong [135] combined EEMD, the Random Decrement Technique (RDT), and Hilbert envelope spectrum for the fast detection of defects in ball bearings. RDT is used to extract the first IMF if its impulse response signal is unclear. Cheng et al. [136] proposed Complementary Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CCEEMDAN) to analyze non-stationary vibration signals for fault detection of rolling element bearings. This improved method of EEMD improves the performance of decomposition by reducing reconstruction error and minimizing the effect of mode mixing. Zhen et al. [137] proposed Weighted Average EEMD (WAEEMD) and Modulation Signal Bispectrum (MSB) for detection of faults in REB. They used EEMD for the decomposition of vibration signal into IMFs with a different frequency band and then used the weighted average method, called WAEEMD, based on Teager energy kurtosis (TEK) to reconstruct the IMFs into a new signal. Finally, they applied MSB to decompose the modulated components in the reconstructed signal and to extract fault features of bearings.

e) Local Mode Decomposition (LMD). The LMD is a newly developed self-adaptive time-frequency analysis technique for signal processing of both non-linear and non-stationary signals. This method is proposed by Smith J.S. in 2005 and is recently used by many researchers for fault diagnosis of machinery [138].

LMD decomposes the Amplitude Modulated (AM) and Frequency Modulated (FM) vibration signal into a small set of mono-components named Product Functions (PFs). Each PF is the product of an envelope signal and a frequency modulated signal with uniform amplitude. The separation is carried out by smoothing the original signal, subtracting this smoothed signal from the original one, and then amplitude demodulates the result using envelope estimation [138], [139], [140].

The final decomposition result of an original signal $x(t)$ can be given by

$$x(t) = \sum_{i=1}^{n} PF_i(t) + u_n(t) \tag{21}$$

where n is the number of PFs and $u_n(t)$ is the residue signal.

The difference between LMD and EMD is shown in fig. 15. LMD bypasses the need for Hilbert transform totally.

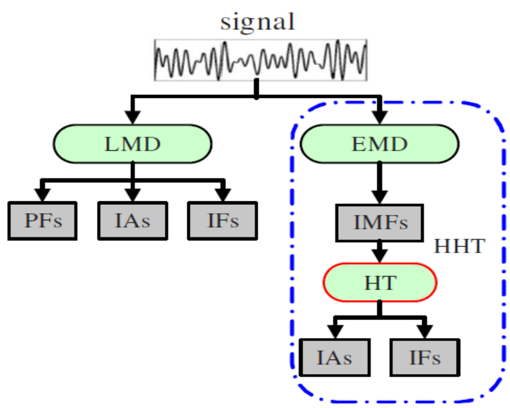


Fig. 15 Computation of IAs and IFs by LMD and EMD[141]

Since 2005, many researchers have adopted the LMD method for fault detection of bearings and other machinery. You no et al. [142] presented a comprehensive review on the use of LMD for the diagnosis of faults in the rotating machinery like bearings, gears, rotors, etc. They also described the theory, advantages, disadvantages of LMD methods, and some improved LMD methods. Chen et al. [139], [143] applied LMD to analyze vibration signals of bearings and gearboxes and successfully identified their fault frequencies. Li H. [140], [144] conducted envelope spectrum analysis of selected PFs obtained from LMD of the gearbox and bearing vibration signals. They experimentally demonstrated the effectiveness of LMD in gear wear fault diagnosis and in bearing fault diagnosis, respectively. Cheng J. et al. [145] applied the LMD method for fault diagnosis of gear and roller bearing, and they also showed the superiority of the LMD method over the EMD method. Ma et al. [146] applied LMD with time-frequency analysis for diagnosis of the outer race and inner race defects of rolling bearing. They also compared the results of the LMD method with that of the EEMD method. Wang et al. [147] used the LMD method to extract the fault features of rolling bearings with outer race faults and demonstrated its effectiveness experimentally. Li et al.[148] proposed a new method called Optimized LMD (OLMD) to select the suitable PF in the sifting process. Experimental results validated the effectiveness of OLMD in the gearbox and bearing fault diagnosis. Ma et al. [149] proposed the LMD and envelope demodulation technique for the fault feature extraction of the rolling bearing. First, LMD is used to decompose the signal and to obtain a series of production functions (PFs), then envelope demodulation of the signal is done by Hilbert transform (HT) and Teager energy operator (TEO), and finally, Fourier transform (FT) is used to predict the rolling bearing failure condition. Li and Jiang [150] proposed LMD, multi-scale entropy (MSE), and SVM for fault diagnosis of roller bearing. Liu et al. [151] presented a time-frequency representation method based on robust LMD to solve the end effect and mode mixing problems of conventional LMD. Improved LMD is used for fault diagnosis of bearings along with the fast kurtogram.

Various improved LMD methods like ensemble LMD (ELMD), complete ELMD with adaptive noise (CELMDAN), etc., have been recently developed by the researchers. ELMD overcome the problem of mode mixing in LMD by adding white noise to the investigated signal. Wang et al. [152] proposed a time-frequency analysis method based on ELMD and fast kurtogram (FK) for gearbox and bearing fault diagnosis. Wang et al. [153] developed a new method called complete ELMD with adaptive noise (CELMDAN) to eliminate residual noise and generate the same number of PFs at different trials. Their diagnosis results indicated that CELMDAN could extract more fault characteristic information of rolling bearings with less interference than ELMD. Cheng et al. [154] proposed a hybrid time-frequency analysis method combining ELMD and the Teager-Kaiser energy operator (TKEO) for the fault diagnosis of high-speed train bearings. Rao and Saralika [155] carried out thermal and vibration signal analysis of deep groove ball bearing.

IV. CONCLUSIONS

In this paper, an attempt has been made to review the recent research and developments in the field of defect detection in roller element bearings using vibration signal analysis techniques. The following points are concluded after the review of literature on VSA techniques :

1) There is a number of condition monitoring techniques available for the diagnosis of defects in bearings, but vibration signal analysis is the most useful technique.
2) Defective bearings generate peaks at particular frequencies. By knowing these frequencies, the type of defect in bearings can be identified. ‘Amplitude’ in time waveform and in frequency spectrum indicates the severity of the defect in bearings, and ‘frequency’ of vibration in frequency spectrum indicates the exact location of the defect in bearing.
3) Among various statistical parameters of the time domain, Kurtosis is a better fault indicator than the crest factor. Kurtosis initially increases with defect size but then decreases. RMS increases with an increase in speed, load, and defect size. The defect detection performance of RMS increases with an increase in speed. The crest factor is a poor defect detector. Skewness is the worst parameter than RMS and Kurtosis. Kurtosis and Skewness are independent of Load and Speed. Kurtosis and Skewness detect only small pits at low speed.
4) Time-frequency analysis techniques such as STFT, WT, WVD, HHT, and LMD are effective in monitoring the transient or time-varying (non-stationery) characteristics of machinery vibration signals. Among these, WT and HHT based on EMD are the most used techniques for defect diagnosis in bearings. LMD is the latest one.

5) In most of the papers, researchers analyzed localized single defect in rolling elements of bearings using newly developed time-frequency domain signal processing techniques like HHT and LMD, and not much research work has been done on the analysis of distributed and multi-defects in bearings using these techniques.

This paper will be helpful for the researchers to understand the recent developments and improvements in various VSA techniques used for defect detection of bearings.

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