International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 3 Issue 7, July-2014, pp: (18-25), Impact Factor: 1.252, Available online at: www.erpublications.com

Review on Condition Monitoring Techniques Oil Analysis, Thermography and Vibration Analysis

Ashutosh Verma[1], Shakun Srivastava[2],
[12]Mechanical Engineering Department, Lucknow, UP, India

Abstract: There are four main indicators to determine bearing condition; oil or particle analysis, temperature, mechanical vibration and acoustic vibration. Condition monitoring of machines is essential for maintenance management in any industry which generally involves five distinct phases: detection of fault, diagnosis of fault, prognosis of fault progression, prescription for treatment of a problem and effective maintenance program for treatment of problems.

Keywords: Oil analysis, Thermography, Vibration analysis, Time domain Techniques, Frequency domain techniques, Time- Frequency domain techniques.

Introduction

Condition monitoring of rotary machinery is associated to the mechanical condition of the rotary machine such as vibration, bearing temperature, oil pressure, oil debris, and performance which makes it possible to decide whether the machinery is in good or bad mechanical condition. Condition monitoring makes it possible to determine the cause of the problem [1].

Bearing fault diagnosis is important in condition monitoring of any rotating machine [2]. There are several reasons of bearing damage. It is not always easy to conclude the exact cause of bearing failures.

Oil Analysis

Oil analysis can give an indication of microscopic wear particles present in the lubricant, which can be deemed as bearing wear and analyses can periodically be performed to trend bearing conditions. The oil analysis technique can be classified in following sub categories:

A. Spectrographic oil analysis

Spectrographic oil analysis tests the chemical composition of the oil can be used to predict failure modes. Very small concentrations of metallic wear products (1 to 2 ppm) suspended in used lubricating oil can be identified by spectrographic analysis [3]. For example high silicon content indicates contamination of grit etc., and high iron levels indicate wearing components. Detection of trace elements can give information about the part where wear is taking place.

B. Magnetic chip detector

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations.

C. Ferrography

Ferrography is a technique developed to separate wear debris from the lubricant and spread it according to size on a transparent substrate for examination in an optical or scanning electron microscope [5]. The analyzer consists of a pump to deliver a diluted oil sample at low rate, a magnet to provide a high-gradient magnetic field near its poles, and an inclined transparent substrate (Ferrogram slide) on which the particles are deposited. The quantity of wear particles and their size distribution can be determined by optical density measurement.

D. Radioactive tracer methods

The use of radioisotopes, artificially produced by neutron irradiation, offers a convenient method for following the movement of material during deformation, transfer, or the formation of wear debris [6]. In recent years, a great reduction has been obtained in background radiation by implanting radioactive ions instead of activating the sample. A thin-layer activation technique enables differentiation between the wear of different parts of moving machine elements.

Thermography

Bearing makers have long been conscious of the relationship of heat to bearing life and have developed formulas to accurately calculate safe operating temperatures [7]. The results show a temperature band in which both bearings and lubricants will work at peak performance with the least stress. Once outside the ideal temperature range, they will diminish at an accelerated rate. This technique can be used for recognizing the effect of fault on the bearing system but is not more suitable for bearing condition monitoring [8].

Vibration analysis

In this analysis, the healths of the machine based on collected data are analyzed [9]. This allows the changes within the machine to be determined precisely and appropriate corrective action can be initiated [10]. Although there are several methods of condition monitoring, vibration analysis was chosen for several reasons.

Table 1.1: Comparisons among vibration analysis, thermography and oil analysis technique

Process/Function	Vibration analysis	Thermography	Oil analysis
Time efficient	✓	✓	×
Cost-effective	✓	×	×
Damaged rolling element bearings fault detection	✓	✓	✓
Damaged rolling element bearings fault isolation	✓	×	×
Weak fault diagnosis of bearing	✓	×	×

The measurement of vibration is still a very effective tool to determine machine condition, especially since it can detect abnormal operating conditions long before there is any permanent damage to the machine. This feature is often not possible when other more traditional techniques are used [11].

1. Time domain Techniques

Vibration signals are initially obtained as a series of digital values representing proximity, velocity, or acceleration in the time domain. The time waveforms can be processed to achieve diagnostic objectives. Certain features such as statistical parameters can be signified using time domain vibration analysis techniques [12]. The Measurement of signal energy can be a good indicator of a bearing's health. This method has been applied with limited success for the detection of localized defects [13]. In time domain techniques, vibration signal is represented in amplitude versus time plot [14]. A typical time domain plot is shown in Figure 1. Although this technique fails when the vibration/acoustic signature may combine several other signals with different frequencies, amplitudes and phases, it results in opacity in identifying defect.

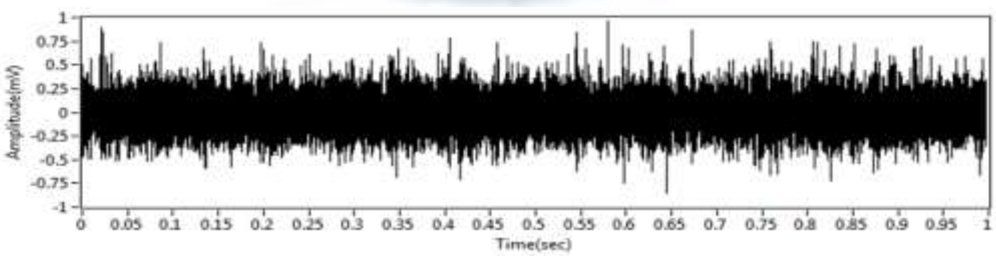

Figure 1: A time domain signal for defective bearing

1.1Statistical parameters

It includes mainly Root mean square (RMS), Mean, Variance, Skewness, Kurtosis, Peak level detection and Crest factor statistics is an area, which can provide many ideas for vibration analysis in fault diagnosis of bearing. Statistical analyses of vibration signals have proved to be useful in detecting rolling elements bearing faults.

a) The root mean square (RMS)

The root mean square value of a vibration signal is a time analysis feature, which is the measure of the power content in the vibration signature [15]. This feature is good for tracking the overall noise level, but it will not provide any information on which component is failing. It can be very effective in detecting a major out of balance in rotating systems. RMS can be defined by mathematical expression is as follows [16]:

$$RMS = \sqrt{\frac{\sum_{k=1}^{n} {x_k}^2}{n}} \qquad 1.1$$

Where, x_k is the amplitude of signal and n is the number of data points taken of the signal.

The greatest limitation of this approach is the lack of sensitivity and information available in the data. Unless a problem is severe, the overall level measurements may not change significantly. Unfortunately the machine monitoring community has relied too heavily in the past on these measurements alone, resulting in unanticipated machine failure [17]. The RMS level is calculated over a time period analysis that should be set in the configuration window. RMS level should be calculated over different time periods to separate the various faults components. Figure 2 show the RMS value of a healthy bearing and faulty bearing.

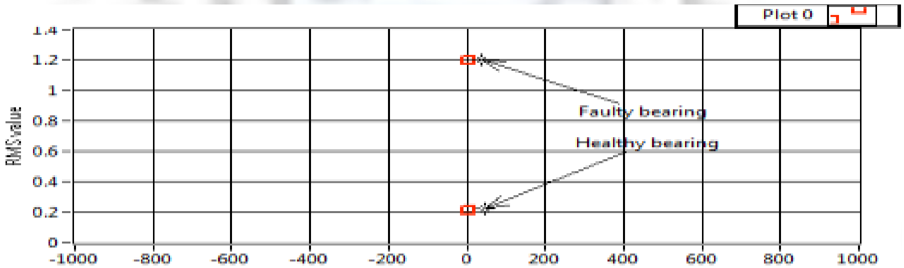

Figure 2: Scatter plot of RMS value for healthy and faulty bearing

b) Kurtosis

Kurtosis is defined as the fourth moment of the distribution and measures the relative peakedness or flatness of a distribution as compared to a normal distribution. Kurtosis provides a measure of the size of the tails of distribution and is used as an indicator of major peaks in a set of data [18]. Mathematically kurtosis factor K_u is expressed as below:

$$K_u = \frac{\frac{1}{n}\sum_{k=1}^{n}\left[x_k - \bar{x}\right]^4}{\left[\frac{1}{n}\sum_{k=1}^{n}\left[x_k - \bar{x}\right]^2\right]^2} \qquad 1.2$$

Where, x_1, x_2 ……. x_n are the population data of the signal, $\bar{x}$ is the mean of x, and n is the number of samples.

A bearing in good condition has a Gaussian distribution function and the Kurtosis value of its signal is equal to three, but a damaged bearing has a Kurtosis value which will be greater than three [19]

The kurtosis technique has the major advantage that the calculated value is independent of load or speed variations. The kurtosis analysis is a good parameter for faults and transient effect detection, but it does not give any indication of the diagnosis of the problem [20].

c) Crest factor

The ratio of the peak level to the root mean square level of the signal is called the crest factor [17]. The crest factor behaves as an indicator of bearing condition [21]. The crest factor limits are as follows: 2 to 4 indicates a normal bearing, 4to 8 indicate fault initiation and 8 to 10 indicates fault growth. Figure 3 show the Crest factor value of a healthy bearing and defective bearing.

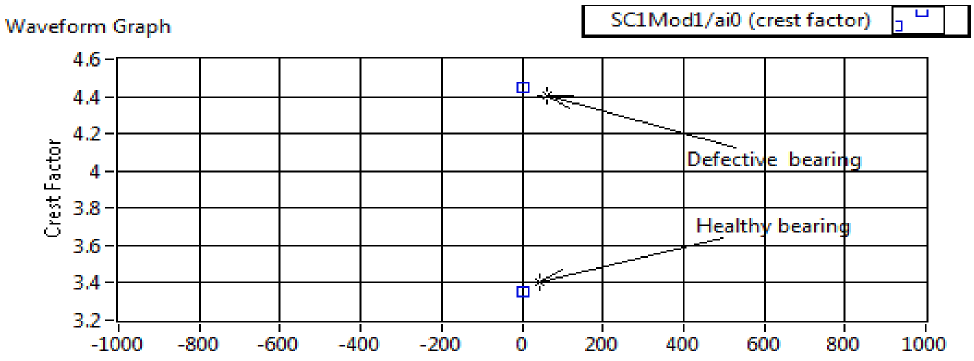

Figure 3: Scatter plot of Crest factor value for healthy and defective bearing

d) Peak level detection

The peak level indicator is the maximum value of amplitude present in the amplitude-time waveform of the signal [22].This is particularly useful for monitoring the change in the amount of impulsiveness, possibly due to increased bearing damage. However, on its own this method is not reliable, as other effects can also increase the peak level of a signal, but in conjunction with RMS level measurements it is a useful technique to identify bearing faults.

1.2 Time synchronous averaging analysis

Time synchronous averaging analysis (TSA) signals are the signals obtained by time synchronous averaging of the initial data and reducing redundant noise. The repetitive signals after TSA can indicate the information related to the faults, which need to be diagnosed. The TSA including FM0 and Comblet [23] requires knowing the repetitive frequency of the desired signal such as defect frequencies of rolling bearings. Synchronous averaged signals were utilized to diagnose faults in rolling bearings and gears successfully.

Filter based methods

Filters are widely used in feature extraction techniques for removing noise and isolating signals. Filter based methods include demodulation, prony model, and adaptive noise cancelling (ANC).

a) Demodulation model

Demodulation including phase and amplitude demodulation is an important signal processing technique. The amplitude demodulation was also known as envelope, or resonance demodulation, or high frequency resonance demodulation techniques [24]. The amplitude demodulation separates low-level, low-frequency signals from background noise, enabling them to be easily measured. Generally the demodulation procedure starts with using conventional Infinite Impulse Response (IIR) Filters such as Butterworth, Chebyshev, Bessel, and Elliptic in pass band or band stop.

b) Prony's model

Prony's model was used as an algorithm for finding an IIR filter with a prescribed time domain impulse response. A Prony model based method [25] was applied to bearing faults diagnosis. The method shows potential for analyzing transient vibration signals created from faulty low speed rolling element bearings. Spectral plots can be generated by applying the procedure to very short data samples, as well as trending parameters based on these spectral estimations and Prony parameters. It is shown that application of the Prony model based method has the potential to be an effective as well as efficient machine condition monitoring and diagnostic tool where short duration transient vibration signals are being generated.

c) Adaptive noise cancelling (ANC)

Adaptive noise cancelling is an approach to reduce noise based on reference signals. In conventional adaptive noise cancelling systems, the primary input signal is a combined signal and noise and the reference signal is a noise signal. Asynchronous adaptive noise cancelling technology was employed to detect self-aligning roller bearing faults successfully [26].

1.3 Stochastic methods and other advanced methods

Advanced methods such as stochastic parameters have been used to analyze vibrations in the time domain. Chaos, whose computation parameters are known as the correlation dimension, is used to characterize several induced faults of varying severity in a rolling element bearing [27].

Statistical methods have been combined with artificial intelligence techniques such as Neural Networks in order to diagnose faults more efficiently [28]. An artificial Neural Network has been used successfully for on-line monitoring of ball bearing conditions. Peak amplitude in the frequency domain, peak RMS, and the power spectrum of vibration signals have been used as inputs of the Neural Network while the outputs indicate the bearing states.

2. Frequency domain techniques

In this technique data is presented in terms of frequency and its magnitude. Frequency domain techniques are used when information of frequency in signal is important to identify cause of periodicity [19]. This technique is quite useful for analyzing stationary signals whose frequency components do not change over time. In other words, this technique is very accurate if the rpm of the shaft does not change over time or does not change at least during each updated duration of time analysis [12]. Some of the frequency domain techniques for analysis of vibration/acoustic signal are discussed below.

a) Spectrum analysis

The common technique for spectrum analysis is the Fourier transform (FT). FT split the signal into its sinusoidal components. The FT contains ability to convert a time domain signal into its frequency contents [29]. A change in the spectrum is related to the nature of the faults. The source of some spikes can not be explained in the spectrum due to the some micro-structural components in the machine [30].

For a continuous-time signal, $x(t)$, the Fourier transform, $X(f)$ can be expressed as:

$$X(f) = \int_{-\infty}^{+\infty} x(t).e^{-i2\pi ft}\,dt \qquad 1.3$$

Here, f represents global frequency and t denotes the time. The signal can then be analyzed for its frequency content because the value of the transformed function represents the contribution of sine and cosine function at each frequency. The $x(t)$ can be obtained from its Fourier transform in the following way:

$$x(t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} X(f).e^{i2\pi ft}\,dt \qquad 1.4$$

FFT plot of a defective bearing is shown in Figure 4

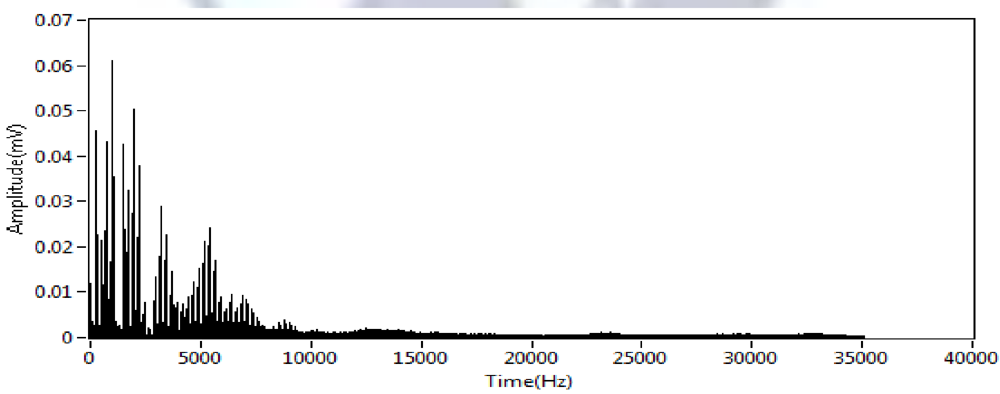

Figure 4: FFT for defective bearing signal

b) Cepstrum analysis

The cepstrum is the spectrum of the logarithm of the power spectrum, it is used to highlight periodicities in the vibrations spectrum, in the same way that the spectrum is used to highlight periodicities in the time waveform [31]. Thus, harmonics and sidebands in the spectrum are summed into one peak in the cepstrum (called rahmonic), allowing simplified identification and trending of specific fault frequencies. Cepstrum of a defective bearing is shown in Figure 5. It can be explain mathematically as:

$$C(\tau) = FFT^{-1}[\log G_{xx}(f)] \quad 1.5$$

Where, $G_{xx}(f)$ is frequency dependent correlation function.

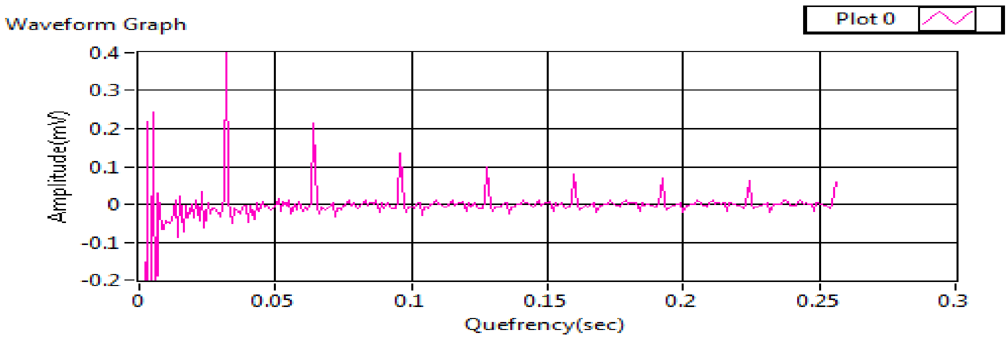

Figure 5: Cepstrum of the defective bearing

The cepstrum is very good indicator for bearing and gearbox faults, is used for both faults detection and diagnostic [32]. For fault detection point of view, the data of harmonics and sidebands are reduced to one line and is not subjected to amplitude and frequency modulation.

c) Waterfall plot

Waterfall analysis is a tool that is often used to evaluate the acoustic and/or vibratory performance of rotating element bearing. The process involves calculating spectra using fast fourier transform (FFT) methods at incremental steps in rpm (revolutions per minute) as the rotational speed changes either increasing (run up) or decreasing (coast down). Because it takes time to sample enough data to fill a time block for a single FFT calculation (the actual calculation time is minimal), the rotational speed of the machine being tested will have changed from the beginning of the time block to the end of the time block. The changing of the rpm during the time required to capture each time block produces a phenomenon known as smearing of the data.

This method is used to examine sub synchronous and super-synchronous components of a machine [33].

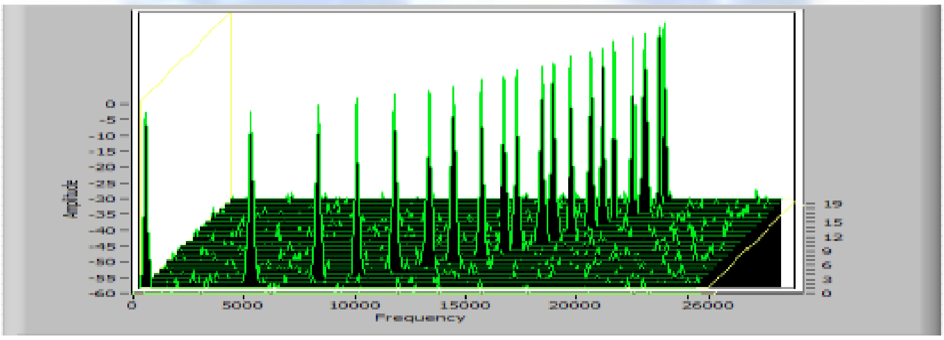

Figure 6: Water fall of the defective bearing

3. Time- Frequency domain techniques

When the rotating speed of the shaft is changing over time due to variances in load or commences of fault in the shaft then frequency changes over time and the FFT will not give accurate results [34]. Till FT contains a capacity to capture signal's frequency content as long as is composed of little stationary components. Though, any sudden change in time for non-stationary signal is extent over the whole frequency axis. Hence the time-domain signal sampled with Dirac-delta function is localized in time however spills over entire frequency band and vice versa. The drawback of FT is that it cannot offer both time and frequency localization of a signal at the same time. Therefore, instead of distinct observation of the time from the frequency characteristics of a signal, it is prefer to use a joint time-frequency technique.

Time-frequency (TF) analysis results are presented in a spectrogram or scalogram, which shows the energy distribution of a signal in the time-frequency domain. A spectrogram/ scalogram are an intensity graph contains time in abscissa and frequency in ordinate. Intensity of color explains the power of the signal at the corresponding time and frequency. In this transform, sine wave basis functions are modified which are more concentrated in time but less concentrated in frequency. It uses an arbitrary but fixed-length window function "*w*" for analysis, over which the actual non-stationary signal is assumed to be approximately stationary. TF analysis decomposes such a non-stationary signal into a two dimensional time-frequency representation $S(t, f)$ of the signal $x(t)$ using that sliding window at different times.

The Short-time Fourier transform (STFT) is defined as:

$$s_x^{(w)}(\tau, f) = \int_{-\infty}^{+\infty} [x(t).w^*(t-\tau)].e^{-i2\pi ft} dt \qquad 1.6$$

Where $x(t)$ is the signal itself, $w(t)$ is the window function, and "*" stands for its complex conjugate. For every τ and f, a new STFT coefficient is computed to obtain a true time- frequency representation of the signal. Limitation of STFT is that it is only suitable for non-stationary signals [35]. Once a window has been chosen for STFT, the time-frequency resolution is fixed over the entire time-frequency plane since the same window is used at all frequencies. There is always a tradeoff between time resolution and frequency resolution in STFT. To overcome the boundaries of the standard STFT, Wavelet Transform (WT) was introduced in the field of signal processing. WT in its continuous form delivers a flexible time-frequency window, which narrows when detecting high frequency phenomena and widens when examining low frequency behavior. Thus time resolution becomes arbitrarily good at high frequencies, although the frequency resolution becomes arbitrarily good at low frequencies. Therefore WT is highly preferable tool to fulfill both time and frequency resolution requirements more accurately.

The wavelet transform can be imagine as an extension of the classic Fourier transform while excepting that instead of working on single scale, it works on a multi-scale basis. The wavelet transform can be categorized as continuous or discrete. [39]

The main advantage of the continuous wavelet transformation (CWT) is its ability to deliver information simultaneously in time and scale with adaptive windows [36]. Using CWT, Calculating wavelet coefficients at every feasible scale is a large quantity of work, and produces a disagreeable lot of data [37].

To overcome such a problem an analytical wavelet transformation based on the Morlet wavelet was introduced by Lin [38].

Acknowledgment

I would like to express my gratitude to my supervisor **Mr. Shakun Srivastava**, Assistant professor of Mechanical Engineering Department UP India, for his exceptional patience, Thank you for providing me with valuable feedback in my work which made it stronger and more valuable. I am sincerely grateful for his priceless support and contribution toward my research.
Also, I would like thank to **Dr. Brajesh Varshney** and **Mr. A. S. Verma** for providing me the opportunity to carry out the present study and thesis work. I extend my sincere thanks to my brother Mr. Abhishek Verma, Finally, I would like to thank my family for their help, encouragement, prayers and cooperation during my research work.

References

[1]. Mitchell, J. S. 1981. An introduction to machinery analysis and monitoring. Penwell Publishing Company, Tulsa, Okla. pp. 171-173.
[2]. Bently, D. E., Zimmer, S., Palmatier, G. E. and Muszynskq, A. 1986. Interpreting vibration information from rotating machinery. Sound and Vibration. 20: 14-23.
[3]. Beerbower, A. 1976. Spectrometry and other analysis tools for failur prognosis. Lubrication Engineer. 32(6): 285-293.
[4]. Junemann, H. 1976. Mechanical tests for lubricants. Erdgas-Petrochem. Verneigt Brennstoff-Chemie. 25(8): 459-464.
[5]. Scott, D., Seifert, W. W. and Westcott, V. C. 1975. Ferrography- an advanced design aid for the 80´s. Wear. 34(3): 251-260.
[6]. Gerve, A. 1973. Applicability of radio nuclides for the investigation of the influences of design and lubrication on the wear of machines elements. VDl-Berichte. 196: 43-49.
[7]. Kim, W., Choi, M. and Park, J. 2005. Diagnosis of defect points in materials using infrared thermography. Key Engineering materials. 297(1): 2169-2175.
[8]. Randall, R. B. 2011. Vibration-based Condition Monitoring: Industrial, Aerospace and Automotive Applications. John Wiley and Sons Ltd. UK. pp. 285-287.
[9]. Hall, L. D. and Mba, D. 2004. Acoustic emissions diagnosis of rotor-stator rubs using the KS statistic. Mechanical Systems and Signal Processing. 18(4): 849–868.
[10]. Darpe, A. K., Gupta, K. and Chawla, A. 2003. Experimental investigations of the response of a cracked rotor to axial excitation. Journal of Sound and Vibration 260(2): 265-286.
[11]. Sun, Q. and Tang, Y. 2002. Singularity analysis using continuous wavelet transform for bearing fault diagnosis. Mechanical Systems and Signal Processing. 16(6): 1025-1041.
[12]. Igarashi, T. and Hamada, H. 1982. Studies on the vibration and sound of defective rolling bearings. (First report: vibration of ball bearings with one defect). Bull. JSME. 25(204): 994-1001.

[13]. Miyachi, T. and Seki. K. 1986. An investigation of the early detection of defects in ball bearings using vibration monitoring - practical limit of detectability and growth speed of defects. Proceedings of the International Conference on Rotor dynamics, Tokyo. pp. 403-408.
[14]. Eshleman, R. L. 1983. Machinery diagnostics and your FFT. Sound and Vibration. 17(4) : 12-18.
[15]. Barkov, A., Barkova, N. and Mitchell, J. S. 1995. Condition assessment and life prediction of rolling element bearing- Part 1. Journal of Sound and Vibration. 29: 10-17.
[16]. Kiral, Z and Karagulle, H. 2003. Simulation and analysis of vibration signals generated by rolling element bearing with defects. Tribology International. 36(9): 667–678.
[17]. Archambault, R. 1989. Getting more out of vibration signals: Using the logarithmic scale. Proceeding 1st International Machinery Monitoring & Diagnostic Conference & Exhibit, Las Vegas, Nevada. pp. 567-571 .
[18]. Sugumaran, V., Sabareesh, G. R. and Ramachandran, K. I. 2008. Fault diagnostics of roller bearing using kernel based neighborhood score multi-class support vector machine. Expert Systems with Applications. 34(4): 3090–3098.
[19]. Tandon, N. and Choudhury, A. 1999. A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings. Tribology International. 32(8): 469–480.
[20]. Dron, J. P., Bolaers, F. and Rasolofondraibe, L. 2004. Improvement of the sensitivity of the scalar indicators (crest factor, kurtosis) using a de-noising method by spectral subtraction: Application to the detection of defects in ball bearings. Journal of Sound and Vibration. 270(1-2): 61–73.
[21]. Weichbordt, B. and Bowden, F. J. 1970. Instrumentation for predicting bearing damage. G.E.C. Technical Report. pp. 1021-1037.
[22]. Collacott, A.R. 1979. Vïbration Monitoring Diagnosis. John Wiley & Sons, Ltd. UK. pp. 207-211.
[23]. Lebold, M., McClintic, K., Campbell, R., Byington, C., and Maynard, K. 2000. Review of vibration analysis methods for gearbox diagnostics and prognostics Proceedings of 54th meeting of the Society for Machinery Failure Prevention Technology, Virginia Beach (VA). pp. 623-634.
[24]. Wang, W. Q., Ismail, F. and Golnaraghi, M. F. 2001. Assessment of gear damage monitoring techniques using vibration measurements. Mechanical Systems and Signal Processing. 15(5): 905-22.
[25]. Chen, Z. and Mechefske, C. K. 1993. Diagnosis of machinery fault status using transient vibration signal parameters. Journal of Vibration and Control. 8(3): 321-335.
[26]. Shao, Y. and Nezu, K. 1999. Detection of self-aligning roller bearing fault by asynchronous adaptive noise cancelling technology. JSME International Journal. 42(1): 33-43.
[27]. Wang, W. J., Chen, J., Wu, X .K. and Wu, Z. T. 2001. The application of some non-linear methods in rotating machinery fault diagnosis. Mechanical Systems and Signal Processing. 15(4): 697-705
[28]. Liu, T. I. and Mengel, J. M. 1991. Detection of ball bearing conditions by an A.I. approach. Sensors, Controls, and Quality Issues in Manufacturing. American Society of Mechanical Engineers, Production Engineering Division. 55: 13-21.
[29]. Stein, E., and Weiss, G. 1971. Introduction to Fourier analysis on Euclidean Spaces. Princeton University Press, New Jersey. pp. 25-27.
[30]. Guastafson, Q. and Tallian, T. 1963. Final report on the study of the vibration characteristics of bearings. U. S. Navy Contract No. N06578.552, U. S. Dept. of Navy, Bureau of Ships, Washington D.C. pp. 23-27.
[31]. Martin, A. 1987. Vibration monitoring of machines. Bruel & Kjaer Technical Review, No. 1, pp. 32-36.
[32]. Debao, L., Hongcheng, Z. and Bo, W. 1989. Cepstrum analysis and the fault diagnosis of rotating machine. Proceedings of the 1st International Machinery Monitoring & Diagnostic Conference & Exhibit, Las Veagas, Nevada. pp. 596-611 .
[33]. Trevillion, B., Parge, P., Carle, P. and Good, M. 1989. Machinery interactive display and analysis system description and applications. Proceedings of the 1st International Machinery Monitoring & Diagnostic Conference & Exhibit, Las Veagas, Nevada. pp. 176-183.
[34]. Meltzer, G. and Dien, N. P. 2004. Fault diagnosis in gears operating under non-stationary rotational speed using polar wavelet amplitude maps. Mechanical Systems and Signal Processing. 18(5): 985–992.
[35]. Rohrbaugh, R. A. and Cohen, L. 1995. Time-Frequency analysis of a cam operated pump. Life Extension of Aging Machinery and Structures: Proc. 49th Meet of MFPT Soc. Vibration Inst.: Virginia Beach. 49. pp. 349-364.
[36]. Samuel, P. D. and Pines, P. J. 2000. Vibration separation methodology for planetary gear health monitoring. Proceedings of the SPIE, the International Society for Optical Engineering, 3985. pp. 250-60.
[37]. Tse, P. W., Yang, W. and Tam, H. Y. 2004. Machine fault diagnosis through an effective exact wavelet analysis. Journal of Sound and Vibration. 277(4-5): 1005-1024.
[38]. Lin, J. and Zuo, M. J., 2003. Gearbox fault diagnosis using adaptive wavelet filter. Mechanical Systems and Signal Processing, 17(6): 1259-1269.
[39]. Verma, A and Srivastava, S, 2014. International Journal of Engineering Research & Technology, Vol. 3 Issue 6, 1020-1025.