Vibration Based Condition Monitoring and Fault Diagnosis Technologies For Bearing and Gear Components-A Review

S. Devendiran
School of Mechanical Engineering, VIT University, Vellore, Tamil Nadu, India.

Dr. K. Manivannan
School of Mechanical Engineering, VIT University, Vellore, Tamil Nadu, India.

Abstract
All machines with moving parts give rise to sound and vibration and each machine has a specific vibration signature related to the construction and the state of the machine. If the state of the machine changes the vibration signature will also change and a change in the vibration signature can be used to detect incipient defects before they become critical. This is the basics of vibration based condition monitoring (CM) methods. The CM technique is based on detecting the presence of a fault, diagnosing the root cause of the fault, assessing its level of severity and making arrangements for its correction. A broad review of the state-of-art of condition monitoring and fault diagnosis techniques has been carried out for improving the accuracy and ability of condition monitoring and prognosis systems for bearing and gear components.

Keywords: Condition monitoring; fault diagnosis; bearing, gear; signal processing; operation and maintenance

Introduction
Gear and bearing components plays an important role in many of the industrial rotating and transport machinery applications. Early fault diagnosis of gear and bearings may prevent unnecessary failures of most of the rotating machinery system and there by increase operational reliability and availability of machine. Fault diagnosis techniques are important for monitor the conditions in bearing and gear. Currently available fault diagnosis techniques have a variety of limitations. An effective and method has to be researched and automated system has to be developed for industrial machinery component health diagnostic activities. (Taylor, 1995) discussed the dynamic performance of the rotating components is highly influential in the performance of any rotating machinery. The developments in electronic data acquisition equipment, sensors, computers and software made an automated supervision system in condition monitoring of machines. (Endo and Randall, 2007) gave the importance of gear and bearings in the industrial rotating and transport machinery applications. Fault detection is the process of observing the measured system data and system status information and comparing them with a normal range of observed attributes to determine whether some measurements fall outside the range representing the healthy condition of the system. Unfortunately, no one technique is able to detect all machine faults. However, it has been suggested that vibration measurement, which is the most widely used CM technique in industry, can accurately identify 90% of all machinery failures by the change in vibration signals which they produce and the level of signal can give an accurate prediction of future failure (Randall, 2010). The task is to diagnose the fault at an early stage so corrective action can be taken as early as possible to extend the life of the machine (Latino, 1999).

Significance of Bearing In Rotating Machinery and Bearing Failures
This review focuses on health monitoring of rolling element bearings because they are widely used machine component in rotating machinery and the consequences of bearing failure are the cause of widespread and substantial economic loss and, sometimes, catastrophic failure, (Bently, 1982). Most rolling bearings have four basic elements: inner race, outer race, rolling elements, and cage or separator has shown in Fig. 1. The inner race, outer race, and rolling elements support the bearing load, while the cage separates adjacent rolling elements to avoid friction between them.

Figure 1: Schematic representation of single row ball bearing

The rolling elements may be balls, cylindrical rollers, tapered rollers, needles, or barrel rollers, encased in a cage that provides equal spacing and prevents internal strikes. Among that rolling element bearings are used in entire range of sizes of motors and pumps and surveys have shown that failure in these elements accounts for just over half of electric motor failures. Bearing defects are often a warning of other faults in the machine because, for example, misalignment and/or
imbalance can be the cause of the bearing defects. Thus the CM of rolling element bearings is a very important component of many industrial maintenance programmes (Moore et al., 1993). Rolling element bearings are among the mechanical parts used widely, and are easily damageable (Yuna et al., 2009). It is used as the interface between the stationary and the rotating part of the machine. Statistics show, about 30% of the rotating machinery faults are caused by the damage of the bearings. Therefore bearing is considered as the important parts we have to improve the detecting ability of fault diagnosis of bearing (Li et al., 2013). The running condition of bearing plays a crucial role in the performance of mechanical equipment. Bearing failure can lead to costly loss in production and even human casualties. Effective prediction of bearing life is necessary to prevent abrupt bearing breakdown, and is also benefit to improve productivity, reduce costs and repairing time. Accurately estimating the life of bearing is a challenging problem. In the conventional life prediction methods, the statistical model is predominant. It is significant for a batch of bearings life prediction. However, due to the randomness of bearing failure time, it is lack of accuracy for life prediction of single bearing in practice. In recent years, modelling methods of bearing life prediction based on the condition monitoring data, such as temperature, vibration and sound emission signal, have obtained more and more attention. These models are data-driven models, and they can establish the non-linear relationship between condition monitoring data and actual bearing operating time directly. Of all the bearing monitoring data, vibration signal is more effective and suitable for reflecting bearing running condition (Runqing et al., 2007). The vibration is small and smooth when the bearing is under normal condition. And the occurrence of bearing defect can cause fluctuation of vibration. During the process of degradation, the amplitude of vibration increases obviously. Thus vibration signal becomes the convenient variable to investigate the degeneration process of bearing. In the review paper presented by Kim (1984) and Tandon (1994) have noticed that mainly two approaches have been adopted by researchers, one is to run the bearing for its entire life and wait to observe the changes in vibration response until bearing failure occurs and the other approach is to prepared artificially defective bearing and compare it with that of good bearings.

**Bearing Condition Monitoring Using Signal Processing Techniques**

The majority of the research on the diagnosis and prognosis of bearings is based on signal processing techniques, independent of bearing vibration characteristics. In these works, first a localized or distributed defect is created on a bearing by means of grinding, acid etching, drilling, overloading, or over speeding to intentionally introduce defects in the bearing components. After a vibration signal is measured usually, by accelerometers, different signal processing techniques are employed to extract the fault sensitive features to serve as the monitoring indices. This procedure is quite similar among the published literature. The reported signal processing methods are categorized as time domain, frequency domain, and time-frequency domain. These techniques are not totally independent, and in many cases, they are complementary to each other. Time domain analysis has been widely employed. Successful results of Root Mean Square (RMS) (Tandon, 1994), Kurtosis (Dyer and Stewart, 1978), skewness, peak value (Mathew and Alfredson, 1984), Crest Factor (Ingarashi, 1980) and synchronous averaging (Hemmings and Smith, 1976) have been reported in the low frequency range of <5 kHz. In bearing fault diagnosis, frequency domain, or spectral analysis, is the most popular approach. Many researchers have reported successful results for detecting damaged bearings through spectral analysis. Usually, it is carried out at low-range frequencies and the defects are identified by the change of the spectral amplitude at each of the characteristic frequencies. Taylor (1980) has formulated the sequence of appearing and disappearing spikes in the spectrum. In addition, he has proposed a method for measuring the size of the defects on the raceways. Mathew and Alfredson, (1984) have offered the amplitude difference between healthy and damaged spectra as a fault diagnosis technique. The envelope detection is a well-defined technique for bearing fault diagnosis. The efficiency of this method has been evaluated by many researchers (Kadushin 1991, Mohan 1991). Four characteristic fault frequencies of a ball bearing can be calculating using the following equations given by T. A. Harris (1991).

Shaft rotational frequency in Hz :
\[ F_s = \frac{\text{shaft speed}}{60} \]  
(1)

Ball pass frequency outer race :
\[ (BPFO) \text{ Hz} = F_s \left( \frac{N_b}{2} \right) \left( 1 - \frac{B_d}{P_d} \cos \phi \right) \]  
(2)

Ball pass frequency inner race :
\[ (BPFI) \text{ Hz} = F_s \left( \frac{N_b}{2} \right) \left( 1 + \frac{B_d}{P_d} \cos \phi \right) \]  
(3)

Train or cage frequency (FTF) :
\[ Hz = F_s \left( \frac{1}{2} \right) \left( 1 - \frac{B_d}{P_d} \cos \phi \right) \]  
(4)

Ball spin frequency (BSF) :
\[ Hz = F_s \left( \frac{P_d}{2B_d} \right) \left( 1 - \frac{B_d^2}{P_d^2} \cos^2 \phi \right) \]  
(5)

Where, \( N_b \) the number of balls, \( B_d \) the ball diameter, \( P_d \) the pitch diameter \( \phi \) the contact angle of ball in degree.

If the rotational speed of the races is constant, the impact repetition rates can be determined by the geometry of the bearing. These repetition rates are called characteristic bearing frequencies. When a contact ball bearing is mounted in such a way that the outer race is fixed in the housing and the inner race is rotating at the same speed as the shaft mentioned characteristic bearing frequencies will be generated. These characteristic frequencies are useful to find the defects of the bearing components from the concern component frequencies and its harmonics. Frequency analysis may be the most fundamental approach for bearing condition monitoring and fault detection. When a fault occurs in a bearing, periodic or quasi-periodic impulses appear in the time domain of the vibration signal, while the corresponding Bearing
Characteristic Frequencies (BCF) and their harmonics emerge in the frequency domain (Antoni and Randall, 2002). However, in the early stage of bearing failures, the BCFs usually carry very little energy and are often suppressed/hidden by severe noise and higher-level vibrations. Consequently an effective signal processing method is of utmost importance for the extraction of damage sensitive features during the condition monitoring of bearings, especially during the initial fault occurrence (Georgoulas, 2013).

Tandon and Nakara, (1992) compared the most commonly used vibration analysis methods for mechanical fault diagnosis such as time domain analysis, frequency domain analysis; time frequency analysis for defect detection in bearings. Su and Lin (1992) have discussed to characterize the vibrations measured from bearings subject to various loading conditions and with defects located on any bearing components. They have determined the periodic characteristics of various loading, transmission path and their influence on the vibration amplitude. Su and Sheen (1993) have obtained a reliable model to predict the possible bearing frequencies, harmonics and sidebands for the various types of localized fatigue damage, the pattern of expected frequencies can be searched for as part of routine bearing condition monitoring. Tandon and Choudhury, (1999) made a review on vibration and acoustic measurement methods for the detection of defects in rolling element bearings and discussed about the fault detection at the initial stage is difficult through envelope analysis and the wavelet transform method has been suggested to extract very weak signals for which Fourier transform becomes ineffective. Rubiniand Meneghetti(2001) applied the wavelet transform and proved its significance in bearing fault detection and gives the information regarding frequency at any particular time is difficult to achieve either from frequency domain or time domain. Prabhakar et al, (2002) applied the wavelet transform and inferred wavelets provide time-scale information of a signal, enabling the extraction of features that vary in time. The Discrete Wavelet Transform (DWT) is derived from the discretization of Continuous Wavelet Transform (CWT).

Li et al. (1995)argues that Fourier analysis provides a poor representation of signals well-localized in time because the FFT assumes a stationary signal and contains no information on when an event occurred. The article used the WT as a means of extracting time frequency information from the vibration signal. Jardine et al. (2006) made a review on machinery diagnostics and prognostics implementing Condition Based Maintenance (CBM) in mechanical systems and emphasis on models, algorithms and technologies for data processing and maintenance decision-making. They conclude with a brief discussion on current practices and possible future trends of CBM. Patil et al. (2010) have varied the defect size and studied its effect on vibration response. Authors have noticed that the vibration amplitude increases with defect size. Patel et al. (2010) have developed dynamic model of deep groove ball bearing in presence of defects on either of races under steady and dynamic loading condition. They have concluded that the amplitude of vibration velocity in case of multiple defects is more as compared to single defect on either race. Although, the defect detection for multiple defects is difficult due to same vibration spectra as single defect. Xu et al. (2012) proposed a methodology based on translation-invariant de noising and HHT to detect rolling element bearing faults from strong background noise. Li and Wang (2013) have summarizes the development and application of Hilbert-Huang Transform for solving the problem of rolling bearing fault diagnosis from several aspects and sums up the practical applicability of HHT method through the comparison of rolling bearing fault diagnosis with other methods. Fan and Li, (2015) presents a hybrid approach for fault diagnosis of planetary bearings(with seeded bearing faults) using an internal vibration sensor and novel signal processing strategies.. Advanced signal processing techniques, including Cepstrum whitening, Minimum Entropy Deconvolution (MED), Spectral Kurtosis (SK) and envelope analysis were applied.

**Bearing Condition Monitoring Using Artificial Intelligent Diagnostics Techniques**

Due to advancement in technology of measurement equipment and modern computer, the information/data from condition monitoring of machinery becomes vital. According to the automated diagnostic process shown in Fig. 2

![Figure 2: Schematic representation of intelligent fault diagnosis process](image-url)

The first step is data acquisition from rotating machinery system through the sensor; subsequently signal pre-processing along with feature extraction process has to be carried out to reduce the dimension of raw data to obtain useful information from the signal. The raw data always in nonlinear, heterogeneous and distributed form. Handling proper data pre-processing can improve the performance of fault diagnosis. The performance of machine fault diagnosis, largely depend on appropriate features extraction and features selection techniques. The selection of vital features from targeted
machine is the main contribution to increase the effectiveness of fault diagnosis process. Features extraction techniques can be categorized into three categories: time domain, frequency domain and time-frequency domain. Time domain features extraction techniques include statistical analysis, which in turn includes mean, standard deviation, RMS, skewness, kurtosis, maximum, minimum, and crest factor are selected as statistical features extraction (Mahamad and Hiyama, 2008).

In general it is unnecessary to employ all the features for fault diagnosis purposes. Some features can contribute significant information of faulty sign while some only contribute less information. Thus, it is necessary to have appropriate feature selection to increase the accuracy of fault diagnosis process. Various methods can be used for feature selection such as modified distance discriminant technique (Xu et al., 2009), distance evaluation technique (Lei et al., 2007), neural network (Matsaura, 2004), J48 decision tree algorithm (Saravan et al., 2009). The selection of features selection is essential to increase the accuracy of fault diagnosis system. Failure detection entails the classification of the indices into different categories. For this purpose, an intelligent processing tool is used to map the features into monitoring decisions. The traditional methods for fault diagnosis are categorized as pattern classification, knowledge-based inference, and numerical modelling. In these methods, human expert looks for particular patterns in the vibration signature that might indicate the presence of a fault in the bearing. Alternatively, statistical analysis and Artificial Neural Network(ANN) are utilized for the automated fault detection systems (Baillie and Mathew, 1996). ANNs are capable of learning the behaviour of nonlinear systems. In a fuzzy inference system, a set of logical rules is extracted from an expert knowledge database, independent of the system’s configuration. Liu et al. (1996) have developed a fuzzy expert system for bearing diagnosis. Final diagnosis was done by using classification algorithms. Sugumaran and Ramachandran (2007) applied automatic rule learning using decision tree for fuzzy classifier in fault diagnosis of roller bearing, a rule set is formed from the extracted features and input to a fuzzy classifier. Decision tree is used to generate the rules automatically from the feature set. Nguyen et al. (2008) Utilized genetic algorithm for optimal feature selection in mechanical fault detection of induction motor. Based on specific distance criteria, a Genetic Algorithm (GA) is introduced to reduce the number of features. A decision tree and multi-class support vector machine are used to illustrate the potentiality and efficiency of this selection (classification) method. Unal et al. (2014) suggested some methods to extract features using envelope analysis accompanied by Hilbert Transform and Fast Fourier Transform. The proposed ANN based fault estimation algorithm was verified with experimental tests and ANN model was modified using a genetic algorithm providing, optimal skilful fast-reacting network architecture with improved classification results. Jack and Nandi (2000a) made a Comparison of neural networks and support vector machines in condition monitoring application.

**Significance of Gear Box and Gear Failures**

Gearbox (Dalpiaz, 2000) is one of the complex machinery and is a critical component in mechanical power transmission system. Gearboxes have wide applications in automobile, cement, petrochemical, power, paper & pulp, steel and sugar industries. The gear drives are the most effective means of transmitting power in machines due to their high degree of reliability and compactness. A gearbox is used in transmission systems either for reducing or increasing of speeds. The gears themselves are the most important elements in the gearbox, and the degree of wear and fatigue to which they are subjected even under normal operating conditions means that they are often subject to premature failure. Li et al. (1995) claim that up to two thirds of gearbox failures are due to faults which develop in the gears, and almost all of these are due to localised defects such as fatigue induced fractures.

Gear failures tend to occur when a gear is working under high stress conditions (Merritt, 1954; Smith, 1983; Alban, 1985). Local faults are the more dangerous because they tend to develop rapidly once initiated, and usually have significant effects on power transmission. If not detected early there can be dramatic consequences with tooth breakage, pitting and scoring are the most important local faults. Tooth breakage is the most dangerous type of gear failure and leads to disenablement of the drive and often damage of other gearbox components such as the shaft, bearing, etc., by pieces of the broken tooth. Tooth breakage can be due to overload and/or impact and damage. However, the most common cause bending fatigue due to repetitive loads on the gear teeth. These usually begin with a small crack which spreads until part or the entire tooth breaks off. The remnants of the remaining tooth will have greater impact loading and be prone to further breakage (Dudley, 1962). Pitting is a surface fatigue failure of the gear tooth. It occurs when contact stress is greater than the fatigue tolerance limit and typical tooth pitting damage. After a certain period of operation with repeated variation of the load, small areas of metal on the tooth surface fatigue and drop off. Once pitting has occurred it tends to spread at an accelerating rate because the un-pitted areas which remain must support the extra load previously carried by the damaged area. Scoring is happened because of inadequate or unsuitable lubrication, overloading and misalignment can all cause the lubricant film to break down and allow direct metal-to-metal contact. The result can be very high temperatures and local welding of mating surfaces. These welded spots break away as the gear rotates causing other problems elsewhere. With distributed faults there is a significant, possibly substantial, delay between failure initiation and complete loss of service. These faults tend to progress slowly and the gear can still transmit power as the fault develops. A typical distributed gear fault is called tooth wear. Wear occurs when layers of metal are removed more or less uniformly from the surface and can take two forms such as Adhesive Wear and Abrasive Wear. Adhesive Wear is occurred because it is characterized by transfer of metal particles from one tooth to its mating tooth by welding action and Abrasive Wear caused by to abrasive particles in the meshing area. Other distributed gear defects include surface inaccuracy and misalignment. Both localized and distributed gear faults generate transmission errors and increase vibration
levels of the machinery. Localized defects are more important from the CM point of view, especially tooth breakage which can occur with little warning and cause catastrophic failure in machines such as helicopters (Choy et al., 1996; Dalpiaz et al., 2000).

**Gear Condition Monitoring Using Signal Processing Techniques**

This section presents a review of signal processing techniques which are used to monitor the condition of geared transmission systems based on vibration signals. McFadden (1986) investigated fatigue cracks in gears by amplitude and phase demodulation of meshing vibration and mention gear health condition is directly proportional to the performance of the machinery. Meng et al. (1991) presented that; any real world signal can be broken down into a combination of unique sine waves. Every sine wave separated from the signal appears as a vertical line in the frequency domain. Its height represents its amplitude and its position represents the frequency. The frequency domain completely defines the vibration. Frequency domain analysis not only detects the faults in rotating machinery but also indicates the cause of the defect. Staszewski and Tomlinson (1994); Wang and McFadden (1996) applied wavelet transform to waveform data analysis in fault diagnostics of gears and carried out the fault diagnosis. Randall (1982) in his classical work on gear vibration, classified the vibrations generated by gear meshing as being caused by:

- Deviations from the ideal tooth profile producing a vibration signal at \( f_m \), the tooth-meshing frequency.
- Variations in tooth loading which generate amplitude modulation,
- Fluctuations in the rotational speed, and/or non-uniform tooth spacing which produce frequency modulation effects, and local tooth faults which generate additional impulses.

During real gear meshing the load and its direction on the tooth vary with time, causing tooth deflection to also vary. This produces the dominant vibration at the gear meshing frequency, \( f_m \), and its harmonics.

\[
f_m = N_t f_t
\]

Where: \( N_t \) is the number of teeth on the gear and \( f_t \) is the shaft rotation frequency.

This basic signal will be modulated in amplitude and phase due to imperfection in the gears and teeth such as eccentricity. This modulation appears as sidebands either side of the gear meshing frequency (and the harmonics) in the vibration spectrum, and is separated from them by multiples of the modulating frequency (White, 1972). In fact there will be a number of modulation frequencies and determination of these is often very useful in diagnosis of faults. Even the vibration signal generated by healthy gears will contain harmonics and sidebands of the gear meshing frequency. Thus the sideband frequencies will be:

\[
f_{sb} = m f_m \pm k f_t
\]

Where: \( m \) is the number of the meshing harmonic, and \( k \) is an integer.

Dalpiaz et al., (1997) presents the time-domain analysis which calculates characteristic features from time waveform signals as a descriptive statistics such as peak, peak to-peak interval, mean, standard deviation, crest factor and high-order statistics: skewness, kurtosis, root mean square. These features are usually called time-domain features in local fault detection in gears. Andrade et al. (1999) made a comparative study on time-frequency methods (STFT and Wigner-Ville distribution) and harmonic wavelet in Gearbox fault detection. Bunks et al., (2000) applied an HMM to analyse the Westland helicopter data which consists of gearbox fault class information and vibration measurements with different faults. The fault classes were treated as states in the hidden Markov chain, whereas the vibration measurements were treated as realisations of the observation process. Baydar et al. (2001) investigated the use of a multivariate statistical technique known as principal component analysis (PCA) for analysis of the time waveform signals in gear fault diagnostics. De Almeida et al. (2002) discuss about the most widely used conventional spectrum analysis by means of fast Fourier transform (FFT). The main idea of spectrum analysis is to look at the whole spectrum or at certain frequency components of interest. Harry (2002) has proposed two new detection techniques. The time synchronous averaging concept was extended from revolution-based to tooth engagement. The detection techniques are based on statistical comparisons among the averages for the individual teeth. These techniques were applied to a series of three seeded fault crack propagation tests. FFT-based methods are not suitable for non-stationary signal analysis and are not able to reveal the inherent information of non-stationary signals. However, various kinds of factors, such as the change of the environment and the faults from the machine itself, often make the output signals of the running machine contain non-stationary components. Usually, these non-stationary components contain abundant information about machine faults; therefore, it is important to analyze the non-stationary signals. Most algorithms recently developed for mechanical fault detection are based on the assumption of stationarity of the vibration signals. Some of these, including cepstrum, time-domain averaging, adaptive noise cancellation, demodulation analysis, etc(Francois et al., 1995; Pan et al., 1996; Koo et al., 2000). Polyschuk et al. (2002) has presents the development of a novel method in gear damage detection using a new gear fault detection parameter based on the energy change in the joint time-frequency analysis of the vibration analysis of the vibration signal. Lin and Zuo (2003) has introduced an adaptive wavelet filter based on Morlet Wavelet, the parameters in the Morlet wavelet function are optimized based on the kurtosis maximization principle. The adaptive wavelet filter is found to be very effective in detection of symptoms from vibration signals of a gearbox with early fatigue tooth crack.
Tian et al. (2003) used independent component analysis (ICA) in frequency domain and wavelet filtering for gearbox fault diagnostics. Yu et al. (2007) applied Hilbert-Huang transform and mention that it can offer an accurate energy-frequency-time distribution. On the other hand, Shannon entropy could give a useful for analysing the signals and offer a measure of the information of any distribution. When the gear condition changes, the time-frequency entropy based on Hilbert-Huang transform would vary as well, which indicates that the energy distribution in time-frequency plane changes when the gear with faulty condition is operating. Therefore, the time-frequency entropy based on Hilbert-Huang transform can be adopted to identify the work condition of gear. Elforjani et al. (2012) discussed about the Condition monitoring of key components in rotating machines such as gearboxes ensure reduction in costly unscheduled machine down time and explores the possibility of monitoring seeded defects on worm gears with vibration analysis. Unlike other types of gearboxes, monitoring of worm gearboxes is not widely documented. Guoji et al. (2014) applied bispectrum to the analysis of helicopter gearbox vibration. The peaks in the bispectrum along the harmonic meshing frequencies can be explained by the modulation phenomena related to the local defect of gear.

Gear condition monitoring using artificial intelligent techniques

Vibration analysis can be carried out using Fourier transform techniques like Fourier series expansion (FSE), Fourier integral transform (FIT) and discrete Fourier transform (DFT) (Collacott, xxxx). After the development of large-scale integration and the associated microprocessor technology, fast Fourier transform (FFT) analyzers became cost effective for general applications. The raw signatures acquired through a vibration sensor needed further processing and classification of the data for any meaningful surveillance of the condition of the system being monitored (Saravanan et al., 2009). In automated decision making condition monitoring system, after the signal acquisition and extracting fault features from it, it is necessary to apply decision making process to determine the gear status. There are different algorithms for decision making. The most commonly used algorithms are artificial neural networks and fuzzy clustering. However, designing and training of these algorithms need a lot of data by Paul et al. (2001), Staszewski and Worden (2004). In some recent works, several combinations of wavelet transform, Wigner Ville transform would vary as well, which indicates that the energy distribution in time-frequency plane changes when the gear with faulty condition is operating. Therefore, the time-frequency entropy based on Hilbert-Huang transform can be adopted to identify the work condition of gear. Elforjani et al. (2012) discussed about the Condition monitoring of key components in rotating machines such as gearboxes ensure reduction in costly unscheduled machine down time and explores the possibility of monitoring seeded defects on worm gears with vibration analysis. Unlike other types of gearboxes, monitoring of worm gearboxes is not widely documented. Guoji et al. (2014) applied bispectrum to the analysis of helicopter gearbox vibration. The peaks in the bispectrum along the harmonic meshing frequencies can be explained by the modulation phenomena related to the local defect of gear.

Saravanan et al. (2008) presents the use of decision tree for selecting best statistical features that will discriminate the fault conditions of the gear box from the signals extracted. A rule set is formed from the extracted features and fed to a fuzzy classifier. This paper also presents the usage of decision tree to generate the rules automatically from the feature set. Again Saravanan et al. (2009) deals fault diagnosis of spur bevel gear box using statistical feature vectors from Morlet wavelet coefficients it is and classified using J48 algorithm and the predominant features were fed as input for training and testing multiclass proximal support vector machine the efficiency and time consumption in classifying the twenty four classes all-at-once is reported. Saravanan et al. (2010) again made an attempt of fault diagnosis of spur bevel gear box by extracted features from the DWT and features used as inputs in a neural network for classification purposes. The results show that the developed method can reliably diagnose different conditions of the gear box. The wavelet transform is used to represent all possible types of transients in vibration signals generated by faults in a gear box.

Sûn et al. (2007) used decision making scheme beyond conventional fault testing. They proposed a new method based on C4.5 decision tree and principal component analysis (PCA). It was found that compared to BPNN C4.5 extracts knowledge quickly from the testing and is even superior to neural networks. Lei and Zuo (2009) used a Two Stage Feature Selection and Weighting Technique (TFSWT) via Euclidian Distance Evaluation Technique (EDET) to select sensitive features and remove fault unrelated features. They used a Weighted K Nearest Neighbour (WKNN) classification algorithm and the predominant features were fed as input for training and testing multiclass proximal support vector machine (TSVM), which is applied to diagnose the faults of the gear reducer. Yang et al. (2015) presented the methodology utilize artificial bee colony algorithm is used for SVM parameter optimization of gearbox fault diagnosis, compared with genetic algorithm, the particle swarm optimization and found that the accuracy of the artificial bee colony algorithm is higher. Rajeswari et al. 2015 Utilized ensemble empirical mode decomposition for signal processing and feature extraction, hybrid binary bat algorithm for feature selection and machine learning algorithms for classification purposes in gear fault diagnosis.
Conclusions
Recent advances in automated condition monitoring technologies have significantly improved the diagnosis and prognosis of bearing and gear component health condition and it reduced the operation and maintenance costs of the rotating machinery. However, accurate fault detection and reliable prognosis in rotating machinery remain challenging due to the congenital complexities in their mechanical systems and operation conditions. In order to accomplish robust condition monitoring for bearing and gear component, the following research areas need to be further strengthened.

References


