The rolling element bearing is one of the most critical part in modern production machineries that determines its health and remaining lifetime. Robust predictive condition monitoring schemes are needed to assure the health state of bearings during its operations. A predictive condition monitoring scheme (PCM) determines the early failures which thus results into the early fault detection of rolling bearing. Early fault detection of rolling bearing provides sufficient lead time for maintenance planning. PCM scheme procedures contain fault detection, fault diagnosis and prognosis analysis, which are required to extract the fault related features of bearing and determine the remaining useful life.

The literature review here provides the broad insights related to the mathematical modelling of rolling element bearings, experimental analysis of faulty rolling element bearing, diagnosis of faults and its classification through expert systems, and statistical approach for determining the impact of bearing fault severity.

2.1 Introduction

The rolling element bearings (REBs) is one of the most critical part in modern production machineries that determines its health and remaining useful life. Robust predictive condition monitoring schemes are needed to assure the health state of bearings during its operations. The PCM scheme aims to determine deterioration i.e evolution of wear rather than just detecting the defects. Number of reviews are available for condition monitoring of REBs [1-6]. The available literature review explains the various techniques of fault diagnosis of REBs, including signal processing, mathematical modelling and prognosis. Over the years, several dynamic models have been developed by various researchers to investigate the dynamic behavior of rolling element bearings [7-15]. The defective bearing is assumed to generate impulses due to passing of rolling element over the defected outer race or inner race. The impulses generated by defective bearings are non-stationary in nature and contains lots of noise due to the other components of machinery. These leads to the application of signal processing upon the defective bearing signals, to remove unwanted features and to obtain fault related information. Some simple signal processing (SP) techniques have been applied to process the signals such as RMS, Skewness, FFT etc. However, simple signal processing techniques are not sufficient enough for removing background noise, smearing effects and fluctuations effect caused by varying speed. Therefore, more advanced signal processing techniques are required to overcome this issue. The various SP techniques so far developed and applied successfully by various researchers are envelope detection, wavelet transform, cyclostationary analysis, data-driven methods, fuzzy logic techniques, expert systems etc.

In the area of machinery vibration analysis and monitoring, significant relevant standards are developed and published by ISO. Numerous ISO standards describes vibration limits within acceptable range. Few such ISO standards are ISO/7919 series (5 Parts) "Mechanical vibration of non-reciprocating machines-Measurements on rotary shafts and evaluation criteria" and ISO/10816 series (6 Parts) "Mechanical Vibration-Estimation of machine vibration measurements on non-rotating parts". These standards mainly cover the techniques of measurements, acquiring and processing data, generally required for performing condition monitoring and diagnosis of machineries. At an industrial scale, commonly used diagnostic techniques are various probability density functions (Mean, Standard Deviation, Skewness, Kurtosis), RMS, Crest factor, Power spectrum, Cepstrum analysis and Shock pulse method. These methods help in extracting the defect related features. Vibration component of a particular frequency generated by defects on the components of bearing (Outer race, inner race, rolling element and cage), mainly provides theoretical basis for estimating defect related frequencies. By estimating these bearing characteristic frequencies, the cause of the defect may be determined. These characteristic defect frequencies are in the same range as the low frequency vibrations (0-2 KHZ) caused by the normal operation of a machine making it difficult to distinguish these peaks from the normal machinery noise. It is assumed that these peaks are caused whenever rolling element traverses upon the localized defect of bearing surfaces. The ultimate purpose of PCM system is to obtain the early failures so as to provide sufficient lead time for maintenance planning.

Here PCM system comprises of analytical, numerical and experimental studies. Numerical and analytical studies mainly simulate faulty rolling element bearing, which verifies the ability of signal processing to extract defect features. Numerical methods are also important for predicting the remaining useful life of the faulty rolling element bearing. PCM system not only performs diagnosis, but also prognosis of the machinery. Several studies have been carried out based upon the data-driven and model-based prognosis for rolling element bearings.

Therefore, this chapter presents the broad review upon the condition monitoring of rolling element bearing, with a deep insight upon various dynamic modelling, monitoring methods, signal processing techniques, experimental analysis, statistical methods and machine learning algorithms for diagnostics of rolling bearing.

2.2 Bearing Faults and Dynamic Simulation Methods

Rolling bearing is a mechanical component which carries loads and eliminates the sliding friction by placing rolling elements i.e balls or rollers between two bearings i.e outer and inner raceway. Rolling bearings based upon the design may be classified as radial bearings, which carries radial loads and thrust bearings which carries the axial loads. All rolling bearings practically consists of four basic parts: inner ring, outer ring, rolling elements and cage. Therefore, faults of bearings may be classified based upon their locations as inner raceway fault, outer raceway fault, rolling element fault and cage fault. The main reason behind the occurrence of these faults is a contact fatigue, as described in Chapter 1. Contact fatigue is a kind of surface damage which occurs due to operational wear of rolling bearings. Such a damage is characterized by spalling, pitting or flaking surfaces of bearing components. Other significant mode of failure of rolling bearing is fatigue spalling. Fatigue spalling is the onset of micro-scale subsurface fatigue cracks, which commences below highly stressed rolling surfaces. These cracks occur at micro-scale discontinuities, such as contaminants, inhomogeneity or carbide clusters, which is a result of micro-plastic deformation in the area of maximum stresses. Misalignment, Mechanical looseness, and unbalance are some of the sources of stress generation, due to which rolling bearings may fail. Stress generation due to any source leads to topological changes. Topological changes at the contact area develops stress concentration points and disturbances into fluid film lubrication, which results into wear evolution process, as described in chapter 1. El-Thalji and Jantunin [16] found experimentally the process of wear evolution over the lifetime of the rolling bearings. In summary, the process of wear evolution is considered to be complex due to the involvement of various wear mechanisms such as fatigue, adhesive, abrasive and corrosive. The involvement of wear mechanisms and their interactions, propagates the wear evolution, which thus varies with respect to the surface topography and tribology changes. As the topography of fault is significantly changing over the lifetime, the fault features are also changing with lifetime. In such a way, the assumption of the fault topology in the dynamic modeling is also changing. However, there is a necessity to determine clearly fault features of particular wear evolution stages and to realize about various signal analysis methods to deal with such fault features, so as to efficiently monitor the diagnosed fault features.

2.2.1 Mathematical Modelling

Over the years, several mathematical models have been developed to investigate the dynamic nature and features of rolling element bearings, as shown in **Table 2.1.** Palmgren [17] and Harris [18] were the first who introduced the mathematical models of REBs. However, at that time total non-linearity and time varying characteristics were not addressed. Gupta [19] provided the first complete mathematical model of REB and after that Fukata et.al [20] presented a comprehensive time-varying and non-linear model. The more complex issues of time-varying characteristics and non-linearity were explored and studied by several authors. For example, Wijnat et.al [21] studied the effect of elasto-hydrodynamic lubrication on the dynamics of REB. Tiwari and Vyas [22] and Tiwari et.al.in [23] and [24] reviewed the studies for the effect of ball bearing clearance upon the vibration response of a rigid rotor. Sopanen and Mikokola [10] studied various mathematical models stating the effect of waviness, EHL, clearance effect and localized faults. In order to obtain more accurate results, finite element method (FEM) was used. Kiral and karagulle[25], performed FEM vibration analysis of REBs for fault detection with single and multiple faults. The vibration signal includes impulses developed by the defects, effect of modulation due to non-uniformity into load distribution, vibrations induced by bearings and vibrations induced by machinery and the noise effects are experienced by any measurement system. Sopanen and Mikkola [10] executed multi-body system software application MSC.ADAMS upon the proposed ball bearing model. The

FEM model was firstly utilized for simulating the variation of the mesh stiffness under two types of defects with variations into static load conditions. Then the integration of the model was carried out into lumped parameter mathematical model. The results obtained from the study was dynamic transmission error and responses due to acceleration under different loads and speeds. Sawalhi and Randall [14] developed a 34-dof gearbox model to simulate spalls and cracks in the rolling bearing based on Endo's model of 16-dof. Massi et.al [26] studied the wear occurring due to false brinelling at the interface of contact surfaces between the rolling elements and races of bearings.

Number of mathematical models have been developed to study the effects of extended and localized defects: Waviness effect [10,15,27], clearance effect [19,10,20-21], and localized faults effect [38,39] etc.

Table 2.1 Summary of Dynamic Models of Bearing Faults.

References	Bearing Contact	Clearances	EHL Contact	Distributed defects	Localized defects
24	×				×
17,18	×				
19	×	×			
22	×			×	
10	×	×	×	×	×
23	×				
20	×	×			
13	×				×
14,25	×		×		×
15	×	×		×	×
24-31	×				×
21	×	×			×

×- indicates the work done by the author(s) cited in reference.

2.2.2 Numerical models of localized defects

Localized defects, one of the most important class of bearing defect, includes cracks, spalls and pits on different components of rolling element bearing. Localized defects are considered to be an ultimate mode of failure of a perfectly installed and well lubricated bearing during its normal operations. The maximum share of the studies has imposed upon localized faults using various modelling techniques as shown in **Table 2.2**. Mcfadden and Smith [27], Mcfadden and Smith [28], Tandon and Choudhury [29] and Swalhi and Randall [14] modelled the defect as a signal function of impulsive train in the modelled system. For example, Tandon and Choudhury have introduced the defect as a function of pulse with three different shapes: triangular, rectangular and half sine. Wang and kootsooks [30] have introduced defects as a function of series of impulses. Ghafari et.al [31] have introduced a defect virtually into dynamic equation of motion as a triangular impulse train corresponding to the characteristic frequencies of a defect. Rafsanjani et.al [32] presented the localized defect in their model as s series of repetitive impulses belonging to defect frequencies. The amplitude obtained from the repetitive impulses is due to the loading and angular velocity at contact point. Kiral and karagulle[25], Sopanen and Mikkola[10], Massi et.al [33], and Liu et.al[34] have introduced the bearing defect as a function of force in the finite element models. They introduced as a constant impact factor. More particularly Liu et.al [34] introduced the defect as a piecewise function.

Ashtekar and Sadeghi [35] , Sassi et.al[13], Cao and Xiao[15], Rafsanjani et.al[32], Patil et.al[36],and Tadina and Boltezar[37] used geometrical features for modelling the localized defect. They used length, width and depth for modelling the surface defects. Tadina and Boltezar[37] modelled the defect with a shape of impressed ellipsoid upon the races and with a shape of flatted sphere for rolling elements. Nakhaeinejad[38] performed the study upon bearing vibrations due to bearing defects by using bond graph. In their study, they included various effects such as gyroscopic and centrifugal effects, forces and contact deflection, separations and contact slips and localized defects. Dents and pits upon outer race, inner race and rolling elements were modelled through changes in surface profile, such as type, shape and size of defects. The major difficulty with the use of complex mathematical models lies in verifying experimentally the predicted results. [1]

Table 2.2 Dynamic Models of Localized Defects.

References	Analytical dynamic	FEM	Geometrical defect function	Force defect function	Defect function
24,38,39	×				×
40-42		×		×	
10,23	×			×	
14		×			×
13,15,21,24,26,27	×				
43	×	×	×	×	
30	×			×	

×- indicates the work done by the author(s) cited in reference.

2.2.3 Non-linear dynamic modelling

The non-linear dynamic modelling of rolling element bearings and corresponding systems are lumped parameter models. Lumped parameter models are those models which simulates various elements or components of a mechanical system as a lumped mass connected with series of linear or non-linear springs and dampers (for energy dissipation).

The non-linear dynamic models are used for estimating vibration response of a bearing, bearing housing and rotor-bearing systems, due to the presence of surface defects [39-44]. In modelling, outer and inner rings are generally considered as lumped (rigid) masses and the contact between the rolling elements to raceways contact interfaces as non-linear springs. The various types of localized defects considered by various researchers are point spalls [9,12,13,15,47,27], circular spalls [26,28]. Elliptical spalls (as ellipsoids for ball bearings) [25] presented as a function of Hertzian elastic deformation [33] and line (or rectangular) spalls [10,11,14,48-52] as a function of length, width and depth. Most of the models in the literature considered non-linear contact deformation at the rolling element to raceway contact interference. Here a systematic review is presented for line[rectangular] spall, due to the consideration of line spall for mathematical modelling and experimental validation for this thesis work.

Table 2.3 Wear Monitoring techniques for rolling bearing.

References	Test Type	Vibration/SPM	AE	Electrostatic	Ultrasound	Oil/debris
79	RC	×				
80	RC	×	×	×		
14,81	REB	×				
82-84	REB	×	×	×	×	
85-93	RC		×	×		
94-97	REB		×	×		
98	REB	×				
99	RC		×	×		×
100	REB	×			×	
4	REB	×	×	×		×
101	REB	×			×	×
102	RC	×				

RC: - Rolling Contact, REB: - Rolling element bearing.
×- indicates the work done by the author(s) cited in reference.

2.2.3.1 Line(rectangular) spall

With the objective of acting as an element at interface between the supporting structure and the rotor, Sopanen et.al [10,11] developed a nonlinear multi-body dynamic model of a deep-groove ball bearing. They developed the model by using 6-dof, by considering the outer and inner rings of the bearing are rigidly connected to the housing and shaft, respectively. They even considered the rolling element ton raceway contact as non-liner Hertzian deformation [33] and the presence of EHL fluid film in rolling contacts [45,46-52]. Other than modelling the localized defects on the inner and outer raceways, surface waviness as a distributed defect [53-62] of raceways were also considered. Commercial multi-body software package, MSC Adams [63] was used to solve the model. While Sopanen et .al [10,11] did not validate the model experimentally, they compared their results of modelling with similar work available in the literature. For example, the predicted results obtained from localized raceway defects were compared with the results presented in reference [24], whereas for the surface waviness, the numerical results were compared with the results present in references [56,57,62]. Sopanen et.al [10,11] investigated following observations through their dynamic modelling, which are as such.

1] Significant effect upon the vibration response of modelled rotor bearing system due to the presence of diametral clearance.

2] The amplitude of the characteristics defect frequency for similar size of defects was higher for the outer raceway defect compared to the inner raceway defect.

Sopanen et.al [10,11] has ignored rolling elements slippage and neglected the centrifugal forces acting on the rolling elements.

Sawalhi et.al [14], in 2008, extended the work of Fukata et.al [64] and Feng et.al [65], while developing a dynamic model for simulating the vibration response due to localized defect of ball bearing present in a gearbox. In relation to the 2 and 4 DOF models presented in references [64] and [65] respectively, Sawalhi[14] developed the model using 5 DOF (translations in global cartesian X and Y directions). They used 2-dof for inner raceway, 2-dof for bearing housing and 1-dof for measuring high resonant frequency of bearing housing. Unlike other dynamic models [9-13], the lumped mass-spring-damper bearing - pedestal modelled by Sawalhi included rolling elements slippage [66] as a variation into percentage of characteristics defect frequencies, so as to improve the accuracy of theoretical vibration response with measured vibration signals. Localized rectangular spalls were considered upon the outer, inner raceways and rolling elements into model. Although the rectangular shape of the defect was modelled, but the modelling was based upon the hypothesis that the rolling elements enter into and exit out of the spall gradually. They ignored the centrifugal and inertial effects of the rolling elements. Swalhi used Simulink [67] to solve sets of ordinary differential equation of motion for simulating vibration response of rotor-bearing systems. A unique feature presented by their model is that, bearing housing was modelled by using additional mass-spring-damper system, termed as resonant changer. With an objective of simulating a typical high-frequency resonant response of a bearing, the bearing was excited at 15 KHZ(with a damping of 5%), with a mass of 1 kg and the stiffness of the resonant changer of 8.89N/m. Since the mode of the resonance of bearing structure was particularly chosen to be at 15 KHZ, the amplitude of the simulated vibration response due to the presence of the localized defects was higher close to that frequency as compared to the response of healthy bearing.

Table 2.4 Summary of SP analysis studied for REBs

References	SM	TSA	MA	PIM	NPIM	FFT	CA	HSM	EA	WT	OT
4,80,82-84,89,91,94-97,98-102,103,104	×					×					
105-107		×									
108,109			×								
110				×							
111-114					×						
72,115-116							×				
117-119								×			
72,120-125									×		
126,127										×	
128											×
129										×	
130	×								×	×	
131											
132											

Abbreviations: SM- Statistical Measure, TSA:- Time-synchronous average, MA:- Morphological Analysis, PIM:- Parametric identification method, NPIM:- Non-parametric identification method, CA:- Cyclostationary Analysis, HSM:- High-order spectral method, EA:- Envelope analysis, WT:- Wavelet transform, OT:- Other transforms. ×- indicates the work done by the author(s) cited in reference.

Sawallhi[14] has made the following observations through their modelling and experimental analysis.

1] Mismatch between the modelled and actual resonant modes of structure.

2] Good agreement between the simulated and experimental results, due to the analysis in time and frequency domain techniques [68-69].

3] Measured and simulated characteristic defect related non-periodic signals were consists of two impulse events a) the first event was the entry of the ball into the defect. b) the second event was the exit of the ball out of the defect.

Such a phenomenon related to two events was named as double impulse phenomenon.

Sawalhi et.al[14] did not investigate the vibration signatures related to double-impulse phenomenon in detail.

Most of the dynamic modelling in literature [10-15,26,27,47] considered only single point localized defect.

Patil et.al [36] in 2010, incorporated two localized rectangular defects on both inner and outer raceways in their dynamic modelling for investigating the vibration response of a deep-groove ball bearing.

For both raceway defects, two different pulses were generated and proportionally separated to the angular distance of the defects. They presented their mathematical model by using 3 Dof. The assumptions of their model during its development were similar to those considered in reference [27]. Following are the results obtained by them from mathematical model.

1] For no defect case, the peaks at the cage frequency fc, shaft rotational frequency fs and its harmonics, are predicted.

2] For two defects on outer raceway, the vibration amplitudes of characteristic outer race defect frequency were larger than vibration amplitude obtained from single defect.

In the year 2011, Nakhaeinijad et.al [70], presented a unique approach for modelling the vibration response by using vector bond graphs of a deep grove ball bearings due to localized defect. They proposed 33-dof multi-body dynamic model of a bearing with nine rolling elements and two raceways (Outer and inner) considering the translations in radial and axial planes. They developed their model by considering slippage of rolling elements and their inertial and centrifugal effects. Localized defect of various widths and heights upon outer and inner raceway and one of the rolling elements was introduced into modelling. They validated their simulated vibration response with experimental vibration response. They found higher amplitudes are generated for large size of defect.

Extending the work of Sawalhi et.al [14], Petersen et.al [71], in 2014, developed an analytical dynamic model for predicting the vibration response of a defective bearing with rectangular shaped raceways defects and as well extended spalls. They kept most of the assumptions of their model similar to those of references [14]; Some modifications were made in their model for improving prediction capability of vibration response due to defective bearings. They introduced an additional mass-spring-damper, attached to the outer raceway. This modification was made for enabling the prediction of high resonant frequency response in both x and y directions. They replaced a global damping in model of Sawalhi et.al [14] by a lubrication film damping at the interface of rolling-element to raceway contact. They extended their model from previously developed model of single row defective bearing [72,73] to a double row bearing. The model also presented quasi-static load distribution and variation in stiffness of a radially loaded defective double row bearing. The results obtained from the model in reference [71] agrees considerably with the results present in reference [14].

Moazen Ahmadi et.al [74], developed an analytical model for predicting the vibration response of a defective rolling element bearing. the model was developed with a unique feature of modelling the finite size of rolling elements.

This means, rolling elements as point masses have not been considered like in other models [75-78]. Similar to previous models [79], by using a mass-spring-damper system, a resonant frequency of 10 KHZ was chosen for outer ring of a bearing. the simulated vibration response agreed favorably with experimental vibration response. Other than predicting high frequency response due to the exit of rolling elements from defect, the model also predicted the low frequency response due to the entry of rolling element into defect.

2.3 Monitoring Methods

Various experiments have been performed for investigating the effect of defective bearing upon the rotor-bearing system. The study specific monitoring techniques and their applications in detecting the faults in REBs, are as such, vibration, acoustic emission (AE), oil-debris, ultrasound, electrostatic, SPM, etc. Many experimental studies have applied simple signal/data processing techniques such as kurtosis, RMS, FFT etc. However, major share of analysis has focused in developing new and advanced SP techniques: wavelets, envelope, intelligent methods, expert systems, data-based methods etc. Measurements of vibration was prime concern in majority of advanced SP techniques. Generally, there are two approaches for testing: one is accelerated testing with the application of overload, adjustment of lubricant film thickness. Second by seeding artificial defects using spark erosion techniques or false brinelling. **Table 2.3** highlights the tests, that have been applied for deteriorating REB.

2.3.1 Testing Techniques

Various experiments have been performed by using vibration measurements upon bearings such as [14,81]. AE measurements also been performed with bearings such as [94-97]. Comparative studies comparing vibration and AE measurements have been performed for exploring defect features by using defective REBs [82-84]. The studies presented in [100-102] have investigated the ability of ultrasound measurements for fault diagnosis of low speed bearings. Table1 presents a clear view about maximum application of vibration and AE measurements as a monitoring technique. Supportive techniques such as oil/debris technique have been commonly used in several studies [4,98,101].

2.3.2 Influencing factors

Many critical issues related to the detection have been studied such as surface roughness effect [2], influence of operating parameters on the AE of REB, the running-in process [98], low speed -effects, large size bearings and operating conditions (load, temperature) and the effects of geometrical errors (i.e variation in rolling element diameter, surface waviness of inner ring), and fatigue wear. Concentrated contaminant effect on vibration has also studied [151].

2.3.3 Crack detection

[152] have conducted some studies using AE measurements to detect the surface crack initiation. Swalhi and Randall [81] in the study of dynamic response observed impulse effects due to dent shoulders. Few studies have been conducted for subsurface crack detection [85,153,154]. For detecting subsurface cracks before it reaches to surface, AE proved to be highly capable technique. However, it is assumed that bursts in the signal indicates near-surface cracking. Studies has been carried out for detecting defect propagation in [83,100]. It was observed for this studies that increment in width of defect increases the ratio of amplitude burst to noise. Secondly, increase in the defect length increases the duration of bursts. At low speeds ultrasound signals were observed with number of impulses due to the presence of localized defects [100]

Table 2.5 A Summary of diagnostics methods studied for REBs

References	Raw signals	Time domain	FFT	Envelope analysis	Wavelet analysis	Supervised ANN	UnSupervised ANN	SVM
133	×	×						
110,134								
135,136	×		×					
137,138					×			
139								
140-143						×		
144-145				×				
146-147								×
104,148							×	
149,150								

×- indicates the work done by the author(s) cited in reference.

2.4 Signal Analysis Method

Over the years, various SP methods have been developed for extracting defect related features from rolling elements bearings. A summary of several signal processing methods for fault detection of REB is described in **Table 2.4**.

2.4.1 Statistical measures

At the earlier stages of condition monitoring development, SP methods were very simple and mainly based upon statistical parameters such as kurtosis, RMS, peak-peak etc. The trend based upon the RMS value is one of the most used technique for showing the correlation between amplitudes of vibration and deterioration of bearing over whole lifetime [4,102,154,103]. As the peakidness of vibration increases, kurtosis and crest factors values also increases. In this way, kurtosis and crest factors are very sensitive to the peakidness of signal. However, third central moment (Skewness) of probability density function found to be a poor measure of defect features in rolling bearings [155], in general skewness is more effective for the signals with non-symmetry i.e non-linearity, since skewness is the measure of lack of symmetry. The kurtosis is the good measure of rotational speed and frequency bandwidth. It is efficient at high frequencies in narrow bands, especially for incipient defects. Parameter recognition methods are seemed to be advanced approach of time-domain analysis. In this method, features are extracted by fixing the waveform data to a parametric time series model [3]. Bailie and Mathew [110] performed the fault diagnosis of slow speed machinery under transient conditions, by applying the concept of an observer bank autoregressive (AR) time series models, where a small data set of vibration is needed. Due to instant variations in mass loading conditions, damping, stiffness or friction, machine systems are often subjected to non-linear behavior. Therefore, methods for estimating non-linear variable provides a good alternative for extracting fault features present in recorded signals [113]. Many non-linear variable recognition techniques have been introduced, such as complexity measure [156] and correlation dimension [111-113]. As the rolling bearing starts deteriorating due to the propagation of defects upon the surface, the amplitude of vibration signal will increase, results in a decrease in regularity of signal, and this in turn increases its corresponding entropy value [113]. At the early stage of faults in machinery, the signal to noise ratio (SNR) is low due to weak signals. Therefore, [111,112,114] introduced chaotic oscillator for extracting bearing fault features due to its sensitiveness for weak signals. Change in complexity value under complexity measure analysis shows the correlation between the inception and growth of defects in machinery system [156]. The major drawback of the statistical methods is the requirement of suitable volume of data for training and testing the algorithms during initial stages. Large number of data points are needed to be estimated for the process of fault diagnosis, leads to lengthy computations, which is thus not suitable for on-line, real time applications [113].

2.4.2 Frequency Domain Methods

Frequency domain methods have been introduced as another way for detecting fault related signals. FFT is commonly used method to transform the signal from time domain to frequency domain and to produce spectrum. However, it is not a clear method for observing the faulty peaks occurring due to slip and masking by different strong vibrations, besides the presence of defect harmonic frequencies and sidebands [104]. FFT method assumes signals to be periodic in nature, and hence not suitable for non-periodic or non-stationary signals like bearing defect signals. The signals generating from defective bearing contains non-linear components due to the variation found in running conditions and presence of other defects in machine [156]. To deal with non-stationary signals, time-frequency analysis is found to be most efficient method. The Wigner-ville distribution (WVD), wavelet transform (WT) and short time fourier transform (STFT), develops a better compromise between the time and frequency perspective of signal and contains information about both time and frequency. Mori.et.al [127] predicted the occurrence of spalling by applying discrete WT (DWT). Shibata et.al [157] analyzed the bearing sound signals by using WT. Peng et.al [114] found the good computational efficiency of Hilbert-haung transform (HHT), without involvement of challenges dur to time and frequency resolution.

2.4.3 Challenges of Feature Extraction Process

There are challenges such as removal of background noise, speed fluctuations, smearing effect of signal transfer path. Chirp signals generating due to the effect of speed fluctuations is important and need to be removed. The chirp signal or sweep signal are of two types: Up-chirp, in which frequency increases and down chirp, in which frequency decreases, with respect to time. Several methods have been proposed to deal with this chirp signals such as chirp fourier transform, chirp z-transform, adaptive chirplet transforms and high order estimations. The order tracking methods are generally used for avoiding smearing effects of discrete frequency components due to fluctuation of speed [6]. To solve the problem of smearing effect, [124,125] developed minimum entropy de-convolution method (MED).

For the carpet or background noise problem, several denoising filters have been developed such as discrete/random separation (DRS) [117], self-adaptive noise cancellation (SANC) , Adaptive noise cancellation (ANC) [121]. However, for a situation, where the frequency range and noise type are unknown, the conventional designs of filters could become intense processes computationally [122]. For example, the WT methods shows good performance on gaussian noise and almost reduces the noise optimally while preserving the signal. However, there is still a challenge of selecting optimal wavelets for a particular type of signal. Performing thresholding is another challenge. Two major wavelet-based methods are generally used for machinery fault diagnosis: wavelet filter-based method and wavelet decomposition based. Depending upon WT, various fault features can be obtained, which can be classified into wavelet energy based, wavelet coefficients based, singularity based and wavelet function based [156].

Lin and Qu [158] used continuous WT of morlet wavelet functions. Junsheng et.al [159] for representing the vibration signal characteristics of the faulty rolling element bearing, with proposed impulse response wavelet base function. Liu et.al [126] synthesizes the wavelet coefficient functions with proposed weighted Shannon function for enhancing feature characteristics i.e minimizes the interference information and optimized wavelet shape factor. Liu et.al [160] conducted fault diagnosis of bearing with proposed wavelet packet method, where they considered co-efficient of wavelet packet as features.

2.4.4 Bearing Fault Signals

Some studies [109,132] described the most of a relevant information about signal is carried by singularity points, such as discontinuities, peaks etc. therefore, detection methods for singularity are proposed [132] based upon the calculation of lipschitz exponents of a vibration signals. Regular point in the signal is the indication of large lipschitz exponent whereas singular point is the indication of small lipschitz exponent. WT proved to be successful method for singularity detection, however prior to singularity detection, signal pre-processing need to be conducted [156]. Hao and chu[109] found that impulse components cannot be observed clearly because of the presence of harmonic waves.

Filtration through WT removes the noise, but the waves due to harmonics were not suppressed, since the impulse frequency was found to be very nearer to harmonic waves frequencies [109]. Therefore scalogram (visual method of displaying WT) proved to be efficient tool for revealing more information about signal.

There are various methods available for extracting the periodic information of impulsive nature of faulty rolling bearing. One such significant method is Time synchronous average (TSA) [105-107]. Fault signals of a bearing have two parts: deterministic and quasi-cyclostationary. To overcome this problem, envelope and squared envelope of bearing vibration signal is the method used [72]. Envelope analysis is based upon the idea of detection of fault impulses that are amplified due to resonance of structure.Randall[72] has determined the suitable demodulation band by using spectral kurtosis (SK)[25,120-123] Tse et.al[129] diagnosed the rolling element bearing faults by comparing the capabilities of wavelets and envelope detection methods. They found that wavelet is less time-consuming process in detecting the faults than squared envelope. Envelope detection approach is not very effective for the vibration signals with low SNR [161], where the fault related signal is masked by noise and other components of frequency. To overcome such problem, morphological operators are proposed [109] with an objective of extracting the envelope of periodic vibration signals with impulsiveness, by modification of geometrical features of vibration signals in time domain. Such a modification, build a envelope which gather the information corresponding to the series of impulses produced due to faults. The impulses produced by the faults are not exactly periodic in nature, due to random slips, speed fluctuations and axial to radial loading ratio conditions. Therefore, fault signals of bearing are most likely described as cyclostationary [115,116], quasi-cyclostationary[72], pseudo-cyclostationary[116] and poly – cyclostationary[162]. The cyclostationary signal is defined as a random signal where statistical parameters of signal vary with time or multiple periodicities [161]. The quasi-cyclostationary signal generates when existence of a normal cycle is not allowed, because of some rotary components are not locked together such as the case of REBs. Antoni et.al[162] highlighted that polycyclostationary signals are generated because of generation of periodicities by many mechanical components in machinery, thereby they are combination of cyclostationary processes with their basic cycles. Antoni et.al explained that all kinematical parameters in machinery, that are periodic with respect to rotational angles, are particularly angle-cyclostationary rather than time-cyclostationary. The various first order cyclostationary methods are synchronous averaging, blind filters, comb-filters and adaptive comb-filters. Second -order cyclostationary methods, are auto-covariance function, spectral correlation density and instantaneous variance. Based upon the methods of first order cyclostationary and second order cyclostationary various studies have been discussed for fault detection of REB [72,115,116,161-162].

2.5 Feature Diagnosis Methods

The task of fault diagnosis consists of determining the type of fault with important details such as fault size, its location and time to detection. Since a machine has many complex components, diagnosis of a machine faults requires expertise and technical skills. It also requires thorough understanding of the machine's structure and its operations, basic concepts of diagnosis and an expertise for domain specific knowledge of system. In reality, an expert engineer is either too busy due to other tasks or a component specific expert is not available [137]. Therefore, in order to automate the decision making about the health state of rolling element bearing very accurate, several automatic feature diagnosis techniques have been developed. The various techniques proposed for diagnosis of faulty REBs such as artificial neural network (ANN), fuzzy logic, expert systems, support vector machine (SVM), model-based methods and state observes. Among these techniques, ANN and SVM are reviewed here thoroughly, due to its application in these thesis work.

Table 2.5 provides the summary of various feature diagnostic methods used for REBs. These techniques are comprehensively used and are in maximum application for fault detection in machineries. The major advantage of this techniques is to increase accuracy and reduces human error. [137]

2.5.1 Artificial Neural Network Methods (ANN)

The ANN methods have been applied for fault diagnosis of REBs such as [144-145]. Larson et.al[163] used neural networks for phase demodulation. Li et.al [164] performed fault diagnosis by utilizing FFT as a pre-processor for feed-forward neural network (FFNN). Samanta and Al-balushi[134] developed a back propagation neural network BPNN model, for reducing the number of inputs that leads to faster training of model with less iterations. Baillie and Mathew [110] presented better noise reduction abilities of back-propagation networks compared to conventional linear methods. However, noise still remains as a problem, and the best way to deal with noise reduction is to make use of voluminous data so that the noise can be effectively eliminated by SNR averaging process. Alternatively, importance of signal pre-processing techniques also highlighted, such as amplitude demodulation of REBs signals [110]. Cascade correlation algorithm (CCA) offers the advantage of not determining the number of hidden units prior to training. Spoerre[133] used CCA for determining the imbalance in rotor-bearing system. Baillie and Mathew[110] used radial basis functions for diagnosis of REB and compared with back-propagation networks, radial basis showed better outcome due to their fast training time. Unsupervised learning do not require external inputs, Wang and Too[135] used unsupervised neural networks, learning vector quantization and self-organizing map (SOM) for fault detection in rotating machine. Trial and error approach and some experience is required for training and building neural networks[110]. The vast applications of reviewed ANN is for classifying fault features such as type of defects, location of defect, defect severity, health state etc. Samanta and Al- Balushi [134] developed a BPNN model for obtaining fault features by simply pre-processing time domain vibration signals, to classify the health state of machine in terms of normal or defective bearings.

2.5.2 Support Vector Machine (SVM).

Practically, the huge number of measuring situations makes the ANN task complicated. Therefore, it is always recommended that training results should be moved from one machine to another. An SVM is other classification technique based upon statistical learning theory. There are three different methods in SVM to find the separating hyperplane namely quadratic programming, least squares and sequential minimal optimization method. Yang et.al [144] classified the bearing faults by using intrinsic mode function as inputs to SVM. Yang [146] performed bearing fault detection with the help of improved wavelet packets and SVMs. Abbrasion et.al [140] used SVM as a classifier for computing optimal wavelet signal decomposition level, with an aim to find reliable method for multiple-fault diagnosis. Gryllias et.al [141] conducted automated fault diagnosis of REB with hybrid two stage one-against -all SVM approach. In SVM approach, optimization of the parameters is important for enhancing classification. Li.et.al [142] proposed an improved ant colony optimization (IACO) algorithm to predict key parameters, and then IACO-SVM algorithm is used for fault detection. Liu et.al [143] used WSVM for proposing multi-fault classification model and applied particle swarm optimization (PSO) for seeking the optimal parameters of WSVM and used empirical mode decomposition for pre-processing. The SVM is originally designed for two-class classification case. Tyagi [101] performed classification of defective bearing by using ANN and SVM and found more accurate classification by SVM compared to ANN. In fact, ANN uses conventional empirical risk minimization principles for minimizing the training data error, whereas SVM uses structural risk minimization principles for minimizing the upper bound of expected risk. [145]

The other non-linear classifiers like hidden markov model (HMM) and gaussian mixture model (GMM) have also been used for classification problems in some specific applications [104,148].

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Based upon the detailed literature review upon the condition monitoring of rolling element bearing, following research gaps have been determined.

2.6 Research Gaps

It has been found from the literature, that there is shortcoming in a complete parametric study of rolling element bearing. Thus, a complete parametric study will be conducted which will include matrix of parameters, with the provision of variations in parameters. These parameters may be load (both radial and axial) on a bearing, rotational speed, clearance within a bearing and multiple defect. The multiple defects traditionally range from line to rectangular, having different profiles of surface roughness. So far, no such research work has been found where different profiles of surface roughness are made similar to operational defects observed in real world applications, which will be prime focus of this research. Another important area which were never attempted previously in any work is the variation of the raceway spalls in and out of the bearing load zone, so as to understand differences between the vibration responses. From the literature, it had been observed imperatively, that early detection of the fault due to contact stresses has not been attempted effectively along with vibration study of rolling element bearing. Thus, looking to this shortcoming, vibro-acoustic study will be established to understand the characteristics of multiple defect types. In its extension of understanding the characteristics of multiple defect types, there will be the establishment of study for the dynamics of interaction between multiple defects. The study will not only improve the diagnosis of defective bearing but also results in reliable prognosis of defects, which will result in estimating the remaining useful life of a bearing, eventually saving significant operations and maintenance cost. Thus, economy of the system will be improved.

The above research gaps presented have been addressed and executed with the various objectives of this thesis work. Thus, the objectives of thesis are

2.7 Objectives

1] Nonlinear dynamic modeling of rolling element bearing with six degrees of freedom and simulation of nonlinear modeling using MATLAB.

2] Experimental setup for the fault diagnosis of rolling element bearing.

3] Data Acquisition from experimental setup.

4] Analysis of experimental data and its comparison with analytical results.

5] Development of fault diagnosis scheme and final conclusions.