

AN AUTONOMOUS BEARING FAULT DIAGNOSIS SYSTEM

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TANVI DOVEDI

Registration No. 801661027

Under Supervision of

Dr. Rahul Upadhyay

Assistant Professor, ECED



THAPAR INSTITUTE
OF ENGINEERING & TECHNOLOGY
(Deemed to be University)

ELECTRONICS AND COMMUNICATION ENGINEERING DEPARTMENT

THAPAR INSTITUTE OF ENGINEERING & TECHNOLOGY

(A DEEMED TO BE UNIVERSITY), PATIALA, PUNJAB

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DECLARATION

I, Tanvi Dovedi hereby declare that the work presented in this thesis entitled “An Autonomous Bearing Fault Diagnosis System” in fulfillment of the requirement for the award of degree of Master of Engineering (ECE) submitted at Electronics and Communication Engineering Department, Thapar Institute of Engineering & Technology (Deemed to be university), Patiala is an authentic record of work carried out under supervision of Dr. Rahul Upadhyay (Assistant Professor, Electronics and Communication Engineering Department, Thapar Institute of Engineering & Technology) from July 2017 to June 2018 . The matter presented in this thesis has not been submitted either in part or full to any other university or institute for the award of any other degree.


Date: 15/06/18



Tanvi Dovedi
801661027

It is certified that the above statement made by the candidate is correct to the best of my knowledge and belief.

Date: 15/06/18



Dr. Rahul Upadhyay
Assistant Professor
Electronics and Communication Engineering Department
Thapar Institute of Engineering & Technology
(A Deemed To Be University), Patiala, Punjab

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Tanvi Dovedi

801661027

ABSTRACT

The rolling element bearing plays a significant role in any mechanical manufacturing industry. The failures in bearing leads to sudden shut down of the machineries causing heavy losses to the industry. Therefore, bearing fault diagnosis using vibration signal processing has been a vital subject of study in past years. A sensitive and reliable fault diagnosis system is required to identify bearing faults in early stages to prevent sudden failures in machines. This research work proposes autonomous bearing fault diagnosis techniques which are capable of diagnosing three kind of bearing faults from vibration signals. Two different fault diagnosis techniques are proposed and analyzed in this work for efficient classification of vibration signals. Firstly, Tunable Q-factor Wavelet Transform based feature extraction technique is proposed. In proposed technique, vibration signals are decomposed into time-frequency coefficients using Tunable Q-factor Wavelet Transform and entropy based features are computed from decomposed time-frequency coefficients. Classification of vibration signals is performed using three soft computing methods viz. Support Vector Machine, Artificial Neural Network and Random Forest Tree classifier.

Another technique of feature extraction based on double decomposition of vibration signals using Empirical Mode Decomposition and Tunable Q-factor Wavelet Transform is proposed and evaluated for bearing fault diagnosis. In this work, vibration signals are first decomposed using Empirical Mode Decomposition and then using Tunable Q- factor Wavelet Transform. Further, Higuchi's Fractal Dimension is evaluated from the decomposed sub-bands as features and feature vector is prepared. This feature vector is fed to Support Vector Machine classifier for recognition of bearing faults. Multiple experiments are carried out with varying values of user defined parameters and classification is performed to attain the best set of parameters to attain the highest classification performance in bearing fault diagnosis task. Classification results revealed that proposed techniques have a potential to design and develop a real time bearing fault diagnosis system.

TABLE OF CONTENTS

Sr. No	Name of the Chapters	Page No
	<i>Pre-pages</i>	<i>i</i>
	<i>Declaration</i>	<i>ii</i>
	<i>Acknowledgement</i>	<i>iii</i>
	<i>Abstract</i>	<i>iv</i>
	<i>Table of contents</i>	<i>v-vi</i>
	<i>List of Tables</i>	<i>vii</i>
	<i>List of Figures</i>	<i>viii-ix</i>
	<i>List of Abbreviations</i>	<i>x</i>
<i>Chapter 1</i>	Introduction.....	1-7
	1.1 Overview.....	1-6
	1.1.1 Types of bearing faults.....	2-6
	1.2 Research Objective and Scope.....	6-7
	1.3 Thesis Outline.....	7
<i>Chapter 2</i>	Literature Review.....	8-11
<i>Chapter 3</i>	Bearing fault diagnosis using TQWT based entropy features.....	12-24
	3.1 Introduction.....	12-13
	3.2 Material and Methods.....	13-15
	3.2.1 Bearing Data.....	13
	3.2.2 Tunable Q-factor Wavelet Transform (TQWT).....	14
	3.2.3 Permutation Entropy (PE).....	15
	3.3 Feature Extraction and Classification.....	15-19
	3.3.1 Feature Extraction Methodology.....	15-17
	3.3.2 Soft Computing Techniques.....	17-19
	3.3.2.1 Support Vector Machine (SVM).....	18
	3.3.2.2 Artificial Neural Network (ANN).....	18-19
	3.3.2.3 Random Forest (RF).....	19
	3.4 Results and Discussions.....	19-24
	3.4.1 Performance Evaluation.....	22-24
	3.5 Summary.....	24

<i>Chapter 4</i>	Double decomposition bearing fault diagnosis technique.....	25-39
4.1	Introduction.....	25-26
4.2	Material and Methods.....	26-30
4.2.1	Bearing vibration database.....	26
4.2.2	Feature extraction techniques.....	26-28
4.2.2.1	Empirical Mode Decomposition.....	26-27
4.2.2.2	Higuchi's Fractal Dimension.....	27-38
4.2.3	Classification algorithm.....	28
4.3	Proposed Methodology.....	28-30
4.4	Results and Discussion.....	30-38
4.5	Summary	39
<i>Chapter 5</i>	Conclusion and future scope.....	40-41
	References.....	42-46
	<i>List of Publications</i>	47

LISTS OF TABLES

Sr. No	Tables Details	Page No
<i>Table 2.1</i>	<i>Feature Extraction Methods Available in the literature.....</i>	<i>10</i>
<i>Table 3.1</i>	<i>Classification performance of SVM, ANN and RF classifiers with optimized classifiers' parameters.....</i>	<i>21</i>
<i>Table 3.2</i>	<i>Confusion matrix of 10-fold cross validation with SVM classifier.....</i>	<i>23</i>
<i>Table 3.3</i>	<i>Confusion matrix of 10-fold cross validation with ANN Classifier.....</i>	<i>23</i>
<i>Table 3.4</i>	<i>Confusion matrix of 10-fold cross validation with RF classifier...</i>	<i>23</i>
<i>Table 3.5</i>	<i>A comparative study between proposed work and previous work published in literature.....</i>	<i>24</i>
<i>Table 4.1</i>	<i>Sample input vector to soft computing techniques.....</i>	<i>32</i>
<i>Table 4.2</i>	<i>Confusion Matrix of 10-Fold Cross Validation with SVM classifier at Q=20 and number of features were 9.....</i>	<i>41</i>

LISTS OF FIGURES

Sr. No	Figures Details	Page No
Figure 1.1	Ball bearing.....	1
Figure 1.2	Rolling element showing indentations.....	2
Figure 1.3	Dented inner raceway.....	2
Figure 1.4	Outer raceway worn by abrasive particle.....	3
Figure 1.5	Deep seated rust in the outer ring of a deep groove ball bearing	4
Figure 1.6	Smeared outer race of spherical roller bearing.....	5
Figure 1.7	Flaking in the outer ring of spherical roller bearing.....	5
Figure 1.8	Flowchart of bearing fault diagnosis algorithm.....	6
Figure 3.1	Two stage decomposition process of TQWT.....	14
Figure 3.2	Schematic diagram of proposed methodology of bearing fault diagnosis.....	17
Figure 3.3	(a)TQWT coefficients plot of healthy bearing vibration signals..	18
	(b)TQWT coefficients plot of faulty bearing (ball defect) vibration signals.....	18
Figure 3.4	Hyperplane splitting two classes.....	19
Figure 3.5	(a)Boxplot of TQWT based PE feature of healthy bearing	20
	(b)Boxplot of TQWT based PE feature of faulty (ball defect) bearing	20
	(c) Boxplot of TQWT based PE feature of faulty (inner race defect) bearing	20
	(d) Boxplot of TQWT based PE feature of faulty (outer race defect) bearing	20
Figure 3.6	Classification accuracy achieved with varying Q-factor values using SVM, ANN and RF classifiers.....	21
Figure 4.1	Schematic diagram of proposed methodology of fault diagnosis.	29
Figure 4.2	IMFs obtained after applying EMD on healthy bearing vibration signal.....	31

<i>Figure 4.3</i>	<i>IMFs obtained after applying EMD on ball defect vibration signal.....</i>	<i>31</i>
<i>Figure 4.4</i>	<i>(a) Classification accuracy (%) corresponding to varying values of qResol, qResid and Q-factor for four selected IMFs....</i>	<i>33</i>
	<i>(b) Classification accuracy (%) corresponding to varying values of qResol, qResid and Q-factor for three selected IMFs...</i>	<i>33</i>
	<i>(c) Classification accuracy (%) corresponding to varying values of qResol, qResid and Q-factor for two selected IMFs.....</i>	<i>34</i>
	<i>(d) Classification accuracy (%) corresponding to varying values of qResol, qResid and Q-factor for single selected IMFs..</i>	<i>34</i>
<i>Figure 4.5</i>	<i>(a-k)Accuracy (%)after feaature reduction at different values of Q-factor.....</i>	<i>35-36</i>
<i>Figure 4.6</i>	<i>(a)Boxplot of EMD-TQWT based HFD features of healthy bearing.....</i>	<i>36</i>
	<i>(b) Boxplot of EMD-TQWT based HFD feature of faulty (ball defect) bearing.....</i>	<i>36</i>
	<i>(c)Boxplot of EMD-TQWT based HFD feature of faulty (inner race defect) bearing</i>	<i>37</i>
	<i>(d)Boxplot of EMD-TQWT based HFD feature of faulty (outer race defect) bearing.....</i>	<i>37</i>

LIST OF ABBREVIATIONS

TQWT	Tunable Q-factor Wavelet Transform
SVM	Support Vector Machine
SRM	Structural Risk Minimization
ERM	Empirical Risk Minimization
ANN	Artificial Neural Network
RF	Random Forest
EMD	Empirical Mode Decomposition
HFD	Higuchi's Fractal Dimension
FFT	Fast Fourier Transform
STFT	Short Time Fourier Transform
HHT	Hilbert-Huang Transform
MRA	Multi-Resolution Analysis
DRS	Discrete Random Separation
EEMD	Ensemble Empirical Mode Decomposition
PCA	Principal Component Analysis
CWT	Continuous Wavelet Transform
WPT	Wavelet Packet Transform
LMD	Local Mean Decomposition
SACA	Spectral Auto-Correlation Analysis
WT	Wavelet Transform
DWT	Discrete Wavelet Transform
HB	Healthy Bearing
BD	Ball Defect
IRD	Inner Race Defect
ORD	Outer Race Defect
ROC	Receiver Operating Characteristics
AR	Auto Regressive
IMFs	Intrinsic Mode Functions
KNN	K-Nearest Neighbour

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Rotary machines are vital equipment in manufacturing industries. Bearings are the major components of the rotary machines. The bearings faults are a major source of malfunctioning in rotary machines. Such faults in bearings lead to sudden shut down of machineries and may cause heavy loss to the manufacturing industries. This is the reason why autonomous bearing fault diagnosis has gained attention of various researchers across the globe. An effective fault diagnosis method can prevent catastrophic failure of the bearings and reduce the cost of repair and shut down time. A sensitive and reliable monitoring system is required to identify bearing faults at early stages giving warnings of possible malfunctions. Such a monitoring system can avoid the expensive repairs by quickly identifying the faults without examining the entire machine.



Figure 1.1 Ball bearing [1]

A bearing is a system comprising two rings and a set of rolling elements running between the two rings as shown in Figure 1.1. Rolling elements shape can be ball, needles, tapered roller, cylindrical roller or barrel roller. Under continuous operation the performance of the bearing degrades due to a number of factors such as inadequate operating conditions, wear and, rolling contact fatigue etc. Bearing fault diagnosis is a challenging task since, the bearing signals are

non-stationary in nature due to slippage between the coupling components particularly when the operating environment of the machine is very noisy.

1.1.1 Types of bearing faults

Defects of a bearing can be broadly classified as:

- Distributed defects and
- Point local defects

Distributed defects comprise off size rolling elements, waviness, surface roughness and misaligned race. On the other hand point local defects include brinelling, cracks, spall on the bearing surface and corrosion pitting.

Even a properly loaded, correctly mounted and timely lubricated bearing fails after certain running time due to material fatigue. This time period is known as fatigue life of the bearing after which either a localized or distributed defect occurs.

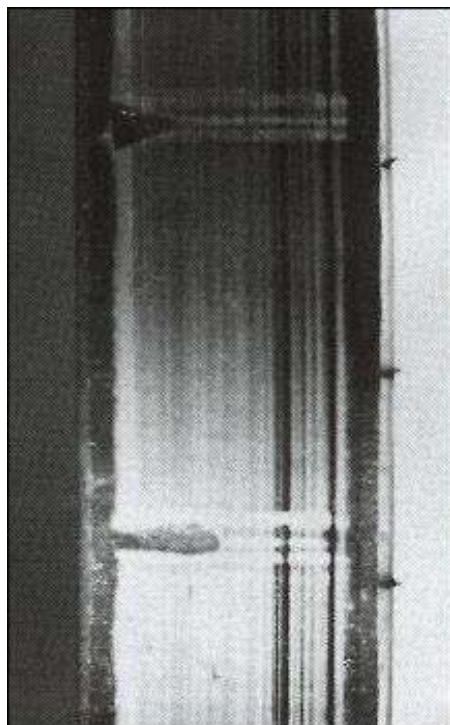


Figure 1.2 Rolling element showing indentations [2]

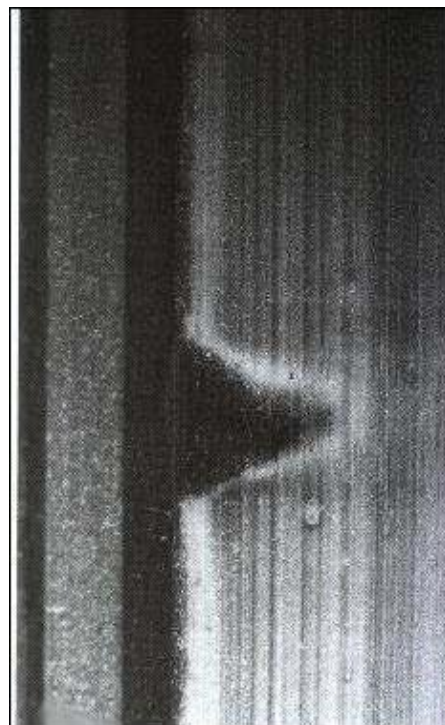


Figure 1.3 Dented inner raceway [2]

Based on the type of damage caused, bearing faults can be classified as:

- Primary damage faults and
- Secondary damage faults

Various primary damage faults are:

- **Indentation:** Indentation is a fault which occurs when mounting pressure is applied to the incorrect ring and rollings elements or raceways become dented. Indentation occurs in a rotating system if applied pressure passes through the balls during mounting or dismounting operations. Foreign particles and unusual loading can also cause indentation even when bearing is not running.

Dust and foreign particles present in the contaminated lubricant are the main sources of indentations when rolling elements are moving in raceways. Small particles such as, thread from cotton waste, clothes used for drying, thin pieces of paper etc. also generate indentations. However, these dents are small and distributed all over the raceways in maximum cases.

- **Wear:** Wear is defined as “a progressive loss of the substance from operating surface of the body occurring as a result of relative motion at surface” [3]. Wear is the reason of bearing malfunction in most cases. It is induced due to material fatigue in a bearing component. Foreign particles such as dust, grit and sand which enter in the bearing due to improper sealing arrangements also cause wear in the rotating system. When lubricant is insufficient or contaminated, it is not possible to provide sufficient oil film between the rolling elements and raceways, due to this wear is generated. When lubrication is insufficient, the material becomes softer at high temperature and surface contains blue to brown hues. Also, at much higher temperature the bearing will seize.

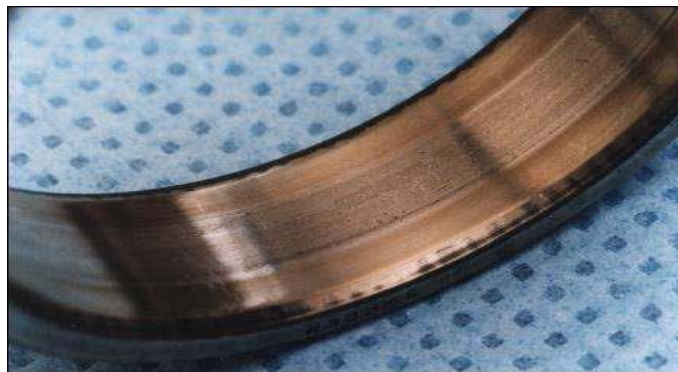


Figure 1.4 Outer race worn by abrasive particle [3]

Presence of vibration signal also generates wear in the bearing. This vibration signal causes small relative movement between the rolling elements and the ring and this will lead small

particles to break away from the surface and produce fault in raceway. The magnitude of the damage depends on the amount of vibration energy.

- **Surface distress:** When the width of the lubricant film between the rolling elements and raceways become very less, the peaks of the uneven surfaces come into contact with each other and due to this situation small cracks are formed in the surfaces, this is known as surface distress. The surface distress cracks are very small which increase very slowly into a size in which they can obstruct the smooth functioning of the bearing. These cracks are different from the fatigue cracks that originate under the surface causing flakes. However, these cracks may accelerate the formation of fatigue cracks and hence decreasing the life of the bearing.
- **Corrosion:** If the moisture or corrosive substances reach inside the bearing in adequate amount they cause corrosion. If the lubrication provided in the bearing cannot give enough protection to the metal surfaces, patches of etching will appear. If the corrosive agents make contact with the steel surfaces for long time, this leads to deep seated rust and thereby initiating cracks and flaking.



Figure 1.5 Deep seated rust in outer ring of a deep groove ball bearing [4]

- **Smearing:** In the absence of sufficient lubrication during the loading conditions, when two surfaces slide against one another the material is transferred from one surface to the other. This phenomenon is known as smearing. The temperature increases due to the friction caused by sliding of the surfaces and at a certain temperature, rehardening of metal takes place. This introduces stress that may cause flaking or cracking. Smearing also depends upon the relative motion of the bearing with respect to the shaft or housing.



Figure 1.6 Smeared outer race of spherical roller bearing [5]

- **Damage caused by electric current:** When electric current passes from one ring to the other via rolling elements, heat is produced and this rise in temperature can form small craters when material reaches to its melting point.

The above explained primary damage faults can lead to flaking and cracks which can further cause various secondary defects in the bearing. Secondary defects are explained as follows:

- **Cage damage:** Cage damage in the bearing system is caused by various sources such as vibration, wear, excessive speed and blockage. The vibration signals generated in the ball bearing system give rise to fatigue cracks in the cage material. With time these cracks grow as fractures. Cage is made of softer material as compared to the other components; this is the reason it wears relatively fast. In the same way, when lubrication is insufficient then cage is affected quickly.
- **Flaking:** Under continuous operation of the bearing, the pits formed by rolling sliding contact fatigue may give rise to a more severe form of damage known as flaking. Flaking cause quick deterioration and failure of bearing due to the large irregular pits.

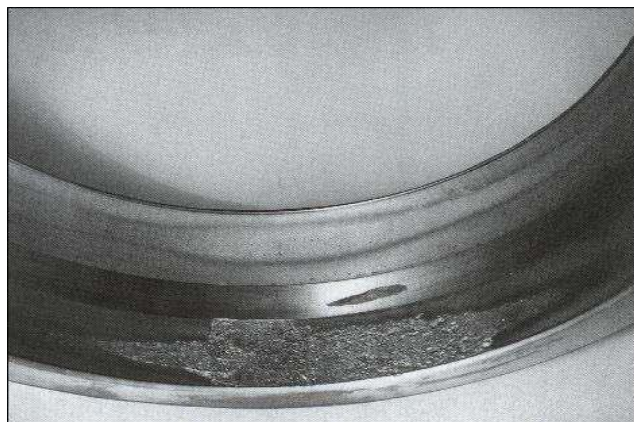


Figure 1.7 Flaking in the outer ring of spherical roller bearing [6]

The accuracy and efficiency of bearing fault diagnosis system depends on accuracy maintained during recording, feature extraction & selection and classification of vibration signals.

The major steps involved in bearing fault diagnosis include:

- **Bearing vibration signal recording:** Firstly, vibration signals are recorded from the bearing.
- **Feature extraction & selection:** In the process of feature extraction relevant information is extracted from recorded vibration signals in the terms of features. Further, the best features are selected from the extracted features for efficient classification.
- **Classification:** A classification algorithm is trained with the set of elements from each class. Each class represents different kind of faults in the bearing. Once training is completed, the classification algorithm is used for validation of input signals.

The overall system of automatic bearing fault diagnosis can be expressed by the fundamental block diagram shown in Fig 1.8.

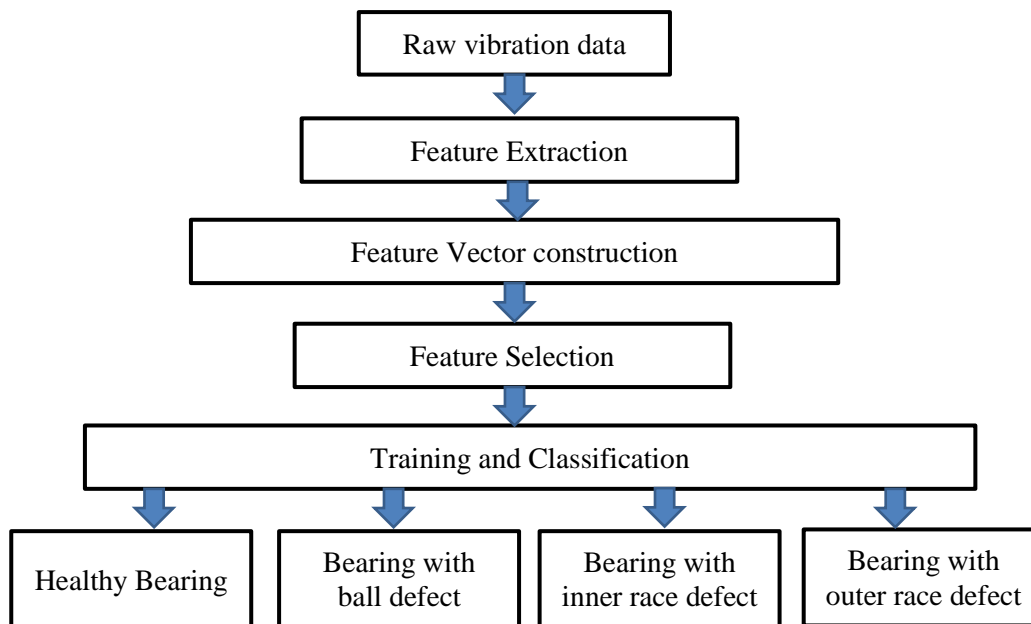


Figure 1.8 Flowchart of bearing fault diagnosis algorithm

1.2 RESEARCH OBJECTIVE AND SCOPE

Shut down of machinery due to bearing faults is a major cause of loss in the manufacturing industry. An effective fault diagnosis method can prevent catastrophic failure of the bearing and reduce the cost of repair and shut down time. A sensitive and reliable monitoring system is

required to identify bearing faults at early stages giving warnings of the possible malfunctions. Such a monitoring system can avoid the expensive repairs by quickly identifying the faults without examining the entire machine.

Many researches are being held for developing an efficient automated bearing fault diagnosis system. These techniques are proved efficient in early diagnosis of the bearing faults. However, still there is scope of improvement in this regard. This thesis work aims to study bearing vibration signal for different fault conditions and propose an effective algorithm to detect bearing faults.

1.3 THESIS OUTLINE

In this thesis work, bearing vibration signals are studied for the diagnosis of three types of bearing faults viz. inner race defect, ball defect and outer race defect. In order to detect bearing faults automatically, algorithms for feature extraction and classification of vibration signals have been proposed. In addition, a survey of previously proposed different types of bearing fault diagnosis techniques has been performed. Present thesis work is divided into five chapters:

In chapter two, a detailed literature survey of previous research work carried for the diagnosis of bearing faults is discussed. In chapter three, vibration signals recorded for four different classes' i.e. Healthy bearing, ball defect bearing, inner race defect bearing and outer race defect bearing. These signals are analyzed using Tunable Q-factor Wavelet Transform (TQWT) and Permutation Entropy (PE) features are extracted from decomposed vibration signals. Further, vibration signals are classified for automatic bearing fault diagnosis by machine learning techniques. Three soft computing techniques have been used in this chapter for classification of vibration data.

In chapter four, the study is extended in order to achieve better classification efficiency for diagnosing bearing faults. In this chapter, a double decomposition technique is proposed for bearing fault diagnosis. The vibration signals are decomposed using Empirical Mode Decomposition (EMD) and Tunable-Q Wavelet Transform (TQWT) and features are extracted from the decomposed vibration signals using Higuchi's Fractal Dimension (HFD). Further, classification of the vibration signals is performed using SVM classifier. Further in chapter five, conclusion and future scope of the present thesis work is discussed.

CHAPTER 2

LITERATURE REVIEW

This thesis work surveys various vibration signal processing techniques used for bearing fault diagnosis. Bearing fault detection methods can be categorized into electric current analysis, acoustic signal analysis, temperature measurement, vibration measurements and lubricant analysis [7]. Interaction between bearing defect and coupling elements produces vibration signals. The method of vibration measurement can be used for the diagnosis of all types of faults. Vibration measurement is extensively used in various industries [8-10]. Vibration analysis based bearing fault diagnosis technique is proposed in this work due to ease of measurement and analysis.

Vibration signals can be analyzed in frequency domain, time domain or time-frequency domain methods. In time domain analysis, statistical indexes such as skewness, kurtosis and crest factor are estimated from the vibration signals. It is observed that frequency domain based methods are most commonly used techniques for analysis of bearing signals. In frequency domain methods, analysis of spectrum is performed to attain fault information of the bearing. However, for the analysis of non-stationary signals generated through machinery defects, time-frequency based techniques are gaining popularity in recent years.

In past, various signal processing techniques have been proposed for diagnosing the faults of rolling elements bearings. The earliest signal processing techniques of fault diagnosis were simple and were mostly dependent on the calculation of statistical parameters such as kurtosis, mean, root mean square (mostly time-domain features) etc. These methods were not much effective and could not effectively minimize the effect of interferences and noises due to other parts of the machine.

The use of normalized kurtosis and normalized skewness values of the bearing data for detecting faults of bearing in early stages was proposed by Martin *et al.* [11]. These authors extended their work suggesting new statistical moments for bearing faults monitoring [12]. The results proved that statistical moments are insensitive to changes in speed and load conditions and can be effectively used for diagnosing rolling element bearing faults. Mechefske *et al.* [13] used autoregressive models to detect bearing faults. These time domain methods do not provide information of the frequency contents of the signals. To overcome this problem, frequency

domain and time-frequency domain methods were used for bearing fault diagnosis. These methods include Short Time Fourier Transform (STFT), Fast Fourier Transform (FFT), Wigner-Vile distribution, etc.

Later, various modern signal processing techniques such as Hilbert-Huang Transform (HHT), morphological signal processing, wavelet transform based techniques etc. were used by researchers for diagnosing bearing faults. Mori *et al.* [14] used Discrete Wavelet Transform (DWT) to predict spalling of ball bearings. Alt-mann *et al.* [15] proposed a novel method ‘Envelope Autoregressive Spectrum’ for diagnosing faults of low speed rolling element bearings. Seker *et al.* [16] used a combination of wavelet transform along with Multi-Resolution Analysis (MRA) for diagnosing the bearing faults of electric motors. Lou *et al.* [17] used the wavelet transform extracted feature vectors of the normalized vibration signals for training an adaptive neural-fuzzy inference system.

Li *et al.* [18] developed a demodulation technique depending on the concept of cyclic spectrum and cyclic autocorrelation for attaining the fault information present in the modulators of the bearing vibration signals. A new denoising technique named as DRS (Discrete Random Separation) was proposed by Randall *et al.* [19] and was applied on vibration signals of the faulty bearings in the gearboxes of Sea Hawk helicopters of the US navy. Yang *et al.* [20] applied Hilbert–Huang Transform (HHT) to decompose the vibration signals of faulty bearings resulting in satisfactory extraction of the bearing faulty features. Zvokelj *et al.* [21] concluded that the low speed bearing data is difficult to analyze due to its multi-scale and multi-dimensional nature. Zvokelj *et al.* applied a new approach by combining the Ensemble Empirical Mode Decomposition (EEMD) method and Principal Component Analysis (PCA) to diagnose such non-stationary signals. A hybrid method merging the Morlet wavelet filter along with the sparse code shrinkage was suggested by He *et al.* [22] for detecting impulses generated from bearing faults.

Researchers also applied several supplementary methods such as histograms, complexity measures and entropy based schemes to recover the faults in the vibration signals spawned by bearings. Wyk *et al.* [23] used Difference Histograms for extracting features of rolling element bearings. The normalized Lempel-Ziv complexity values were used as a measure to find faults of the bearings by Hong *et al.* [24].

Table 2.1 Feature Extraction Methods Available in the Literature

Type of Methodology	Reference ID
Time domain methods	Martin <i>et al.</i> 1995[11], Honavar <i>et al.</i> 1997 [12]
Cyclostationary methods	Li <i>et al.</i> 2004[18], Randall <i>et al.</i> 2004 [19], Zhou <i>et al.</i> 2012[26], Ming <i>et al.</i> 2013[27]
Autoregressive model based methods	Mechefske <i>et al.</i> 1992 [13], Altmann <i>et al.</i> 2001[15]
Wavelet based approaches	Mori <i>et al.</i> 1996 [14], Seker <i>et al.</i> 2003[16], Lou <i>et al.</i> 2004 [17], He <i>et al.</i> 2009[22], Hong <i>et al.</i> 2009[24], Li <i>et al.</i> 2015[28],
Empirical Mode Decomposition (EMD)	Zhao <i>et al.</i> 2013[29]
Ensemble Empirical Mode Decomposition (EEMD)	Žvokelj <i>et al.</i> 2010 [21]
Hilbert–Huang transform (HHT)	Yang <i>et al.</i> 2007[20], Patel <i>et al.</i> 2012[31]
Difference Histograms	Wyk <i>et al.</i> 2009[23]
Improved kurtogram using (Wavelet Packet Transform) WPT filter	Lei <i>et al.</i> 2011 [25]
Local Mean Decomposition (LMD)	Liu <i>et al.</i> 2014 [30]
Image processing based techniques	Klein <i>et al.</i> 2014[32]

For the calculation of the complexity values Continuous wavelet transform (CWT) was applied to the bearing vibration signals in order to find the best scale level with minimum value of noise and interference. The results specified that the proposed method was valuable for detecting single point defects in bearings.

In recent years, some new techniques were proposed by the researchers. Lei *et al.* [25] suggested an improved kurtogram method combined with the benefits of Daubechies-wavelet based Wavelet Packet Transform (WPT) filter. The idea of cyclic bi-spectrum was introduced by Zhou *et al.* [26]. Ming *et al.* [27] introduced a new technique described as Spectral Auto-Correlation Analysis (SACA) with an intention to distinguish the bearing faults. In this technique Ming *et al.* performed autocorrelation analysis on the signals transformed using FFT.

Another new fault diagnostic technique known as Reassigned Wavelet Scalogram was proposed by Li *et al.* [28]. This technique was based on CWT. Zhao *et al.* [29] combined Empirical Mode Decomposition (EMD) with the approximate entropy method in order to diagnose bearing faults more accurately. Liu *et al.* [30] provided a new feature extraction methodology stated as Local Mean Decomposition (LMD), which decomposed the bearing vibration signals into a series of product functions which is defined as the product of amplitude envelope signal and the subsequent frequency modulated signal. Patel *et al.* [31] suggested the use of Hilbert transform supplemented by the duffing oscillator for recognizing localized defects in ball bearings. An advanced dimension of research in the area of bearing fault diagnosis was introduced by Klein *et al.* [32] by using the image processing techniques viz. ridge tracking and related algorithms on the time frequency representation of the bearing vibration signals.

CHAPTER 3

TQWT TECHNIQUE FOR BEARING FAULT DIAGNOSIS

3.1 INTRODUCTION

Bearings are one of the most significant components being used in any manufacturing industry. These bearings may undergo unexpected failure due to wear, corrosion, fatigue and overloading conditions [33]. Failure in the rolling element bearing leads to sudden shut down of machineries and may cause heavy loss to the manufacturing industry. This is the reason why autonomous bearing fault diagnosis has gained significant attention of various researchers across the globe. An effective fault diagnosis method can prevent catastrophic failure of machine due bearing faults and reduce cost of repair and shut down time. Feature extraction and classification of vibration signals are the two crucial stages in any fault diagnosis mechanism [34]. Vibration signals are non-linear and non-stationary in nature. In addition, these signals are also affected by external noises. This makes it necessary to exploit an efficient feature extraction methodology to generate highly discriminative features.

Out of various available techniques, Wavelet Transform (WT) is the most extensively used feature extraction technique for bearing fault diagnosis due to its excellent band pass filtering capability and high time-frequency resolution. However, the classical WT has constant Q-factor i.e. WT has constant central frequency to Bandwidth ratio. To overcome this limitation of WT, Selesnick proposed the concept of WT with Tunable Q-factor [35]. Tunable Q-factor Wavelet Transform (TQWT) is a variant of Discrete Wavelet Transform (DWT) with capability of tuning its Q-factor.

Considering its capabilities, TQWT has been used in previous studies for extraction of weak bursts of bearing vibration signals. Cai et.al used TQWT for extracting faults in gearboxes [36]. Tunable Q-factor Wavelet Transform (TQWT) has also been used in combination with Hilbert transform for examining vibration features of bearing faults [37]. Weak bursts of vibration signals of angular contact bearing were extracted by Kumar et.al using TQWT along with envelope demodulation [38]. However, TQWT alone is not capable of extracting faulty features from vibration signals effectively. Therefore, it is needed to propose a supplementary extraction technique to ensure extraction of discriminative features from TQWT coefficients.

Entropy serves as an excellent tool for measuring disorderliness and complexity of signals. Yan *et al.* used Approximate Entropy as a tool for monitoring machine health [39]. In similar work, Tiwari *et al.* employed multi-scale Permutation Entropy for diagnosing bearing faults [40]. In another work, Vakharia *et al.* proposed use of multi-scale Permutation Entropy for selecting wavelets for diagnosing faults of ball bearings [41]. Considering significance of entropies in bearing fault diagnosis, TQWT based Permutation Entropy (PE) feature extraction technique is proposed in present chapter. Permutation Entropy (PE) is considered here due to its simplicity, robustness and low computational time. Initially, vibration signals are decomposed into multiple number of sub-bands using TQWT. Further, Permutation Entropy is computed on each sub-band for extraction of useful vibration features and preparation of feature vector. The feature vector obtained is used to train and validate the soft computing methods for bearing fault diagnosis. In this chapter, three soft computing methods viz. Artificial Neural Networks (ANN), Random Forest (RF) and Support Vector Machine (SVM) have been employed for fault classification. Outcome of the study reveals that the proposed technique yields significantly better results compared to conventional techniques of bearing fault diagnosis.

3.2 MATERIAL AND METHODS

3.2.1 Bearing Data

The bearing vibration data analyzed in present chapter is borrowed from Case Western Reserve University bearing data center. Four classes of bearing data are utilized in this work which includes Healthy Bearing (HB) data, Ball Defect (BD) data, Inner Race defect (IRD) data and Outer Race Defect (ORD) data. Healthy Bearing (HB) data is considered as the base data to diagnose faulty condition of ball bearing. The bearing data was taken from drive end with sampling frequency of 48000 Hz. The available vibration data was acquired for four rotation speeds of 1797, 1772, 1750 and 1730 rpm. Faults ranging between 0.007 inches to 0.040 inches in diameter were introduced in the rolling element, inner raceway and the outer raceway of bearing respectively, to record vibration activity corresponding to three classes of bearing faults.

3.2.2 Tunable Q-factor Wavelet Transform (TQWT)

The Tunable Q-factor Wavelet Transform (TQWT) is a variant of Discrete Wavelet Transform (DWT). However, Tunable Q-factor Wavelet Transform (TQWT) differs from DWT in terms of capability to tune Q-factor as per the application requirements. Various parameters of TQWT

includes Q-factor, number of decomposition level j and redundancy r . Here, Q-factor is the ratio of central frequency and the bandwidth of the Wavelet, which controls the oscillating behavior of the Wavelet and is given as:

$$Q = f_o/BW \quad (3.1)$$

The redundancy (r) is the ratio of number of wavelet coefficients and the length of the signal. Tunable Q-Factor Wavelet Transform (TQWT) has a sequence of two-channel filter banks. For each iteration, the low pass output of each filter bank is used as the input to the successive filter bank. It is followed by two parameters, a low pass scaling parameter denoted by α and a high pass scaling parameter denoted by β . The relationship among the parameters of TQWT i.e. Q and r and the scaling parameters i.e. α and β is described by Eq. (3.2) [42].

$$\beta = \frac{2}{Q+1} \text{ and } \alpha = 1 - \frac{\beta}{r} \quad (3.2)$$

A two stage TQWT process is shown in Figure 3.1. The original signal $x(n)$ is passed through the high and the low pass filter bank producing three sub-bands. $d_1(n)$ and $d_2(n)$ are detail sub-bands formed by high pass filtering at the first and second stage of decomposition respectively. The sub-band $a_2(n)$ is the sub-band at the second stage of decomposition as a result of low pass filtering of approximate signal generated at the first stage of decomposition. It is called the approximate sub-band.

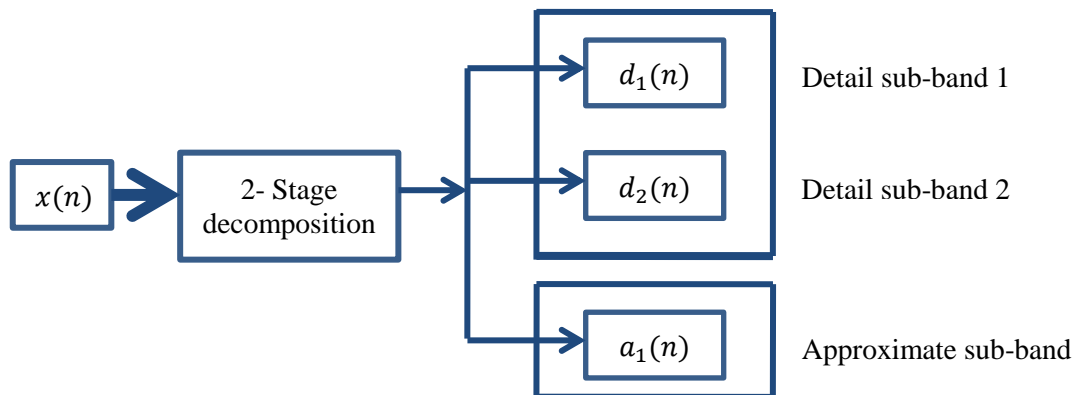


Figure 3.1 Two stage decomposition process of TQWT

3.2.3 Permutation Entropy (PE)

Bandt and Pompe introduced Permutation Entropy in 2002 [43]. It is used for the measurement of complexity of the time series by comparing the neighbour values. Permutation Entropy (PE)

has been effectively applied to various areas due to its advantages of fast calculation, simplicity, invariance to nonlinear monotonous transforms and robustness. The principle of Permutation Entropy is described below:

The continuous time series is mapped on a symbolic sequence by embedding a scalar time series say $\{s(n); n-1, 2, 3, \dots\}$ to an e -dimensional space such as:

$$S_n = [s(n), s(n+l), \dots, s(n+(e-1)l)] \quad (3.3)$$

where l and e are the time delay and embedded dimension respectively. Each point of the e -dimensional space can be mapped onto one of the $e!$. Each reconstruction trajectory in the e -dimensional space has probability distribution of P_i which is denoted by a symbol sequence i . If $P_1, P_2, P_3, \dots, P_i$, is used for representing the distribution of probability of each such sequence, then the Permutation Entropy of the given time series can be obtained based on the definition of Shannon Entropy as:

$$H_p(n) = \sum_i^l P_i \ln(P_i) \quad (3.4)$$

Permutation Entropy of any time series depends upon two user defined parameters i.e. embedded dimension ' m ' and time delay ' l '. Bandt and Pompe suggested that the value of embedded dimension should be kept between 3 and 7 [43]. In this chapter, value of embedded dimension is taken as $m = 3$ and time delay is set to $l = 1$ during calculation of PE.

3.3 FEATURE EXTRACTION AND CLASSIFICATION

3.3.1 Feature Extraction Methodology

In this chapter, vibration signals of the bearing are decomposed into time-frequency sub-bands using TQWT, initially. While calculating time-frequency coefficients using TQWT, the redundancy parameter (r) is kept as $r=3$ and number of decomposition levels is set to 10, which yields 11 sub-bands of decomposed vibration activity. The value of Q-factor is selected based upon the experimental results carried out on vibration data. In present work, Q-factor is optimized for SVM, ANN and RF classifiers separately to attain highest classification efficiency during fault diagnosis task. The value of Q-factor is varied from 1-50 and classification results are analysed. The proposed methodology of bearing fault diagnosis is illustrated by schematic diagram presented in Figure 3.2. Figure 3.3(a-b) represents the TQWT coefficients plot for healthy and faulty (ball defect) bearing vibration signals. As depicted in Figure 3.3(a-b), the

given vibration activity is decomposed into 11 time-frequency sub-bands. Very significant deviation in TQWT coefficient values can be observed from sub-bands 3, 4, 5 and 6 of healthy and faulty (ball defect) bearing vibration signals.

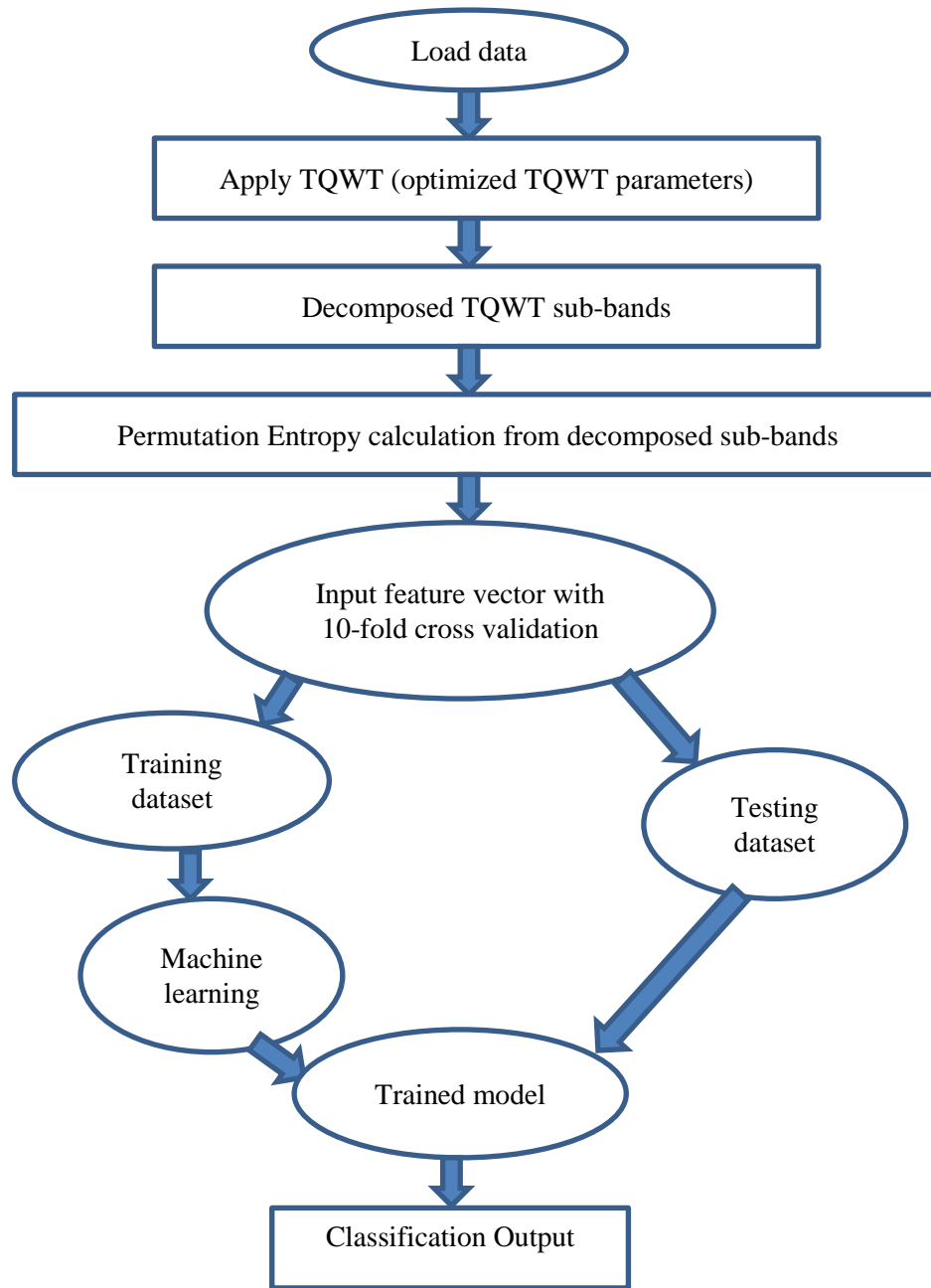


Figure 3.2 Schematic diagram of proposed methodology of bearing fault diagnosis

Further, PE is calculated from each decomposed time-frequency sub-band of vibration activity and corresponding feature vector is prepared. Since, PE value is estimated from 11 time-

frequency sub-bands, therefore, total 11 features are available in the feature vector corresponding to single vibration signal.

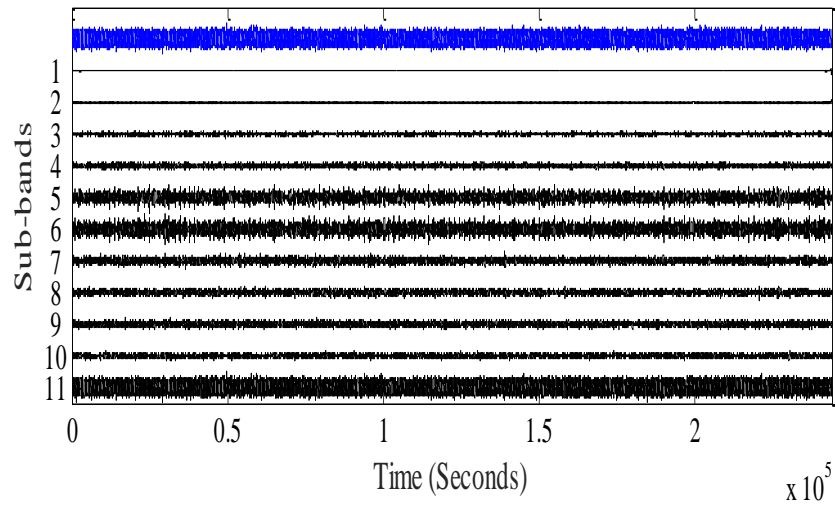


Figure 3.3(a) TQWT coefficients plot of healthy bearing vibration signals

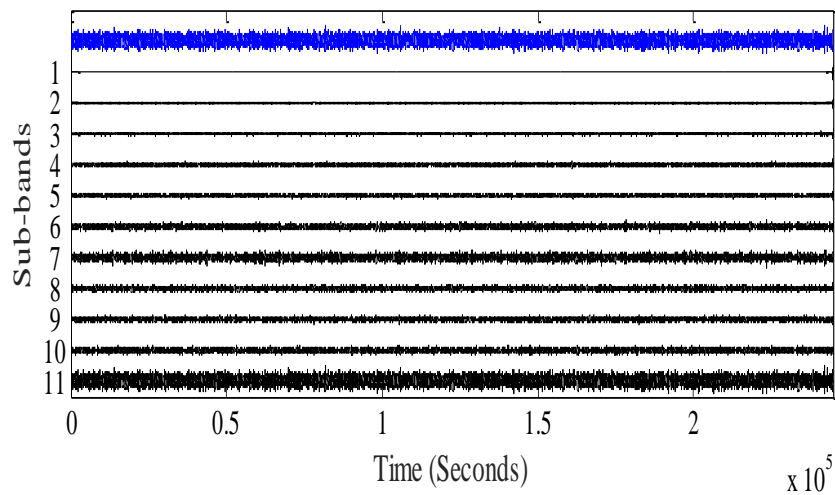


Figure 3.3(b) TQWT coefficients plot of faulty bearing (ball defect) vibration signals

3.3.2 Soft Computing Techniques

In this work, three soft computing techniques viz. SVM, ANN and RF have been employed for illustrating efficiency of the methodology proposed for feature extraction in bearing fault diagnosis. Various parameters of SVM, ANN and RF classifiers are selected and optimized based on the results of multiple classification experiments carried out on vibration data. Training and validation of classifier algorithm is carried out using data mining toolkit WEKA version 3.6.4 [44].

3.3.2.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a statistical learning technique. It was introduced by Cortes and Vapnik in 1995 and is based upon the principle of Structural Risk Minimization (SRM) and Empirical Risk Minimization (ERM) [45]. Support Vector Machine (SVM) is a supervised learning algorithm in which learning machine is provided by set of features along with class labels. Support Vector Machine (SVM) training algorithm builds a model on the basis of labelled classes. During training process, a hyperplane is drawn between two different classes of data. This hyperplane separates hyperspace to achieve maximum separation between the two classes. The nearest data point is known as support vector which is used to define the margins for SVM classifier. In present work, SVM classifier is implemented with PUK kernel function and Penalty parameter was set to 20.

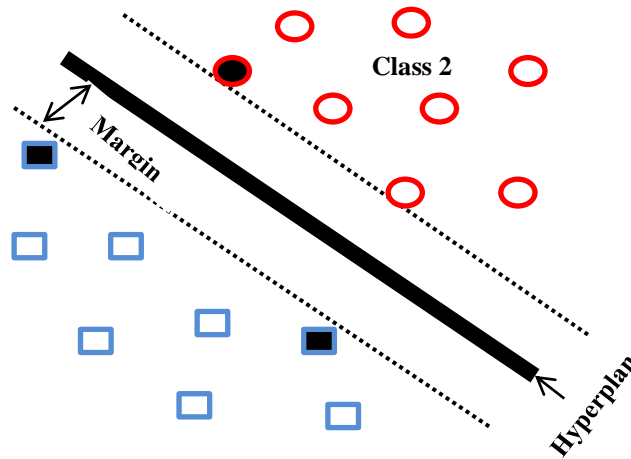


Figure 3.4 Hyperplane splitting two classes

3.3.2.2 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a machine learning method, which learns from the experimental dataset. Artificial Neural Network (ANN) has three layers formed by artificial neurons which are interconnected. The input layer serves data to the network, output layer produces ANN's response, and the third layer is a hidden layer. Artificial Neural Network (ANN) changes its structure by learning from the previous experiences [46]. In order to attain classification using ANN classifier, three hidden layered architecture with back propagation learning algorithm is employed. In present work, the learning rate was set to 0.3 for ANN classification.

3.3.2.3 *Random Forest (RF)*

Random Forest (RF) is an ensemble learning classification algorithm developed by Breiman in 2001 and is a modification of bagging method [47]. It consists of a combination of tree predictors where each tree is dependent on the values of a random vector independently sampled. Random Forest (RF) classifier splits each node by using best amongst a subset of predictors which are chosen randomly at that node. Finally, the classification outputs of all trees are combined and an overall classification output is obtained by selecting the outputs with most votes. In present work, twelve trees structure is used for the classification purpose.

3.4 RESULTS AND DISCUSSIONS

In this work, an effort has been made to study capability of TQWT and PE based features in diagnosing various faulty conditions of ball bearing. Figure 3.5 represents the box plot of extracted PE feature value for four classes of vibration activity. It is observed from Figure 3.5 that distribution of feature value is little/very less for healthy bearing case. However, significant amount of distribution can be observed in PE feature values of 8th and 11th sub-band in the faulty bearing cases. The nature of skewness is similar for ball defect and inner race defect. However, it is significantly different for outer race defect case.

A total of 40 instances are considered in present study, out of which 4 instances are of healthy bearing and 12 instances are of inner race, outer race and ball defects each. The obtained feature vector is used as an input for the soft computing techniques viz. ANN, SVM and RF for training and validation purposes. The classification of vibration signals is performed using 10-fold cross validation approach, which ensures no statistical biasing is present in the classification results. Figure 3.6 represents the classification accuracies obtained using SVM, ANN and RF classifiers for different values of Q-factor (ranging from 1-50). It is evident from Figure 3.6 that highest classification accuracy is obtained by SVM classifier for Q-factor=25. Classification results obtained using ANN and RF classifiers are almost comparable and highest classification accuracy is obtained for Q-factor value of 20. Results of the classification suggest that Q-factor value should be maintained between 20 and 25 to ensure the highest classification performance.

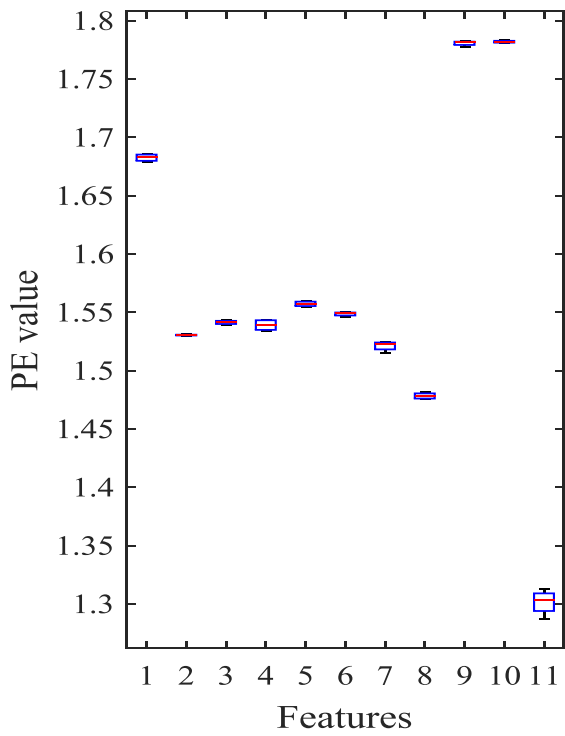


Figure 3.5(a) Boxplot of TQWT based PE feature of healthy bearing

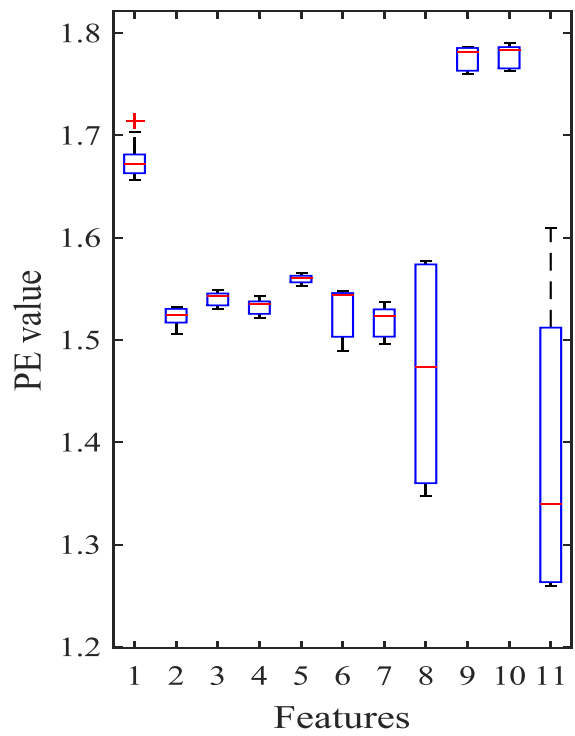


Figure 3.5(b) Boxplot of TQWT based PE feature of faulty (ball defect) bearing

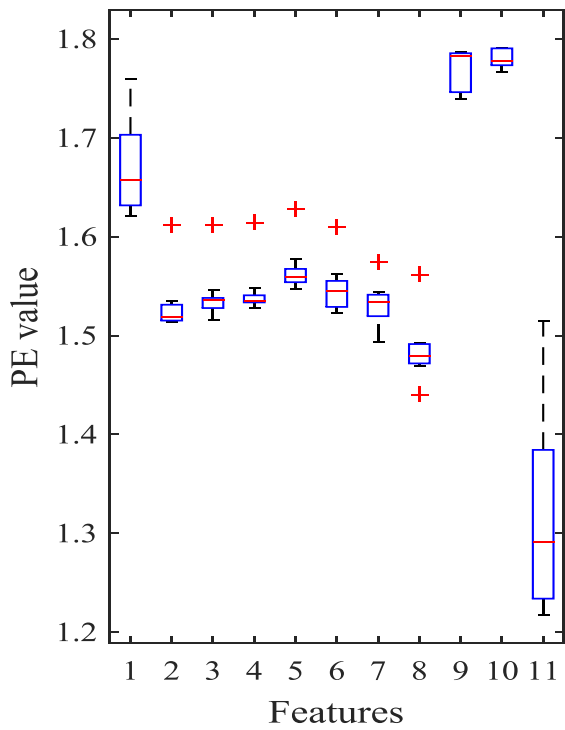


Figure 3.5(c) Boxplot of TQWT based PE feature of faulty (inner race defect) bearing

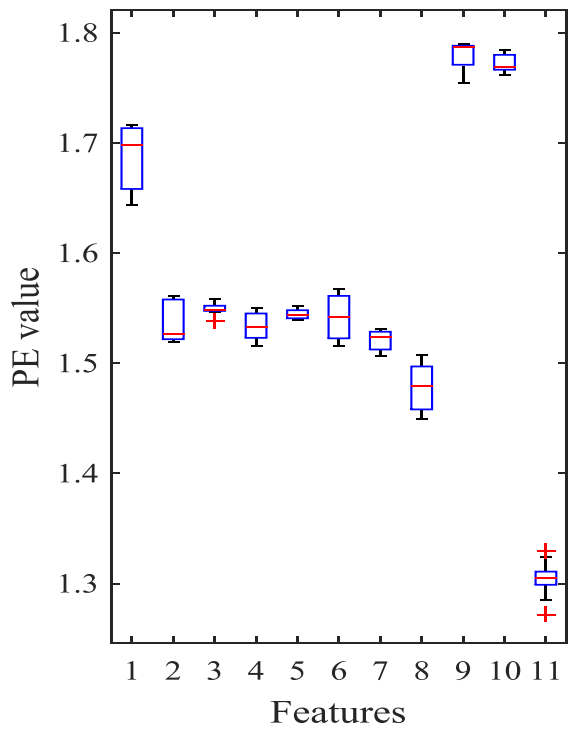


Figure 3.5(d) Boxplot of TQWT based PE feature of faulty (outer race defect) bearing

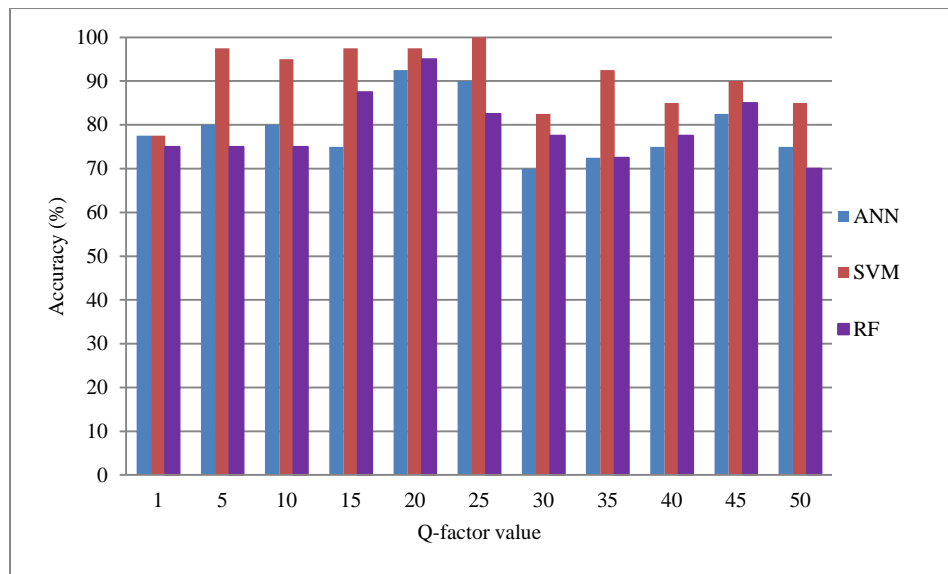


Figure 3.6 Classification accuracy achieved with varying Q-factor values using SVM, ANN and RF classifiers

TABLE 3.1 Classification performance of SVM, ANN and RF classifiers with optimized classifiers' parameters

Parameter	Classifier		
	SVM	ANN	RF
Classifier's parameters	Kernel: PUK, Penalty parameter: 20	hidden layers=8, learning rate= 0.3	Trees: 12
Q-factor	25	20	20
Total number of instances	40	40	40
Correctly classified instances	40	37	38
Incorrectly classified instances	0	3	2
Precision	1	0.929	0.957
F- measure	1	0.926	0.951
ROC	1	0.961	0.971
Classification efficiency	100%	92.5%	95%

SVM: Support vector machine, ANN: Artificial neural network, RF: Random forest.

The classification results shown in this work are calculated at Q-factor=25 for SVM classifier and at Q-factor=20 for ANN and RF classifiers. The optimized values of various classifiers' parameters in addition to the respective classifier' performances are shown in Table 3.1.

3.4.1 Performance Evaluation

The classification performance of SVM, ANN and RF classifiers is evaluated by four parameters i.e. Classification Accuracy, Precision, F-measure and Receiver Operating Characteristic Curve (ROC) values. Here, Precision is the measure of accuracy provided that a particular class is predicted [48]. Precision value is given as:

$$\text{Precision} = \text{TP}/\text{TP}+\text{FP} \quad (3.5)$$

Here, TP and FP stands for True Positive and False Positive instances respectively. The ideal value of precision is 1. In this work, Precision value of 1 is obtained in the case of SVM classifier whereas ANN and RF gives Precision value of 0.929 and 0.957 respectively. Another parameter, F-measure value represents the harmonic mean of precision and sensitivity and is given as [48].

$$\text{F-measure} = (2*\text{precision}*\text{recall}) / (\text{precision}+\text{recall}) \quad (3.6)$$

Ideally, value of F-measure should be 1. In this work, F-measure value is found to be 1, 0.926 and 0.951 in the case of SVM, ANN and RF classifiers, respectively.

Receiver Operating Characteristic (ROC) is used to differentiate between True and False Positive rate. Receiver Operating Characteristic (ROC) is produced from the plot of Sensitivity versus Specificity. For ideal case, the area under ROC curve is 1. In this work, area under ROC curve is found to be 1, 0.961 and 0.971 for SVM, ANN and RF classifiers respectively.

The confusion matrices of 10-fold cross validation with SVM, ANN and RF classifiers are shown in Table 3.2, Table 3.3 and Table 3.4 respectively. It can be observed from Table 3.1 and Table 3.2 that the classification performance achieved with SVM classifier is 100% for given classifier parameters. It can be observed from Table 3.3 and Table 3.4 that classification performance achieved with ANN and RF classifier is satisfactory, however, it is significantly low as compared to SVM classifier. It can be observed from Table 3.3 and Table 3.4 that ANN and RF classifiers confused most between inner race defect and outer race defect. However, both classifiers successfully recognized healthy bearing vibration signals. It is evident from the classification results that the SVM classifier outperforms the other two classifier algorithms in bearing fault diagnosis application.

TABLE 3.2 Confusion matrix of 10-fold cross validation with SVM classifier

HB	BD	IRD	ORD	Classified as
4	0	0	0	HB
0	12	0	0	BD
0	0	12	0	IRD
0	0	0	12	ORD

HB: Healthy Bearing, BD: Ball Defect, IRD: Inner Race Defect, ORD: Outer Race Defect

TABLE 3.3 Confusion matrix of 10-fold cross validation with ANN classifier

HB	BD	IRD	ORD	Classified as
4	0	0	0	HB
0	11	1	0	BD
0	1	11	0	IRD
0	0	1	11	ORD

HB: Healthy Bearing, BD: Ball Defect, IRD: Inner Race Defect, ORD: Outer Race Defect

TABLE 3.4 Confusion matrix of 10-fold cross validation with RF classifier

HB	BD	IRD	ORD	Classified as
4	0	0	0	HB
0	12	0	0	BD
0	1	11	0	IRD
0	1	0	11	ORD

HB: Healthy Bearing, BD: Ball Defect, IRD: Inner Race Defect, ORD: Outer Race Defect

A comparative study between the work proposed in this chapter and previous work published in literature is presented in Table 3.5. Comparison is done on the basis of classification performance achieved in four class (i.e. HB, BD, IRD and ORD) classification task.

TABLE 3.5 A Comparative study between proposed work and previous work published in the literature

References	Machine Learning Technique	Classes	Classification Accuracy (%)
Tyagi (2008) [49]	ANN, SVM	HB, BD, IRD, ORD	ANN - 96, SVM - 97
Yaqub <i>et al.</i> (2012) [50]	kNN	HB, BD, IRD, ORD	91.23
Sun <i>et al.</i> (2012) [51]	Envelope spectrum correlation	HB, BD, IRD, ORD	95
Vakharia <i>et al.</i> [41]	ANN, SVM	HB, BD, IRD, ORD	ANN- 97.5, SVM- 97.5
Present work	SVM, ANN, RF	HB, BD, IRD, ORD	SVM- 100, ANN- 92.5 RF - 95

HB: Healthy Bearing, BD: Ball Defect, IRD: Inner Race Defect, ORD: Outer Race Defect, SVM: Support Vector Machine, ANN: Artificial Neural Network, RF: Random Forest, kNN: k-Nearest Neighbour

3.5 SUMMARY

In this chapter, an automated technique of bearing fault diagnosis is developed and evaluated for detecting three types of ball bearing faults. Proposed technique relies on TQWT based time-frequency representation of vibration signals for extracting PE feature. In order to consider dynamic non-linearity and coupling effects between mechanical parts, PE value is evaluated from 11 decomposed sub-bands of recorded vibration activity. Extracted features are classified by three soft computing techniques i.e. SVM, ANN and RF using 10-fold cross validation approach. Experimental results demonstrate the efficiency of proposed methodology in bearing fault diagnosis application. Proposed technique efficiently classified four classes of vibration signals with 100% classification accuracy using SVM classifier. Also, classification results of ANN and RF classifiers are significant. However, performance of these classifiers is considerably low as compared to SVM classifier. In this chapter, SVM classifier is found to be most suitable classifier for fault diagnosis task. It is evident from the classification results that Q-factor should be maintained in a range of 20 to 25, in order to decompose vibration signals efficiently. However, the best results are obtained for Q-factor value of 25 in present work.

CHAPTER 4

DOUBLE DECOMPOSITION BEARING FAULT DIAGNOSIS TECHNIQUE

4.1 INTRODUCTION

The technique proposed in the previous chapter has the drawback that the range of Q-factor value to get the best classification results is very limited. Moreover, 100% classification accuracy is obtained only at a single Q-factor value. In order to overcome the weaknesses of the previous technique a double decomposition technique using combination of EMD and TQWT based time-frequency decomposition is proposed in this chapter. Proposed technique is implemented in three steps. Firstly, vibration signals are double decomposed by using a combination of Empirical Mode Decomposition and Tunable Q-factor Wavelet Transform. Further, Higuchi's Fractal Dimension (HFD) features are extracted from decomposed time-frequency components in the second step. Thirdly, classification of bearing vibration signals is performed using Support Vector Machine classifier.

Empirical Mode Decomposition (EMD) has shown to be adaptable in various applications where the signals are non-stationary in nature. Researchers have earlier used EMD for detecting bearing faults. Yu et.al [52] proposed EMD as a method for fault diagnosis of rolling bearings showing the superiority of EMD method over the conventional envelope spectrum method. A roller bearing fault diagnosis method was proposed by Yu et.al [53]. In this method inner-race and outer-race faults were analysed on the basis of EMD energy entropy. A combination of EMD method and AR (Auto Regressive) model was used by Junsheng et.al [54] for diagnosis of non-stationary signals of rolling bearings. Dybala et.al [55] also proposed a rolling bearing fault diagnosis technique based on EMD.

In the present work, EMD is applied to the bearing vibration signals. Empirical mode decomposition (EMD) decomposes the vibration signals into multiple set of signals having specific frequency, called Intrinsic Mode Functions (IMFs). Tunable Q-factor Wavelet Transform (TQWT) is applied to the selected IMFs (having highest value of Higuchi's Fractal Dimension (HFD)), which results in multiple decomposed sub-bands. Further, HFD is applied to the sub-bands for extraction of useful vibration signatures and preparation of feature vector.

The obtained feature vector is fed as input to soft computing technique for training and validation purpose. In this work, only Support Vector Machine (SVM) has been employed in fault classification considering the results of the previous chapter (chapter-3). The results revealed that the proposed method gives better results than the conventional methods. The organization of this chapter is as follows: Section 4.2 provides a detailed description of the methods being used in this chapter. The description of proposed methodology of feature extraction is presented in section 4.3. The results of this work are discussed in section 4.4 following the conclusion in section 4.5.

4.2 MATERIAL AND METHODS

4.2.1 Bearing vibration database

The database used in present work is the similar to the database used in chapter 3. This gives more insight and a fair comparison of techniques proposed in chapter 3 and chapter 4.

4.2.2 Feature extraction techniques

4.2.2.1 Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition (EMD) has been proposed by Huang *et al.* [56]. It is developed from an assumption that every signal has different intrinsic modes of oscillations. Empirical Mode Decomposition (EMD) has the parameters as Input signal (x), resolution ($qResol$) (in DBs: $10 \cdot \log (W_{Signal}/Bias \text{ energy})$), Residual energy ($qResid$) (in DBs: $10 \cdot \log (W_{signal}/W_{qResidual})$) and Gradient step size ($qAlfa$). The values of $qResol$ and $qResid$ are normally set between 40 and 60 dB, and $qAlfa$ is normally set to 1.

Empirical Mode Decomposition (EMD) is a self-adaptive method which decomposes signals into multiple numbers of modes called the empirical modes. These empirical modes represent different modes of oscillations embedded in the input signal. This decomposition is done on the basis of enveloping technique and each IMF must satisfy the following conditions [56]:

- The number of zero crossings and the number of extrema must either be equal or differ by at the most one in the whole data set.
- The mean value of the envelopes defined by local maxima and minima at any point should be zero.

In EMD technique, any input signal say $x(t)$ can be decomposed using following steps:

- Identify all the local maxima and connect them by a cubic spline line making the upper envelope.
- Repeat the same procedure for all local minima producing the lower envelope. Whole data should be covered between the upper and lower envelopes.
- Calculate the mean between the upper and lower envelope designating it as m_1 .
- h_1 is the first component representing the difference between $x(t)$ and m_1 .

$$h_1 = x(t) - m_1 \quad (4.1)$$

h_1 is the first component of $x(t)$ if it is an IMF.

- If h_1 is not an IMF, then it is treated as the original signal and the above steps are repeated.

$$h_{11} = h_1 - m_{11} \quad (4.2)$$

After repeated sifting upto n times h_{1n} becomes an IMF, that is

$$h_{1(n)} = h_{1(n-1)} - m_{1n} \quad (4.3)$$

and, it is the first IMF component from original data

$$c_1 = h_{1n} \quad (4.4)$$

- Separating c_1 from $x(t)$, we get

$$r_1 = x(t) - c_1 \quad (4.5)$$

r_1 is treated as the original data and the above process is repeated and the second IMF component c_2 of $x(t)$ could be obtained. Repeating the above process for n times, n -IMFs of signal $x(t)$ could be obtained

$$r_2 = r_1 - c_2 \dots\dots r_k = r_{k-1} - c_k \quad (4.6)$$

The decomposition process stops when r_k becomes a monotonic function and no more IMF can be extracted from it. Each of the IMFs c_1, c_2, \dots, c_n comprises of different frequency bands ranging from high to low and are stationary.

4.2.2.2 Higuchi's Fractal Dimension (HFD)

Higuchi's Fractal Dimension (HFD) is an efficient algorithm for measurement of Fractal Dimension (FD) of discrete time sequences. Higuchi's Fractal Dimension (HFD) algorithm was proposed by Higuchi in 1988 [57]. In Higuchi's algorithm the FD is calculated directly from time series. For a given one dimensional time series $X = x[1], x[2] \dots \dots, x[n]$, the algorithm to compute the HFD can be described as follows [58]:

Form k new time series X_k^m defined by:

$$X_k^m = \{x[m], x[m+k], x[m+2k], \dots, x[m + \text{int}\left(\frac{N-m}{k}\right) \times k]\} \quad (4.7)$$

where k and m are integers, k indicates the discrete time interval between the points, and $m = 1, 2, \dots, k$ represents the initial time value.

Each new time series has a length defined as [59]:

$$L(m, k) = \frac{\{(\sum_{i=1}^{\text{int}((N-m)/k)} |x[m=ik] - x[m+(i-1) \times k] |)\} [(N-1)/(\text{int}(\frac{N-m}{k}) \times k)]}{k} \quad (4.8)$$

where, N is the length of the original time series X and $[(N-1)/(\text{int}(\frac{N-m}{k}) \times k)]$ is the normalization factor.

The length of the curve for the time interval k is defined as the average of k values $L(m, k)$ for $m = 1, 2, \dots, k$:

$$L(k) = \frac{1}{k} \times \sum_{m=1}^k L(m, k) \quad (4.9)$$

when $L(k)$ is plotted against $1/k$ on a double logarithmic scale, with $k = 1, 2, \dots, k_{max}$, the data should fall on a straight line, with a slope equal to the fractal dimension of X . Higuchi's Fractal Dimension (HFD) is defined as the slope of the line that fits the pairs $\{\ln [L(k)], \ln(1/k)\}$ in least square sense.

4.2.3 Classification algorithm

In this work, SVM is used for illustrating efficiency of proposed methodology of feature extraction in bearing fault diagnosis. Various parameters of SVM classifier are selected and optimized based on the results of multiple classification experiments carried out on vibration data. Support Vector Machine (SVM) classifier is implemented with PUK kernel function and Penalty parameter was set to 20. Training and validation of classifier algorithm is carried out using data mining toolkit WEKA version 3.6.4 [42].

4.3 PROPOSED METHODOLOGY

In present work, vibration signals are decomposed into time-frequency sub-bands using EMD and TQWT, initially. A total of 40 instances of vibration signals are considered, of which 4 are of healthy bearing and 12 each of inner race defect, outer race defect and ball defect. Empirical Mode Decomposition (EMD) is applied to the vibration signals for decomposition purpose.

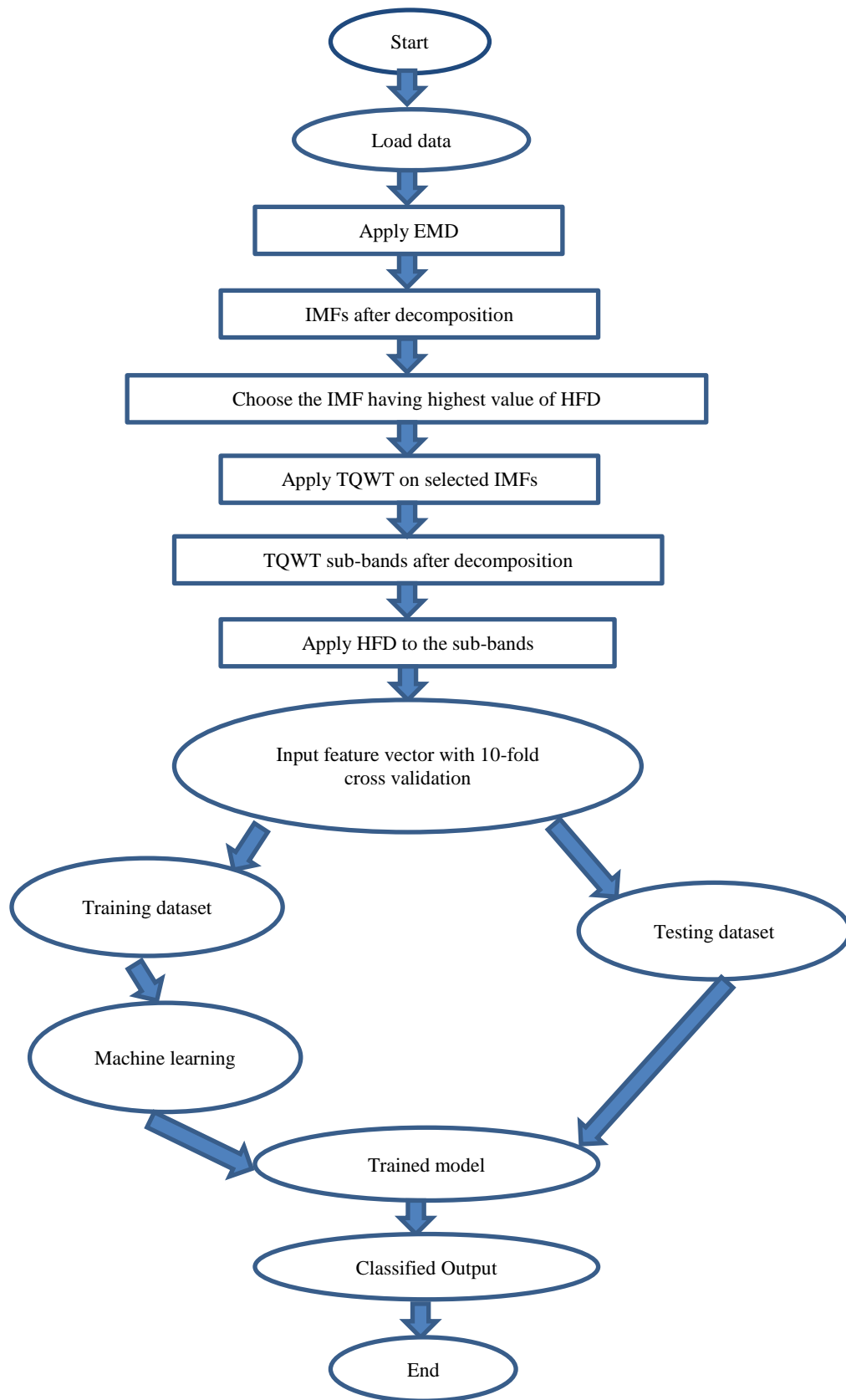


Figure 4.1 Schematic diagram of proposed methodology of fault diagnosis

Empirical Mode Decomposition (EMD) decomposes the vibration signals into Intrinsic Mode Functions (IMFs). While calculating the time-frequency coefficients using EMD, the parameters $qResol$ and $qResid$ are varied from 40-50 with a step size of 10 and $qAlfa$ is set to 1. Different IMFs are obtained for the vibration signals and their HFD value is calculated from each decomposed IMF. Initially, four IMFs with the highest HFD value are selected after performing decomposition using EMD.

Further, TQWT is applied to each of the selected IMFs. Tunable Q-factor Wavelet Transform (TQWT) decomposes each IMF into multiple sub-bands. Higuchi's Fractal Dimension (HFD) value is calculated from each decomposed time-frequency sub-band of vibration activity and corresponding feature vector is prepared. While calculating TQWT coefficients, the redundancy r is taken as $r=3$ and number of decomposition levels is set to 9, which yields 10 sub-bands of decomposed vibration activity. The value of Q-factor is varied from 1-50 and is optimized to attain the highest classification efficiency during fault diagnosis task. The proposed methodology is illustrated by schematic diagram presented in Figure 4.1.

The obtained feature vector is fed as an input to the soft computing technique for fault classification. Fault classification is done by Support Vector Machine (SVM) classifier using WEKA software [42]. Different feature vectors were obtained for different values of Q-factor and the values which gave the best classification accuracy (%) are proposed for fault diagnosis purpose.

4.4 RESULTS AND DISCUSSION

In this work an effort has been made to study the capability of EMD and TQWT based HFD features in diagnosing various faults of a rolling element bearing. In the present work, firstly EMD is applied to the vibration signals of the bearing. All the 40 input signals are decomposed into various numbers of IMFs. Figure 4.2 and Figure 4.3 shows the IMFs obtained after applying EMD to a healthy bearing signal and a signal with ball defect respectively. The parameters of EMD are varied and results are analyzed against these variations. Firstly, four IMFs with the highest value of HFD are selected corresponding to each input vibration signal. The selected IMFs are further decomposed using TQWT and feature vectors are prepared from decomposed TQWT sub-bands for different values of Q-factor.

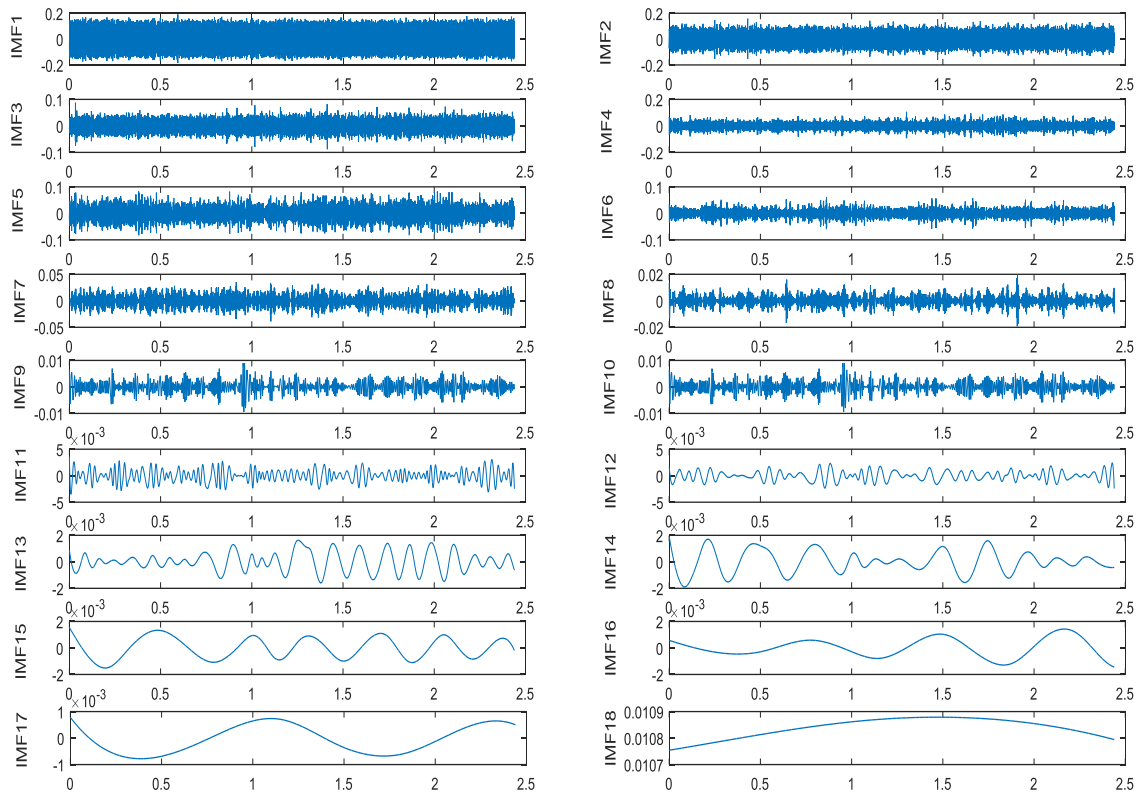


Figure 4.2 IMFs obtained after applying EMD on healthy bearing vibration signals

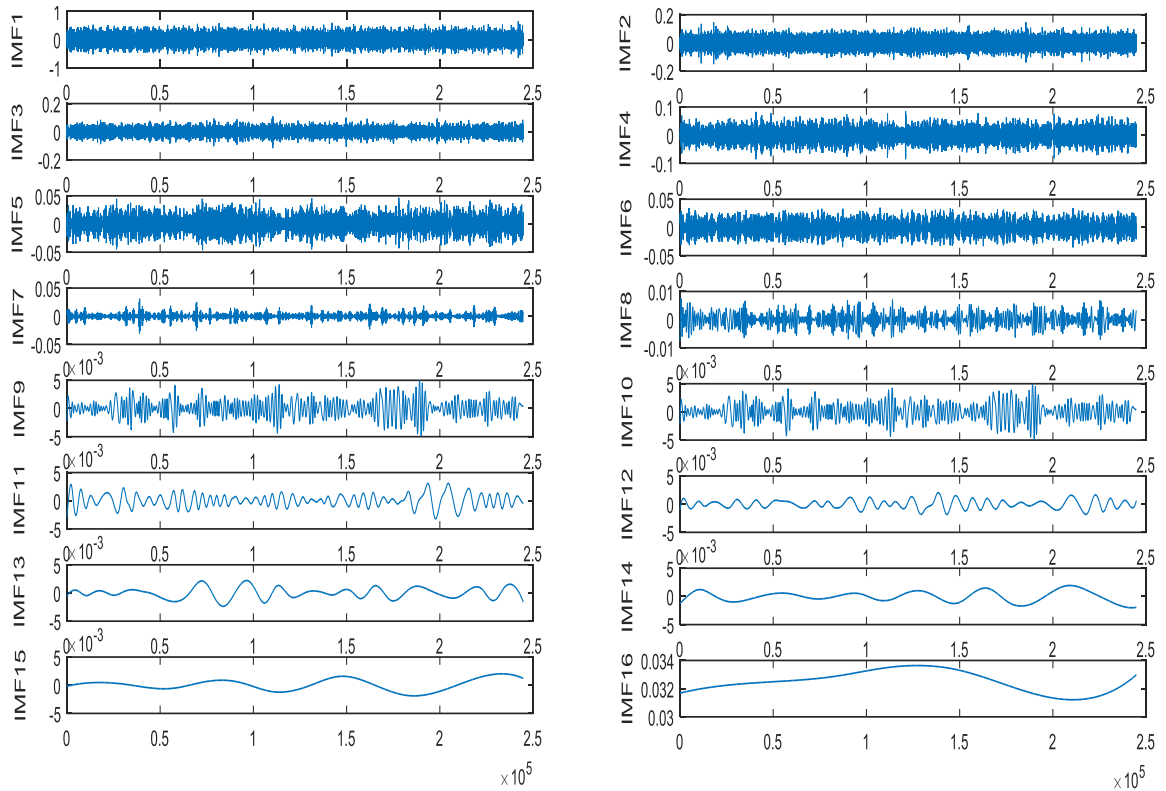


Figure 4.3 IMFs obtained after applying EMD on ball defect vibration signal

Apart from the Q-factor variations, in present work, four types of feature vectors (of different sizes) are evaluated, where HFD features were calculated from four IMFs (40 features), three IMFs (30 features), two IMFs (20 features) and one IMF (10 features). The ranking of the IMFs is done based on their HFD values. Classification is performed for all four types of feature vectors. Table 4.1 shows a sample input feature vector obtained from single IMF (having highest value of HFD).

Table 4.1 Sample input vector to soft computing techniques

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	CLASS
1.76	1.65	1.66	1.81	1.47	2.02	1.88	1.63	1.75	1.40	HB
1.76	1.66	1.69	1.75	1.47	2.00	1.88	1.65	1.74	2.00	HB
1.71	1.66	1.69	1.77	1.47	1.99	1.88	1.63	1.75	2.03	HB
1.72	1.69	1.70	1.89	1.72	1.59	1.79	1.78	1.69	1.11	BD
1.73	1.69	1.74	1.85	1.71	1.59	1.78	1.81	1.68	1.12	BD
1.74	1.69	1.73	1.85	1.72	1.58	1.78	1.83	1.68	1.13	BD
1.71	1.68	1.73	1.73	1.75	1.61	1.86	1.83	1.70	1.21	IRD
1.75	1.70	1.73	1.70	1.76	1.57	1.87	1.84	1.66	1.29	IRD
1.79	1.71	1.75	1.71	1.74	1.60	1.85	1.88	1.61	1.36	IRD
1.79	1.70	1.66	1.85	1.69	1.53	1.87	1.65	1.65	1.12	ORD
1.72	1.72	1.67	1.86	1.67	1.55	1.87	1.64	1.63	1.11	ORD
1.76	1.73	1.66	1.86	1.65	1.55	1.89	1.62	1.67	1.11	ORD

HB: Healthy Bearing, BD: Ball Defect, IRD: Inner Race Defect, ORD: Outer Race Defect, F1:HFD of 1st sub-band of selected IMF, F2: HFD of 2nd sub-band of selected IMF

The Figure 4.4(a) shows the classification accuracy obtained for different values of Q-factor for the selected four IMFs (40 features in the feature vector) with the highest value of HFD, where:

EMD_40 denotes that the value of $qResol$ and $qResid = 40$ each.

EMD_45 denotes that the value of $qResol$ and $qResid = 45$ each.

EMD_50 denotes that the value of $qResol$ and $qResid = 50$ each.

Figures 4.4(b), Figure 4.4(c) and Figure 4.4(d) show the classification accuracy obtained for different values of Q-factor when the number of selected IMFs are decreased from four to one (i.e. number of features are reduced from 40 to 10). The results show highest classification accuracy is obtained for feature vector with least number of features (10 features) obtained from single IMF with highest HFD value.

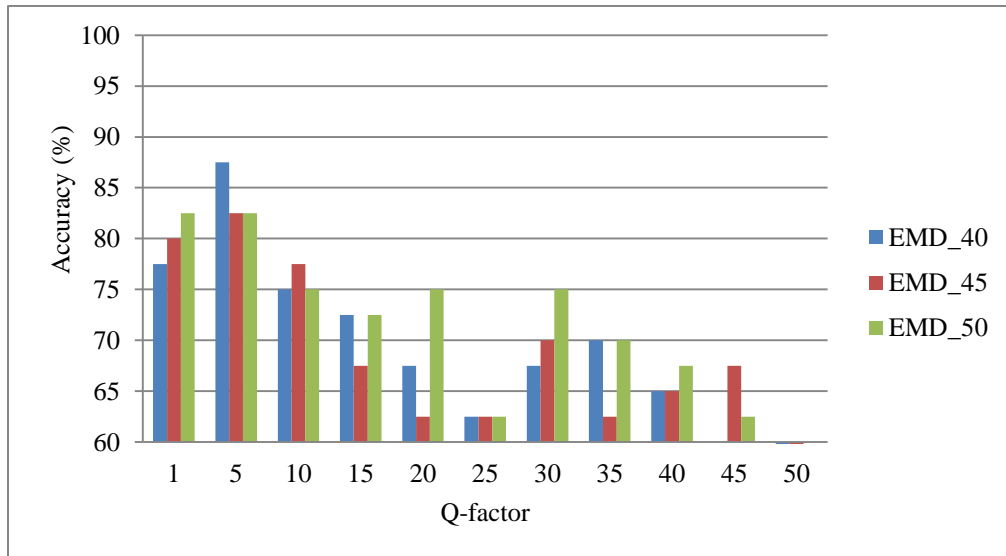


Figure 4.4(a) Classification accuracy (%) corresponding to varying values of $qResol$, $qResid$ and Q -factor for four selected IMFs

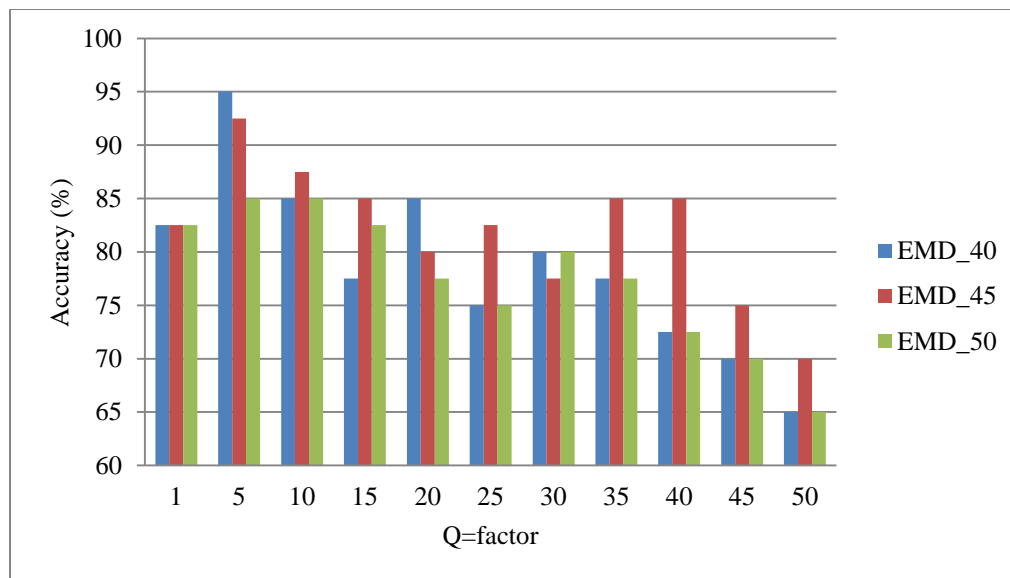


Figure 4.4(b) Classification accuracy (%) corresponding to varying values of $qResol$, $qResid$ and Q -factor for three selected IMFs

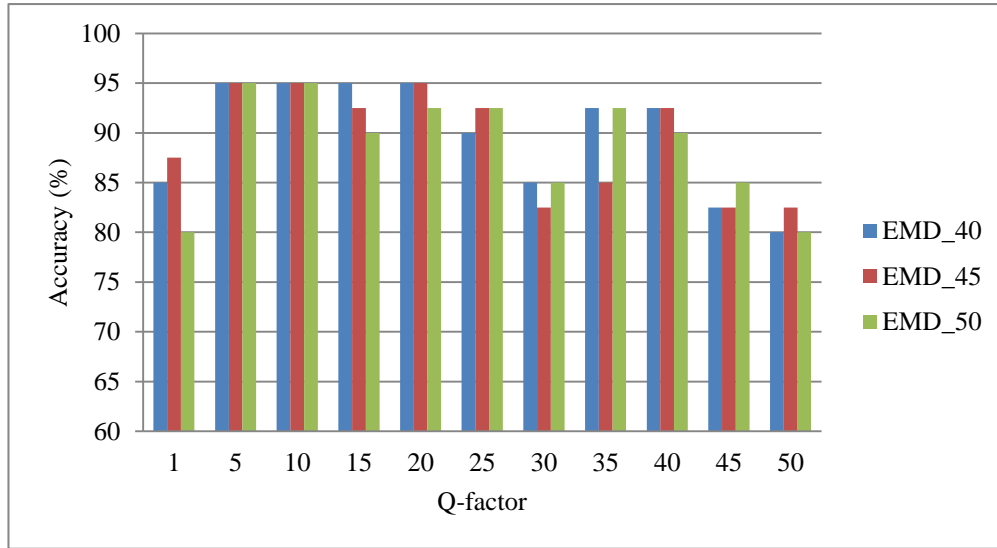


Figure 4.4(c) Classification accuracy (%) corresponding to varying values of $qResol$, $qResid$ and Q -factor for two selected IMFs

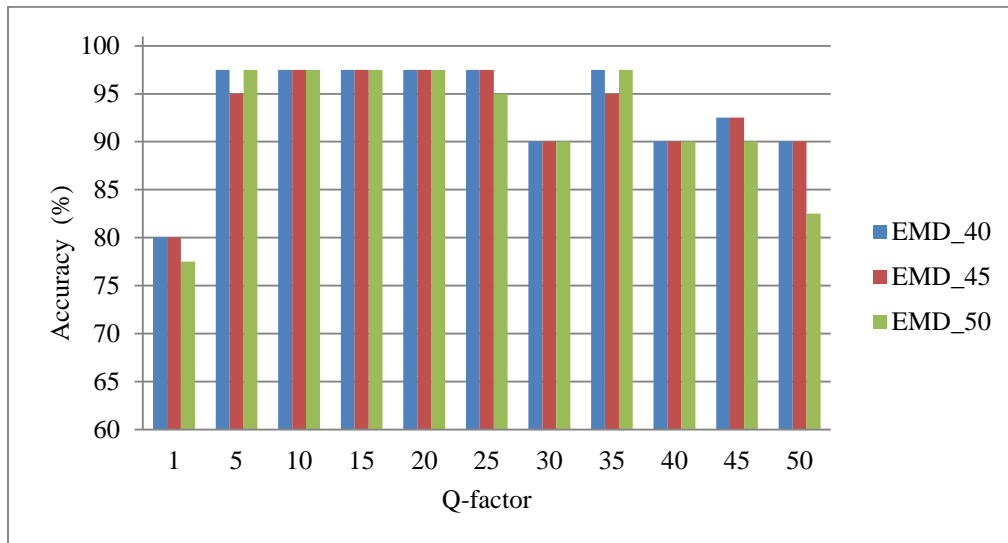
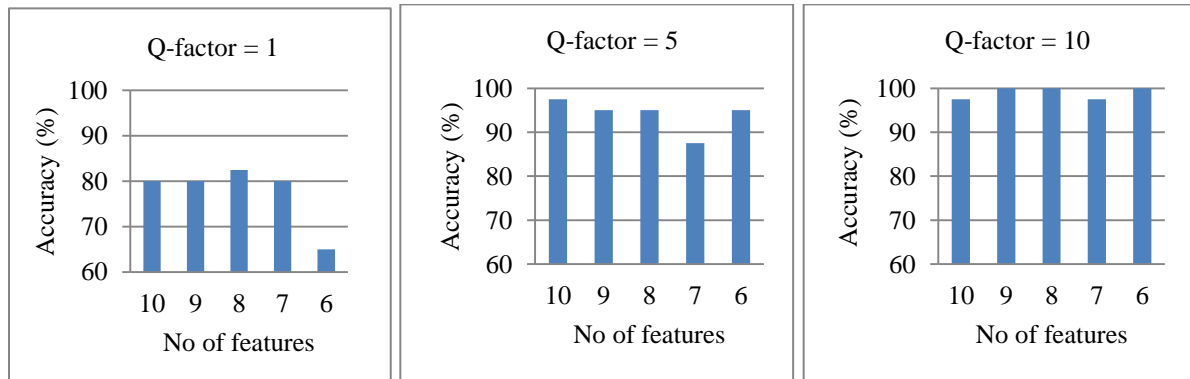


Figure 4.4(d) Classification accuracy (%) corresponding to varying values of $qResol$, $qResid$ and Q -factor for single selected IMF

From the results, it is observed that the IMF with the highest value of HFD is the most significant IMF among the four selected IMFs. Considering the efficacy of single IMF with the highest value of HFD in bearing fault diagnosis, another stage of feature reduction is performed on the feature vectors obtained for different Q -factor values and the results are shown in Figure 4.5(a-k). It is observed from Figure 4.5(a-k) that reduction in number of features significantly increases the classification accuracy and highest classification accuracy is obtained while

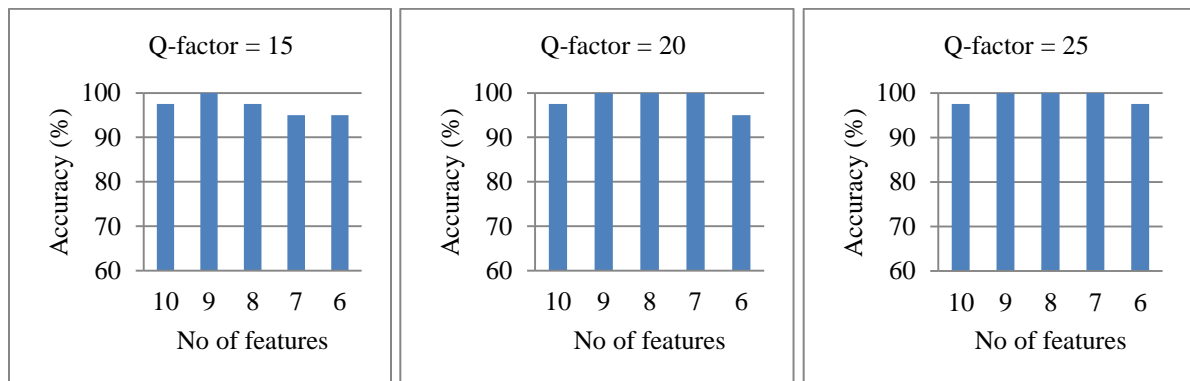
considering features extracted from nine sub-bands of the decomposed IMF. However, further reduction in number of features results in reduction in the classification accuracy in certain cases. In addition, it is observed from Figure 4.5 that the classification accuracy is the minimum for Q-factor=1 and it increases with increasing value of Q-factor until Q-factor is greater than 25. However, the best classification performance is observed when Q-factor lies in the range of 10-25. Therefore, classification results suggest that Q-factor value should be maintained in the range of 10-25 to ensure the highest classification performance.



(a)

(b)

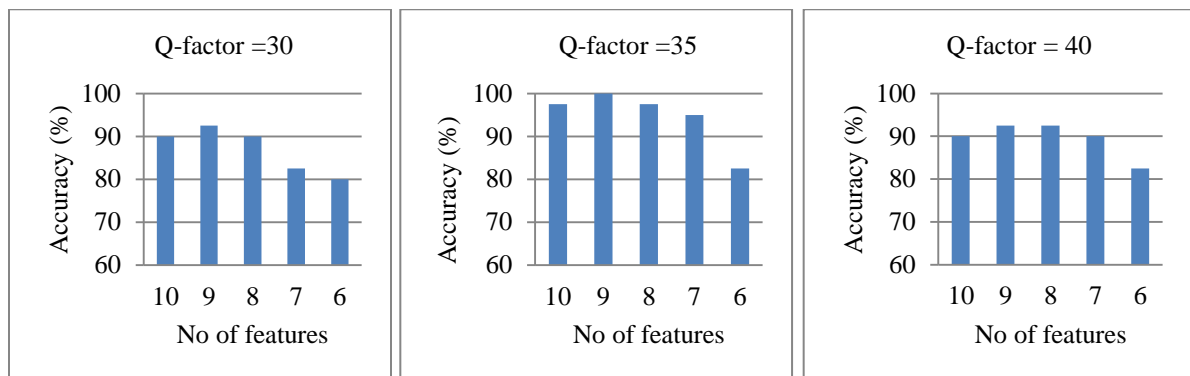
(c)



(d)

(e)

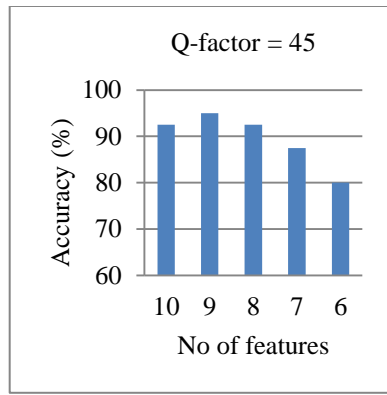
(f)



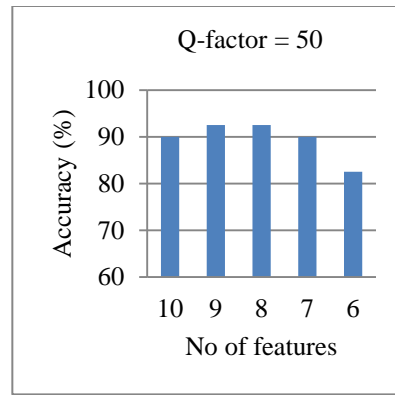
(g)

(h)

(i)



(j)



(k)

Figure 4.5 (a-k) Accuracy (%) after feature reduction at different values of Q-factor

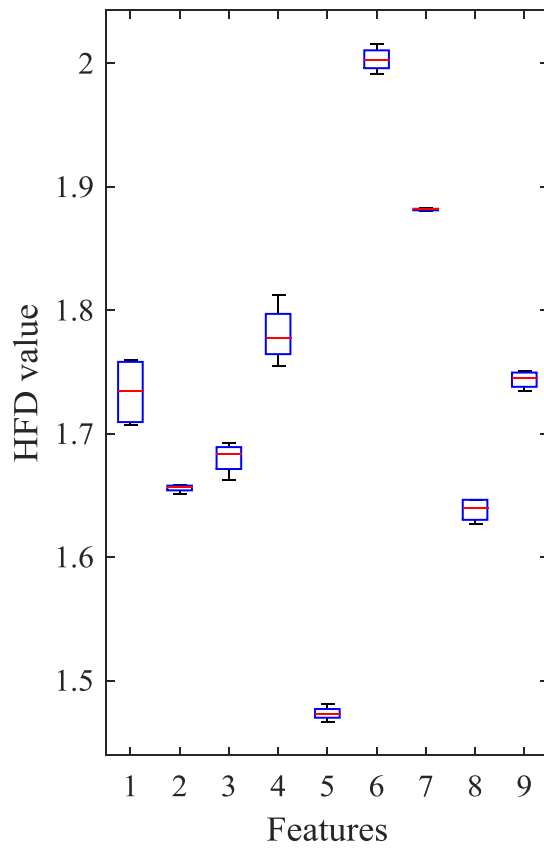


Figure 4.6(a) Boxplot of EMD-TQWT based HFD features of healthy bearing

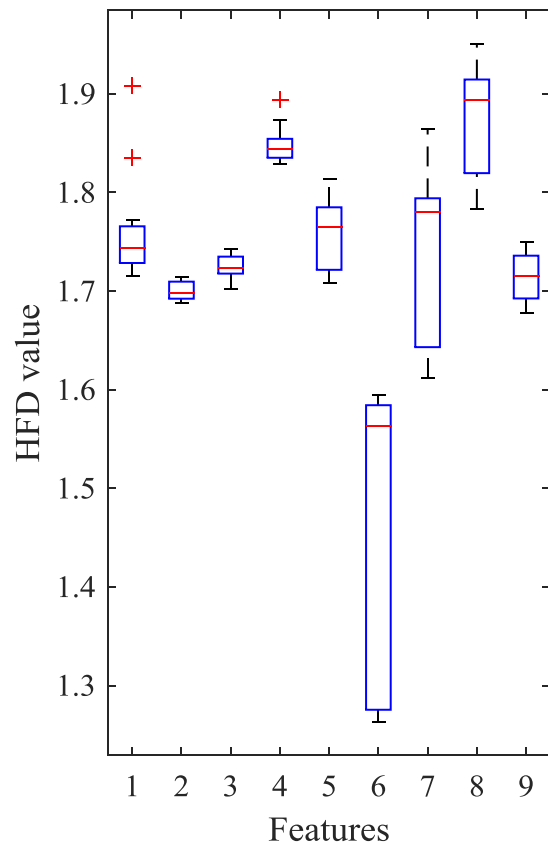


Figure 4.6(b) Boxplot of EMD-TQWT based HFD feature of faulty (ball defect) bearing

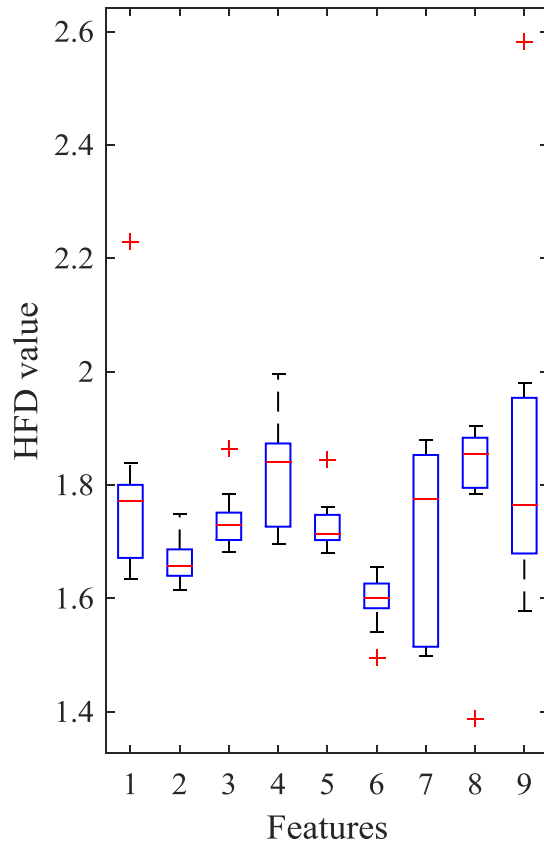


Figure 4.6(c) Boxplot of EMD-TQWT based HFD feature of faulty (inner race defect) bearing

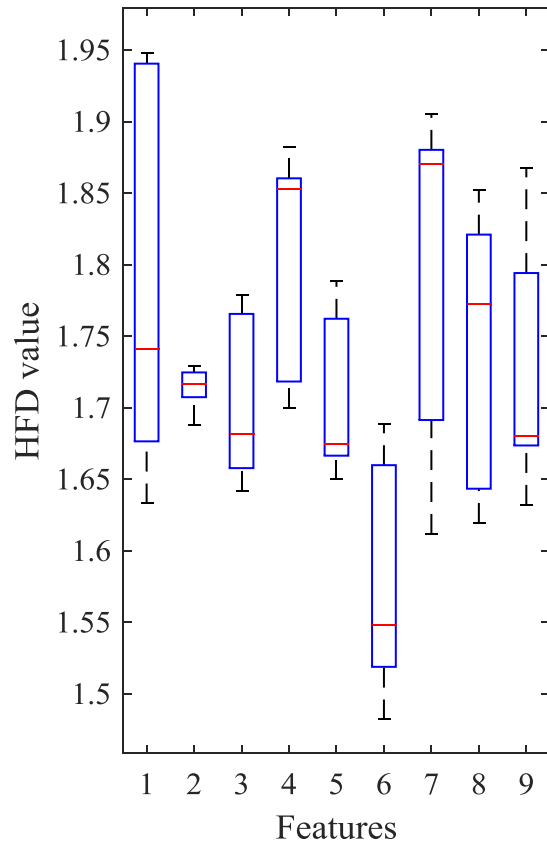


Figure 4.6(d) Boxplot of EMD-TQWT based HFD feature of faulty (outer race defect) bearing

Figure 4.6 represents the box plots of extracted HFD feature values obtained for four classes of vibration activity. It is observed from Figure 4.6 that the distribution of feature values is very less for healthy bearing as compared to the faulty bearing vibration signals. However, the maximum distribution of feature values is observed for bearing with outer race defect. Figure 4.6 describes the class discrimination ability of the extracted EMD-TQWT based HFD features in bearing fault diagnosis.

The feature vectors obtained are used as an input to the SVM classifier for training and validation purpose. In this work also, classification of vibration signal is carried out using 10-fold cross validation approach for ensuring that no statistical biasing is present in the classification results. Table 4.2 represents the confusion matrix of SVM classification keeping Q-factor value as 20 and 9 features were selected. It can be observed from Table 4.2 that all the instances are correctly classified using SVM classifier. Further, a comparison between the proposed work and previous works published in the literature is shown in Table 4.3.

Table 4.2 Confusion matrix of 10-fold cross validation with SVM classifier at $Q = 20$ and number of features were 9

HB	BD	IRD	ORD	CLASSIFIED AS
4	0	0	0	HB
0	12	0	0	BD
0	0	12	0	IRD
0	0	0	12	ORD

HB: Healthy Bearing, BD: Ball Defect, IRD: Inner Race Defect, ORD: Outer Race Defect

TABLE 4.3 A Comparative study between proposed work and previous work published in the literature

Refrences	Machine Learning Technique	Classes	Classification Accuracy (%)
Tyagi (2008) [44]	ANN, SVM	HB, BD, IRD, ORD	ANN - 96 SVM - 97
Yaqub <i>et al.</i> (2012) [45]	kNN	HB, BD, IRD, ORD	91.23
Sun <i>et al.</i> (2012) [46]	Envelope spectrum correlation	HB, BD, IRD, ORD	95
Wu <i>et al.</i> (2012)[60]	SVM	HB, BD, IRD, ORD	97-100
Vakharia <i>et al.</i> (2015) [39]	ANN, SVM	HB, BD, IRD,ORD	ANN - 97.5 SVM - 97.5
Rohit <i>et al.</i> (2015) [38]	ANFC	HB, BD, IRD,ORD	92.50
Present work	SVM	HB, BD, IRD, ORD	100

HB: Healthy Bearing, BD: Ball Defect, IRD: Inner Race Defect, ORD: Outer Race Defect, SVM: Support Vector Machine, ANN: Artificial Neural Network, RF: Random Forest, kNN: k-Nearest Neighbour, ANFC: Adaptive Neuro Fuzzy Classifier

4.5 SUMMARY

In this work, an automated technique for bearing fault diagnosis is developed and evaluated for detecting three types of bearing faults. The proposed technique is based on combination of EMD and TQWT based time-frequency representation of bearing vibration signals for extracting HFD features. Initially, the vibration signals are decomposed using EMD into multiple IMFs. HFD of these IMFs is calculated and initially four IMFs (with highest HFD values) are selected. The selected IMFs are further decomposed into multiple sub-bands using TQWT and feature vectors for various Q-factor values are prepared by applying HFD to the decomposed TQWT sub-bands. Extracted features are classified using SVM classifier. The study is further extended with reduced number of IMFs from four to one considering their HFD values and the classification is performed with varying Q-factor values (1-50). Experimental results demonstrate that the proposed technique is highly efficient in diagnosing bearing faults. In this case, a single IMF (with highest HFD value) proves most significant. The value of Q-factor is optimized in order to get the maximum classification accuracy. It is evident from the classification results that the Q-factor should be maintained from 10-25, in order to decompose the bearing vibration signals efficiently for fault diagnosis application.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

This thesis work is focused upon feature extraction and classification of bearing vibration signals designing an effective autonomous bearing fault diagnosis system. The main objective of this thesis was to detect three types of bearing faults (ball defects, inner race defects and outer race defects) with high classification accuracy. Various techniques available for bearing fault diagnosis are discussed in the literature survey. In present work, two techniques for bearing fault diagnosis are proposed and evaluated for the best classification performance.

The first technique diagnoses the bearing faults with TQWT based entropy features. In this technique, the input vibration signals are decomposed in multiple time-frequency sub-bands using TQWT. Further, feature vector is formed using PE for training and validation of the classifier algorithms. The classification is done using three soft computing techniques viz. SVM, ANN and RF. The value of Q-factor is optimized in accordance with the classification accuracies obtained. The classification results suggest that the Q-factor value should be kept in a range of 20-25 in order to get the best classification results. The best results are obtained at a Q-factor value of 25 by SVM classifier in this work. However, there is a limitation of allowable range of Q-factor value in this methodology.

In order to overcome the limitations of fault diagnosis technique proposed in Chapter 3, another technique is introduced in chapter 4 for diagnosing the bearing faults more efficiently. This technique is based on a double decomposition method using EMD and TQWT. Initially, the vibration signals are decomposed using EMD into multiple IMFs. The values of HFD are calculated for all these IMFs and four IMFs having the highest HFD value corresponding to each input signal are considered for further implementation. TQWT is applied to the selected IMFs for decomposing them into multiple time-frequency sub-bands. A final feature vector is formed from these decomposed sub-bands using HFD. Several feature vectors are formed for variable Q-factor values and classification results are analysed. Classification is done using SVM classifier as it gave the best results in the previous work as well. For further improvement in classification performance, the number of selected IMFs is decreased from four to a single IMF (having highest HFD value). Analysing the classification results, it is suggested that HFD features calculated from single IMF (with highest HFD value) should be used in bearing fault diagnosis.

It is further analysed from the results that the Q-factor value should be kept in a range of 10-25 to obtain the maximum classification accuracy. Therefore, a considerably large range of Q-factor value is available for selection in dual decomposition based feature extraction methodology.

In future, these techniques can be used for developing a real time bearing fault diagnosis system. Also, the advanced distributed faults and bearing defects can be included for the analysis. Effect of severity of different defects on bearing vibrations and systems stability may be investigated. This study can be further extended to explore new signal processing and artificial intelligence techniques, which can classify severity of defects in bearing components. Further, the proposed system may also be considered for application to other mechanical systems such as gear box, shafts and engines.

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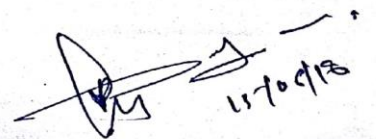
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