AUTOMETED METHODS FOR GEARBOX FAULT DIAGNOSIS USING ADVANCED SIGNAL PROCESSING TECHNIQUES

Ph.D. Thesis

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INDIAN INSTITUTE OF TECHNOLOGY INDORE

APRIL 2023

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A THESIS

Submitted in partial fulfillment of the

requirements for the award of the degree

of

DOCTOR OF PHILOSOPHY

by

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INDIAN INSTITUTE OF TECHNOLOGY INDORE

APRIL 2023

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **AUTOMETED METHODS FOR GEARBOX FAULT DIAGNOSIS USING ADVANCED SIGNAL PROCESSING TECHNIQUES** in the partial fulfillment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY** and submitted in the **DISCIPLINE OF MECHANICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from August 2016 to April 2023 under the supervisions of Prof. Anand Parey and Prof. Ram Bilas Pachori.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

15/01/24

(DADA SAHEB RAMTEKE)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

15/01/2024 15.01.2024

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Signature of Head of Discipline
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Dedicated to

My parents (late)Shri Teklal and Smt. Kamla
who shaped me the person I am today

and

My wife Dr. Gautami has been a tremendous
source of support for me in achieving my goals

ACKNOWLEDGEMENT

I would like to express my sincere gratitude goes first to my supervisors **Prof. Anand Parey** and **Prof. Ram Bilas Pachori** for providing me the opportunity and resources to work on this project. Without his unwavering support, direction at every turn, motivation, and guidance, this project would not have come to fruition.

I would like to express my gratitude to **Dr. Ritunesh Kumar** and **Dr. Amod C. Umarikar** for their insightful comments and direction, both of which were crucial in guiding me to substantially improve the standards of my work.

I would like to always acknowledge the **Dr. Pavan Kumar Kankar** for unwavering support and guidance to completion of my Ph.D. journey.

My gratitude should also go to **Mr. Sandeep Patil,** Deputy Manager of the Solid Mechanics Laboratory at the Indian Institute of Technology in Indore, for the endless support he provided in the process of acquiring vibration signatures from the experimental set-up.

I would like to express my heartfelt thanks to my laboratory colleagues, **Dr. Vikas Sharma, Dr. Ankur Saxena, Dr. Naresh Kumar Raghuwanshi, Dr. Pavan Gupta, Dr. Palash Dewangan, Mr. Anupam Kumar, Dr. Vipin Gupta, and Dr. Mohit Kumar,** for their unwavering support and encouragement throughout the entirety of my Ph.D. journey. To everyone in the Mechanical Engineering Department who helped me out, either directly or indirectly, I owed an enormous lot of thanks.

A very special thank you to my loved ones. My mother, brother, and sisters, together with my In-law's family, were the ones who constantly encouraged me to finish my thesis work, and I will be forever thankful to them. Your prayers for me have been the only thing that has kept me going up to this moment. I would also like to extend my gratitude to all my friends who have encouraged me to work hard towards achieving my goal by supporting me in my writing endeavors. Before concluding, I want to express my sincere gratitude to my beloved wife, **Dr. Gautami,** who suffered many restless nights with me and was always there for me as a source of support all the way through this journey. I would want to show the utmost appreciation to my boys and my family in general for the constant support and encouragement they have given me in all my endeavours.

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ABSTRACT

For mechanical power transmission, gears play an important role in this process. It is very incredibly cost-effective and efficient for power transmission. Gearboxes have a broad multitude of purposes and may be found in a wide variety of sectors, including the industries workshop, automobile sector, marine propulsion systems, the aviation sector, and many more. A malfunction in the gear train can not only lead to large financial losses but also has the potential to be lethal. Because of this, it is essential to locate a problem in a gearbox before it results in a breakdown of catastrophic proportions. Several different modes might cause a gear to fail, including fatigue, impact, wear, or plastic deformation. The most common cause of failure in gearing is fatigue. Where the fault is going to propagate, then the system generates the vibration. Further, gear failure occurred due to excessive vibration.

Vibration measurement is an effective, non-intrusive, robust, economical method to monitor machine conditions during start-ups, shutdowns, and normal operation. Three types of techniques are used in vibration analysis: time-domain analysis, frequency-domain analysis, and time-frequency domain analysis. In real situations, a gearbox generates non-stationary vibration signals. Time-domain and frequency-domain techniques are not suitable for non-stationary or time-varying signals because these are amplitude and frequency-modulated signals. Numerous innovative gear faults diagnosis methods have been developed by researchers. Various time-frequency techniques such as short-time Fourier transform (STFT), wavelet transform (WT), Hilbert-Huang transform (HHT), and Wigner-Ville distribution (WVD), have been employed for the study of non-stationary signals. Due to limitations in these techniques, the impact has been reduced in performance. Therefore, we have proposed new techniques that can automatically diagnose gearbox faults. In those methods, the gear vibrations signals are decomposed to sub-band signals using flexible analytic wavelet

transform (FAWT), iterative variation mode decomposition (VMD), Fourier- Bessel series expansion (FBSE)-empirical wavelet transform (EWT). Various statical and entropy-based features are extracted from all of the sub-band signals. The Kruskal–Wallis test is used to obtain statistically meaningful results. Subsequently, these quantitative features are fed to the different multiclass classifiers like Least-Squares Support Vector Machine (LS-SVM), random forest, multilayer perceptron, and J48 classifiers.

In the previous work, various faults such as chipped tooth fault, missing tooth fault, wear, crack, and pitting have been investigated in spur gears using different classifiers. But micron level of wear and crack fault analysis has not been studied. Hence, this work is focused on the diagnosis of micron level of wear and crack faults in gears.

The purpose of this work is too automated gearbox fault diagnosis using advanced signal processing techniques.

Keywords: Gearbox; Gear fault detection; vibration; non-stationary signals; feature extraction; flexible analytic wavelet transform (FAWT); iterative variation mode decomposition (VMD); Fourier- Bessel series expansion (FBSE)-empirical wavelet transform (EWT); multiclass classifiers; Least-Squares Support Vector Machine (LS-SVM); random forest; multilayer perceptron; J48 classifiers.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

H(w)	Frequency response of the scaling function
$G(w)$	Frequency response of the analytic wavelet function
a and b	Parameter that controls the sampling rate of the low-pass channel
c and d	Parameter that controls the sampling rate of high-pass channels
w_s	Stopband frequency of low pass filter
w_p	Passband frequency of low pass filter
X	Cross-correntropy
C and *D*	Random variables
N	Number of samples
E_{LgEn}	Log energy entropy
E_s	Stein's Unbiased Risk Estimate entropy
x_i	Coefficient of signal x
E_{sh}	Shannon entropy
E_N	Norm entropy
E_{Th}	Threshold entropy
S	Kruskal-Wallis statistical test statics
y (m)	Least Square SVM classifier
y_i	Target vector
m_i	i^{th} input vector
$j(m, m_i)$	Kernel function
K	Narrow-band components
$G(t, v_m)$	Tree classifier
$I(.)$	Indicator function
$g[s]$	Gear vibration signal

G_m	Indicates the FBSE coefficients for the input signal
$B_0(\cdot)$	Zero-order Bessel function
C_S	Sample rate
M	Signal length

Greek Symbols

β and ε	Positive constants
υ	Threshold
α_i	Lagrange multiplier
α	Penalty factor
τ	Dual ascent
ϵ	Tight frame
$\delta(t)$	Dirac distribution function

ABBREVIATION

GFD	Gear fault diagnosis
TSA	Time synchronous averaging
SNR	Signal-to-noise ratio
RMS	Root mean square
SLF	Side band level factor
SK	Spectral kurtosis
STFT	Short-time Fourier transform
WT	Wavelet transform
HHT	Hilbert-Huang transform
WVD	Wigner-Ville distribution
EMD	Empirical mode decomposition
WPT	Wavelet packet transform
EFD	Early Fault Diagnosis
CWT	Continuous wavelet transform
DWT	Discrete wavelet transform
IMFs	Intrinsic mode functions
EMD	Empirical mode decomposition
DTCWT	Dual-tree complex wavelet transform
TQWT	Tunable Q-factor wavelet transform
FAWT	Flexible analytic wavelet transform
EEMD	Ensemble empirical mode decomposition
FT	Fourier transform
FBSE	Fourier- Bessel series expansion
ANN	Artificial neural network

SVM	Support vector machine
LS-SVM	Least-squares support vector machine
GA	Genetic algorithms
KNN	K-nearest neighbor
RBF	Radial basis function
FBSE-EWT	Fourier- Bessel series expansion based empirical wavelet transform
TF	Time-Frequency
IFB	Iterative filter bank
SURE	Stein's Unbiased Risk Estimate
ANOVA	One-way analysis of variance
MFS	Machinery Fault Simulator
ACC	Accuracy
SEN	Sensitivity
SPF	Specificity
PPR	Positive predictive rate
NPR	Negative predictive rate
MCC	Matthew's correction coefficient
NBCs	Narrowband components
OCs	Obtained components
MN	Margin function
GR	Generalization error
EEG	Electroencephalography
DESA	Discrete energy separation algorithm
EDM	Electrical Discharge Machine

Chapter 1

Introduction and Literature Review

In the chapter, automated techniques for gearbox faut diagnosis utilising advanced signal processing techniques are discussed and presented. Also, we will go through a detailed evaluation of the previously published work in the field of gearbox fault diagnostics. In addition, a discussion of the objectives of the thesis and its scope are included in this chapter. The outline of the thesis's structure is laid out at the end.

1.1 Introduction

When it comes to power generation and industrial applications, rotating machines, which include motors, rotors, bearings, gears, and generators, are quite substantial components. They serve a broad variety of purposes, including power generation, the propulsion of machines, and many more. However, gears play crucial role in any application, they have a chance to break down with time. The consequences of these shortcomings might include a reduction in efficiency, an increase in energy consumption, even catastrophic failure in extreme cases and significant economic losses [1]. Based on the statistics, gearbox faults are responsible for 80% of all failures that occur in gearbox equipment, and inside the gearbox, gear faults are responsible for 60% of all failures that occur [2]. To prevent these problems, it is essential to diagnose gear faults as soon as possible. When it comes to identifying problems with gear systems, there are many kinds of diagnostic techniques available. Vibration analysis, acoustic emission condition monitoring, oil and lubrication analysis, and thermography are the most popular types of analysis techniques frequently used [3], [4]. Each of these methods comes with a set of benefits and limitations, and the method that proves to be the most effective will be determined by the machine that is being used in particular situations.

Analysis of vibration is one of the diagnostic techniques that is used most frequently in the field of gear fault detection. Vibration analysis can be done using handheld devices or more sophisticated online systems that continuously monitor the machine. Applications of signal processing were first developed in the early 1980s for the purpose of analysing vibrations in gearboxes. Phase modulation was utilised by McFadden et al. [5] for the early identification of defects in gearboxes, whereas both amplitude and phase modulation were utilised for the detection of gear fatigue [6].

In the process of diagnosing problems with rotating equipment, oil and lubrication analysis is another essential approach. It is estimated that the cleanliness of the oil has a significant impact on the life span of gearboxes, with a contribution of up to 50% to the increase or decrease in total run-time [3]. The purpose of this method is to identify any impurities or indications of wear in the machine by analysing samples of the oil that is used in the machine. An analysis of the oil (unhealthy lubricants) can show issues such as excessive wear on gears, damaged bearings, or other components. S. Sheng [7] proposed some first-hand oil and wear debris analysis based on testing of full-scale wind turbine gearboxes. Experiments were carried out using spur gearbox and operating at different load conditions to perform oil/wear debris analysis [8]. The author studied such parameters as lubricant film thickness, viscosity, temperature, and their effects on gear teeth contact.

Thermography is a technique for monitoring the temperature of rotating equipment that does not require physical touch and makes use of infrared cameras. The experts can spot difficulties with the machine such as overheating, problems with the insulation, and bearing wear by analysing the thermal patterns that are created by the machine. Thermography is particularly helpful for locating faults in components or places that are difficult to access, such as those are in locations that are hard to reach. An ensemble tensor decomposition was developed by J. Song et al.[9] for the purpose of extracting a weak target signal from infrared thermography videos for the identification of cracks. The infrared thermography for condition monitoring tool was described by S. Bagavathiappan et al. [10] as a method that does not involve physical touch and can be used to monitor the temperatures of things or processes in real time.

Acoustic analysis, which makes use of sound waves to identify variations, is another method for diagnosing defects in rotating machinery, noisy engines, and equipments. T. Nowakowski et al. [11] proposed a system for monitoring the condition of tram gearboxes that is based on trackside acoustic data. Experimental research conducted by E. Caso et al. [12] on acoustic emissions from active surface deterioration in planetary gears.

In conclusion, it is essential to detect problems with gear machines to ensure the reliable operation of this equipment and to prevent failures that might result in expensive repairs. To determine the reliability of machinery over an extended period, it is necessary to perform periodic preventative maintenance on it.

1.2 Literature review

A literature review is done to become familiar with vibration analysis based advanced signal processing techniques, different types of faults in gear, and classifiers involved in gear fault diagnosis (GFD). The vibration analysis has been done by using various advanced signal processing techniques. Also, the literature survey includes the different methods applicable to GFD.

1.2.1 Gear fault diagnosis using vibration signals

The process of fault diagnosis using vibration signals typically involves several steps:

1. Signal acquisition: Vibration signals are acquired using accelerometers or other sensors mounted on the gear system. Location to mounting the sensor is affected the quality of actual signal of equipment, need to locate a place in scientific manner. The signals can be collected continuously or periodically depending on the monitoring strategy.

2. Pre-processing: The vibration data are pre-processed to get remove any noise or distortions that can mess up the analysis later on. Filtering, resampling, decomposition, and data segmentation are some of the more common pre-processing procedures for signals that are utilised.

3. Feature extraction: The vibration signal is analysed to extract features that are indicative of gear faults. After decomposing the signals, features are extracted from them, like time-domain statistics, frequency-domain indicators, and time-frequency domain parameters.

4. Fault diagnosis: From the extracted features, first identify the significant features. These significant features are fed to various techniques such as rule-based systems, statistical analysis, and machine learning algorithms to diagnose gear faults. The diagnosis can be binary (healthy vs. faulty) or multi-class (identifying specific fault types), which has been used frequently.

T. Wang et al.[13] shown the guideline to working in fields of vibration-based condition monitoring and fault detection of wind turbine planetary gearbox. To defect identification in planetary gearboxes, X. Yu et al.[14] proposed an analytical vibration signal model as well as signature analysis in the resonance zone. The theoretical derivations and proposed approach are validated in this study using numerical simulation and laboratory experiments. V. Gunasegaran, and V.Muralidharan [15] proposed vibration signals based gear fault diagnosis to obtained from a rotating spur gear system with an accelerometer, and the statistical characteristics are extracted for classification.

1.2.2 Vibration signal analysis techniques

A gearbox is going to generate non-stationary vibration signals while operating in real-life situations [16]. Vibration measurement is an effective, non-intrusive, robust, economical method to monitor machine condition during start-ups, shutdowns, and normal operation. The following are vibration signal analysis techniques that are applied for the diagnosis of gear problems:

1. Time-domain analysis: This technique provides information about what the signal values are present with respect to time. This involves analysing the vibration signal in the time domain to extract statistical features. This statistical feature is called a time-domain indicator, such as mean, standard deviation, skewness, kurtosis, energy ratio, time synchronous averaging (TSA) etc. These features can provide insights into the amplitude and distribution of the vibration signal, which can be indicative of gear faults such as tooth wear and cracks. The drawback of this technique is that it leaves out information about the frequency. Sharma et al. [17] presented enhanced TSA to increase signal-to-noise ratio (SNR), and statistical characteristics were applied to identify gear crack under fluctuating profiles of speed. RMS and peak values of vibration signals were utilised by Igba et al. [18] for the purpose of condition monitoring of wind turbine gearboxes. If the root mean square (RMS) and peak values are used appropriately, it has been shown that they can serve as useful indicators of the gearbox's health. Maximum kurtosis property-based fault diagnosis method has been proposed by W. Youssef [19]. Also, suggested that this feature is very effective for impulsive nature of the gear tooth spall effect.

2. Frequency-domain analysis: It provides information like the frequencies present in the signal. This involves analysing the vibration signal in the frequency domain using various techniques. Frequency-domain features can provide insights into the spectral content of the vibration signal, which can indicate gear faults such as pitting and misalignment. Frequency-domain indicators are side band level factor (SLF), side band index, correlated kurtosis, mean frequency, root mean frequency, spectral kurtosis, etc. For example, the gear mesh frequency and its harmonics are important features in diagnosing gear faults. The drawback of this technique is that it loses time information. Y. Wang et al.[20] showed the details of spectral kurtosis for fault detection, diagnosis, and prognostics of rotating machines. Also highlights the spectral kurtosis (SK) approach, which expands the idea of kurtosis to that of a function of frequency that indicates how the impulsiveness of a signal. The spectral kurtosis-based approach was proposed by T. Barszcz et al.[21] as a technique to diagnose tooth cracking in the planetary gear of a wind turbine.

3. Time-frequency domain analysis: The primary objective behind time-frequency (TF) domain analysis is to develop a joint function that can explain the characteristics of signals on a time-frequency plan. The limitations of the above approaches are overcome by using this TF analysis method. This approach has been growing in prominence in the field of gear problem diagnostics over the past two decades. TF techniques [22] are short-time Fourier transform (STFT), the wavelet transform (WT), the Hilbert-Huang transform (HHT), the Wigner-Ville distribution (WVD), the empirical mode decomposition (EMD), wavelet packet transform (WPT), spectrograms and wavelet scalograms etc. TF domain indicators can provide insights into the dynamic behaviour of the gear system, such as dynamic misalignment, looseness, and other issues. Those indicators are entropy-based indicators, such as Shannon entropy, cross-correntropy, log energy entropy, Stein’s unbiased risk estimate entropy, Shannon entropy, norm entropy, threshold entropy, and NP4 (fourth order normalization power), etc. Y. Wei et al [23] reviewed TF techniques called Early Fault

Diagnosis (EFD) approaches for fault diagnosis of rotating machinery like gears, rotors, and bearings. A. Kumar et al. [24] reviewed the latest and most widely used diagnostic methods and their developments in vibration-based condition monitoring for gear defects.

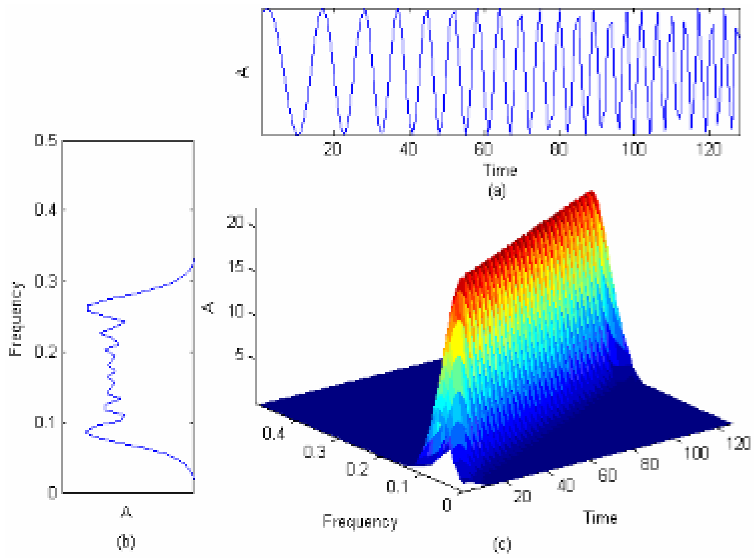


Figure 1. 1 A chirp signal can be described in all three domains: (a) in terms of time, (b) in terms of frequency, and (c) in terms of both time and frequency [22].

In addition to these techniques, machine learning algorithms such as neural networks and support vector machines can be used for gear fault diagnosis using vibration signals. These algorithms can learn the complex relationships between vibration signal features and gear faults and provide accurate and automated diagnosis.

1.2.3 Advanced signal processing techniques

Advanced signal processing methods are employed to extract more complex and hidden features from signals, which can be used to identify and fix the problems in gear machinery more accurately and reliably. Some of the advanced signal processing methods are described below. For more detailed

TF analysis based advanced signal processing technique are referred from [22].

1. **Wavelet analysis:** Morlet and Grossmam, et al., introduced the WT in the 1980s. Wavelet analysis is a TF analysis technique that can provide high-resolution time-frequency representations of non-stationary signals such as sound and vibration signals [25]. Wavelet based TF analysis techniques are continuous wavelet transform (CWT), discrete wavelet transform (DWT), WPT, etc.
2. **Wigner-Ville Distribution:** In 1932, Wigner published the WVD in the context of the study of quantum physics. Ville later extended the WVD to the field of signal processing. The time-frequency distribution that provides a high-resolution representation of the time-varying spectral content of a signal [22], [26].
3. **Hilbert-Huang transform:** The HHT is a technique for signal processing that may give a TF analysis of non-stationary and nonlinear data such as vibration signals. HHT is a useful tool for locating and diagnosing problems, such as the wear and tear on gear teeth and cracks [27], [28].
4. **Cyclostationary analysis:** This technique is for signal processing that may give spectral analysis of cyclostationary signals such as vibration signals. It may be utilised to detect and diagnose problems such gear pitting, wear, and misalignment [29], [30].
5. **Empirical mode decomposition:** EMD is a technique for signal processing that may deconstruct a signal into a sequence of intrinsic mode functions (IMFs). These IMFs can be used to locate and diagnose defects in rotating gear. EMD may be utilised to locate and diagnose problems such as gear tooth wear and cracks in mechanical components [31], [32].
6. **Variational mode decomposition:** Variational Mode Decomposition (VMD) is a signal processing technique used to

decompose a signal into a finite number of modes. It achieves this by minimizing the cross-term energy between modes while preserving the intrinsic mode properties. VMD iteratively separates signal components with distinct frequencies, providing a spectral decomposition useful in analyzing non-stationary signals.

In general, Time-domain and frequency-domain techniques are not suitable for non-stationary or time-varying signals because these are amplitude and frequency modulated signals [22]. Various TF techniques such as STFT, WT, HHT, and WVD, have been employed for the study of non-stationary signals [22]. Due to limitations in these techniques, the impact has been reduced in performance. STFT has a problem of selection of size and type of windowing, and WT has a problem of selecting mother wavelet and the number of levels [33]. The CWT method would be extremely useful for the identification of gear faults. There are several studies, where a combination of different mother wavelets and classifiers were used for the fault diagnosis of gearboxes [34], [35], [36]. Disadvantage of CWT is Lower computation efficiency [33]. It was further found that the efficiency of the CWT can be improved by using the dyadic dilation and translation parameter [37], giving rise to a new technique, which is commonly known as the DWT. The DWT-based techniques with the addition of different classifiers are now widely used for fault diagnosis of gearboxes [38], [39], [40]. However, there are a few inevitable limitations single fixed wavelet basis of DWT [33], [41]. For example, for the enhancement of DWT, and WPT is being used to deduce and discern the high-frequency region for transient components [42]. But the limitation of WPT and DWT is the single fixed wavelet basis subsampling, which reduces the time-based resolution. Y. Hong et al. [43] combined the Hilbert spectrum based on the maximal overlap discrete WPT to analyze the gear fault vibration signals. Y. Wang et al. [44] proposed the dual-tree complex wavelet transform (DTCWT) based signal denoising method for fault diagnosis rotating machinery. The DTCWT was also used for the analysis of the gearbox vibration signals [45], and biomedical signals

[46]. Cai et al. [47] presented a new approach by sparsity-enabled signal decomposition using the tunable Q-factor wavelet transform (TQWT). The authors also verified their approach by using both the simulated and practical gearbox vibration signals. Compared to the other WT, the TQWT was found to adjust the Q-factor and the redundancy. However, for the selection-based Q-factor and the redundancy, the TQWT could not provide the proper selection of the dilation factor [48]. The flexible analytic wavelet transform (FAWT) was initially introduced by I. Bayram [48]. The FAWT is a relatively new concept, which provides an easy way to control redundancy, dilation factor, and Q-factor. Although FAWT was mainly used in biomedical signals [49], [50], [51] its use has not been explored for mechanical signals.

In contrast, the WVD has higher resolution in time-frequency domain, but a couple of cross terms appear in the distribution. The HHT utilizes EMD for the signal analysis [52]. EMD is a powerful technique widely used for condition monitoring of a gearbox [31]. It decomposes a time domain signal into a set of oscillatory modes. After decomposition, each signal becomes a monocomponent signal called as IMFs [31]. A. Parey et al. [32] applied EMD on simulated torsional vibration signal from a spur gear pair and demonstrated that the kurtosis of IMF allows detection of the fault before the same statistical parameter calculated on the original signal. C. Junsheng et al. [53] proposed that IMFs defined by the energy difference tracking method reflect the natural and realistic information of the analyzed signal. EMD has been used for gear and other faults analysis by many other researchers [54], [55], [56], [57], [58], [59], [60], [61]. However, EMD lacks a mathematical theory and has a problem of mode mixing and end effects, sensitivity to noise and sampling, high computational complexity, and requires a large data series. Over the past decade, researchers have resolved a few problems of EMD using required amendments [62], [63], [64], [65], [66] and some work may be found using a modified EMD method showing good results [67], [68] [69]. But still, amendments are required to reduce the limitations. Recently, a new emerging technique known as VMD was introduced by K. Dragomiretskiy and D. Zosso [70]. VMD is a multiresolution technique that overcomes the limitations of EMD [16], [70].

For the investigation of non-stationary signals, J. Gilles [71] developed an innovative constructing approach called the EWT. The authors [72] conducted more research on the EWT method to determine its applicability with multivariate signals, also they presented a multivariate TF formulation that was based on the EWT method. The EWT performs substantially better than the ensemble empirical mode decomposition (EEMD) and the EMD when it comes to estimating mode, and it also greatly cuts down the amount of time needed for computation [73]. EWT is a method of adaptive decomposition that eliminates narrow-band frequency bands within the examined signal depending on the frequency details of the spectrum. After locating the boundary frequencies in the fourier transform (FT) based spectrum, it next applies adaptive wavelet-based filters to the signals to deconstruct them [72]. However, EWT is unable to accurately depict frequency components that are tightly spaced. Challenges similar to those experienced by the EWT approach have been found in the suggested method. A limited work has been reported for the fault detection of gear considering EWT, A. Kumar et al. [74] applied EWT technique over polymer gear to detect faults, but they have not worked in enhancing the EWT performance with combination of other filter methods such Fourier-Bessel series expansion (FBSE). In this study, the established EWT procedure is revised using the FBSE, so newly method is called Fourier-Bessel series expansion (FBSE)-empirical wavelet transform. It has been noted that the non-stationary class of the Bessel function bases in the FBSE [75] in nature. Further, it is what makes the FBSE coefficients effective for the spectrum analysis of non-stationary signals.

1.2.4 Gear and gear faults

A gear is part of a rotating machine; it has teeth that connect with other toothed parts and transfer the torque. It's called a gearbox when there are two or more gears functioning together. There are several types of gears used in mechanical systems. Listed are spur gears, helical gears, bevel gears, worm gears, rack and pinion gears, planetary gears, and hypoid gears. Each gear has its own specific requirements and strength. For this research work, bevel gears are considered. There are many applications of bevel gears in mechanical systems, including differential drives, power transmission systems of helicopters and aircraft, lifts to flood gates, industrial plants, and marine transmissions. On the other hand, gears are subject to wear, damage, and collapse over time as a result of various factors such as high stress concentration, material fatigue, misalignment, lubrication failure, and overload situations. This can result in expensive downtime, malfunctioning machinery, and safety issues. In Fig. 1.2, the different types of faults in gears are shown.

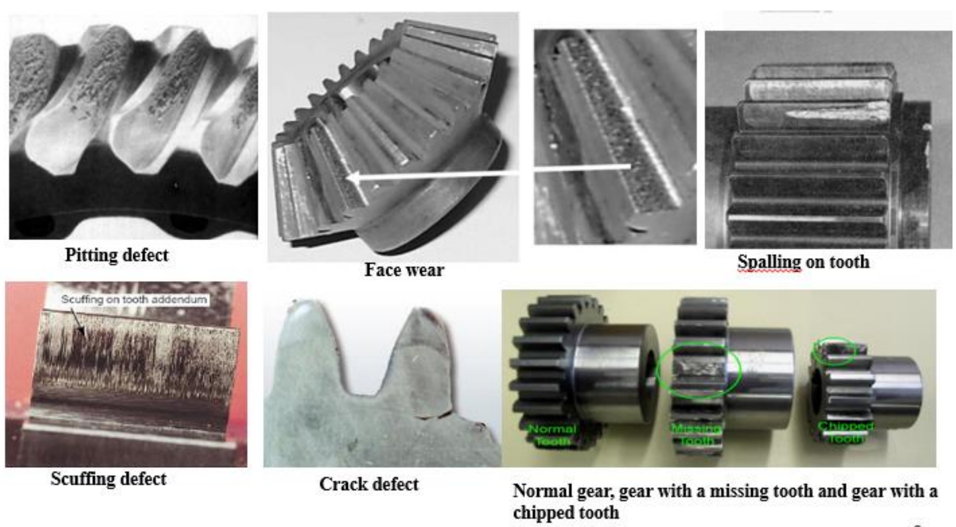


Figure 1. 2 Various type of gear faults. [Ref: Google images]

For this research, mainly wear and crack as faults in the gear systems have been focused. Wear is a persistent service condition that can be seen in a wide range of engineering applications. It can have significant financial and technical consequences. It has been estimated that the cost of abrasive wear can range anywhere from 1-4% of the gross national product of an industrialised nation [76]. This figure comes from an analysis of economic data. It is also observed from Fig. 1.3 that the loss of usefulness of material objects due to wear is 55% [76]. It is too high; it seems necessary to analyse wear faults for gear fault diagnosis. Resercher frequently investigated various faults in the fault diagnosis of gearboxes, such as a chipped tooth, a missing tooth, a crack at the root, and face wear [34], [35], [38], [39], [77], [78] in spur gears [79]. Micron levels of wear fault analysis has not been studied. Hence, this work is focused on the diagnosis of micron level of wear and varying levels of crack faults in bevel gears.

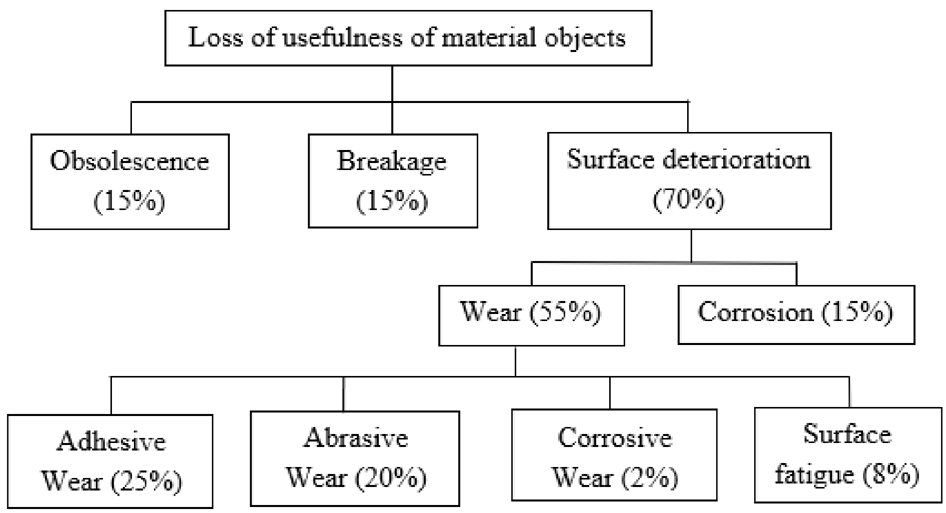


Figure 1. 3 Material things' causes of loss of uselessness and their percentage estimate of the economic value.

1.2.5 Selection of features and classifiers

Pattern detection and collection of information-based knowledge is needed for proper selection of features. In this way, Refs. [80], [81], [35] has shown that statistically based features are suitable for the identification of bevel gear vibration signal analysis. Therefore, in this work statistical based features such as kurtosis, standard deviation, skewness, root mean square, create factor were used for feature extraction. The Kruskal-Wallis test is used for identifying significant features from a given set of samples and its use as an input parameter for classification [50]. The non-stationary characteristics of a signal create an inferior condition of gear vibration signals by changing the frequency component during the operation [82]. Hence, it is very difficult to analyze such signals during the faulty condition. Machine learning based fault detection provides a better solution in this regard [82]. Over the last decade, researchers have frequently used a classifier to improve the performance of the applied signal processing methods for fault diagnosis.

Based on machine learning method such as artificial neural network (ANN), support vector machine (SVM), least-squares support vector machine (LS-SVM), genetic algorithms (GA), fuzzy logic, Bayesian networks, random forest, multilayer perceptron and decision tree are used as a classification tool for weak fault detection and health monitoring of gearbox [35], [64], [67], [68], [69], [74], [79], [82], [83].

SVM overshoots the problem of risk minimization [81]. Muralidharan et al. [82] reported that decision tree algorithm-based classification provided better accuracy for fault detection of the gearbox. It was further found that the multi-class classification via LS-SVM can produce good results as compared to other classifiers, such as SVM, and K-nearest neighbor (KNN) [84], [85].

Therefore, there is ambiguity about the performance of the classifier for gear fault analysis. To resolve this issue a comparative study of classifiers such as LS-SVM, random forest, J48, and multilayer perceptron was performed in this work.

1.2.6 Summary of the literature

According to the findings of the aforementioned literature review, which is mainly based on advanced signal processing techniques, gear faults, feature selection, and classifiers, it is showing a new era for working on gear fault diagnoses.

The literature review has revealed that the performance of advanced signal processing techniques are reliable for fault detection in gear systems. FAWT is a new concept, and this methodology overcomes the limitations of other wavelets. The emerging properties of this methodology are that it provides an easy way to control redundancy, dilation factor, and Q-factor. Mostly, this method has been applied to only biomedical signals. So, it is acceptable for further work. On the other hand, EMD lacks a mathematical theory, has issues with mode mixing and end effects, is sensitive to noise and sampling, has high computational complexity, and it requires huge data series. The limitations of EMD are circumvented with the multiresolution approach known as VMD. As a result, it gets included in the new work. The EWT cannot correctly show frequency components that are closely spaced due to this limitation. It has been pointed out that the FBSE structure may be found in the non-stationary class of the Bessel function. In addition, it is what makes the FBSE coefficients useful for the investigation of the spectrum of non-stationary signals. Therefore, the application of these two methods together has a very positive effect when it comes to resolving the issue of gear problems. From the literature, it has been observed that statistically and entropy-based features are suitable for the identification of bevel gear vibration signal analysis. Therefore, in this work statistical based features such as kurtosis, standard deviation, skewness, root mean square, create factor, and entropy are used for feature extraction. Literature has shown the classifier’s reliability in detecting gear issues, but it remains uncertain. However, some compared-based strategies have been incorporated to see which one is the most effective in this condition: the random forest, the J48, and the multilayer perceptron.

1.3 Motivation

This thesis aims to explore and evaluate the effectiveness of various advanced signal processing techniques for gearbox fault diagnosis, including machine learning, and other artificial intelligence-based approaches. The research will investigate the performance parameters (accuracy, sensitivity, specificity, etc.) of these techniques in time domain signals and demonstrate their potential to improve gearbox fault diagnosis.

The FAWT is a relatively new concept, which provides an easy way to control redundancy, dilation factor, and Q-factor. These features were missing in the other WT [48], [49] and hence cannot help to find important properties, such as flexible time-frequency plane, better shift-invariance, and tunable oscillatory for weak fault detection of mechanical signature [86]. Based on such remarkable properties of FAWT signal processing technique applied to micron level wear in bevel gears signals. Further, entropy-based features are extracted from all of the sub-band signals. The Kruskal–Wallis test is used to obtain statistically meaningful results. Subsequently, these quantitative features are fed to LS-SVM. After that, an investigation of the performance parameter and a comparative study has been done with previously published methods. For this work, micron levels of wear bevel gears are used. Wear is a persistent service condition in many engineering applications with important economic and technical consequences. In terms of economics, the cost of abrasive wear has been estimated as ranging from up to 4% of the gross national product of an industrialized nation [76]. The micron levels of wear are difficult to diagnose in the gear, which encouraged further addition in work. It has been observed that the FAWT based methodology has given the best performance compared to the existing methodologies.

Researchers use EMD to analyse gear faults and other defects [54], [55], [56], [57], [58], [59], [60], [61]. EMD lacks the mathematical theory and has a problem with mode mixing and end effects, sensitivity to noise and sampling, high computational complexity, and requires a large data series. K. Dragomiretskiy and D. Zosso presented a novel method that goes by the name VMD [70]. It is a multiresolution technique that overcomes the limitations of EMD [16]. It is similar to EMD in structure, but a new approach based on constrained optimization makes it a more influential technique [16]. It was reported that VMD provided better results as compared to other existing techniques [16], [80], [87]. This technique is also used in speech signals [88], [89], and yet only a few works have been explored for mechanical signals. Iterative VMD has been used to improve the accuracy of signal processing algorithms, especially in cases where the data is noisy. Hence, it is taken up for study.

In the study, the FBSE-EWT technique was used for the automated classification of gearbox fault diagnosis. EWT is an adaptive decomposition approach that extracts narrow-band frequency components from the analysed signal depending on the frequency information richness in the signal spectrum. After locating the boundary frequencies in the FT based spectrum, it next applies adaptive wavelet-based filters to the signals to decompose them. However, EWT is unable to accurately depict frequency components that are tightly spaced. Challenges similar to those experienced by the EWT approach have been found in the suggested method. In this study, the established EWT procedure is revised using the FBSE. It has been noted that the non-stationary nature of the Bessel function bases in the FBSE [75] is what makes the FBSE coefficients effective for the spectral analysis of non-stationary signals.

A comparative study is a useful way to learn more about methods, figure out how well they work, make well-informed decisions, and find new opportunities. But it is important to figure out which methods give the most accurate classifications. The method demonstrated its effectiveness based on the efficacy of its classification. Therefore, it is necessary to conduct an analysis of the recommended approaches side by side.

1.4 Objectives and scope of the present work

To attain these objectives, the following studies have been carried out:

- To study the automated gearbox fault diagnosis using entropy-based features in the FAWT domain.
- To study the automated gear fault detection of micron level wear in bevel gears using VMD.
- To study the FBSE-EWT technique used for automated classification of gearbox fault diagnosis.
- A comparative study between the proposed advanced signal processing techniques.

1.5 Proposed outline of the thesis

This section offers an overview of the research work that was completed for the thesis. In addition to this, it discusses the most important findings and outcomes of the research study.

Chapter 1 covers the research that addresses the introduction and provides a listing of the studies that have been carried out in the past decades to developing an automated method for diagnosing faults with gearboxes by employing the use of advanced signal processing techniques. In this chapter, we will also talk about the objectives and the overall scope of the thesis that is now being presented.

Chapter 2 presents the vibration-based technique to automate bevel gear wear fault diagnosis is presented. A flexible analytic wavelet transform method was used to decompose the bevel gear wear signal into sub-band signals. Various entropies were used for feature extraction from all of the sub-band signals. The Kruskal-Wallis test was also used to obtain statistically meaningful results. Subsequently, these quantitative features were fed to the LS-SVM classifier. These methodologies are found to produce the most accurate results by using the log energy entropy-based multi-class LS-SVM classifier and the radial basis function (RBF) kernel function. The results obtained here are compared with the previous results obtained by different existing methods.

Chapter 3 aims to automate the fault diagnosis of gears having a level of wear fault at micron using VMD. VMD has been applied iteratively with specific input parameters. The OCs of gear signals are then used to evaluate features such as kurtosis, skewness, standard deviation, root mean square, and crest factor. Statistically significant features are decided using the Kruskal-Wallis statistical test to improve the realization. These statistically significant features are fed to all three classifiers random forest, multilayer perceptron, and J48. The key benefit of the proposed technique is that it can identify wear gear faults automatically with high accuracy.

Chapter 4 utilized FBSE as the basis for an EWT, a novel automated technique has been proposed. The existing EWT is to be reformed using the FBSE method to increase the frequency resolution. A comparative study has been done between existing EWT and proposed a novel methodology FBSE-EWT. It has been observed that FBSE-EWT with a random forest classifier shows better gear fault detection performance as compared to existing EWT.

Chapter 5 presents a comparative study carried out between the proposed methodology. In addition, it is of the utmost significance to carry out comparative research to establish which diagnostic approaches offer the most accurate results for gear problems. Micron level of wear gear signals with different faults has been decomposed using the FAWT, iterative VMD, and FBSE-EWT signal processing methods. It has been observed from the comparative study, FAWT-based methodology exhibits high accuracy using a random forest classifier with combined kurtosis, skewness, standard deviation, and RMS features.

Chapter 6 includes the conclusion that may be drawn from the thesis throughout its entirety. In the last part of the thesis, we will discuss the potential reach of the study in the future.

Chapter 2

Automated gearbox fault diagnosis using Entropy-Based features in Flexible analytic wavelet transform domain

In this chapter, a vibration-based technique to automate the bevel gear wear fault diagnosis. It is thus expected that our novel systematic and procedural analysis would help to accurately identify multi-class gearbox faults. A flexible analytic wavelet transform method was used to decompose the bevel gear wear signal into sub-band signals. Various entropies, such as cross-correntropy, log energy entropy, Stein's unbiased risk estimate entropy, Shannon entropy, norm entropy, and threshold entropy were used for feature extraction from all of the sub-band signals. The Kruskal-Wallis test was also used to obtain statistically meaningful results. Subsequently, these quantitative features were fed to the LS-SVM classifier. These methodologies are found to produce the most accurate results by using the log energy entropy-based multi-class LS-SVM classifier and the RBF kernel function. The results obtained here are compared with the previous results obtained by different methods, such as the CWT, DWT, WPT, DTCWT, and TQWT.

2.1 Introduction

Fault diagnosis of the gearboxes is very important to maintain the efficacy of the rotary systems. The gearbox failure may lead to an increase in downtime and production loss [90]. Hence, effective and reliable working gearboxes are needed for regular health monitoring and controlling of the excessive vibration of the system [91]. In this chapter, the vibration analysis is performed using FAWT technique. The FAWT was initially introduced by I. Bayram [48]. The FAWT is a relatively new concept, which provides an easy way to control redundancy, dilation factor, and Q-factor. These features were missing in the DWT [48], [49] and hence cannot help to find important properties, such as flexible TF plane, better shift-invariance, and tunable oscillatory for weak fault detection of mechanical signature [86]. It was found that the FAWT based LS-SVM with Radial Basis Function (RBF), and other kernels classifier with 10-fold cross-validation methods, can provide better results than those of other existing techniques [49], [50]. Although FAWT was mainly applied in biomedical signals [49], [50], [51], its use has not been explored for mechanical signals to address different faults, that are frequently reported in fault diagnosis of gearboxes, such as a chipped tooth, missing tooth, crack at root, and face wear [34], [35], [38], [39], [77], [78] in spur gears [79]. It was found that the multi-class classification using the LS-SVM is capable of producing good results when compared to other classifiers such as the SVM and the KNN [84], [85].

To address these shortcomings, a new fault diagnosis method is proposed, based on the FAWT. In this work, the FAWT technique with ten levels of decompositions by employing the LS-SVM classifier for classifying the multi-classes of gear signals and to address different faults of the bevel gearbox has been used. In doing so, vibration signals of healthy bevel gear, gear with different levels of wear tooth faults were acquired for gear fault detection. The significance of this work is to automate the gear fault diagnosis using entropy-based features in the FAWT domain. It is thus expected that our novel systematic and procedural analysis would help to accurately identify multi-class gearbox faults.

2.2 Proposed methodology

In this section, the steps in the proposed methodology are illustrated in Fig. 2.1. The proposed methodology is based on the FAWT technique. It decomposes the signals into the nth level of sub-bands with different frequency scales. In this proposed methodology, gear signals under different wear fault conditions were acquired from the bevel gear test setup. The acquired signals were then decomposed into various sub-bands using the FAWT technique. Subsequently, entropy-based features were extracted for each band. The Kruskal-Wallis test was performed on the entropy-based features to obtain statistically meaningful results [50]. Consequently, classification of the fault was carried out by employing the multi-class LS-SVM classifier.

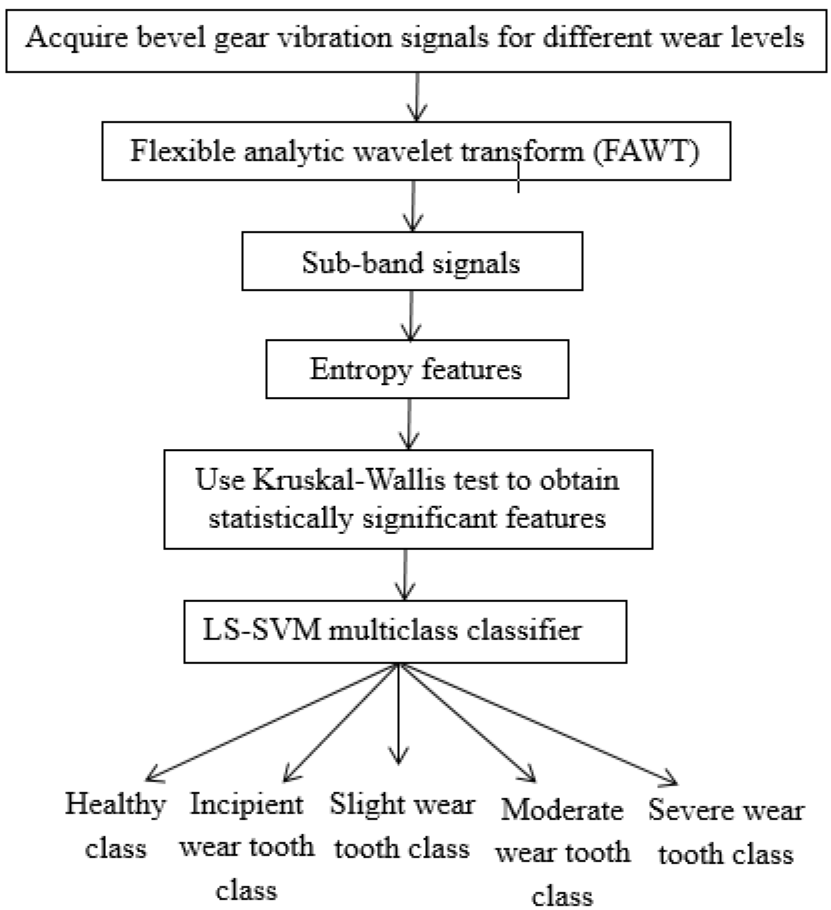


Figure 2. 1 Block diagram of the proposed method

2.2.1. Flexible Analytic Wavelet Transform

The FAWT was formed by an iterative filter bank (IFB) of one low pass and two high pass channels. Two high-pass channels were utilized to analyze the positive-negative frequency, and one low pass channel was used to analyze the low-pass frequency [49], [50]. Due to this remarkable property of positive and negative frequency separation, the FAWT helped to select sampling rates arbitrarily in high-pass channels [49], [50], [51]. As a result, the redundancy, dilation factor, and Q-factor were controlled flexibly by using the Hilbert transform pairs. The frequency response of the low-pass channel can be defined by equation (1), where $H(w)$ refers to the frequency response of the scaling function [19-22].

$$H(w)=\begin{cases}\sqrt{ab}, & |w|<w_p \\ \sqrt{ab}\theta\left[\dfrac{(w-w_p)}{(w_s-w_p)}\right], & w_p\le w\le w_s \\ \sqrt{ab}\theta\left[\dfrac{(\pi-w+w_p)}{(w_s-w_p)}\right], & -w_s\le w\le -w_p \\ 0 & |w|\ge w_s\end{cases} \tag{1}$$

where parameters *a* and *b* control the sampling rate of the low-pass channel. The frequency response of the high-pass channel can be defined by equation (2), where the $G(w)$ denotes the frequency response of the analytic wavelet function [48], [49], [50], [51].

$$G(w)=\begin{cases}\sqrt{2cd}\theta\left[\dfrac{(\pi-w-w_0)}{(w_1-w_0)}\right], & w_0\le w<w_1 \\ \sqrt{2cd}, & w_1\le w<w_2 \\ \sqrt{2cd}\theta\left[\dfrac{(w-w_2)}{(w_3-w_2)}\right], & w_2\le w\le w_3 \\ 0 & w\in[0,w_0]\cup\ [w_3,2\pi]\end{cases} \tag{2}$$

where c and d are the parameters that control the sampling rate of high-pass channels.

The w_s and w_p denote the stopband, and passband frequencies of the low-pass filter. Also, other parameters can be written as [48], [49], [50], [51]:

$$w_p=\frac{(1-\beta)\pi}{a}+\frac{\varepsilon}{a},\ w_s=\frac{\pi}{b},\ w_0=\frac{(1-\beta)\pi}{c}+\frac{\varepsilon}{c},\ w_1=\frac{a\pi}{bc},\ w_2=\frac{\pi}{c}-\frac{\varepsilon}{c},\ \text{and } w_3=\frac{\pi}{c}+\frac{\varepsilon}{c}.$$

The $\theta(w)$ is expressed as [19];

$$\theta(w) = \frac{1}{2}(1+\cos w)\sqrt{2-\cos w} \qquad \text{for } w \in [0, \pi] \tag{3}$$

$$\varepsilon \le \frac{a-b+\beta b}{a+b}\pi$$

β and ε are the positive constants.

Following conditions (equations 4 and 5) are needed for reconstruction of the filter bank in the FAWT,

$$|\theta(\pi - w)|^2 + |\theta(w)|^2 = 1 \tag{4}$$

$$\left(1-\frac{a}{b}\right) \le \beta \le \frac{c}{d} \tag{5}$$

Redundancy is expressed by equation (6) [48], [49],

$$R = \frac{c/d}{1-a/b} \tag{6}$$

Q-factor is expressed by equation (7) [48], [49],

$$Q = \frac{2-\beta}{\beta} \tag{7}$$

For the analysis of gear vibration signals, the FAWT provides the facility to use the adjustable parameter for controlling the quality factor, dilation factor, and redundancy. For the implementation of the FAWT, a toolbox based on MATLAB was employed [92].

2.2.2 Entropy-based features

Entropy is a quantitative measure of the degree of "disorder" of the system [93]. According to the information theory, it provides information about the system in a more general probability distribution [51], [94]. Evaluations of several entropies were carried out here, which are defined in the next subsections.

2.2.2.1 Cross-correntropy

The cross-correntropy can be used to estimate the similarity of two random variables. Mathematically, it can be expressed as [50],

$$X_{N,\sigma}(C,D)=\frac{1}{N}\sum_{i=1}^{N}k_{\sigma}(U_i-V_i) \tag{8}$$

where C and D are random variables and N represents the number of samples mention by $(U_i,V_i)_{i=1}^{N}$.

The Gaussian kernel $k_{\sigma}(U_i-V_i)$ can be defined as,

$$k_{\sigma}(U_i-V_i)=\exp\left(-\frac{\|U_i-V_i\|^2}{2\sigma^2}\right) \tag{9}$$

Eq. (9), $\sigma=0.5$ is used to control the width of the kernel parameter.

2.2.2.2 Log-energy entropy

The degree of complexity in signals is assessed using log energy entropy [50]. It can be expressed as [50], [93],

$$E_{LgEn}=\sum_{i=1}^{N}\log(x_i^2) \tag{10}$$

where log (0) = 0, N represents the number of samples, and x_i is the coefficient of signal x.

2.2.2.3 Stein's Unbiased Risk Estimate entropy (SURE entropy)

SURE, entropy provides the information of a signal which shows the accurate representation. It can be defined as [50], [93],

$$E_S=N-\#\left\{i \text{ such that } |x_i|\le \nu\right\}+\sum_{i}\min\left(x_i^2,\nu^2\right) \tag{11}$$

where N represents the number of samples, x_i is the coefficient of signal x, and ν is the threshold.

2.2.2.4 Shannon entropy

The uncertainty about the event is measured by Shannon entropy. It measures the data and flat probability distribution with high entropy value. But, the data with narrow and peaked distribution has low entropy values [93], [94]. The Shannon entropy can be expressed as [50], [93],

$$E_{Sh}=-\sum_{i}x_i^{2}\log\left(x_i^2\right) \tag{12}$$

where x_i is the coefficient of signal x.

2.2.2.5 Norm entropy

Norm entropy provides the power or energy content of a signal. It can be defined as [93],

$$E_N = |x_i|^{\nu} \tag{13}$$

where N represents the number of samples, x_i is the coefficient of signal x, and ν is the threshold.

2.2.2.6 Threshold entropy

The threshold entropy of a signal is expressed as [93],

$$E_{Th} = \begin{cases} 1, & \text{if } |x_i| > \nu, \quad \text{and} \\ 0, & \text{elsewhere} \end{cases} \tag{14}$$

where x_i is the coefficient of signal x and ν is the threshold.

2.2.3 Kruskal-Wallis statistical test

The Kruskal–Wallis test (1952) [95] is based on a nonparametric approach to the one-way analysis of variance (ANOVA). This test provides a better statistically significant difference between two more classes for given features. The statistically significant difference was measured by using probability (p) computation. If $p < 0.05$ then it is considered statistically significant difference [50]. The maximum differentiation of features between the classes is based on the minimum p-value [50]. The Kruskal-Wallis statistical test was performed using software MATLAB in the present work. The test statistic (S) is calculated using the following formula:

$$S = \left(\frac{12}{O(O+1)} \sum_{i=1}^{k} \frac{W^i}{o_i} \right) - 3(O+1) \tag{15}$$

where W represents the sum of the rankings of each of the samples, O is the total sample size and o is the size of each sample, k is the number of samples.

2.2.4 Least Square SVM classifier

The statistical learning theory was used to construct the SVM classifier [96]. It was utilized to classify the patterns [97]. The multi-class classification task was solved by dividing *M* classes into *L* binary classification tasks. For classification, "one vs. all" and "one vs. one" coding algorithms were used to represent the output of the classifier [85]. It was further simplified with the least-squares formulation version of SVM [78]. It can be defined as follows [50], [51] [97].

$$y(m) = \text{sign}\left[\sum_{i=1}^{n} \alpha_i y_i j\left(m, m_i\right) + b\right] \tag{16}$$

In Eq. (16), the expression has shown y_i, m_i, j (m, m_i), b, n, and α_i represent target vector, *i*th input vector, kernel function, bias term, total data points, and Lagrange multiplier, respectively.

For the multi-class problem, a training set defined as [85],

$$\left\{m_i, y_i^c\right\}_{i=1,c=1}^{i=n,c=C}, x_i \in \mathbb{R}^n, y_i \in \left\{1, \ldots, G\right\} \tag{17}$$

where n, C, and G represent the index of training pattern, the number of classes, size of the multiclass label set.

The mathematical expression for the RBF kernel can be written as by the following [49]:

$$j\left(m, m_i\right) = e^{\frac{-\left\|m - m_i\right\|^2}{2\rho^2}} \tag{18}$$

where ρ controls the width of the RBF kernel function.

The mathematical expression for the polynomial kernel function can be represented as [49]:

$$j\left(m, m_i\right) = \left(m_i^T m + 1\right)^r \tag{19}$$

In Eq. (19), the parameter r represents the order of the polynomial kernel.

2.2.5 Performance metrics

In the present work, six parameters were determined for measuring the classification performance [84]. The definition of the six parameters is as follows: (1) Accuracy (ACC) is defined as a percentage of correctly identified faulty and healthy gear signals divided by the total number of gear signals. (2) Sensitivity (SEN) is the percentage of the faulty gear signals indicated as faulty gear signals. (3) Specificity (SPF) is used to measure the percentage of healthy gear signals recognized as healthy gear signals. (4) Positive predictive rate (PPR) gives the percentage of results accurately indicated as faulty gear signals. (5) Negative predictive rate (NPR) is called the percentage of results which is accurately indicated as healthy gear signals. (6) Matthew's correction coefficient (MCC) assesses the classification accuracy of imbalanced samples of faulty and healthy gear signals. These are expressed as follows:

$$\mathrm{ACC} = \frac{RP + RN}{RP + RN + WP + WN} \times 100\%$$

$$\mathrm{SEN} = \frac{RP}{RP + WN} \times 100\%$$

$$\mathrm{SPF} = \frac{RN}{RN + WP} \times 100\%$$

$$\mathrm{PPR} = \frac{RP}{RP + WP} \times 100\%$$

$$\mathrm{NPR} = \frac{RN}{RN + WN} \times 100\%$$

$$\mathrm{MCC} = \frac{RP \times RN - WN \times WP}{D}$$

Here,

$$D = \sqrt{(RP + WN)(RP + WP)(RN + WN)(RN + WP)}$$

In the above expression *RP*, *RN*, *WP*, and *WN* represent true positives, true negatives, false positives, and false negatives, respectively [84].

2.3 Experimental data collection

The vibration signals were acquired by using the Machinery Fault Simulator (MFS). In this experimental test rig (Fig. 2.2), a three-phase AC motor (3/4 HP, 2850 RPM) was connected to one end of the rotor shaft through a flexible coupling. The other end of the shaft was connected to a belt and pulley arrangement, which was further coupled with a single-stage bevel gearbox. The schematic representation of the MFS is shown in Fig. 2.3. The technical specification of the bevel gearbox is presented in Table 2.1. The healthy gear and gears with different health conditions are shown in Fig. 2.4 and Fig. 2.5, respectively. For the experimental analysis, the level of wear faults in gears was created by the laser cutting machine and the cutting depth was measured by the optical microscope. The laser cutting machine is used to mimic the level of wear in gears. The laser setup consists of a fiber laser (Scantech laser Pvt. Ltd.) doped with rare earth elements like Erbium, Ytterbium, Neodymium, etc. It has a rated capacity of 50 W with a galvo scanner which deflects the beam in two directions with a focal length of 287 mm, and spot diameter 0.2 mm. Details of the operating conditions of laser machine to expand the level of abrasive wear faults in bevel gears are shown in Table 2.2. Optical microscope (Dewinter Optical Inc., modelDEW507) is used for measuring cutting depth, representing wear.

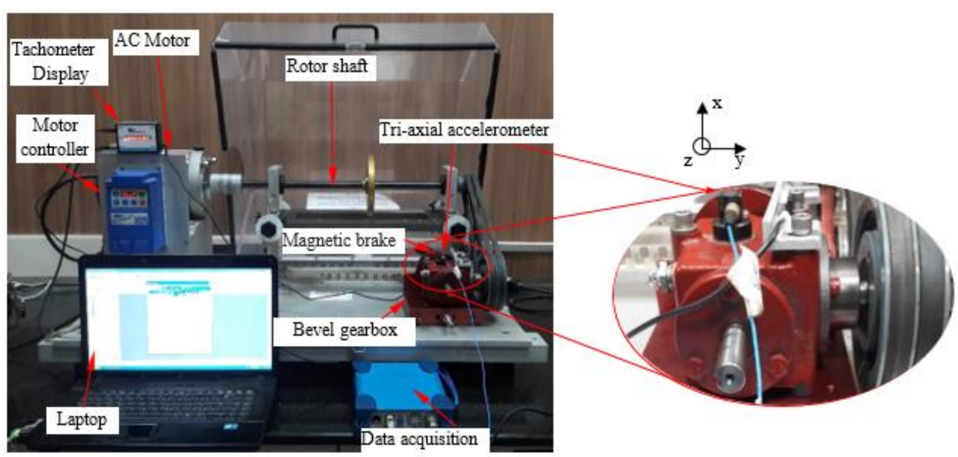


Figure 2. 2 Experimental test setup with the zoomed view of the accelerometer.

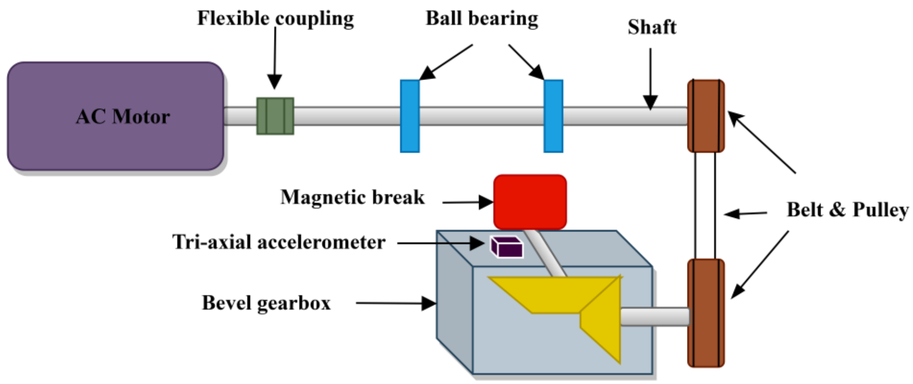


Figure 2. 3 The schematic representation of the MFS.

Figure 2. 4 Healthy bevel gear.

Table 2. 1 Specifications of the gearbox.

Gear ratio	1.5:1
Pitch angle (gear)	56°19’
Pitch angle (pinion)	33°41’
Pressure angle for gear and pinion	20°
Number of teeth in pinion	18
Number of teeth in the gear	27
Module for gear and pinion	2 mm
Pitch diameter (gear)	42.8625 mm
Pitch diameter (pinion)	28.575 mm
Material (gear and pinion)	Forged steel

Table 2. 2 Details of the operating conditions of laser machine for developing the wear faults in bevel gears.

S. No.	Level of abrasive wear fault	Operating power (W)	Number of passes	Cutting depth (micron)
(a)	Incipient	30	10	20
(b)	Slight	40	15	30
(c)	Moderate	50	15	40
(d)	Severe	50	70	50

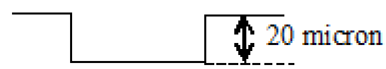
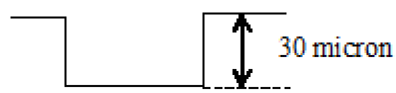
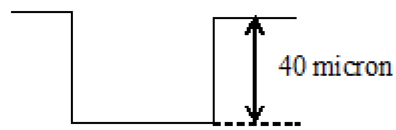
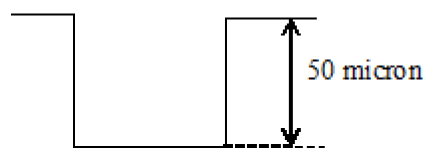
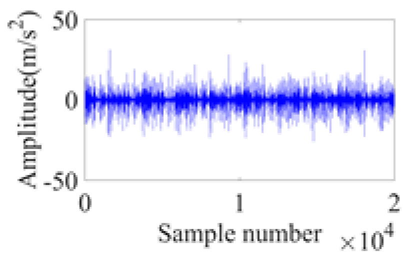
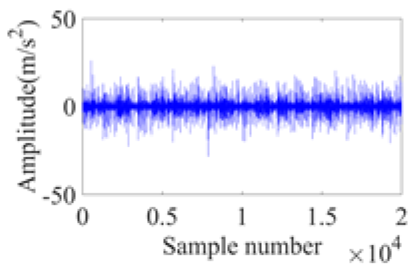
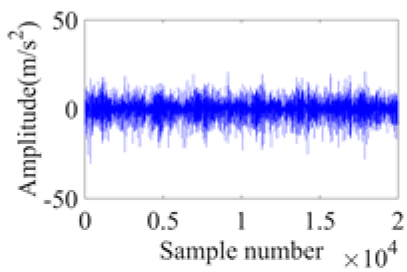
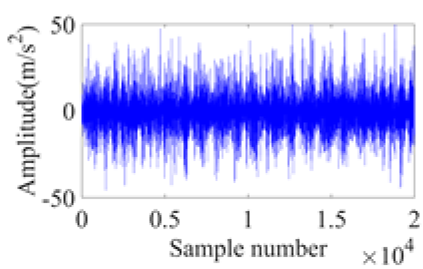
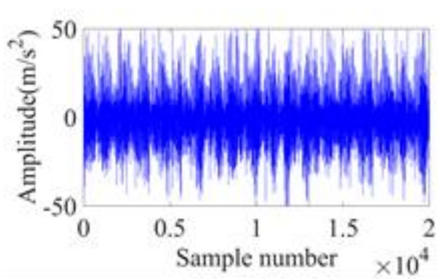
S. No.	Level of abrasive wear faults	Abrasive wear faults created by laser cutting machine	Cutting depth of abrasive wear faults
1.	Incipient		
2.	Slight		
3.	Moderate		
4.	Severe		

Figure 2. 5 Gears with different wear conditions.

Table 2. 3 Bevel-gear vibration signals in z-direction for a different level of wear gear faults.

<table>
<tr><td>Bevel gear condition</td><td>Vibration signal (z-direction)</td></tr>
<tr><td>Healthy gear</td><td>
</td></tr>
<tr><td>Incipient wear</td><td>
</td></tr>
<tr><td>Slight wear</td><td>
</td></tr>
<tr><td>Moderate wear</td><td>
</td></tr>
<tr><td>Severe wear</td><td>
</td></tr>
</table>

The experiments were conducted at various motor speeds, such as 15 Hz, 20 Hz, 25 Hz, and 30 Hz. The controller was used to manually control the speed of the motor. Also, the manually adjustable magnetic brake was used to apply a load of 0-4Nm on the output shaft of the gearbox. For acquiring the real-time data of gear vibration signals, recorded by using a tri-axial accelerometer. The acceleration measurements were carried out in all three directions with a sampling rate of 12.8 kHz. The vibration signal in z-direction for gears with different levels of wear faults is presented in Table 2. 3.

2.4 Results and discussion

The purpose of this work was to perform an automated gear fault diagnosis using the FAWT. The FAWT is a flexible wavelet transform that provides flexibility to decompose a given signal into desired frequency bands with the help of chosen control parameters. It was observed that the maximum accuracy was obtained within the decomposition of an entire frequency spectrum of faulty gear signal in ten sub-bands and one approximation band. For this reason, this method was employed to decompose the gear signals into detailed sub-bands (d1-d10) and approximation sub-band. As the FAWT method utilizes the Hilbert transform pairs of atoms and provides flexibility to the user by using adjustable parameters, such as dilation factor, Q-factor, and redundancy to cover the time-frequency plane by a wavelet frame, it was preferred over others [48], [50]. The value of control parameters (a, b, c, d, and β) was used 2, 3, 1, 2, and 0.50 respectively in the present work. After applying FAWT with 10 levels of decomposition of the aforementioned gear signals (healthy gear signal, incipient wear gear signal, slight wear gear signal, moderate gear signal, and severe wear gear signal), the decomposed signals are shown in Fig. 2.6. The approximation and detail sub-bands at this level 10 represent bands of [0, 0.7] Hz and [0.7, 2.18] Hz respectively and extended up to level 1. The sub-bands were used to extract various entropy features namely, cross-correntropy, log energy entropy, SURE entropy, Shannon entropy, norm entropy, and threshold entropy. The Kruskal–Wallis test is used to determine any statistically significant differences between the classes. It is measured by using probability (p) computation [50]. Table 2.4 has shown the p-value of all entropies features for 120 pairs of gears with different levels of abrasive wear faults signals (healthy gear signal, incipient wear gear signal, slight wear gear signal, moderate gear signal, and severe wear gear signal). From Table 2.4, it is found that there is a need to omit the sub-band signal those $p > 0.05$ [50]. The retentates statistically significant features are fed to the classifier. In the proposed methodology for the classification of the wear faults gear signals, a multi-class LS-SVM classifier with RBF and polynomial kernels is used [50]. Also, the ten-fold cross-validation technique [49], [51] is applied to a classifier. It is estimating errors based on resampling for obtaining robust classification accuracy with training and testing of the data set to train the classifiers [98]. In ten-fold cross-validation, the complete data set is divided into ten subsets with equal size. Processes will be repeated 10 times for Ten-fold cross-validation, each time leaving out one of the subsets from training. This eliminates any possibility of biases in dividing data in training and testing data sets [98]. It can be observed from Table 2.5, for log energy entropy using a multi-class LS-SVM classifier with RBF kernel obtained the maximum value of classification performance. The maximum value of performance parameters ACC, SEN, SPF, PPR, NPR, and MCC are 98.33%, 97.91%, 100%, 100%, 92.30%, and 0.95 respectively.

A comparative study between proposed and previously published work is summarized in Table 2.6. Saravanan et al. [35] investigated the healthy gear and gear with different faults for various loading and lubrication conditions using statistical feature vectors from Morlet wavelet coefficients. CWT-based ANN classifier is achieved for the overall average efficiency to be 97.5%.

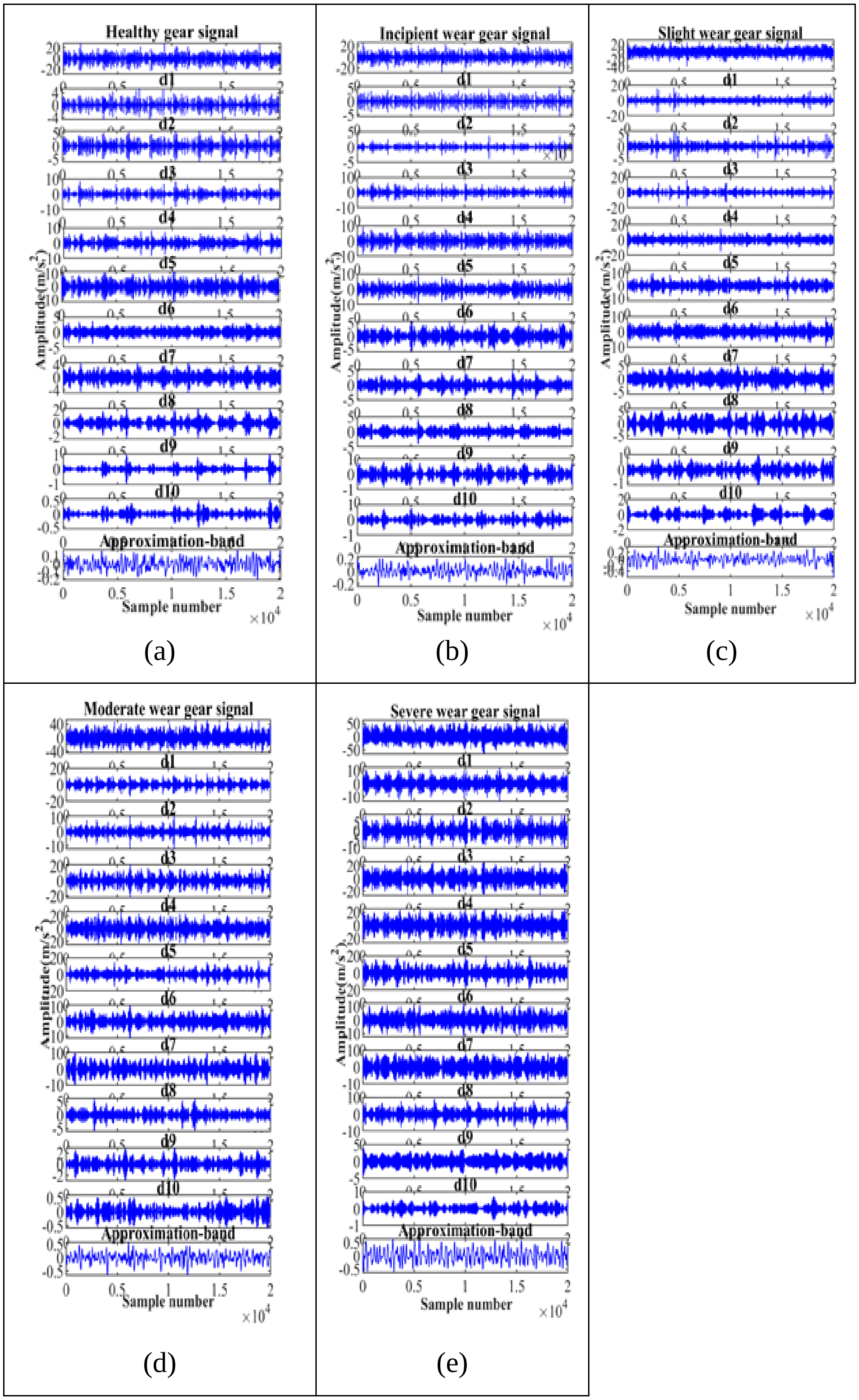


Figure 2. 6 Applied FAWT decomposition (10 levels) on gear signals. (a) healthy gear signal, (b) incipient wear gear signal, (c) slight wear gear signal, (d) moderate wear gear signal, (e) severe wear gear signal

Table 2. 4 Probability (p) value for various entropies features of gear signals.

Bands	Cross correntropy	Log energy entropy	SURE entropy	Shannon entropy	Norm entropy	Threshold entropy
Sub-band 1	0.0265	$4.9112 x 10^{-09}$	$3.9067 x 10^{-08}$	0	0	$3.8432 x 10^{-08}$
Sub-band 2	0.0546	$7.2288 x 10^{-07}$	$2.7819 x 10^{-05}$	0	0	$2.6657 x 10^{-05}$
Sub-band 3	0.0652	0.0057	0.0001	0.0288	0.0278	0.0001
Sub-band 4	0.065	$1.3783 x 10^{-07}$	$6.8544 x 10^{-09}$	$7.2332 x 10^{-06}$	$1.6199 x 10^{-06}$	$6.8446 x 10^{-09}$
Sub-band 5	0.1311	$6.3180 x 10^{-07}$	$3.6202 x 10^{-05}$	0	$7.9828 x 10^{-09}$	$3.5858 x 10^{-05}$
Sub-band 6	0.056	$5.3102 x 10^{-06}$	$2.8369 x 10^{-06}$	$4.7519 x 10^{-06}$	$5.9337 x 10^{-06}$	$2.8467 x 10^{-06}$
Sub-band 7	0.2058	0.1622	0.1125	0.3168	0.2268	0.1118
Sub-band 8	0.025	0	0	0	0	0
Sub-band 9	0.0064	$1.6654 x 10^{-09}$	$1.8462 x 10^{-09}$	$2.7881 x 10^{-05}$	$1.5220 x 10^{-08}$	$1.8425 x 10^{-09}$
Sub-band 10	0.0117	0	0	$3.2698 x 10^{-05}$	0	0
Approximation-band	0.0118	0.0015	0.001	0.0007	0.0011	0.001

This methodology has been applied to the proposed data set and found the overall average efficiency to be 29.78 %. Saravanan and Ramachandran [99] used the DWT-based ANN classification with statistical features of wavelet coefficients using gear fault diagnosis. It has been found that the overall average efficiency of 95% is attained by the ANN classifier. This method is applied to the existing data set and found the overall average efficiency to be 37.52 %. Also, when comparing the proposed method 1-5, based on WPT, DTCWT, TQWT, and FAWT with the previously published method suggested by Saravanan et al. [35], it has been found that the overall average efficiency to be 23.44%, 30.55%, 31.81%, 39.90%, and 53.00%.

Table 2. 5 Performance parameters of multi-class LS-SVM using different kernels for log energy entropy.

Kernel function	Accuracy (%)	Sensitivity (%)	Specificity (%)	Positive predictive rate (%)	Negative predictive rate (%)	Matthew's correction coefficient	Parameters
RBF	**98.33**	97.91	100	100	92.30	0.95	1
Polynomial	95	95.74	92.30	97.82	85.71	0.85	4

Table 2. 6 A comparative study between current and previously published methods using the same data set.

References	Type of signals	Faults	Methods	Features	Classifier	Accuracy of classification (%)
[5]	Gearbox Signals	Gear with wear faults	CWT method	Statistical features	ANN	29.78
[9]	Gearbox Signals	Gear with wear faults	DWT method	Statistical features	ANN	37.52
Proposed method 1	Gearbox Signals	Gear with wear faults	WPT method	Statistical features	ANN	23.44
Proposed method 2	Gearbox Signals	Gear with wear faults	DTCWT method	Statistical features	ANN	30.55
Proposed method 3	Gearbox Signals	Gear with wear faults	TQWT method	Statistical features	ANN	31.81
Proposed method 4	Gearbox Signals	Gear with wear faults	FAWT method	Statistical features	ANN	39.90
Proposed method 5	Gearbox Signals	Gear with wear faults	FAWT method	Statistical features	LS-SVM with RBF kernel	53.00
Proposed method 6	**Gearbox Signals**	**Gear with wear faults**	**FAWT method**	**Entropy features**	**LS-SVM with RBF kernel**	**98.33**

From the comparative analysis, it has been observed that the FAWT based method has given the best performance compared to the existing methodology. So in the present work, the newly proposed method-6 based on FAWT, Entropy features, and LS-SVM classifier has been used. There are many advantages of the proposed method-6. It can be used for non-stationary signals for the classification of normal and abnormal classes. It has been applied in gearbox signals and has provided the best result with 98.33% accuracy.

2.5 Conclusion

In this work, the FAWT method, an advanced technique for signals analysis of micron-level wear of bevel gear, has been implemented for faults diagnosis. The gearbox signals of healthy and faulty gears are decomposed into each sub-band and calculated the entropies are for each sub-band into the nth level. It was observed that the log energy entropy using multi-class LS-SVM classifier with RBF kernel resulted in the maximum value of classification performance of 98.33%, 97.91%, 100%, 100%, 92.30%, and 0.95 for ACC, SEN, SPF, PPR, NPR, and MCC respectively. The results obtained here are compared with the previous results obtained by different methods, such as the CWT, DWT, WPT, DTCWT, and TQWT. Due to this characteristic feature of the log energy entropy outperforms the other entropies and subsequently provides the best classification of the signal classes. This indicates that the proposed methodology is the best suitable method for automated identification for gear faults.

Chapter 3

Automated gear fault detection of micron level wear in bevel gears using variational mode decomposition

In this chapter, aims to automate the fault diagnosis of gears having level of wear fault at micron using variational mode decomposition (VMD). VMD has been applied iteratively with specific input parameters. VMD decomposes the gear vibration signal into different narrowband components (NBCs) or obtained components (OCs). Various statistical features namely kurtosis, skewness, standard deviation, root mean square, and crest factor are extracted from the different OCs. Kruskal-Wallis test based on probability values have been used to identify the significant features. For the automation of fault detection system, a comparative study has been done using the random forest, multilayer perceptron, and J48 classifiers. The proposed method exhibits 96.5% accuracy using random forest classifier with combined kurtosis, skewness, and standard deviation features.

3.1 Introduction

Gears are principally used for power transmission. Bevel gears are used to transmit power between two mutually perpendicular shafts. Generally, they are utilized in hand drill, machine tool equipment, printing machines, automobile machinery etc. Wear fault in a gear tooth is an unavoidable phenomenon and has significant effects on the dynamic behavior of gears. Analysis of wear in gear systems, therefore, is crucial from the economic point of view. Although the vibration-based techniques have been used frequently for analysis of localized gear tooth faults such as pitting, spalling and crack. However, these techniques have not been well- established for monitoring of distributed faults such as wear fault. It is difficult to diagnose the wear fault because wear fault normally occurs in level of micron. The main aim of this work is to develop a vibration-based technique to diagnose the level of wear fault at micron in bevel gears.

There are various time-frequency techniques are available. It's having own advantages and disadvantages. The limitations of the techniques reduce the impact of the performance. Recently, a new emerging technique known as VMD has been introduced by K. Dragomiretskiy and D. Zosso [70]. It is a multiresolution technique that overcomes the limitations of EMD [16]. It is similar to EMD in structure, but a new approach based on constrained optimization makes it a more influential technique [16]. It was reported that VMD provided better results as compared to other existing techniques [16], [80], [82],[87]. This technique is also used in speech signals [88], [89], and yet only a few works have been explored for mechanical signals. Hence, it is taken up for study. Various faults such as chipped tooth fault, missing tooth fault, wear, crack, pitting, etc. have been investigated in spur gears using classifiers [79]. Micron level of wear fault analysis has not been studied. Hence, this work is focused on the diagnosis of micron level of wear faults in gears.

In this paper, MFS equipped with bevel gearbox has been used to conduct experiments. For the analysis of vibration signals, healthy bevel gear and gears with different level of abrasive wear faults have been used. Gear fault diagnosis has been performed using iterative VMD technique. Various statistical features are extracted from different obtained components (OCs) and Kruskal-Wallis test based significant features are used in three different classifiers for classification of multi-class gear signals. The significance of this work is that the gear fault diagnosis using statistical features in VMD domain can be auto-mated. This novel methodology provides high accuracy for gear fault diagnosis.

3.2 Theoretical foundation

3.2.1 Variational mode decomposition

VMD signifies a real-valued signal $a(t)$ with a given number of sub-signals (modes) which have specific sparsity properties. VMD decomposes a signal into set of NBC $a_k(t)$ which are concentrated around corresponding center frequencies ω_k [70], [80], [82], [88], [89]. In this method, a constrained optimization problem is used to compute the bandwidth of NBCs as follows [25-27, 29, 30]:

$$\min_{\{a_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * a_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{1}$$

such that $\sum_{k=1}^{K} a_k(t) = a(t)$

$\{a_k\} = \{a_1, a_2, ..., a_K\}$ constitutes the set of obtained NBCs.

$\{\omega_k\} = \{\omega_1, \omega_2, ..., \omega_K\}$ constitutes the set corresponding centre frequencies.

$\delta(t)$ constitutes dirac distribution function, and K represents the total number of NBCs.

The augmented Lagrangian is used to solve the constrained variational problem and the non-constrained variational problem is obtained by [70], [80], [82], [88], [89].

$$L(\{a_k\},\{\omega_k\},\lambda) := \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * a_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| a(t) - \sum_k a_k(t) \right\|_2^2 ...$$
$$+ \left\langle \lambda(t), a(t) - \sum_k a_k(t) \right\rangle \tag{2}$$

The estimation of NBCs in the frequency domain and their center frequencies can be expressed as follows [70], [80], [82], [88], [89]:

$$\hat{a}_k^{n+1}(\omega) = \frac{\hat{a}(\omega) - \sum_{i \neq k} \hat{a}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \tag{3}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left| \hat{a}_k(\omega)^2 \right| d\omega}{\int_0^\infty \left| \hat{a}_k(\omega)^2 \right| d\omega} \tag{4}$$

Eq. (3) shows that contains of the Wiener filter structure. Using Fourier transform modified expression for λ is given by:

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega) + \tau \left[a(\omega) - \sum_k \hat{a}_k^{n+1}(\omega) \right] \tag{5}$$

where n shows the number of iterations. In this method input paraments take places an important role such as a balancing parameter (α) is the penalty factor, dual ascent (τ), the narrow-band components (K) to be extracted, tolerance of convergence (tol), number of DC components, and ω (init) represent initial frequencies.

3.2.2. Statistical based features extraction

In this work, the statistical operators have been used as features. Expressions and details of features are as follows:

3.2.2.1. Kurtosis

It is a measure of the degree of tailedness of distribution as compared to a normal distribution. Mathematical expression of kurtosis is given as follows [32], [79], [100]:

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2\right]^2} \tag{6}$$

3.2.2.2. Standard deviation

It is used to quantify the amount of variation in signal and mathematically this can be defined as follows [32], [79], [100]:

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[x_i - \bar{x}\right]^2} \tag{7}$$

3.2.2.3. Skewness

It is a measure of the asymmetry of the signal around the sample mean and can be expressed as follows [32], [79], [100]:

$$S = \frac{E\left(x - \bar{x}\right)^3}{\sigma^3} \tag{8}$$

3.2.2.4. Root mean square

Root mean square gives the energy content and vibration amplitude of the signal. Mathematically, it can be expressed as follows [100]:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[x_i\right]^2} \tag{9}$$

3.2.2.5. Crest factor

Crest factor gives an idea about any impacting present in the signal and can be expressed as follows [32], [100]:

$$CF = \frac{\max\left|x_i\right|}{\sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left[x_i\right]^2}} \tag{10}$$

where x is the time domain signal, N is the number of samples, i is the simple index, $\bar{x}$ mean of the signal, σ is the standard deviation of signal, and E is the expectation operator.

3.3 Classifiers

3.3.1. Random Forest

This classification is representing the collective decision of different classification trees. For each class, a separate decision made by each decision tree and allocation of the weight of each tree is used for final decision of each class. The output of the final classification decision is made by the consideration of each tree. Random tree method is enrolled to build a tree [82], [101]. This classification method has been introduced by L. Breiman [102] and developed by Liaw and Wiener [102]. This algorithm consists of the random vector v_m ,with an m th number of the tree. This vector is produced without disturbing the previous distribution of vectors, and it is created separately from each other. Implementation of the training input data t and random vector v_m developing a result in a decision tree. This is shown resulting in tree classifier $G(t, v_m)$. The class is determined based on margin function (MN). It is used for training through two randomly selected vector distribution C, D as [102].

$$\mathrm{MN}(C,D) = kv_m I(G_m(C) = D) - \max_{j \neq D} kv_m I(G_m(C) = j) \tag{11}$$

where $G_m(C) = G\ (t,\ v_m)$ and $I(.)$ represent the indicator function [102]. The operator kv_m denotes the average value. Higher confidence in classification is obtained by large margin value of a respective class. The generalization error (GR) can be expressed as [102].:

$$\mathrm{GR} = P_{c,d}\left[\mathrm{MN}(C,D) < 0\right] \tag{12}$$

where $P_{c,d}$ indicates probability is over the C, D space.

3.3.2. Decision Tree

Decision tree algorithm finds out the way the attributes-vector behaves for several instances [101]. In the construction of decision tree, top-down approach is usually used starting with a training set or tuples [103]. A tuple is defined as a collection of attribute values and a class value [101]. In the waikato environment for knowledge analysis (WEKA) software, J48 is an open-source Java implementation of the C4.5 algorithm. In the WEKA software, J48 is used for execution of C.45 algorithm [104].

The basic contractive guideline has been followed for the algorithm:

1. For the same class instances, tree constitutes a leaf, and the leaf is returned by labeling with the same class.

2. The potential information, given by a test on the attribute, is calculated for every attribute. The gain in information is calculated resulting from a test on the attribute.

3. Selection of the best attribute for branching followed the current selection criterion.

J48 is an addition of iterative dichotomiser 3 (ID3) decision tree algorithm. Features such as decision trees pruning, accounting for missing values, continuous attribute value ranges, derivation of rules, etc. are the additional features of J48.

3.3.3. Multilayer Perceptron

The multilayer perceptron classifier is based on neural network algorithm [35], [101], [104], [105]. It consists of a multilayer feed-forward neural network. The construction of this class network employed with one or more layers (hidden layer) of nodes between the input and output layers as shown in Fig. 3.1. Weight network is used to interconnect different layers for these nodes. Before governing the input and output layer, the hidden layer is used for intermediate computation [101].

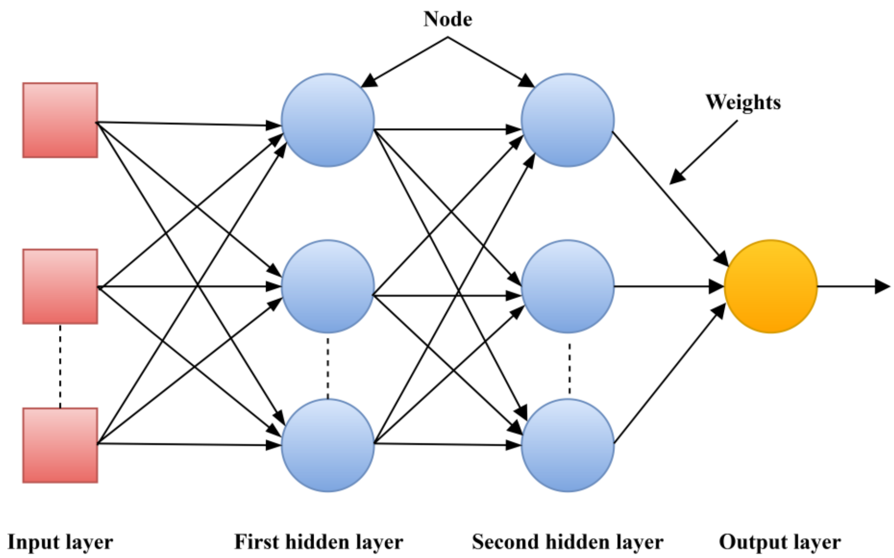


Figure 3. 1 Graphical description of multilayer perceptron

3.4 Proposed methodology

In this section, proposed novel methodology as shown in Fig. 3.2 is used for automation of the gear fault diagnosis. The vibration signals of healthy bevel gear, gear with different level of abrasive wear faults have been acquired. In the view of the proposed methodology, the iterative VMD method is used to analyze the gear vibration signals. OCs by iterative VMD, which are concentrated around the center frequency. For each OCs, statistical parameters such as kurtosis, skewness, standard deviation, root mean square, crest factor are used features extraction. Significant features to be obtained using the performance of the Kruskal-Wallis test. Significant features are used as an input parameter in the multiclass-classifiers. Random forest, J48, and Multilayer perceptron are used for performing classification and finding the classification accuracy. It has been expected that our novel systematic and procedural analysis would help accurately identify multi-class gearbox faults. Fig. 3.3 shows the required steps of the proposed iterative VMD technique which was used in this work for signal decomposition.

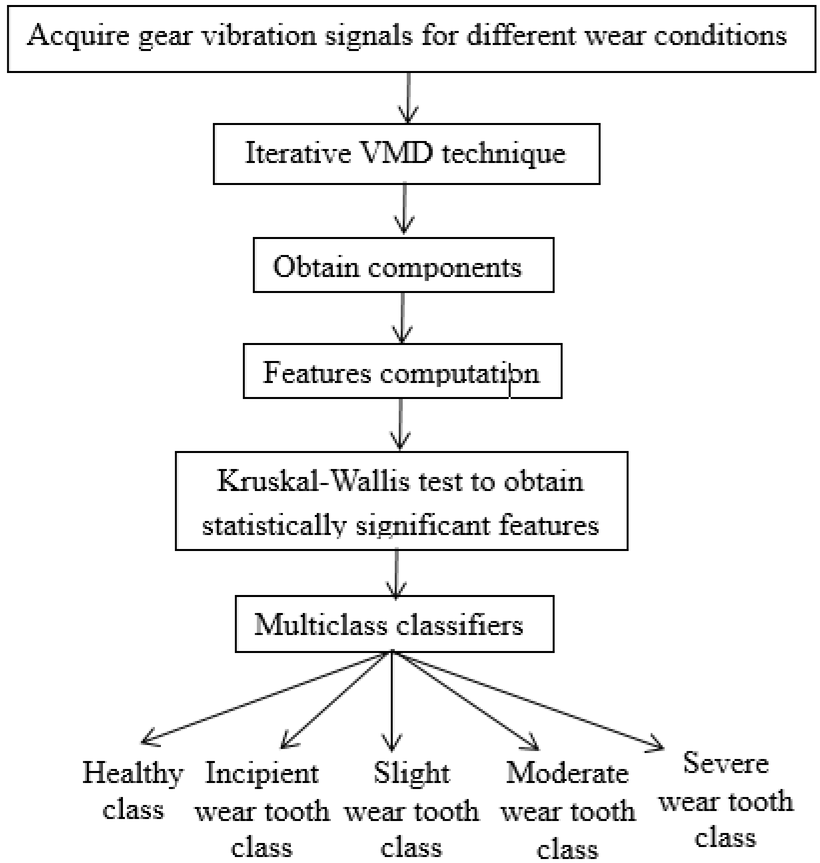


Figure 3. 2 Procedure of the proposed method

VMD technique which has been used in this work for signal decomposition. In the end of this decomposition process, the gear vibration signal $g[s]$ can be written as a sum of OCs by VMD applied in iterative manner and residual which can be expressed as follows:

$$g[s]=\sum_{i=1}^{Q} g_i[s]+r[s] \tag{13}$$

In the Eq. (13) expressed the components $g_i[s]$ and of residual $r[s]$. Thus, one can achieve decomposition of the signal in terms of components and a residual, which is the mean trend of $g[s]$. Fig 3.4 (a) Shows the each of the OCs [OC (I), OC (II), …, OC(VIII)] provided different frequency bands ranging from low to high as shown in Fig 3.4 (b). These OCs have been used to computed statistical parameters.

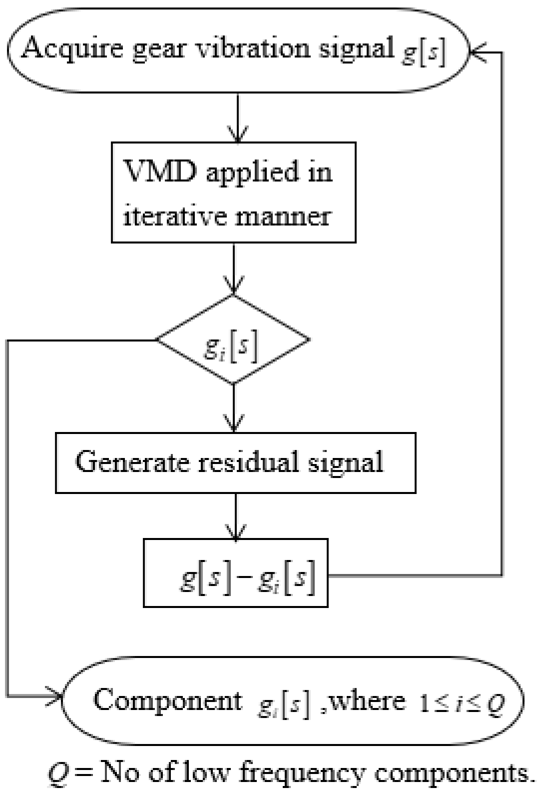


Figure 3. 3 Flowchart of proposed iterative VMD technique

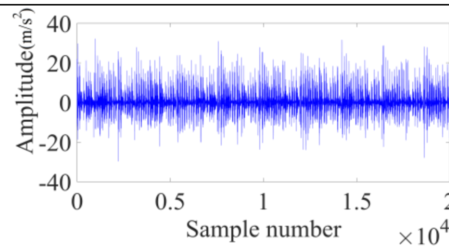
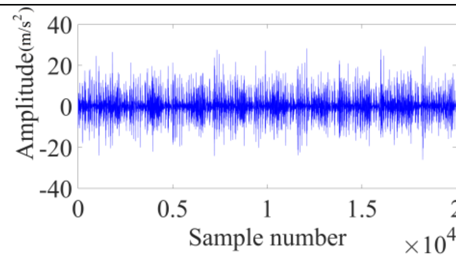
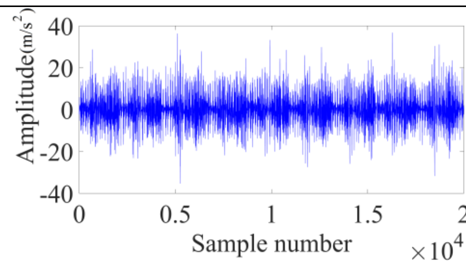
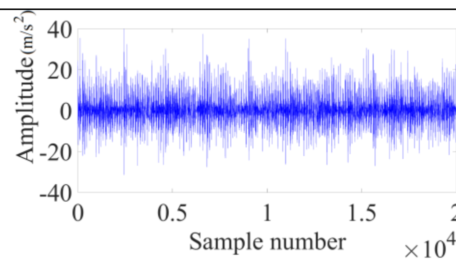
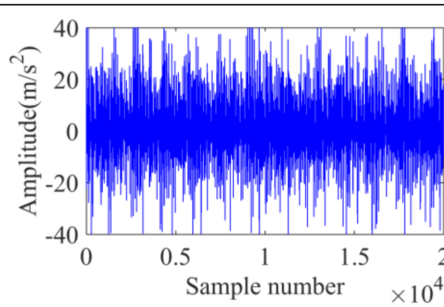
3.5 Experimental analysis

The experimental analysis has been carried out with same signal as mentioned in chapter 2. Reader can follow the chapter 2.3 for more details.

3.6 Results and discussion

Gear wear is a kind of tooth surface fault in gear systems. It occurs in gearbox due to many reasons such as dirt in housing, sand or scale from casting, partially introduced into the housing when filling the lube oil, etc. In this way, the micron level of wear fault has been carried out in this work. Details of the experimental analysis is introduced in section 3.4. Table 3.1 shows gear vibration signals in x-direction for different wear conditions.

Table 3. 1 Bevel-gear vibration signals in x-direction for different level of wear gear faults.

Bevel gear condition	Vibration signal (x-direction)
Healthy gear	
Incipient wear	
Slight wear	
Moderate wear	
Severe wear	

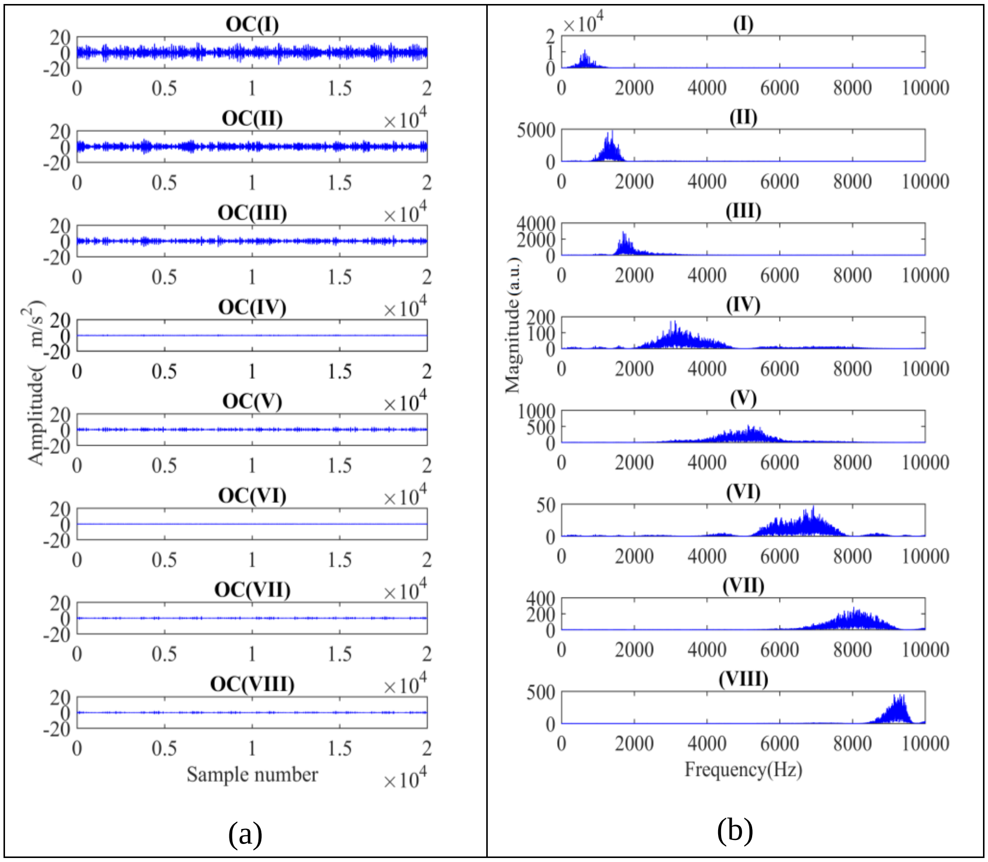


Figure 3. 4 (a) Plots of the OCs using iterative VMD method for healthy bevel gear signal, (b) Plots of the magnitude spectrum of respective OCs using iterative VMD method for healthy bevel gear signal. The unit of Y axis are arbitrary.

The iterative VMD method is applied to decompose the 200 pairs of healthy gears signal and different level of wear faults signals. By using iterative VMD, the gear signals are decomposed using the input parameters DC=0, α =200, K =8, τ =0, tol=10^{-7}, ω (init)=0. Fig. 3.4 (a) shows the plots of the OCs and Fig. 3.4 (b) shows the respective magnitude spectrums of OCs using iterative VMD method for healthy gear signal. The OCs of gear signals are then used to evaluate features such as kurtosis, skewness, standard deviation, root mean square, and crest factor. Statistically significant features are decided using the Kruskal-Wallis statistical test to improve the realization. Table 3.2 shows the p value of various features for acquired of gear signals.

Table 3. 2 Probability (p) value for various statical features of gear signals using all conditions after employed iterative VMD.

Obtained component (OC)	Kurtosis	Skewness	Standard deviation	Root mean square	Crest factor
OC (I)	0	0.336	0.5163	0.5164	0
OC (II)	6.614×10^{-04}	0.006	0.3249	0.3248	0.0226
OC (III)	2.380×10^{-09}	0	9.911×10^{-09}	9.911×10^{-09}	0.0005
OC (IV)	9.3887×10^{-05}	0	3.132×10^{-08}	3.142×10^{-08}	0.0079
OC (V)	1.549×10^{-04}	0.0005	1.821×10^{-05}	1.285×10^{-06}	0
OC (VI)	0	0.0052	0.2355	0.8659	0
OC (VII)	0.584	1.9149×10^{-05}	0	2.022×10^{-08}	0.0095
OC (VIII)	5.2983×10^{-08}	0.0194	0	0	0

Table 3. 3 Details of the architecture of the studied artificial neural network.

Network type	Forward neural network trained with feed back propagation
No. of neurons in input layer	5-30
No. of neurons in hidden layer	5-17
No. of neurons in output layer	5
Transfer function	Sigmoid transfer function in hidden and output layer
Training rule	Back propagation
Leaning rule	Momentum training method
Momentum learning step size	0.3
Momentum learning rate	0.2

It is observed from the Table 3.3 that obtained components can be omitted for those features which have p value greater than 0.05 [50]. It is also observed that the features have high discrimination between their respective classes as p value is close to zero. These statistically significant features are fed to all three classifiers random forest, multilayer perceptron, and J48. Ten-fold cross-validation technique [101] has been used for training and testing of data set to train the classifiers. In cross-validation, complete data set is divided randomly between training set (90%) and testing set (10%). Processes will be repeated 10 times for Ten-fold cross-validation which eliminates any possibility of biasness in dividing data in training and testing data set. In the present study, the parameters of the neural network used for multilayer perceptron are shown in Table 3.3.

Table 3. 4 Details of the architecture of the studied artificial neural network.

S. No.	Features	Performance of the classifiers (%)		
		Random forest	Multilayer perceptron	J48
1	Kurtosis	82.5	77.5	72.5
2	Skewness	82.5	77.5	77.5
3	Standard deviation	86.5	82	72.5
4	RMS	86.5	82	72.5
5	Crest factor	70	69	61
6	Kurtosis and skewness	90.5	88	85
7	Kurtosis, skewness, and standard deviation	**96.5**	89.5	87
8	Kurtosis, skewness, standard deviation, and RMS	86.5	82	72
9	Kurtosis, skewness, standard deviation, RMS, and crest-factor	96	92.5	86

The classification performance of classifiers with significant features has been shown in Table 3.4. From Table 3.4, it has been found that individual features kurtosis, skewness, standard deviation, RMS and crest factor, the random forest classifier has maximum accuracy with 82.5%, 82.5%, 86.5%, 86.5%, and 70% accuracy respectively. For kurtosis and skewness combination, random forest classifier has the maximum accuracy with 90.5%. For kurtosis, skewness, standard deviation, and RMS combination, random forest classifier has the maxi-mum classification performance with 86.5% accuracy. For kurtosis, skewness, standard deviation, RMS, and crest-factor combination, random forest classifier has the maximum classification performance with 96% accuracy. From the Table 3.4 the best classification accuracy of 96.5% is obtained using random forest classifier with combined kurtosis, skewness, and standard deviation features. The key benefit of the proposed technique is that it can identify wear gear fault automatically with high accuracy.

3.7 Conclusion

Gear wear is a major concern in the gear transmission system. In this work, fault diagnosis of gear in the presence of level of wear in micron faults has been done using the iterative VMD method. Experiments have been conducted to acquire vibration signals from bevel gears for different level of wear faults. The iterative VMD has been used to decompose the signals into different OCs. The significant features are extracted using Kruskal-Wallis statistical test. That significant features are fed as an input parameter in the classifiers. Three different classifiers (random forest, multilayer perceptron, and J48) are used to classify the multi-classes. It is observed that random forest classifier achieves the best classification accuracy with the combination of kurtosis, skewness, and standard deviation features.

Chapter 4

Fourier-Bessel series expansion based empirical wavelet transform technique used for automated classification of gearbox fault diagnosis

In this chapter, using Fourier-Bessel series expansion as the basis for an empirical wavelet transform, a novel automated technique, FBSE-EWT, has been proposed. The existing empirical wavelet transform is to be reformed using the FBSE method to increase the frequency resolution. The proposed novel method includes the decomposition of different levels of gear crack vibration signals into NBCs or sub-bands. Features are extracted from the sub-bands and the statistically significant features have been identified using the Kruskal-Wallis test. Three classifiers are used for faults classifications, out two are based on tree construction techniques i.e., random forest, and J48 decision tree classifiers, another one is based on a neural network algorithm multilayer perceptron function classifier. A comparative study has been done between existing EWT and proposed a novel methodology. It has been observed that FBSE-EWT with a random forest classifier shows better gear fault detection performance as compared to existing EWT.

4.1 Introduction

Gearbox fault diagnosis is the process of analyzing the health and performance of gears in machinery to detect potential faults or issues before they become major problems. Several different modes might cause a gear to fail, including fatigue, impact, wear, or plastic deformation. Further, gear failure occurred due to excessive vibration. When it comes to monitoring the status of machines during startups, breakdowns, and regular operations [90], vibration measuring is a technology that is successful, discrete, adaptable, and cost-effective. Furthermore, the article [106] provides a detailed evaluation or selection of signal processing techniques that have been applied to try to minimise the amount of noise that exists in the vibration signals. The fact that non-stationary or variable in time signals are amplitude and frequency modulated. It means that time-domain and frequency-domain methods cannot be used to analyse these types of signals. In real-world circumstances, the operation of a gearbox leads to the generation of non-stationary signals due to vibration [16]. Vibration analysis is an effective tool to diagnose such signals. Local gear faults such as levels of a gear tooth crack [107], identification is needed to prevent any unanticipated gear failure because tooth breakage of gear initiates due to incipient crack in gear [108]. EWT is a new method of adaptive decomposition that eliminates narrow-band frequency bands within the examined signal depending on the frequency details of the spectrum. After locating the boundary frequencies in the FT-based spectrum, it next applies adaptive wavelet-based filters to the signals to deconstruct them [72]. However, EWT is unable to accurately depict frequency components that are tightly spaced. Challenges similar to those experienced by the EWT approach have been found in the suggested method.

In this study, the established EWT procedure is revised using the FBSE. It is what makes the FBSE coefficients effective for the spectrum analysis of such signals. Although FBSE-EWT was mostly employed in biological signals like Vectorcardiogram Signals, Electroencephalography (EEG) signals etc. [109], [110], [111], [112]. Researchers used the multifrequency scale-based two-dimensional FBSE-EWT method for glaucoma detection, which requires the segmentation of fundus photographs into sub-images. This method proposes a rhythm separation technique and enhanced local polynomial (LP) approximation-based total variation (TV) for the filtering of ocular artefacts from the EEG signals. In the process of detecting alcoholism, a select group of researchers, including A. Anuragi et al. [113], created and implemented a technique. They found that by combining least squares support vector machines with radial basis kernels, they were able to reach the highest possible levels of accuracy and sensitivity. FBSE-EWT technique is not used to investigate gear faults like chipped teeth, missing teeth, cracks in the root, and worn gear faces with classifiers [79]. As a result, FBSE-EWT has been applied in this research to identify the gear crack faults with various levels and compare the performance with EWT.

Machine learning-based defect detection is advantageous in this situation [82]. Researchers have made extensive use of classifiers over the past decade to increase the effectiveness of applicable signal-processing algorithms for fault identification. In this research, we compared three well-known classifiers to see which one is the most effective in this condition: the random forest, the J48, and the multilayer perceptron.

4.2 Proposed methodology

Fig. 4.1 here describes the steps in the proposed approach. The bevel gear test rig was used to collect gear signals under various crack fault conditions for the suggested approach. It employed two separate methods EWT and the suggested approach FBSE-EWT to break down the different levels of gear crack vibration signals into the sub-bands. Features were extracted from each sub-bands. Further identification of significant features is obtained using the Kruskal-Wallis test. Therefore, multi-class classifiers were used to carry out the fault diagnosis. Find out how the suggested novel methodology, FBSE-EWT, compares to the existing EWT.

4.2.1. Brief introduction to Fourier-Bessel Series Expansion - Empirical Wavelet Transform (FBSE-EWT).

The FBSE-EWT signal processing technology combines two approaches for studying non-stationary signals, FBSE [114] and EWT [71].

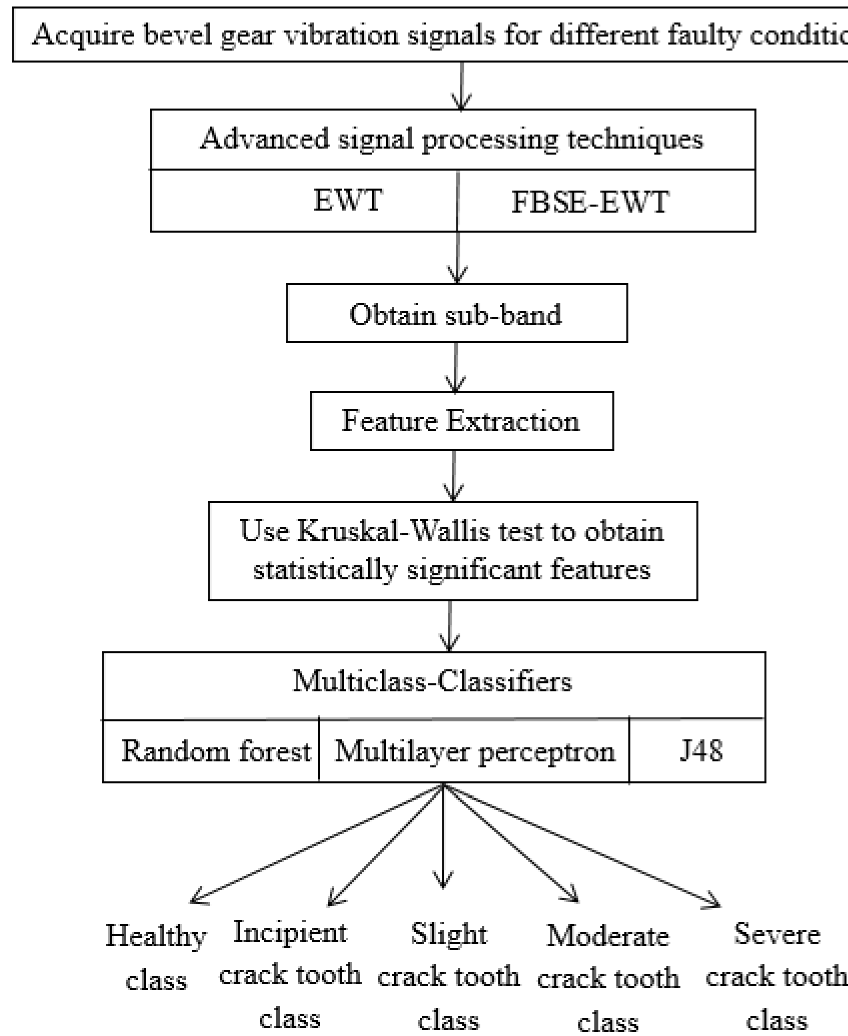


Figure 4. 1 Block diagram showing the suggested approach.

A technique known as FBSE-EWT takes a nonstationary finite energy signal and split it up into many NBCs, each of which indicates the nature of the signal's underlying frequency components. The boundary detection approach in EWT uses the Fourier spectrum [71], whereas the Fourier–Bessel frequency spectrum is used in FBSE-EWT [72], it results in an improvement over the conventional EWT's subsequent wavelet filter bank [71]. EWT sub-band signals have unique center frequencies as well as compactly defined frequency bands. The authors [72] developed EWT in conjunction with FBSE for the analysis of non-stationary signals. It was observed that the time-frequency representation (TFR) with FBSE gives better results as compared to existing EWT which is based on the Fourier transform-based spectrum. The performance analysis of discrete energy separation algorithm (DESA) [115] and WVD techniques [116], FBSE is used to differentiate between mono-component non-stationary signals and multi-component non-stationary signals. Bessel functions with non-stationary properties are utilised as the basis function in FBSE, it is better suited to studying non-stationary data than the Fourier transform. The EWT, on the other hand, uses a segmentation technique to separate narrow-band signals using empirical wavelets created from the spectrum. The EWT is an adaptive signal decomposition approach for non-stationary signals that was proposed in [71]. The generation of adaptive wavelet-based filters is the inherent process of EWT. The spectral information of the signal can potentially be identified with the use of these wavelet-based filters. After EWT decomposition, the resultant sub-band signals have particular center frequencies and compact frequency supports.

The FBSE-EWT is based on the building of an empirical wavelet filter bank for the EEG signal in the FBSE domain [71], [117]. The rhythms from the EEG are separated data using FBSE-EWT. Bessel functions must be used as the base set of functions for the FBSE-based depiction of signals. These Bessel functions have the characteristic of decaying with time, making them well-suited for the efficient encoding and analysis of nonstationary signals [115]. In addition to this, the Bessel functions are convergent and non-periodic [114]. The FBSE-based representation doesn't have any negative frequency components, so the FBSE approach gives double frequency resolution when compared to the Fourier-based representation [72], [111]. A description of the FBSE-EWT approach for the signals is presented in the following steps: [75], [113]:

Step1: The FBSE system is utilised as an analytical tool for the purpose of acquiring the frequency spectrum of a signal $x(n)$ that exists within the frequency band [0, π]. The following is an analytical formulation for the FBSE approach, which is founded zero-order Bessel function:

$$x(n) = \sum_{m=1}^{M} G_m \; B_0\left(\frac{\psi_m n}{M}\right), \;\; n = 0, 1, 2, 3, \ldots \ldots \ldots M - 1 \tag{1}$$

where G_m indicates the FBSE coefficients for the input signal $x(n)$, and these coefficients, which may be represented as [72], are as follows:

$$G_m = \frac{2}{M^2\big(B_1(\psi_m)\big)^2} \sum_{n=0}^{M-1} n y(n) \; B_0\left(\frac{\psi_m n}{M}\right) \tag{2}$$

$B_0(\cdot)$ and $B_1(\cdot)$ are the notations that are refer to the zero-order and first-order Bessel functions, respectively. A zero-order Bessel function's $B_0(\psi) = 0,$ the positive roots are denoted by ψ_m, where $m = 1, 2, 3 \ldots \ldots M$. The appropriate continuous time frequency $C_m(\mathrm{H_Z})$ [72] the m^{th} order of FBSE coefficients is defined as follows:

$$\psi_m \approx \frac{2\pi C_m M}{C_s}, \qquad \text{where } \psi_k \approx \psi_{m-1} + \pi \;\approx m\,\pi \tag{3}$$

where C_S represents the sample rate. The previously mentioned expression may also be presented as [72], [75], [118]:

$$m \approx \frac{2C_m M}{C_s} \tag{4}$$

The range of m should be extended from 1 to M, where M is the signal length, and it is encompassing all frequency bands of the sampled signal. The FBSE spectral is displayed between the absolute values of the FBSE coefficients (G_m) versus frequencies (C_m) [72] ,[75].

Step 2 In order to extract the relevant $N + 1$ boundary frequencies α_i and segment the FBSE spectrum into N sub-band signals, a scale-space boundary recognition technique named [119] is formed. This algorithm's purpose is to extract those frequencies. The EWT boundary recognition technique is utilised in order to determine the $N - 1$ intermediate boundary frequencies that lie between 0 and π. After the FBSE spectral is segmented, the boundary frequency ranges can be mathematically expressed as follows:

$$[0, \alpha_1], [\alpha_1, \alpha_2], [\alpha_2, \alpha_3] \ldots\ldots\ldots [\alpha_{N-1}, \pi]$$

Step 3: The bandpass filters developed by Littlewood-Paley and Meyer [71]. were developed with a combination of scaling and empirical wavelet functions. These are arranged by the various adaptive segregations of the FBSE spectrum. The following mathematical equations can be used to describe scaling and empirical wavelet functions [113]:

$$\mu_i(\alpha) = \begin{cases} 1, & \text{if } |\alpha| \le (1-\epsilon)\alpha_i \\ \cos\left[\frac{\pi\emptyset(\epsilon,\alpha_i)}{2}\right], & \text{if } (1-\epsilon)\alpha_i \le |\alpha| \le (1+\epsilon)\alpha_i \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$\gamma_i(\alpha) = \begin{cases} 1, & \text{if } (1+\epsilon)\alpha_i \le |\alpha| \le (1-\epsilon)\alpha_{i+1} \\ \cos\left[\frac{\pi\emptyset(\epsilon,\alpha_{i+1})}{2}\right], & \text{if } (1-\epsilon)\alpha_{i+1} \le |\alpha| \le (1+\epsilon)\alpha_{i+1} \\ \sin\left[\frac{\pi\emptyset(\epsilon,\alpha_i)}{2}\right], & \text{if } (1-\epsilon)\alpha_i \le |\alpha| \le (1+\epsilon)\alpha_i \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where the variable ϵ signifies the tight frame and the function $\emptyset(\epsilon, \alpha_{i+1})$ is defined in (7). After that, the generation of the tight frame of scaling as well as empirical wavelet functions will be possible if the condition that is given in (8) is achieved. $\delta(z)$ is an arbitrary function, and following is the definition of the parameter δ [71]:

$$\emptyset(\epsilon, \alpha_{i+1}) = \delta\left[\frac{(|\alpha|) - (1-\epsilon)\alpha_i}{2\epsilon\alpha_i}\right] \tag{7}$$

$$\epsilon < \min_i \left(\frac{\alpha_{i+1} - \alpha_i}{\alpha_{i+1} + \alpha_i}\right) \tag{8}$$

$$\delta(z) = \begin{cases} 0, & \text{if } z \le 0 \\ \delta(z) + \delta(1-z), & \text{if } \forall z \in [0\ 1] \\ 1, & \text{if } z \ge 0 \end{cases} \tag{9}$$

The inner product is being utilized for the scaling and the wavelet function towards acquiring detail as well as approximate coefficients from arbitrary signals $x(n)$. The following are a description of the detailed $T_{(i)}(k)$ $(i = 1, 2, 3, \dots \dots \dots \dots J)$, as well as the approximate coefficients $A_1(s)$. Here J gives the total number of coefficients [71]:

$$T_i(k) = \sum_{\Omega=1}^{N} x(\Omega)\overline{\omega_\iota(\Omega - k)} \tag{10}$$

$$E_1(k) = \sum_{\Omega=1}^{N} x(\Omega)\overline{K_\iota(\Omega - k)} \tag{11}$$

The reconstruction of the i^{th} detail and the approximation coefficients signals expressed as [71]:

$$x_{T_{(i)}}(n) = \sum_{k=1}^{N_i} T_{(i)}(k)\omega_i(n - k) \tag{12}$$

$$x_{E_{(1)}}(n) = \sum_{k=1}^{N_1} E_{(1)}(k)K_1(n - k) \tag{13}$$

where $x_{T_{(i)}}(n)$ and $x_{E_{(1)}}(n)$ defines detailed and approximation sub-band signal of i^{th} level, respectively. N_i represents the wavelet length coefficients of i^{th} detailed coefficients, and N_1 denotes the wavelet length vector corresponding to the approximate coefficients.

The following are some advantages of spectrum representation utilising FBSE over traditional FT-based spectral representation:

1. To begin with, when compared to traditional Fourier representation, the FBSE spectrum has a compact representation [72].
2. Second, the FBSE spectrum avoids the spectral representation effect of windowing [72]. To limit the influence of spectral leakage, a

window function is incorporated into the spectral representation that is based on FT. On the other hand, without the influence of windowing, the FBSE spectral can obtain signal characteristics even for signals with a short time.

Furthermore, spectral representation using FBSE necessitates several coefficients equal to the discrete signal's length. This contrasts with the traditional FT spectrum, which has a spectrum length half that of the discrete signal being examined [115]. As a result, the FBSE-based spectrum has a higher spectral resolution than the FT spectrum. Only an interpolated spectrum with a smoother appearance will result from zero-padding with signal to acquire the same length of FT spectral. The aforementioned characteristics of the FBSE spectrum, in comparison to FT spectrum, help to locate the optimal boundary frequencies in a more exact manner, which is especially helpful when the signal is compact and consists of components with closed frequency ranges.

4.2.2 Features extraction

The statistical and entropy features are extracted from EWT, and a novel approach FBSE-EWT based on sub-bands with different frequency scale signals. For the more details of statistical with entropy features and classifiers, reader can follow the chapter 2.2.2, 3.2.2 and 3.3.

4.3 Experimental study:

In this experimental investigation MFS, was utilised for acquiring the gear vibration signals. Fig. 4.2 illustrates a schematic representation of the MFS. The experimental apparatus included a 3-phase alternating current motor that served as the prime mover (3/4 horsepower, 2850 revolutions per minute). This motor was linked to the shaft using a flexible connection.

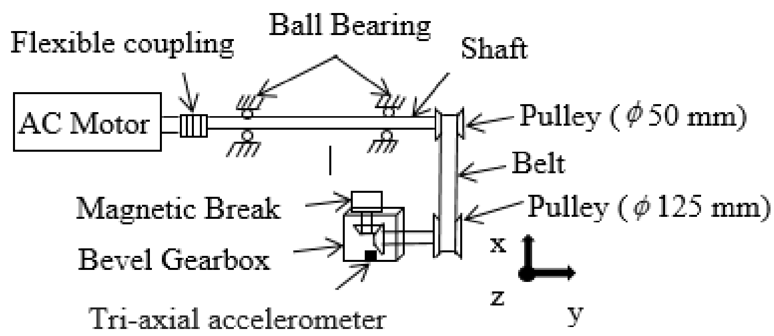


Figure 4. 2 The schematic presentation of the experimental setup.

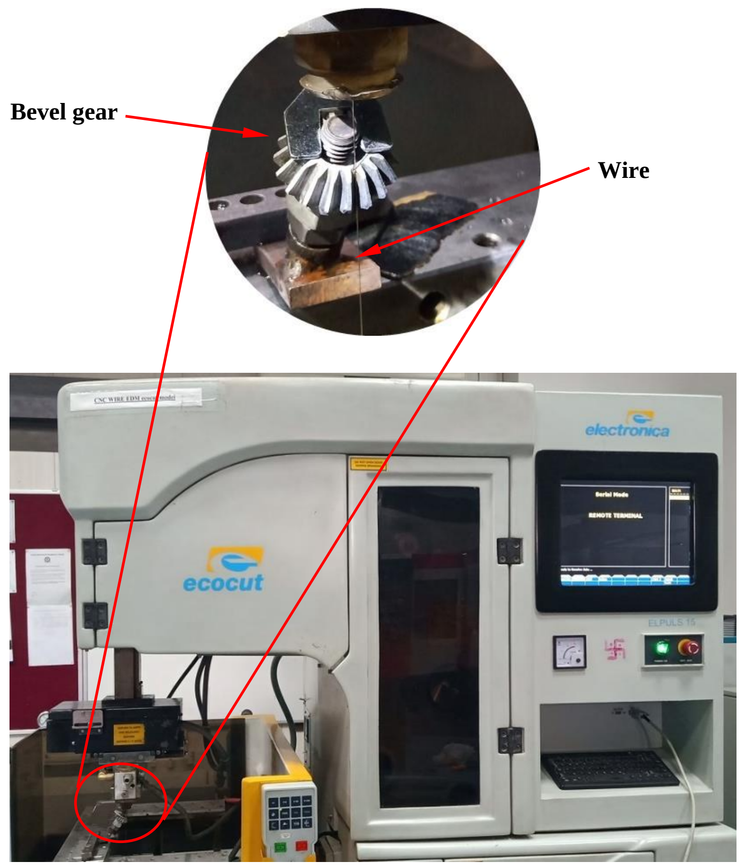


Figure 4. 3 Crack faults created by CNC wire (EDM) machine.

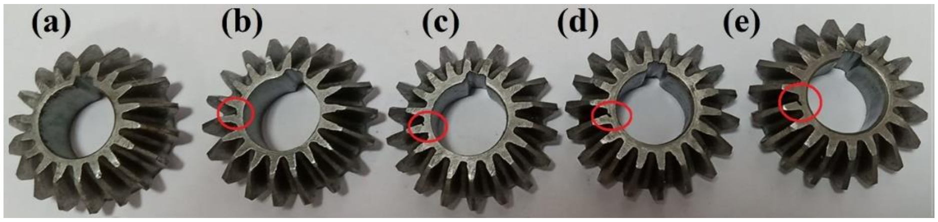


Figure 4. 4 Health of the gears (a) Healthy gear (b) Gear with 0.25 mm crack length (c) Gear with 0.50 mm crack length (d) Gear with 0.75 mm crack length (e) Gear with 1.00 mm crack length

Table 4. 1 Details of the types of gear tooth cracks and their relative crack length in bevel gears.

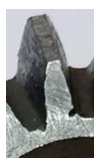
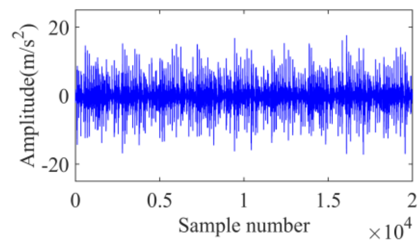
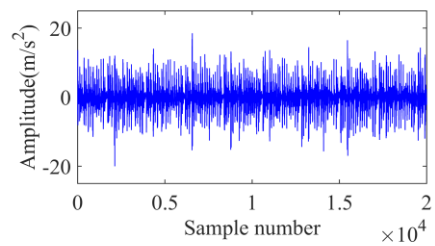
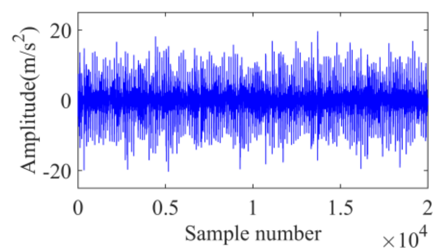
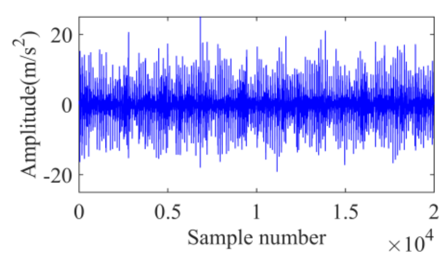
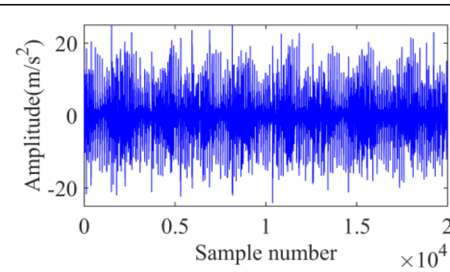
S.No.	Types of gear tooth crack	Crack image	Crack length millimeter (mm)
1.	Incipient crack tooth		0.25
2.	Slight crack tooth		0.50
3.	Moderate crack tooth		0.75
4.	Severe crack tooth		1.00

Table 4. 2 The z-direction of vibration signal for gear with different levels of crack faults.

Bevel gear condition	Vibration signal (z-direction)
Healthy gear	
Incipient crack tooth	
Slight crack tooth	
Moderate crack tooth	
Severe crack tooth	

On the other side of the shaft was coupled with belt and pulley agreement, which was then coupled with a bevel gearbox. For this study, the level of crack faults made by the computer numerical control (CNC) Wire Electrical Discharge Machine (Wire EDM) was shown in Fig. 4.3. In addition, the length of the crack was evaluated using an optical microscope. Fig.4.4 depicts the health of gears, whereas Table 4.1 shows the types of gear tooth cracks and their relative length in bevel gears. The studies were carried out with the motor operating at a speed range, of 15-30 Hz. The motor's speed was manually controlled using the controller. Additionally, a load of 0-4Nm was applied to the gearbox's output shaft using the mechanically controllable magnetic brake. A direct adhesive mounting method was employed for fastening a triaxial accelerometer to the upper surface of the housing of the bearing. This agreement was used to collect gear vibration data. The acceleration readings were recorded with a sample rate of 12.8 kHz in each of the three different directions simultaneously. The vibration signal in the z-direction is displayed in Table 4.2 for gears that have varying degrees of crack defects.

4.4 Results and discussion

In this work, automated gear defect diagnostics using two different techniques EWT and the proposed method FBSE-EWT also found the comparison performance. For the decomposition of signals input parameters such as (global trend removal "none"; regularization "gaussian", detection method "locmax", maximum number of bands "10") were used respectively. Fig. 4.5 (a and b) shows the EWT based decomposed sub-bands for all gear signals (healthy signal, incipient crack signal, slight crack signal, moderate crack signal, and severe crack signal) with the magnitude spectrum of their respective sub-bands. The spectrum analysis is improved by using the FBSE-EWT approach, as illustrated in Fig. 4.6 (a and b) for the same identical signals. Kurtosis, RMS, variance, and Shannon entropy were some of the main characteristics that were extracted using the sub-bands.

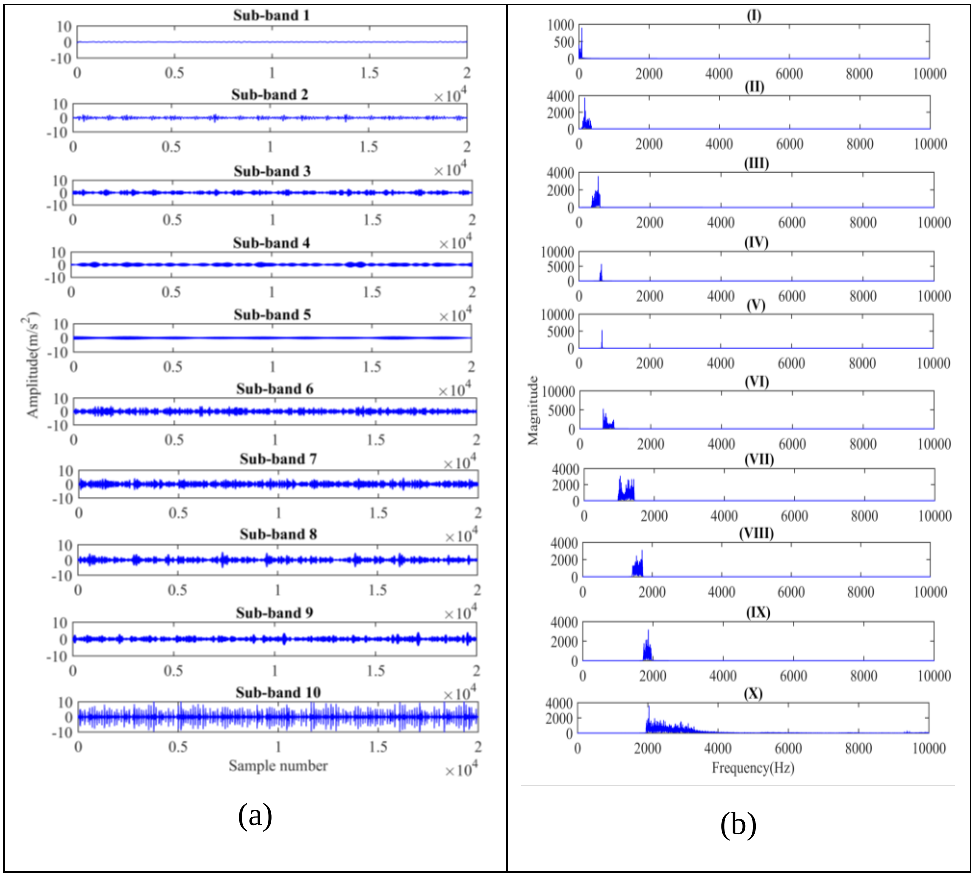


Figure 4. 5 (a) Applied EWT decomposition and find sub-bands, (b) Represent the magnitude spectrum of their respective sub-bands.

The Kruskal-Wallis test is conducted to see if there are substantive distinctions between the categories. A calculation of probability, denoted by p, was used to measure it [25]. Table 4.3 shows the EWT and FBSE-EWT, p-values for 120 different pairs of gear crack signals. Also from Table 4.3, the statistical analysis indicated that it is necessary to omit the sub-bands signal for those with p values that are more than 0.05 [31]. The classifier gets the significant statistical features that are extracted from the retentates. There are three different classifiers utilised in the method that has been presented i.e., random forest, J48 decision tree classifiers, and multilayer perceptron function classifier. To train the classifiers, the ten-fold cross-validation method [31] was applied to both the training data sets and the testing data sets. This was done so that the classifiers could be properly evaluated.

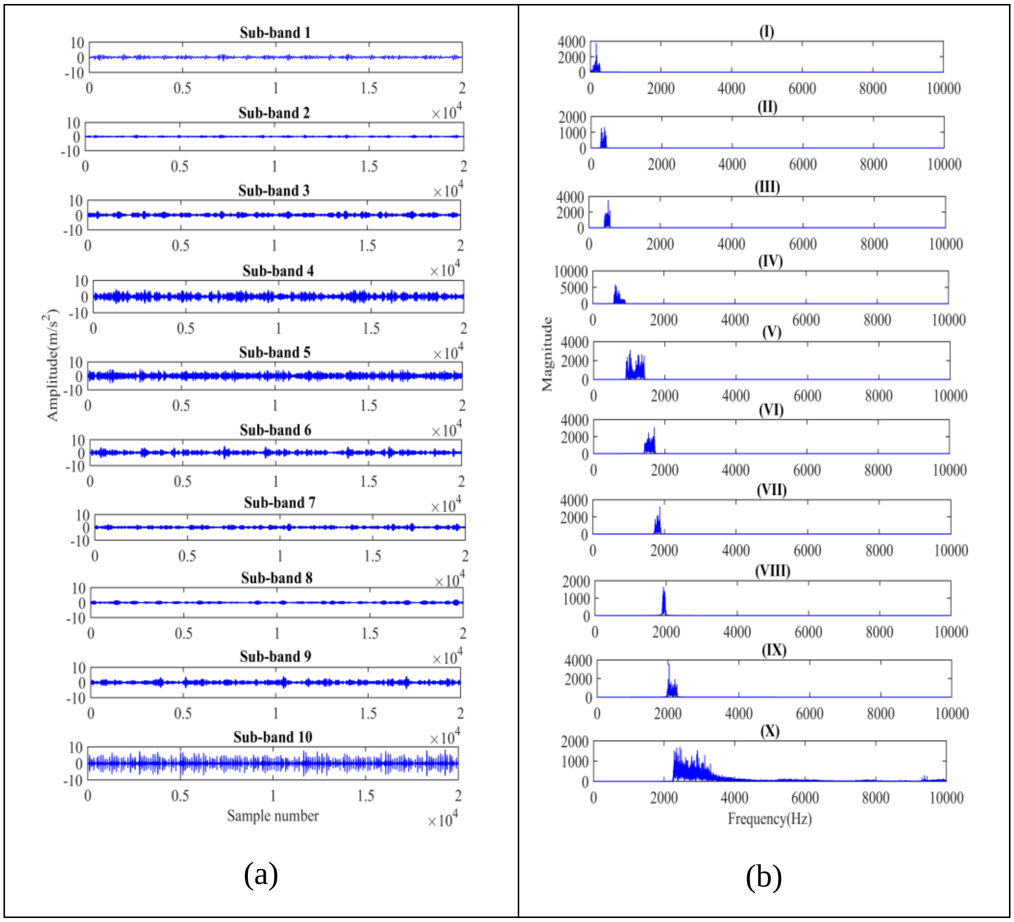


Figure 4. 6 (a) Applied FBSE-EWT decomposition and find sub-bands, (b) Represent the magnitude spectrum of their respective sub-bands.

The complete data set is randomly divided into two groups throughout the cross-validation process. The first group is called the training set, and it contains 90 percent of the total data. The second group is called the testing set (10 percent). The procedures were carried out 10 times to conduct ten-fold cross-validation, which removes any potential sources of bias from the process of separating data into training and testing data sets. According to Table 4.4, EWT-based individual features and their combination features, including kurtosis, RMS, variance, and Shannon entropy, the random forest classifier showed the highest possible performance accuracy with 57%, 62.5%, 59%, 59.5%, 66.5%, 66%, 68.5%, 59%, 59%, 61%, 65.5%, 66%, 60%, and 66.5% accuracy respectively.

Table 4. 3 Probability (p) value for various features of gear signals using EWT and FBSE-EWT (Proposed method).

Methods	**EWT**				**FBSE-EWT (Proposed method)**			
Bands	**Kurtosis**	**RMS**	**Variance**	**Shannon entropy**	**Kurtosis**	**RMS**	**Variance**	**Shannon entropy**
Sub-band 1	1.0591×10^{-09}	7.6275×10^{-05}	7.7517×10^{-05}	4.7474×10^{-07}	1.2526×10^{-06}	0	0	0
Sub-band 2	0	0	0	0	1.3039×10^{-06}	0	0	0
Sub-band 3	0.0001	0	0	0	0	1.0831×10^{-07}	1.0839×10^{-07}	3.4883×10^{-08}
Sub-band 4	0.0021	0	0	0	1.3918×10^{-08}	0	0	0
Sub-band 5	0.0001	0	0	0	0.008	0	0	0
Sub-band 6	0.0010	0	0	0	0.0111	0	0	0
Sub-band 7	0.0075	0	0	0	0.0020	0	0	0
Sub-band 8	0.7022	0	0	0	0.0029	9.0985×10^{-09}	0	8.0157×10^{-09}
Sub-band 9	0.4692	0	0	0	0.0034	1.8916×10^{-07}	1.8847×10^{-07}	1.4926×10^{-07}
Sub-band 10	0	0	0	0	0	0	0	0

Table 4. 4 Details of the classification performance of classifiers for corresponding features using EWT and FBSE-EWT methods.

S. No.	**Features**	**Performance of the classifiers (%) using EWT**			**Performance of the classifiers (%) using FBSE-EWT (Proposed method)**		
		Random forest	**Multilayer perceptron**	**J48**	**Random forest**	**Multilayer perceptron**	**J48**
1	Kurtosis	57	43.5	40	77.5	55	42
2	RMS	62.5	51.5	52	67	61.5	51
3	Variance	59	46	43.5	68.5	48.5	43.5
4	Shannon entropy	59.5	59.5	44	67.5	46.5	44
5	Kurtosis and RMS	66.5	55	50	83.5	66	53
6	Kurtosis and variance	66	51.5	53	73	62.5	53.5
7	Kurtosis and shannon entropy	68.5	50.5	49	**84**	73	55
8	RMS and variance	59	54	46	66.5	63	46
9	RMS and shannon entropy	59	53	43	69.5	60	50
10	Variance and shannon entropy	61	48	41	69.5	48	41
11	Kurtosis, RMS, and variance	65.5	54	44	72.5	68	46.5
12	Kurtosis, variance, and shannon entropy	66	54.5	42	73	61.5	43
13	RMS, variance, and shannon entropy	60	51.5	49	64.5	55	49
14	RMS, shannon entropy, and kurtosis	66.5	53.5	39	82.5	72.5	39
15	Kurtosis RMS, variance, and shannon entropy	66	52	45	73	67	43

Additionally, the random forest classifier has demonstrated a high level of accuracy with 77.5%, 67%, 68.5%,67.5%, 83.5%, 73%, 84%, 66.5%, 69.5%, 69.5%, 72.5%, 73%, 64.5%, and 82.5% from Table 4.4 FBES-EWT based on the same feature combination. According to Table 4.4, FBES-EWT achieved the highest classification accuracy, which was 84%, by employing a random forest classifier that incorporated the Kurtosis and Shannon entropy characteristics.

4.5 Conclusion

Any malfunction in gear systems increases maintenance costs and downtime. Automated fault diagnosis of such systems could be a promising way to deal with such conditions. The EWT and FBSE-EWT method has been used to decompose different level of bevel gear crack fault signals. The obtained sub-bands are used to evaluate features. To improve the realization, statistically, significant features with ($p<0.05$) are decided using the Kruskal-Wallis statistical test. These statistically significant features are fed to the Classifiers. The maximum classification accuracy of 84% is obtained using the FBSE-EWT method with a random forest classifier for kurtosis and Shannon entropy features. It is observed that FBSE-EWT is-better than the EWT for gear fault deduction. It is also observed that the classification accuracy for the random forest is better than that of multilayer perceptron and J48 classifiers. Comparative studies provide confirmatory evidence that the proposed approach FBSE-EWT is superior to EWT. Moreover, the present investigation and findings of the proposed methodology are quite helpful for the automatic identification of crack gear faults to diagnose the system with good accuracy.

Chapter 5

A comparative study between the proposed advanced signal processing techniques

In this chapter, a comparative study is carried out between the proposed methodology. The significance is to find out, which one gives the best classification accuracy. Micron level of wear gear signals with different faults has been decomposed using the FAWT, iterative VMD, and FBSE-EWT signal processing methods. After the 10 levels of decomposition various statistical features namely kurtosis, skewness, standard deviation, root mean square, and crest factor are extracted from the different sub bands. Further, for identification of significant features performed by the Kruskal-Wallis test. Those significant features are fed to different multi-class classifiers, which are random forest, multilayer perceptron, and J48 classifiers. It has been observed from the comparative study, FAWT-based methodology exhibits 97.66% accuracy using a random forest classifier with combined kurtosis, skewness, standard deviation, and RMS features.

5.1 Introduction

Gear condition monitoring is the process of analyzing the health and performance of gears in machinery to identify any potential faults or issues before they become serious problems. It involves the use of various techniques and technologies to detect, diagnose, and analyze the condition of gears, including vibration analysis, oil analysis, acoustic emission testing, and thermography. The importance of gear condition monitoring cannot be overstated, as gears are critical components in many machines and systems, such as automotive engines, wind turbines, and industrial gearboxes. Failure or damage to gears can result in downtime, reduced productivity, and costly repairs, making it essential to monitor their condition regularly. One of the primary benefits of gear condition monitoring is that it allows maintenance teams to identify potential issues early on before they escalate into more significant problems. Another advantage of gear condition monitoring is that it helps to extend the lifespan of gears, reducing the need for costly replacements. A comparative study is a useful way to learn more about methods, figure out how well they work, make well-informed decisions, and find new opportunities. But it is important to figure out which methods give the most accurate classifications. The method demonstrated its effectiveness based on the efficacy of its classification. Therefore, it is necessary to conduct an analysis of the recommended approaches side by side. In this regards, micron level of wear gear signal with different faults has been decomposed using the FAWT, interactive VMD, and FBSE-EWT signal processing.

5.2 Proposed methodology

In this section, the steps in the proposed methodology are illustrated in Fig. 5.1. The proposed methods based on FAWT, VMD, and FBSE-EWT are all signal-processing techniques that are commonly used in various applications. The following is some information that is fundamentally important regarding each of them:

1. FAWT: This method is used to analyse non-stationary data. The FAWT combines the advantages of complex analysis and wavelet analysis into a single process. This method is particularly useful for evaluating signals that display non-stationary behaviour, such as audio, biomedical, and mechanical signals. This is because FAWT allows for the investigation of signals in the time-frequency domain, which includes both positive and negative frequency separation.

2. VMD: Variational Mode Decomposition is a method of signal processing that divides a signal into a limited number of oscillatory components. These components are referred to as IMFs.

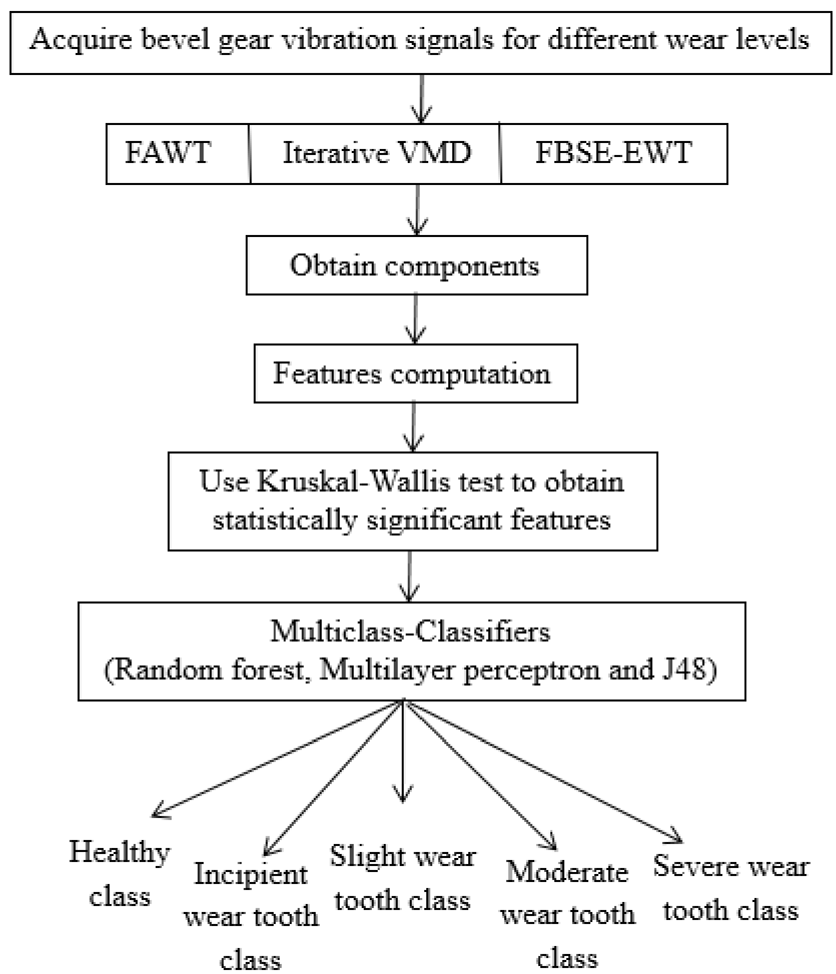


Figure 5. 1 A block diagrammatic representation of the methodology

3. FBSE-EWT: Combining a Fourier-Bessel series expansion method with an empirical wavelet transform is the basis for the signal processing approach known as FBSE-EWT. The FBSE-EWT is particularly helpful for analysing signals with non-stationary behaviour, such as audio and image signals. For more details of signal processing technique, features, the Kruskal-Wallis test, and classifiers, readers can refer to Chapters 2.2, 3.2, and 4.2.

5.3 Experimental data collection

The gear vibration signals have been used as same in Chapter 2. For more details, the reader may refer to Chapter 2.3.

5.4 Results and discussion

The objective of this research is to provide an automated system for the identification of gear faults by doing a comparison analysis with proposed diagnostic approaches.

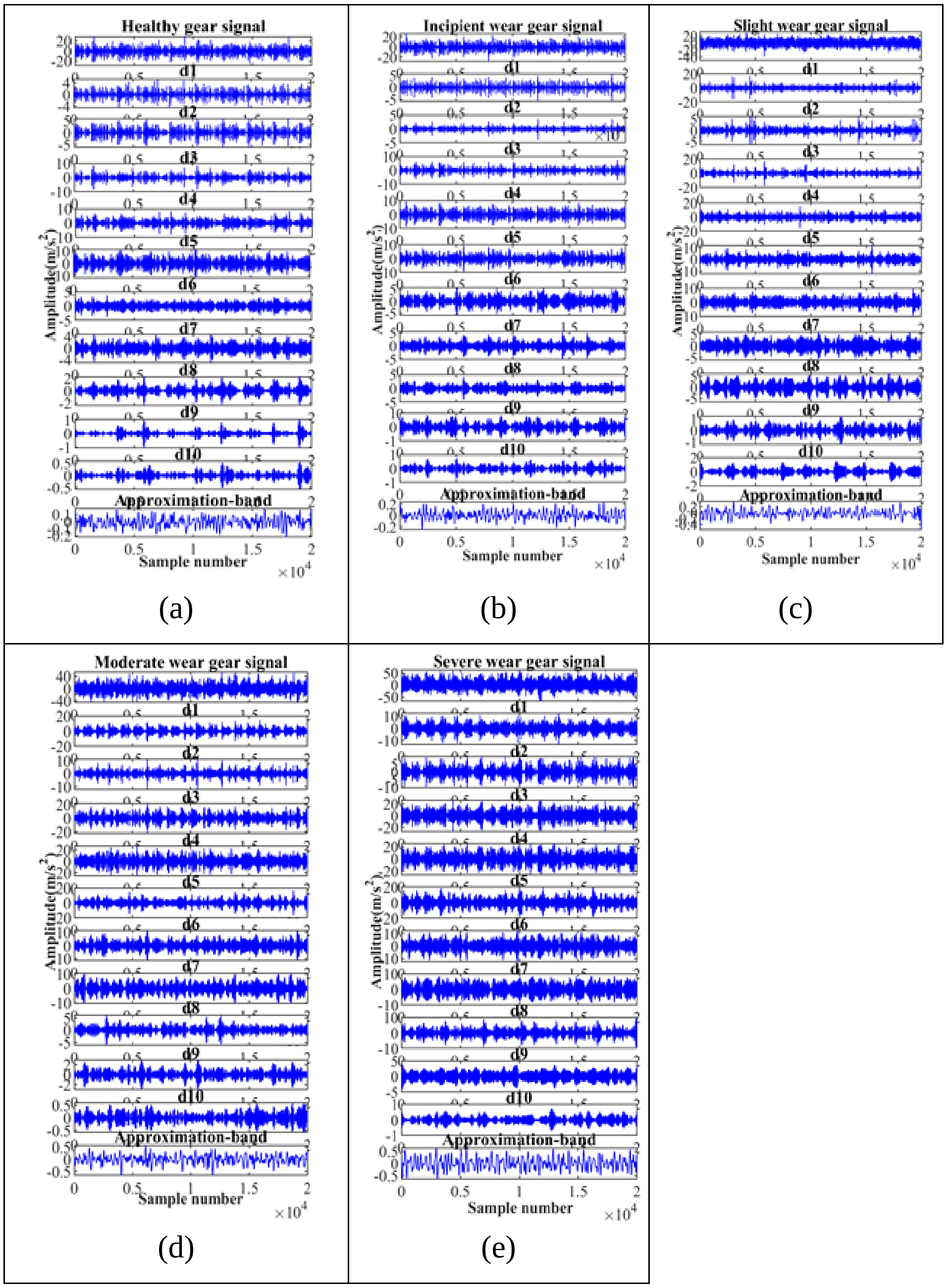


Figure 5. 2 Applied FAWT decomposition (10 levels) on gear signals. (a) healthy gear signal, (b) incipient wear gear signal, (c) slight wear gear signal, (d) moderate wear gear signal, (e) severe wear gear signal

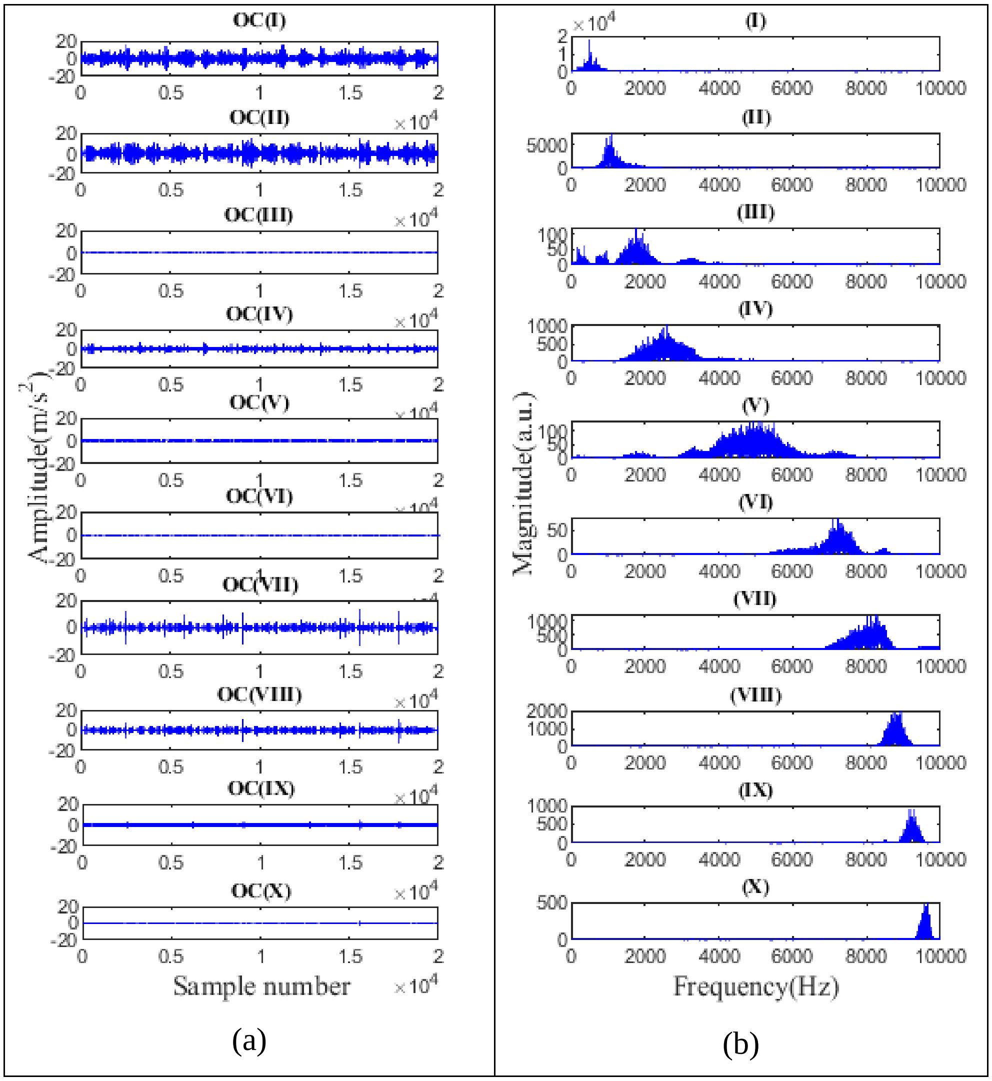


Figure 5. 3 (a) Plots of the OCs using method for healthy bevel gear signal. (b) Plots of the magnitude spectrum of respective OCs using iterative VMD method for healthy bevel gear signal. The unit of Y axis are arbitrary.

The FAWT is a flexible wavelet transform that provides flexibility to decompose a given signal into desired frequency bands with the help of chosen control parameters. It decomposed the gear signals into detailed sub-bands (d1-d10) and approximation sub-band. After applying FAWT with 10 levels of decomposition, the decomposed signals are shown in Fig. 5.2. The approximation and detail sub-bands at this level 10 represent bands of [0, 0.7] Hz and [0.7, 2.18] Hz respectively and extended up to level 1.

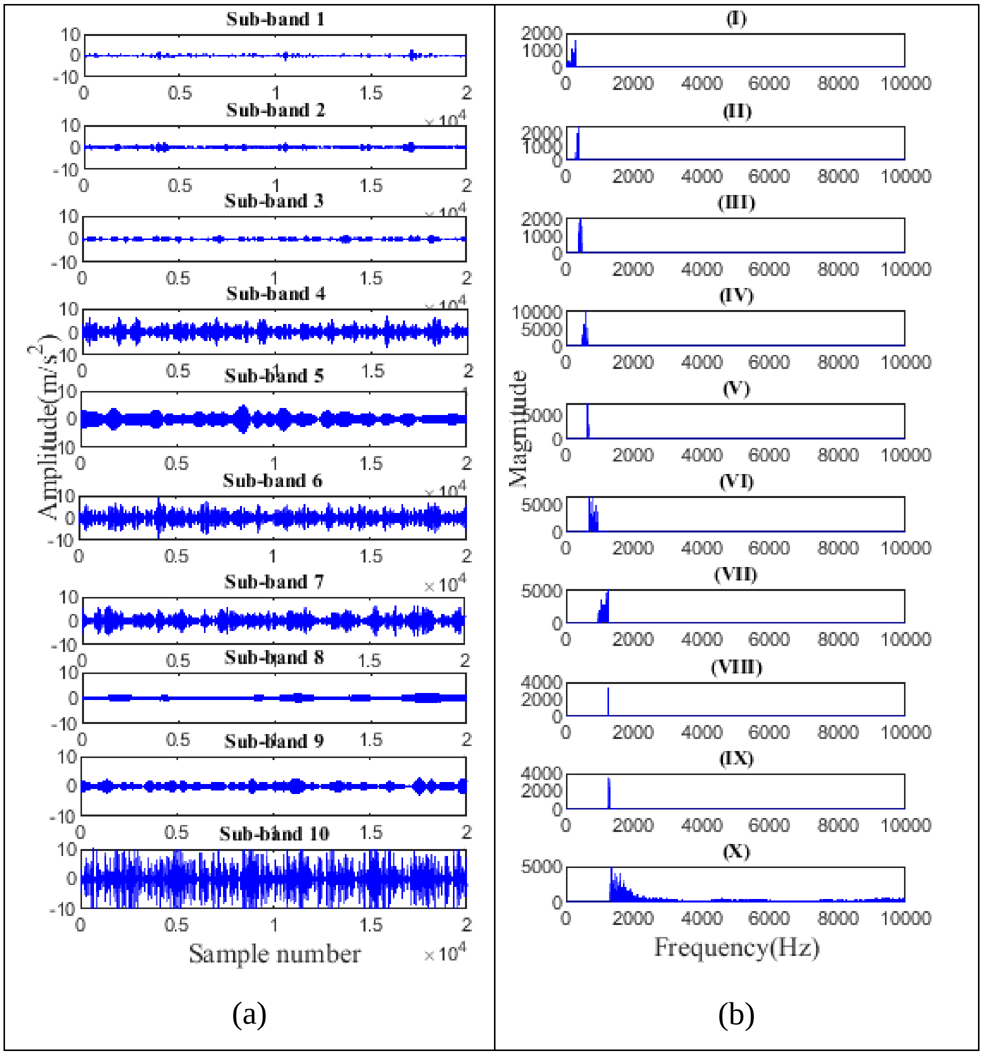


Figure 5. 4 (a) Applied FBSE-EWT decomposition and find sub-bands, (b) Represent the magnitude spectrum of their respective sub-bands.

The iterative VMD method is applied to decomposed healthy gears signal and different level of wear faults signals. By using iterative VMD, the gear signals are decomposed using the input parameters DC=0, α =200, K =10, τ =0, tol=10^{-7}, ω (init)=0. Fig. 5.3 (a) shows the plots of the OCs and Fig. 5.3 (b) shows the respective magnitude spectrums of OCs using iterative VMD Other proposed method FBSE-EWT also found decomposition of signals input parameters such as (global trend removal "none"; regularization "gaussian", detection method "locmax", maximum number of bands "10") were used respectively. Fig. 5.4 (a and b) shows the decomposed sub- bands for all gear with the magnitude spectrum of their

Table 5. 1 Probability (p) value for various features of gear signals using all conditions after employed FAWT.

Obtaind components	Kurtosis	Skewness	Standard deviation	Root mean square	Crest factor
Sub-band 1	0	$1.7726\text{x}10^{-05}$	$4.39704\text{x}10^{-06}$	$9.06345\text{x}10^{-08}$	$1.09622\text{x}10^{-07}$
Sub-band 2	0	0	0	$9.4531\text{x}10^{-08}$	0
Sub-band 3	0	0	0	$9.5472\text{x}10^{-08}$	0
Sub-band 4	0	0	0	$4.17236\text{x}10^{-08}$	0
Sub-band 5	0	$8.06345\text{x}10^{-09}$	$2.77827\text{x}10^{-05}$	$3.93979\text{x}10^{-08}$	0
Sub-band 6	0	0	0	$7.14731\text{x}10^{-08}$	0
Sub-band 7	0	0	0	$5.29836\text{x}10^{-08}$	0
Sub-band 8	0	0	0	$7.5\text{x}10^{-08}$	0
Sub-band 9	0	$1.53793\text{x}10^{-07}$	0	$7.25174\text{x}10^{-08}$	0
Sub-band 10	0	0	0	$6.28929\text{x}10^{-08}$	0
Approximation-band	0	$5.67791\text{x}10^{-07}$	$1.15435\text{x}10^{-05}$	$1.90446\text{x}10^{-08}$	$2.41416\text{x}10^{-08}$

respective sub-bands. From all the sub-bands were used to extract various features namely kurtosis, skewness, standard deviation, root mean square, and crest factor. The Kruskal–Wallis test is used to determine any statistically significant differences between the classes. It is measured by using probability (p) computation. Table 5.1, Table 5.2, and Table 5.3 has shown the p-value of all statistical features for gears with different levels of wear faults signals. From Table 5.1, Table 5.2, and Table 5.3, it is found that there is a need to omit the sub-band signal those $p > 0.05$ [50]. The retentates statistically significant features are fed to the classifier. These statistically significant features are fed to all three classifiers random forest, multilayer perceptron, and J48. Ten-fold cross-validation technique [101] has been used for training and testing of data set to train the classifiers.

Table 5. 2 Probability (p) value for various features of gear signals using all conditions after employed iterative VMD.

Obtaind components	Kurtosis	Skewness	Standard deviation	Root mean square	Crest factor
Sub-band 1	0	0.1365	0.3163	0	0
Sub-band 2	2.3141×10^{-04}	0.006	0.1239	0	0.0226
Sub-band 3	1.3201×10^{-09}	9.5499×10^{-04}	9.9115×10^{-09}	0	0
Sub-band 4	1.4822×10^{-05}	0	3.1324×10^{-08}	0	0
Sub-band 5	0.3841	0.0005	1.8219×10^{-05}	0	0
Sub-band 6	0	0.0052	0	0.4649	0
Sub-band 7	0.05841	1.91493×10^{-05}	0	2.0224×10^{-08}	0.0095
Sub-band 8	0	0.4163	0	2.0224×10^{-08}	0.2165
Sub-band 9	2.1981×10^{-08}	0.1249	0.2365	0	0
Sub-band 10	0	0	0	0	0

Table 5. 3 Probability (p) value for various features of gear signals using all conditions after employed FBSE-EWT.

Obtaind components	Kurtosis	Skewness	Standard deviation	Root mean square	Crest factor
Sub-band 1	1.2526×10^{-06}	0	0	0	0
Sub-band 2	1.3039×10^{-06}	0	0	0	0.0346
Sub-band 3	0	1.0831×10^{-07}	1.08392×10^{-07}	3.4883×10^{-08}	0.1012
Sub-band 4	1.3918×10^{-08}	0	0	0	0.0079
Sub-band 5	0.008	0.4724	0	0.3652	0.1349
Sub-band 6	0.0111	0	0	0	0
Sub-band 7	0.002	0	0	0	0.0295
Sub-band 8	0.0029	9.0985×10^{-09}	0	8.0157×10^{-09}	0
Sub-band 9	0.0034	1.8916×10^{-07}	1.8847×10^{-07}	1.4926×10^{-07}	0.0038
Sub-band 10	0	0	0	0	2.3219×10^{-04}

Table 5. 4 Details of the classification performance of classifiers for corresponding features using FAWT, iterative VMD, and FBSE-EWT.

S. No.	Features	Performance of the classifiers (%) using FAWT			Performance of the classifiers (%) using iterative VMD			Performance of the classifiers (%) using FBSE-EWT		
		Random forest	**Multilayer perceptron**	**J48**	**Random forest**	**Multilayer perceptron**	**J48**	**Random forest**	**Multilayer perceptron**	**J48**
1	Kurtosis	97.16	90.16	89.03	89.30	83.32	76.5	70.50	57	43.5
2	Skewness	90.90	85.5	85.83	75.36	78.20	73.06	60.09	62.5	41.5
3	Standered deviation	92.83	92.83	84.00	84.83	85.40	75.00	68.06	59.03	56.16
4	Root mean square (RMS)	96.83	92	84.16	89.06	85.30	78.09	70.83	59.16	59.5
5	Crest factor	83.66	85.33	80.83	83.03	81.09	76.00	68.16	66.66	45.33
6	Kurtosis, and skewness	89.16	84.33	81.83	85.30	75.80	75.33	70.09	66	51.5
7	Kurtosis, Skewness, and standered deviation	96.66	94.16	75.83	85.32	79.83	70.03	72.05	68.5	50.16
8	Kurtosis, Skewness and standered deviation, and RMS	**97.66**	96.16	73.33	90.31	85.79	83.09	74.83	69.66	54.03
9	Kurtosis, skewness, standered deviation, RMS, and crest factor	96	95.33	75.83	86.16	76.16	70.03	62.05	59.06	43.06

A comparative study between proposed methodologies is summarized in Table 5.4. According to Table 5.4, FAWT-based individual features and their combination features, including kurtosis, skewness, standard deviation, RMS, and crest factor, the random forest classifier showed the highest possible performance accuracy with 97.16%, 90.90%, 92.83%, 96.83%, 83.66%, 89.16%, 96.66%, 97.66%, 96% accuracy respectively. Same details after using iterative VMD, it's 89.30%, 75.36%, 84.83%, 89.06%, 83.03%, 85.30%,85.32%, 90.31%, and 86.16%. And for FBSE-EWT gets 70.50%, 60.09%, 68.06%, 70.83%, 68.16%, 70.09%, 72.05%, 74.83%, and 62.05% accuracy respectively. Finally conclude from the Table 5.4, FAWT-based methodology exhibits 97.66% accuracy using a random forest classifier with combined kurtosis, skewness, standard deviation, and RMS features.

5.5 Conclusion

To analyse the comparison research that was offered between the proposed methodologies, the following purposes were pursued: Examining which one offers the highest degree of classification accuracy is significant for this purpose. According to the performance of the classification, the method demonstrated the power of methodology. It has been observed from the comparative study that FAWT-based methodology exhibits highest degree of classification accuracy 97.66% using a random forest classifier with combined kurtosis, skewness, standard deviation, and RMS features.

Chapter 6

Conclusions and future scope

In this chapter, the findings and noteworthy contributions of this thesis toward the evaluation of automated fault diagnosis of gearbox using advanced signal processing techniques with different classifiers are presented. In addition to that, it presents the potential expansion of the scope of this study in the future.

6.1 Conclusions

In this chapter, the conclusions of gear fault diagnosis using advanced signal processing techniques are summarized as follows:

- the FAWT method, an advanced technique for signals analysis of micron-level wear of bevel gear, has been implemented for faults diagnosis. The gearbox signals of healthy and faulty gears are decomposed into each sub-band and calculated the entropies are for each sub-band into the 10^{th} level. It was observed that the log energy entropy using a multi-class LS-SVM classifier with RBF kernel resulted in the maximum value of classification performance of 98.33%,97.91%, 100%, 100%, 92.30%, and 0.95 for ACC, SEN, SPF, PPR, NPR, and MCC respectively. The results obtained here are compared with the previous results obtained by different methods, such as the CWT, DWT, WPT, DTCWT, and TQWT. Due to this characteristic feature the log energy entropy outperforms the other entropies and subsequently provides the best classification of the signal classes. This indicates that the proposed methodology is the best suitable method for the automated identification of gear faults.

- Gear wear is a major concern in the gear transmission system. In this work, fault diagnosis of gear in the presence of level of wear in micron faults was done using the iterative VMD method. Experiments were conducted to acquire vibration signals from bevel gears for a different levels of wear faults. The iterative VMD was used to decompose the signals into different OCs. Significant features were extracted using the Kruskal-Wallis statistical test. That significant features were fed as input parameters in the classifiers. Three different classifiers (random forest, multilayer perceptron, and J48) were used to classify the multi-classes. It is observed that the random forest classifier achieves the best classification accuracy with the combination of kurtosis, skewness, and standard deviation features.
- Any malfunction in gear systems increases maintenance costs and downtime. Automated fault diagnosis of such systems could be a promising way to deal with such conditions. The EWT and FBSE-EWT method has been used to decompose different level of bevel gear crack fault signals. The obtained sub-bands are used to evaluate features. To improve the realization, statistically, significant features with ($p<0.05$) are decided using the Kruskal-Wallis statistical test. These statistically significant features are fed to the Classifiers. The maximum classification accuracy of 84% is obtained using the FBSE-EWT method with a random forest classifier for kurtosis and Shannon entropy features.
- It has been observed from the comparative study, FAWT-based methodology exhibits 97.66% accuracy using a random forest classifier with combined kurtosis, skewness, standard deviation, and root mean square (RMS) features.

6.2 Scope for future work

This thesis covers essential challenge-based condition monitoring for fault detection in bevel gear systems; however, there remain a few recommendations that may be carried out in the future. For further consideration in the future, the following study directions are suggested.

1. The proposed approaches may also be utilised to diagnose combinations of local defects with levels of micron that may be present in a gearbox.
2. It is also possible to investigate gears other than bevel gears, such as spur gears, helical gears, planetary gears, and so on while trying to diagnose a fault.
3. It is possible to evaluate the efficacy of the presented methods for a variety of biological signals. Those are an electrocardiogram (ECG) or an electromyogram (EMG), which enables one to determine whether they are suitable for certain signal processing. This study can assist in emphasising each methodology's shortcomings and advantages and selecting suitable methodologies for processing different biological information.
4. The feasibility of the suggested techniques may also be examined in terms of their effects on other rotating and reciprocating equipment as well as electrical systems.
5. Based on the efficacy of proposed methodologies and created faults, they can be applied to fault diagnosis for polymer gear.
6. Proposed methodologies can also be implicated in image processing.

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LIST OF PUBLICATIONS

International Journal papers

1. D. S. Ramteke, A. Parey, and R. B. Pachori, "Automated gear fault detection of micron level wear in bevel gears using variational mode decomposition," *J Mech Scie and Tech*, vol 3, no. 12, pp 5769-5777, 2019. https://doi.org/10.1007/s12206-019-1123-2.

2. D. S. Ramteke, R. B. Pachori, and A. Parey, "Automated gearbox fault diagnosis using entropy based features in flexible analytic wavelet transform (FAWT) domain," *J Vib Engi & Tech*, pp 1-11, 2021. https://doi.org/10.1007/s42417-021-00322-w

3. D. S. Ramteke, A. Parey, and R. B. Pachori, "A New Automated Classification Framework for Gear Fault Diagnosis Using Fourier–Bessel Domain-Based Empirical Wavelet Transform," Machines, vol 11, 1055, pp 1-17, 2023. https://doi.org/10.3390/machines11121055

List of Publications (apart from thesis)

Book chapters:

1. A. S. Ahuja, D. S. Ramteke, A. Parey, "Vibration-based fault diagnosis of a bevel and spur gearbox using continuous wavelet transform and adaptive neuro-fuzzy inference system," Springer Book on Soft Computing in Condition Monitoring and Diagnostics of Electrical and Mechanical Systems by Book Series chapter on Advances in Intelligent Systems and Computing Editor of Springer Nature: pp 473-496, 2020. https://doi.org/10.1007/978-981-15-1532-3_22.

2. P. Dewangan, D. S. Ramteke, A. Parey, "Model Based Fault Diagnosis in Bevel Gearbox," publication in Smart Monitoring of rotating machinery for industry 4.0 - Theory and applications,

Springer book series “Applied Condition monitoring”, (Springer), pp 117-133, 2021. https://doi.org/10.1007/978-3-030-79519-1_7.

3. P. Dewangan, D. S. Ramteke, A. Parey, “Modeling of Chipped Tooth Fault in Straight Bevel Gears,” in Recent Trends in Engineering Design, Lecture Notes in Mechanical Engineering (Springer), pp 225-235, 2021. https://doi.org/10.1007/978-981-16-1079-0_23.