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Original Article

Defect Detection in Rotor-Bearing-Gear Systems for Experimental Frequency-Domain Fault Diagnosis using FFT and Machine Learning Techniques

Rahul Ramesh Joshi[1,2], Sanjay Hari Sawant[3], Ajit Ashok Katkar[4]

[1]*Research Scholar, Shivaji University, Kolhapur, MS, India.*
[2]*Assistant Professor, International Institute of Information Technology, Pune, MS, India.*
[3]*PhD Guide & Principal, Sant Gajanan Maharaj College of Engineering, Mahagaon, Kolhapur, MS, India.*
[4]*Associate Professor, Sanjeevan Group of Institutes, Panhala.*

[1]*Corresponding Author : rahul.joshi719@gmail.com*

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***Abstract** - Rotor bearing gear system is mostly used in rotating machinery in industries and has considerable susceptibility to defects such as wear, pitting, and failure in gears, corrosion of components, and damage to bearings under different operating conditions. This paper presents an experimental study of fault diagnosis implemented in the frequency domain using the Fast Fourier Transform (FFT) and Machine Learning Techniques. In the Experimental study, the bevel gearbox test rig was exercised under various operating conditions (200 rpm to 1000 rpm, loading (20 N to 100 N)), and six types of faults were exercised for each case, including mutually imposed multiple fault conditions. For each fault condition, FFT analysis identified characteristic fault frequencies, harmonics, sidebands, and modulation effects were found by FFT analysis. We observed that as the fault level, speed, and load increased, vibration amplitude increased significantly. Frequency-domain vibration features were used in this study with machine learning classifiers to determine fault conditions, demonstrating the effectiveness of the proposed method for condition monitoring and predictive maintenance applications.*

***Keywords** - Bearing faults, Frequency domain data, Gear faults, Vibration analysis.*

1. Introduction

System reliability and performance have a major impact on industrial productivity and efficiency. Mechanical stresses, fatigue loading, thermal effects, lubrication degradation, and environmental contamination are harsh factors that affect rotating machinery operation under varying speed and load conditions [1, 2]. During machine operation, various defects such as gear wear, pitting, tooth fracture, bearing wear, and bearing pitting slowly accumulate. If left undiagnosed, these faults can cause excessive vibration, unpredictable machine failures, higher maintenance costs, and production losses. In industry, condition monitoring is used to detect faults in machines at an early stage [3, 4].

Compared with other condition monitoring techniques, vibration analysis is one of the most effective and non-invasive diagnostic methods, as a machine's vibration behavior is affected by mechanical faults. Vibration-based fault diagnosis techniques learn defect signatures by processing vibration signals produced during machine operation [5, 6]. Vibration-based fault diagnosis, a method that has been firmly established for many years, has, in the last two decades, turned into one of the most popular techniques for rotor condition monitoring. Frequency-domain analysis has been widely used because of its computational efficiency and direct physical interpretation, providing a valuable tool to diagnose characteristic fault frequencies related to gear meshing, bearing defects, shaft imbalance, and misalignment. Various spectral features, such as gear meshing frequency, bearing characteristic frequencies, harmonics, and modulation sidebands, have been shown to be valuable in the early stages of fault initiation and progression. Thus, FFT-based vibration analysis is still a popular tool in the area of industrial condition monitoring because of its ease, reliability, and ability to be performed in real time.

Recent studies have used machine learning algorithms in combination with vibration signal analysis to improve diagnostic accuracy and reduce the need for manual reading of vibration spectra. Various supervised learning algorithms, such as Decision Tree, Random Forest, Support Vector Machine (SVM), Naïve Bayes, and K-Nearest Neighbor (KNN), showed promising results in automatic fault classification using vibration features engineered with a multi-step Algorithm. The engineered vibration features by the multi-step Algorithm resulted in acceptable performance using supervised learning techniques: Decision Tree, Random Forest, Support Vector Machine (SVM), Naïve Bayes, and K-Nearest Neighbor (KNN) algorithms. In recent years, deep learning algorithms have been investigated to extract the fault features directly from vibration signals, including Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks, hybrid neural network architectures, etc. It is found that these methods have a high classification accuracy in laboratory settings, but need a large number of labeled training samples, significant computational power, and a labor-intensive model training process that can limit their use in industrial settings where there is limited data availability and computational power. Despite the progress achieved in these developments, there are still a number of research gaps to be addressed.

The studies that have already been published focus on gear faults or bearing faults separately, or some studies test the defects of both gears and bearings, but in a limited number of operating speeds and loading conditions. Also, numerous new methods are based on deep learning models, which need vast amounts of labeled data, significant computational power, and complicated training procedures, and are therefore not easily applied in industrial settings. Furthermore, less attention has been paid to achieving accurate fault classification in real operating environments using an operationally independent and interpretable diagnosis framework that integrates features extracted from experimentally obtained FFTs with traditional machine learning algorithms.

An experimental fault diagnosis framework that can detect both single and combined gear-bearing defects with low computational complexity and high accuracy, and provide physically interpretable diagnostic information suitable for industrial predictive maintenance, is needed. The field of intelligent fault diagnosis has recently shifted toward end-to-end deep-learning-based approaches that automatically learn discriminative features directly from raw vibration signals without manual feature design.

These deep learning models have been significantly effective at understanding the diagnostic aspects of rotating machinery through capturing complex nonlinear relationships in vibration data, including Convulotional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), Autoencoders, Transformer-based models and hybrid combinations of these. These have improved fault classification accuracy in the laboratory and demonstrated strong fault-discrimination potential across a variety of fault types in gears, bearings, and rotor systems. Their performance typically depends on access to large labeled datasets, substantial computational power, and long training periods, which can limit their utility in real-world industrial condition-monitoring frameworks. In spite of the obvious development of intelligent fault diagnosis systems, the study of simultaneous defects of the gear and bearings is relatively limited, which is easy to understand from the innovation of recent deep learning and transfer learning techniques. Still, so far, no research has been conducted to explicitly consider the influence of various working conditions and rotation speeds while preserving model interpretability and low computational complexity. Moreover, little effort has been made to combine physically meaningful FFT-derived features with classical supervised machine learning algorithms for practical industrial applications. This study takes the state of the art forward to fill this void by introducing an experimentally validated diagnostic framework comprising a mixture of the interpretable FFT-based feature extraction process and the supervised machine learning classifiers for accurate identification under realistic experimental settings, in the three operational domains (Healthy, Single Fault and Combined Fault Mode Operating Conditions).

The novelty of the present work is that nine different gear-bearing health conditions under variable speed and load conditions (200-1000 rpm and 20-100 N) were comprehensively examined experimentally. The proposed approach controls fault conditions simultaneously (gear and bearing). It examines how they influence the frequency-domain aspects of vibration, whereas many existing studies consider only a single fault condition at a time.

Spectral features extracted using FFT are then used for machine-learning-based classification and form a highly efficient diagnostic framework for practical condition monitoring. The planned approach is experimental, frequency-domain-based, and a machine-learning classification effort that can be integrated as a diagnostic tool to enhance fault-discrimination capability without requiring a large amount of training data.

2. Materials and Methods

In this study, extensive laboratory testing has been conducted to understand better the tribological and dynamic characteristics of a single-stage bevel gearbox with healthy and faulty gears. The interaction of gear mesh dynamics with the stiffness of the bearing support, contact mechanics, and vibration signatures received special attention [7, 8].

The hardware platform consists of an experimental test rig that is developed and designed with mechanical component selection, control of the experimental test, generation of artificial tribological defects, Vibration measurement, and Signal processing in mind to create a reliable technique for fault diagnosis. The methodology involves the development and design of the experimental test rig, including the selection of mechanical components, control of the experimental test, artificial generation of tribological defects, vibration signal measurement, and signal processing to establish a reliable framework for fault diagnosis [9, 10].

2.1. Experimental Test Rig

A custom-made experimental test rig (Figure 1) was used to investigate the vibration characteristics of the bevel gearbox under controlled speed and load conditions. The rig comprised a 1 HP, 220 V permanent-magnet DC motor with a flexible coupling, which was coupled to a bevel gearbox capable of operating up to 3000 rpm. The output shaft was fitted with a frame-mounted rope/drum loading system to provide controlled mechanical loads. The applied load was measured using a calibrated load cell, and shaft rotational speed was monitored by using a non-contact speed sensor.

Using a high-speed ADASH 4404 SAB four-channel data acquisition system with high-sensitivity accelerometers (100 mV/g), a wide operating frequency range of 0.3 Hz to 90 kHz was sufficient to capture the high-frequency impacts associated with tribological defects [11, 12]. The test rig configuration allowed the alignment of the shafts, application of the load correctly, and achievement of the correct accuracy for measurements. This setup allowed systematic assessment of the gearbox vibration behavior as a function of operating speed, external load, and fault severity.

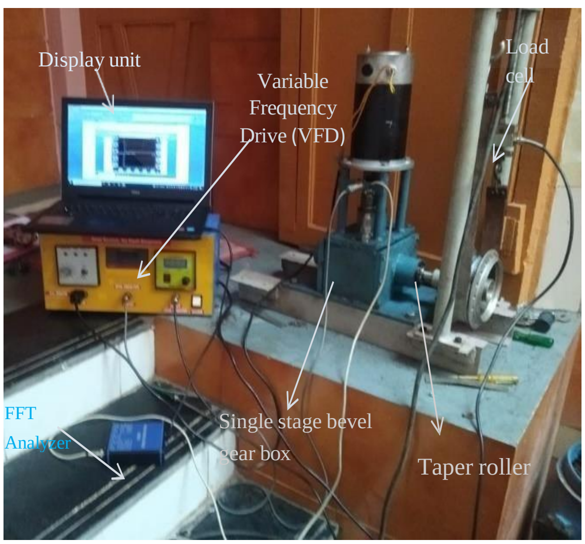

Fig. 1 Experimental test rig

2.2. Experimental Methodology

Repeatability and consistency are expected in the experimental investigation, which is conducted under carefully controlled laboratory conditions to enable vibration measurements. The gearbox assembly was first run under normal operating conditions, and a reference signature was obtained to establish the normal operating condition. Individual and combined combinations of artificial defects, consisting of gear corrosion, gear wear, gear pitting, gear fracture, bearing wear, and bearing pitting, were then added.

Vibration signals were collected across the entire operating range for each operating condition, using identical data acquisition settings and sensor locations. Two separate experimental runs were performed. The rotation speed was changed from 200 rpm to 1000 rpm, but the external load remained constant (50 N) for the first sequence. A second sequence was carried out, with the external load applied between 20 and 100 Newtons, at a fixed rotational speed of 500 rpm. To reduce random variation in measurements and, hence, the uncertainty of the experimental observations, multiple measurements were taken for each operating condition. Acquired vibration signals were then processed using the Fast Fourier Transform to extract representative frequencies, including gear meshing and bearing defect frequencies, which were then used for fault classification via a machine learning algorithm [12, 13].

Table 1. Specifications of SKF 30205 bearing and straight bevel gear

Parameter	Value	Parameter	Value
Bearing type	Single-row tapered roller	Gear type	Straight bevel gear
Bore diameter	25 mm	Number of teeth	20
Outer diameter	52 mm	Gear ratio	1:1
Total width	16.25 mm	Pitch circle diameter	60 mm
Inner ring width	15 mm	Module	3 mm
Outer ring width	13 mm		
Contact angle	14.036°		

2.3. Vibration Acquisition and Signal Processing

Time-domain vibration signals from the gearbox were acquired using the ADASH 4404 SAB system for each test condition. Signal processing was performed using the FFT to transform the signals from the time domain to the frequency domain. The number of teeth, N, and the revolutions per minute (rpm) were used to determine the Gear Meshing Frequency (GMF), as listed in Table 2. According to bearing fault equations, bearing characteristic frequencies of the inner race, outer race, and rolling element are calculated as shown in Table 3 using the standard frequency equations [14].

Table 2. Gear meshing frequency at different speeds

Speed (rpm)	Teeth	GMF (CPM)	GMF (Hz)
200	20	4000	66.67
300	20	6000	100.00
400	20	8000	133.33
500	20	10000	166.67
600	20	12000	200.00
700	20	14000	233.33
800	20	16000	266.67
900	20	18000	300.00
1000	20	20000	333.33

Table 3. Bearing characteristic frequencies

Speed (rpm)	Inner race freq. (Hz)	Outer race freq. (Hz)	Roller freq. (Hz)
200	32.99	23.68	19.30
300	49.98	35.52	28.96
400	65.98	47.36	38.61
500	82.47	59.19	48.26
600	98.97	71.03	57.91
700	115.46	82.87	67.56
800	131.96	94.71	77.21
900	148.45	106.55	86.87
1000	164.95	118.39	96.52

2.4. Feature Engineering and Selection

Feature engineering is an individual, separable step in vibration-based fault diagnosis, as the quality of the extracted features directly affects the classification results. This study applied a frequency-domain signal-processing technique to the raw vibration signals, using the Fast Fourier Transform to extract representative vibration diagnostic information. After the spectral transform, specific frequencies associated with the gearbox and bearing assembly were identified at a particular running speed and mechanical configuration for the experimental equipment. Extracted spectral characteristics were Gear Meshing Frequency (GMF), bearing characteristic frequencies, harmonic components, sideband amplitudes around the GMF, dominant peak features of the spectrum, and the corresponding side vibration amplitude of the dominant feature. These features were chosen because they have direct physical links to point-specific fault mechanisms inside gears and rolling element bearings. Gear defects typically alter the amplitude and harmonic characteristics around the gear-meshing frequency, while bearing defects add amplitude or frequency components containing harmonics of the interactions between rolling elements and damaged raceways. The feature set that is selected, therefore, conveys useful mechanical information without most of the redundant spectral information that would be detrimental to machine learning performance.

Besides physical relevance, feature selection has been carried out, aimed at reducing the amount of computation and enhancing the efficiency of a classifier. All spectral components that showed small energy changes across various operating conditions were omitted from further analysis; others with significant energy variation were kept for machine learning training. This procedure minimized redundant features, enhanced class separation, and facilitated effective discrimination between the healthy, single, and combined fault operating conditions, while being performed efficiently.

The chosen features from the frequency domain thus offer an adequate compromise between the required computing time and the diagnostic power and ease of interpretation of the underlying fault mechanisms.

2.5. Experimental Workflow

In the described investigations, the general sequence of experimental and analytical stages for the overall diagnostic methodology is being followed. For both healthy and faulty gear operating states, experimental bevel gearbox vibration signals were obtained at the specified speed and load. The Fast Fourier Transform was used to convert the acquired time-domain signals to the frequency domain to extract the characteristic spectral components associated with gear meshing and bearing defect frequencies. Later, features were identified in the representative frequencies and arranged into a structured feature set. This generated dataset was split into training and testing sets, and supervised machine learning algorithms, such as Decision Tree, Random Forest, Support Vector Machine, Naïve Bayes, and K-Nearest Neighbour classifiers, were then applied to the training set. Finally, the performance of each classification model has been measured using standard accuracy, precision, recall, and F1_score to assess its diagnostic ability.

2.6. Baseline Diagnostic Approach

The conventional approach to fault diagnosis, which relies solely on manual inspection of FFT spectra, is the one that has been used for years in the condition monitoring of rotating machines. While an experienced analyst can accurately detect the presence of a fault frequency or harmonic behaviour, manual interpretation can become more difficult as operating conditions change over time or when multiple fault frequencies and/or harmonic behaviours exist simultaneously. Most of the methods presented in the current research, as well as the consequent investigations, were thus chosen as the primary feature extraction method: FFT analysis. Supervised machine learning algorithms for automatic fault classification were selected. This integrated methodology maintains the physical structure of current vibration analysis, while preserving its simplicity and consistency within a diagnosis, virtually eliminating the need for expert interpretation. The baseline comparison thus provides evidence of the potential benefits of merging experimentally obtained frequency-domain features with data-driven classification methods for fault diagnosis solutions in practice.

3. Experimental Investigation

Most signals in real life are composed of a unique set of sine waves. Each sine wave will show as a column (or line) in the frequency domain, with the height of the column or line indicating the amplitude, and the frequency at which the wave occurs indicating the position of the line. The amplitude of the frequency-domain analysis is plotted as a function of frequency and compared with the time-domain plot, making it easier to detect the resonant frequency component. This is one of the reasons why frequency-domain methods are favored for detecting faults in the machine. Several characteristics of the signal that are not visible in the time domain can be observed through frequency-domain analysis [15, 16].

3.1. Amplitude Values at Different Speed Conditions

Case I: Healthy Bearing and Healthy Bearing

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.120	0.148	0.163	0.177	0.440
Amplitude(Bearing)(mm/s)	0.145	0.228	0.474	0.489	0.902

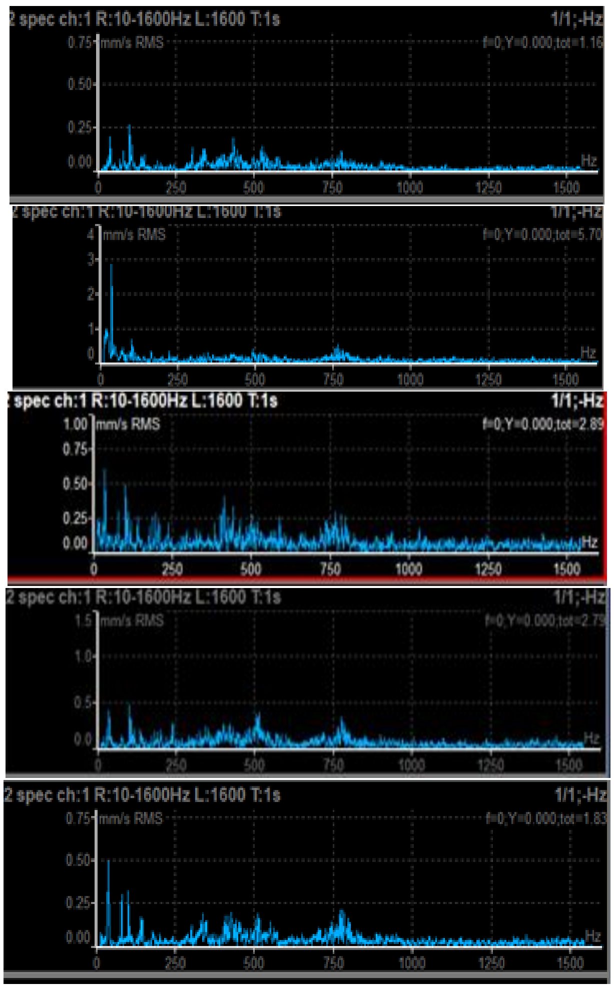

Fig. 2 Frequency domain plot of vibration signals of HGHB at various speeds

The frequency-domain response of the healthy gear and healthy bearing conditions displays clearly discernible and stable spectral features over the operating speed range of 200-1000 rpm. The amplitude at the Gear Meshing Frequency (GMF) gradually increases from 0.120 mm/s to 0.440 mm/s, indicating that vibration energy at the meshing frequency increases with higher speed due to the greater dynamic degrees of freedom. Also, at higher speeds, the amplitude at the peak of the bearing frequency rises from 0.145 mm/s to 0.902 mm/s, indicating the more significant role played by the motion of the rolling elements at higher speeds. There are no additional sidebands or irregular frequency components in the spectrum, indicating no defects-sharp peaks with high resolution, suggesting high-frequency, periodic oscillations. There is no modulation, no harmonic distortion - typical for a healthy system. The velocity is very linear, with amplitude increasing almost in proportion to speed. Dominant peaks are present at expected frequencies, and the noise floor is low. The bearing frequency amplitudes are slightly higher than those of GMF at higher speeds, suggesting a greater contribution from bearing dynamics. Therefore, this value is used to show the normal operation and will be compared with faulty samples.

Case II: Gear Corrosion and Healthy Bearing

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.212	0.347	0.511	0.556	0.977

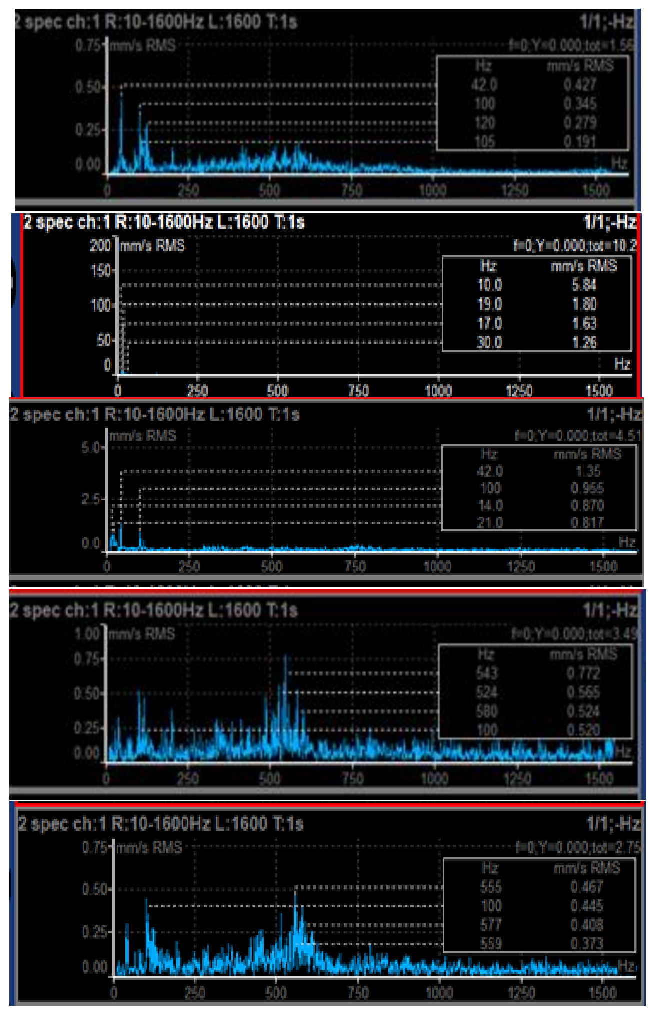

Fig. 3 Frequency domain plot of vibration signals of GCHB at various speeds

For gear corrosion when the bearing is healthy, the response will increase steadily with frequency, reflecting the increased vibration energy due to the degradation of the engagement surface. The lack of strong sidebands indicates that this is not a localized defect but rather a distributed fault caused by corrosion. Therefore, this represents the current vibration amplitude due to gear corrosion and some level of spectral distortion - but the system remains stable.

Case III: Gear Fracture and Healthy Bearing

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.570	0.770	1.507	1.670	1.693

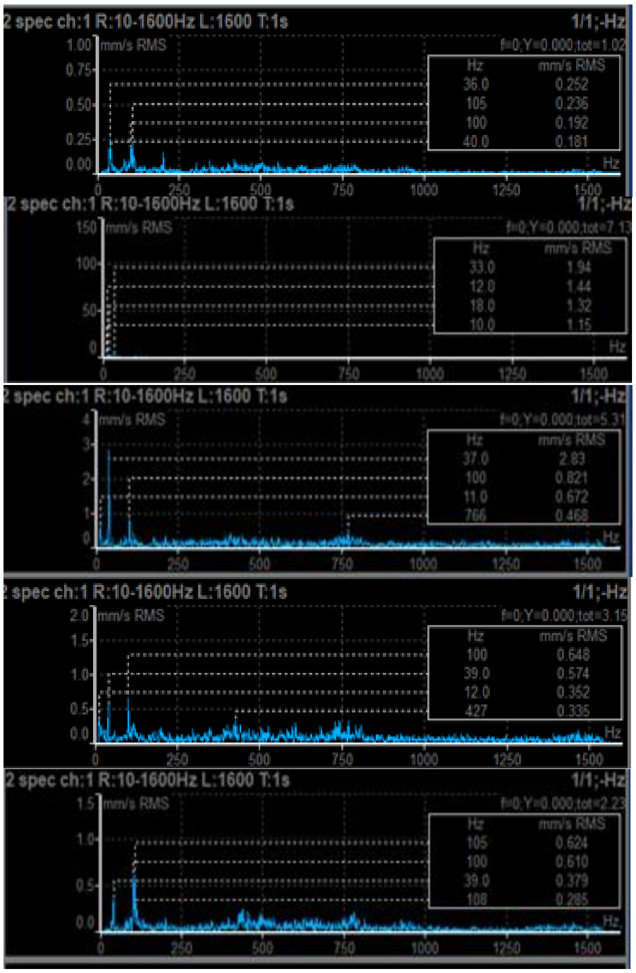

Fig. 4 Frequency domain plot of vibration signals of GFHB at various speeds

For healthy bearings, the amplitude of the frequency-domain response is high at the gear crack frequency, indicating strong vibration caused by the gear crack defect. The gear fracture creates a discontinuity that affects gear engagement, thereby causing impulsive excitation and the creation of high-energy frequency components.

High peaks at GMF and possible harmonics, resulting from repeated impacts, are observed in the spectrum. The more repeated impacts, the more complex the spectrum at higher speeds. This behaviour is easily observed and exhibits strong impulsivity, which clearly makes it more heat-producing than other fault types and more readily recognised as a fracture. Hence, this number indicates severe vibrations associated with gear fracture (high amplitude and complex frequency content).

Case IV: Gear Pitting and Healthy Bearing

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.766	0.638	1.0502	1.0314	1.0923

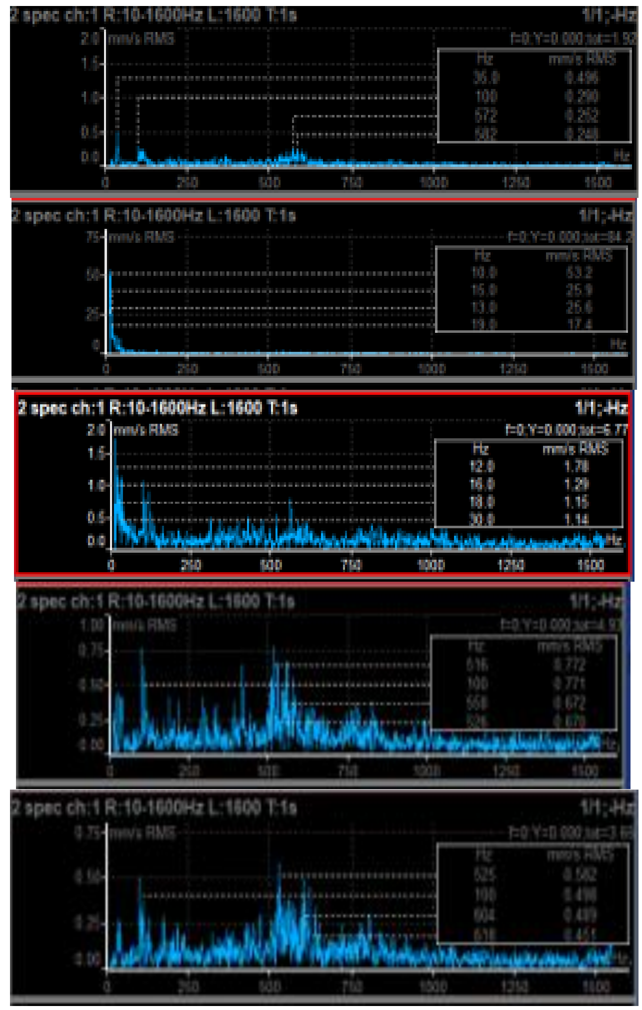

Fig. 5 Frequency domain plot of vibration signals of GPHB at various speeds

The Characteristics prominent in the frequency-domain response of a healthy bearing with gear pitting are identified. This is non-monotonic behavior, suggesting defect interactions and a dynamic system response.

The signal exhibits nonlinear characteristics due to intermittent contact between defects. Therefore, this figure confirms that gear pitting results in characteristic modulation and non-linear variations in frequency response that differ from those of other fault conditions.

Case V: Gear Wear and Healthy Bearing

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.0432	0.1053	0.1547	0.4152	0.8167

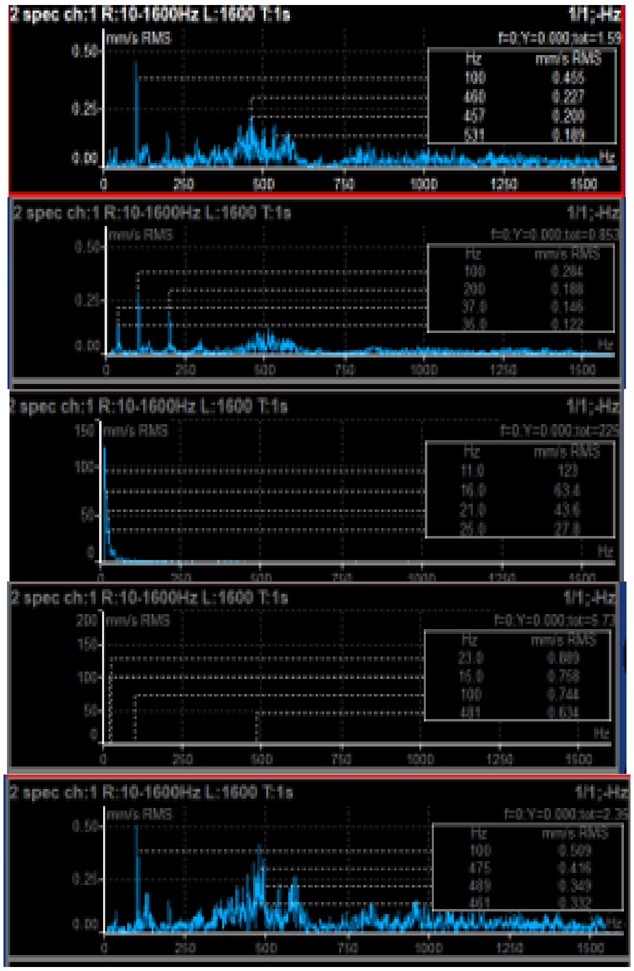

Fig. 6 Frequency domain plot of vibration signals of GWHB at various speeds

The response diagram for the Gear Wear and Healthy Bearing (GWHB) condition shows the typical oscillatory behavior associated with gear-tooth degradation. Worn tooth surfaces from gear wear when operating over time, creating irregularities and loss of material on the profile of the meshed surface and causing changes in meshing stiffness when gears are engaged.

The sideband components around the GMF are also illustrated in the frequency spectra and result from modulation effects arising from non-uniform tooth engagement and variable load distribution. Consequently, the frequency-domain analysis proved an effective method for detecting gear wear. It showed that the GMF amplitude can serve as a reliable tool for monitoring gear degradation in rotating machinery systems.

Case VI: Healthy Gear and Bearing Wear

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.412	0.427	0.492	0.571	0.642

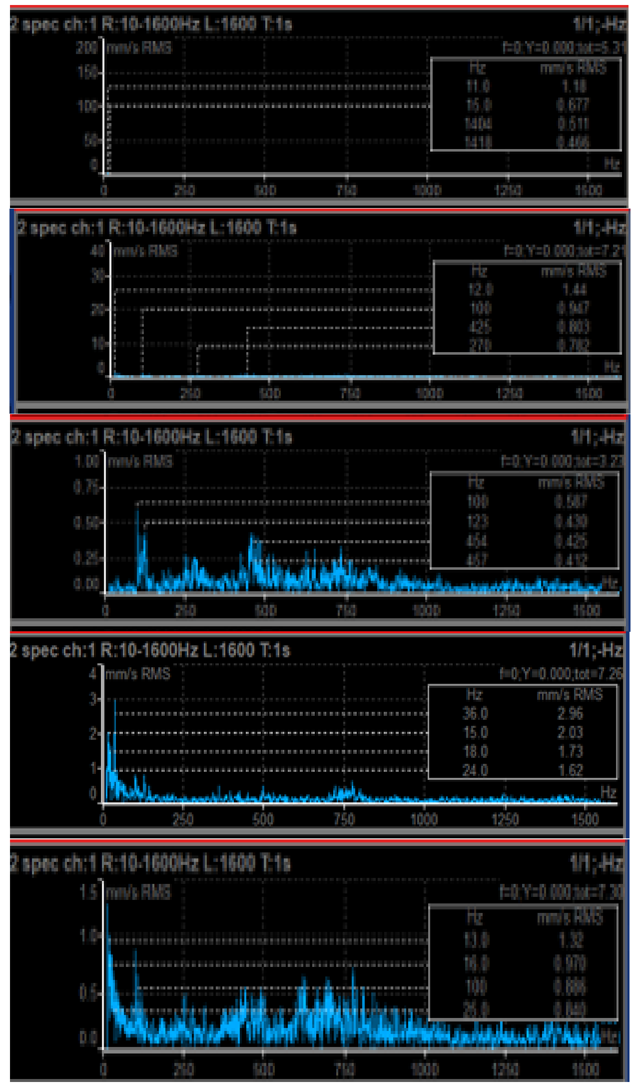

Fig. 7 Frequency domain plot of vibration signals of HGBW at various speeds

The amplitude of the frequency-domain response of a healthy gear with bearing wear increases gradually and consistently. This is a sharp rise in amplitude, indicative of system behavior with a step-by-step increase in speed. They have no sharp or pointed peaks and no obvious broadened peaks despite being near-natural; therefore, no impulsive excitation can be sensed. The harmonics show no sign of shifting from their expected frequencies and are clearly present with corresponding energy levels, indicating stable operation. This implies that the figure above shows an increase in vibration amplitude due to bearing wear, even without severe irregularities in the frequency domain.

Case VII: Healthy Gear and Bearing Pitting

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.235	0.458	0.512	0.526	0.754

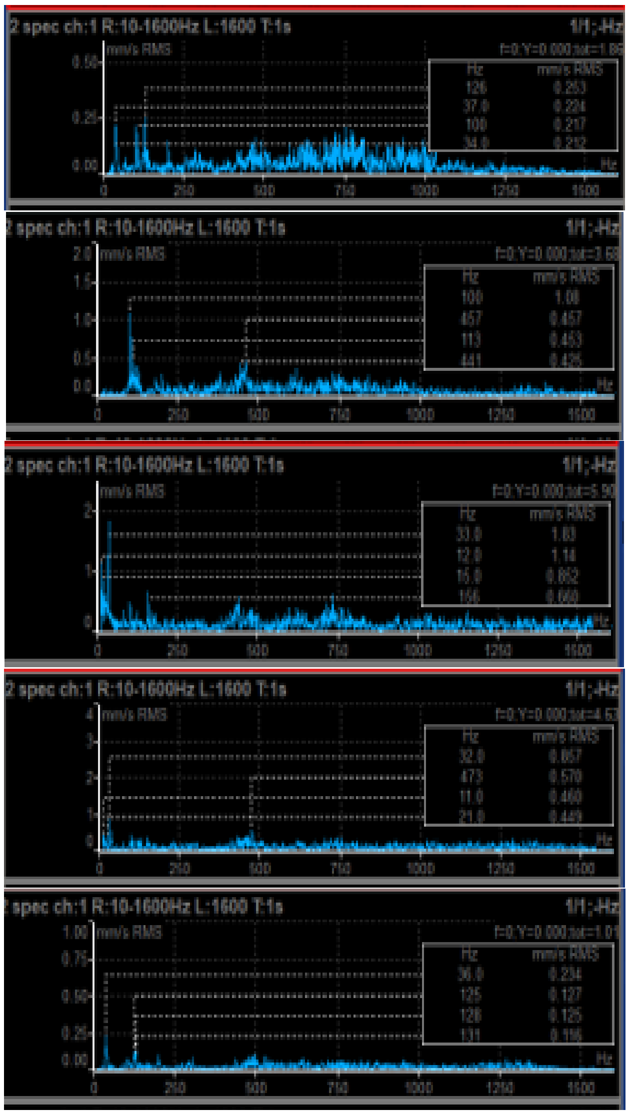

Fig. 8 Frequency domain plot of vibration signals of HGBP at various speeds

The frequency domain is plotted, and the amplitude starts to rise at the Gear Meshing Frequency (GMF), which is clearly visible as speed increases for the healthy gear with bearing pitting. The increase in amplitude is not exactly linear, indicating a non-linear interaction between the excited defects and the system dynamics; however, the main peaks remain visible, indicating that gear meshing still accounts for the majority of the system dynamics. Therefore, this value indicates an increase in vibration amplitude and a small amplitude modulation in the vibration frequency spectrum, caused by bearing pitting.

Case VIII: Gear Fracture and Bearing Pitting

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	1.0449	1.1365	1.1650	1.0512	1.1731
Amplitude(Bearing)(mm/s)	1.0139	1.0844	1.0380	1.1645	1.3796

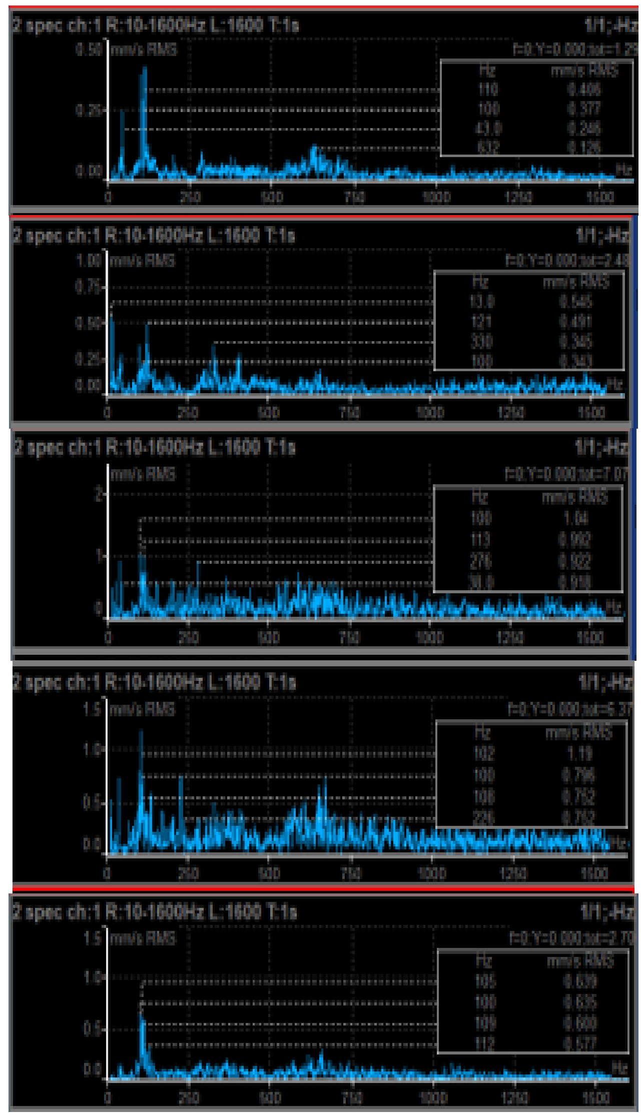

Fig. 9 Frequency domain plot of vibration signals of GFBP at various speeds

The response in the frequency domain for the simultaneous fault of gear fracture and bearing pitting is very complex and exhibits high vibration levels across all operating speeds. The resulting peaks at the GMF and the bearing frequencies are quite distinct but may be less sharp, depending on modulation effects and frequency incongruities. When measured in terms of the interaction between gear fracture and bearing pitting, the behavior is strongly non-linear. Combined faults thus produce complex fault spectra with much greater vibration amplitudes, as clearly shown in this figure.

Case IX: Gear Fracture and Bearing Wear

Speed(RPM)	200	400	600	800	1000
Amplitude(GMF)(mm/s)	0.1014	0.2703	0.4512	1.1372	1.1874
Amplitude(Bearing)(mm/s)	0.2195	0.9796	1.0070	1.1457	1.7524

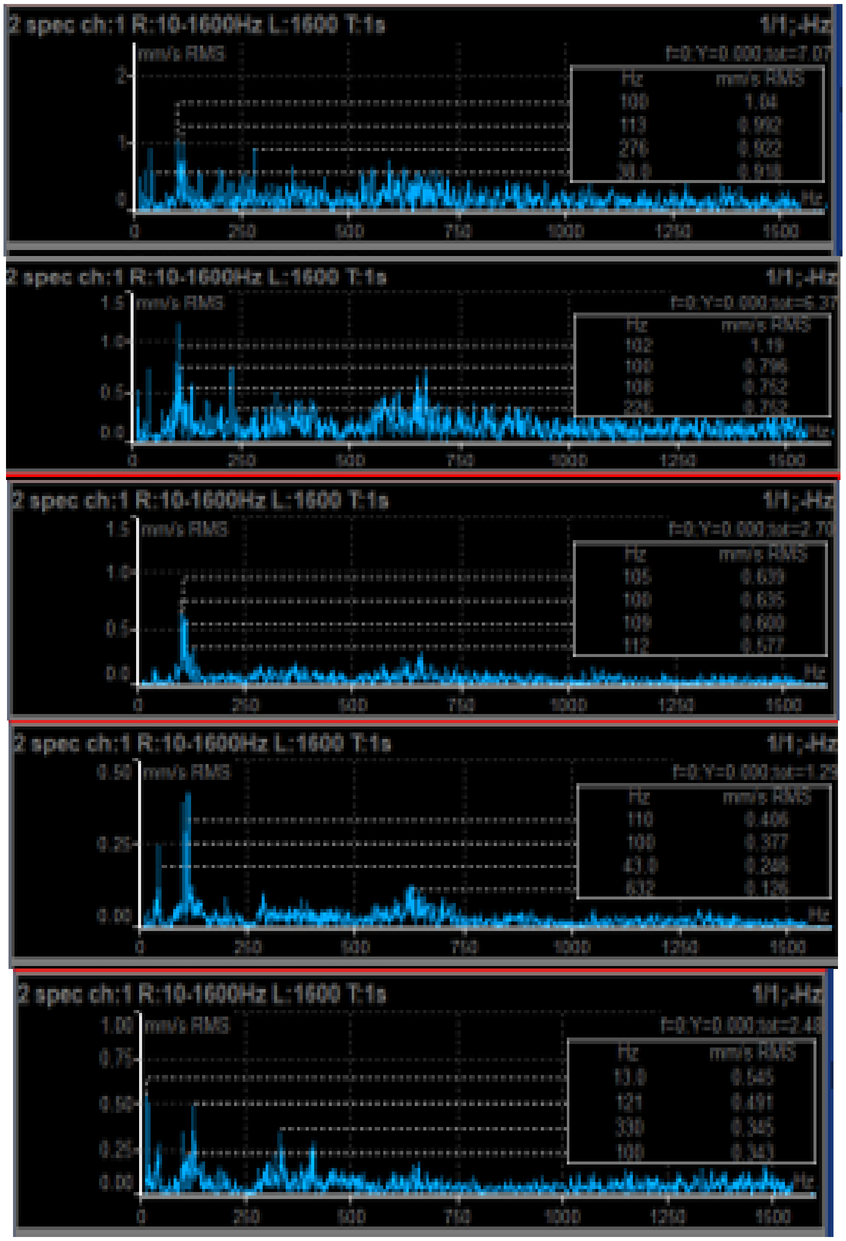

Fig. 10 Frequency domain plot of vibration signals of GFBW at various speeds

The vibration response in the frequency domain, for both gear fracture and bearing wear, shows a significant increase at the Gear Meshing Frequency (GMF) and bearing frequencies; impulsive forces from gear fracture and a smoother but higher vibration response are introduced into the frequency domain. The prominent bands are at the GMF and bearing frequencies, growing stronger at higher speeds. Therefore, this value indicates that as speed increases, vibration amplitude increases due to gear fracture and bearing wear, and the vibration complexity is moderate compared with other gear and bearing faults. Figure 10 Frequency Domain Plot of Vibration Signals of GFBW at Various Speeds.

3.1.1. Influence of Speed on Vibration Amplitude

The effect of rotational speed on vibration amplitude in the frequency domain under various operating conditions is shown in Figure 11. According to the presented graphs, a trend is the generally increasing vibration amplitude with speed, caused by increasing dynamic excitation and/or meshing forces within the gearbox system. The results show that the amplitudes of fault conditions such as gear wear and pitting are higher than those in healthy conditions, and that the amplitude trend is non-linear with respect to rotational speed, indicating that the severity and detectability of these vibration-based fault conditions increase with rotational speed.

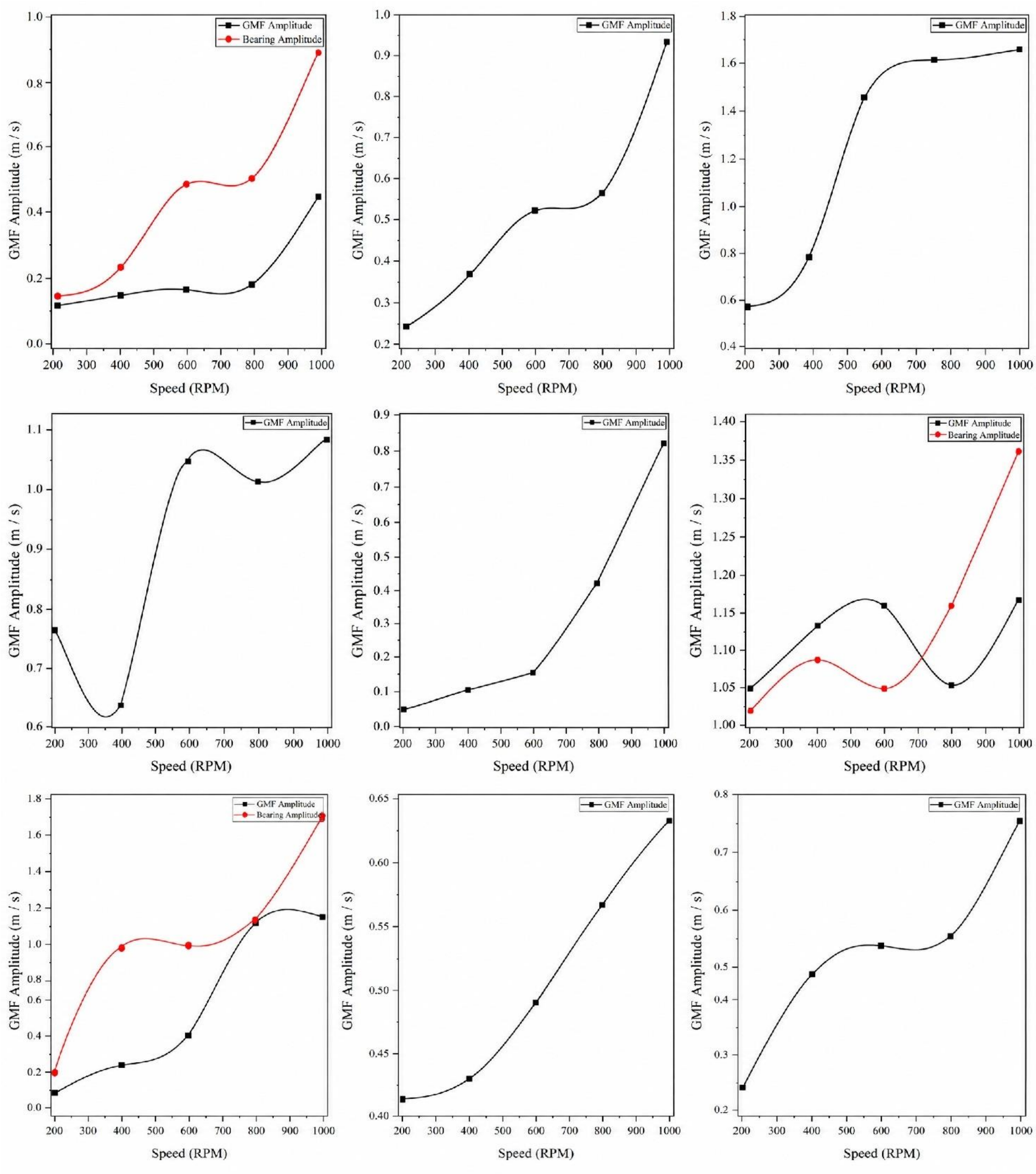

Fig. 11 Graphical representation of amplitude values for frequency domain at various speeds (experimental)

3.2. Amplitude Values at Different Load Conditions

Case I: Healthy Bearing and Healthy Bearing

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.050	0.070	0.102	0.210	0.182
Amplitude(Bearing)(mm/s)	0.010	0.030	0.024	0.050	0.160

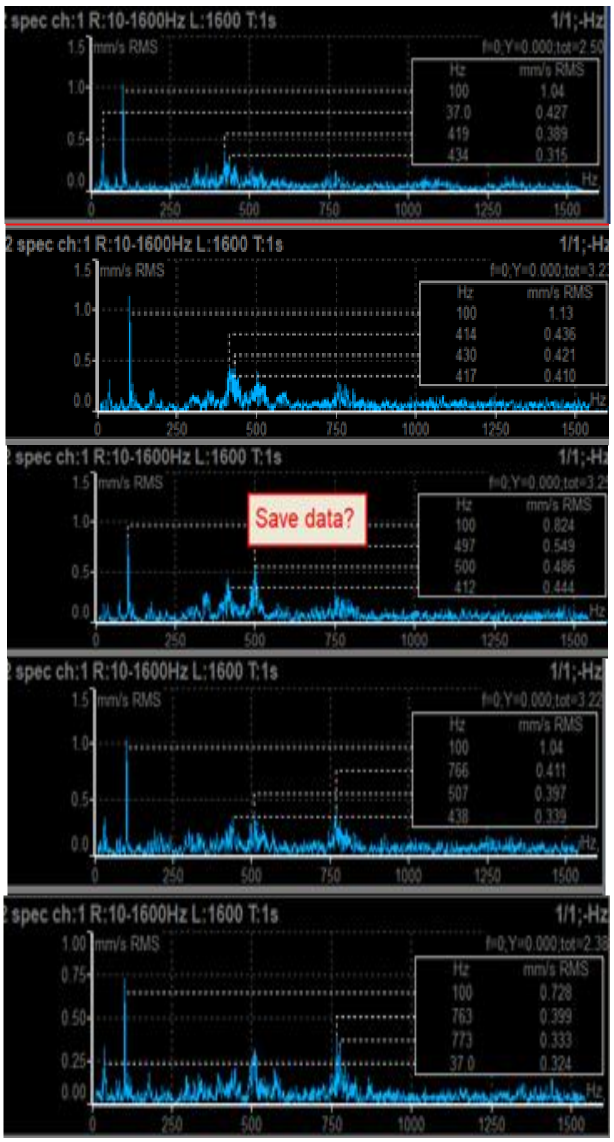

Fig. 12 Frequency domain plot of vibration signals of HGHB at various loads

In a healthy bearing condition, we can see that the vibration magnitude of the gear increases gradually with increasing loading (20n to 100n), and no abnormal frequency peaks are present, indicating that the healthy condition of the gear and bearing is not affected. This behavior confirms that, under fault conditions, the vibration amplitude is strongly influenced by the load, and that if it does not follow this trend, the system is in a fault state.

Case II: Gear Corrosion and Healthy Bearing

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.1001	0.2321	0.2888	0.3065	0.3310

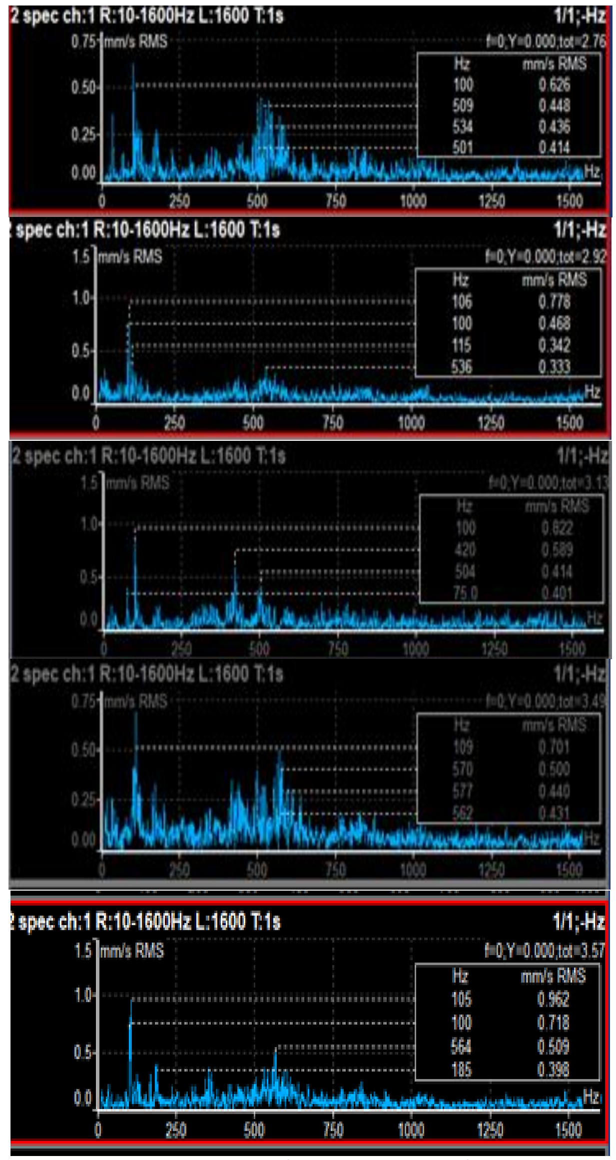

Fig. 13 Frequency domain plot of vibration signals of GCHB at various loads

The amplitude of the GMF increases, indicating that surface irregularities caused by corrosion increase the dynamic interaction between the gear teeth. In addition to higher peak intensities, the frequency spectra show small irregularities that may be attributed to non-uniform contact due by corrosion, compared with the healthy case. This behaviour is clearly indicative of corrosion faults in gears and will result in increased vibration amplitude and load-dependent response, which can be identified in frequency-domain analysis.

Case III: Gear Fracture and Healthy Bearing

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.0091	0.0230	0.0241	0.0515	0.4881

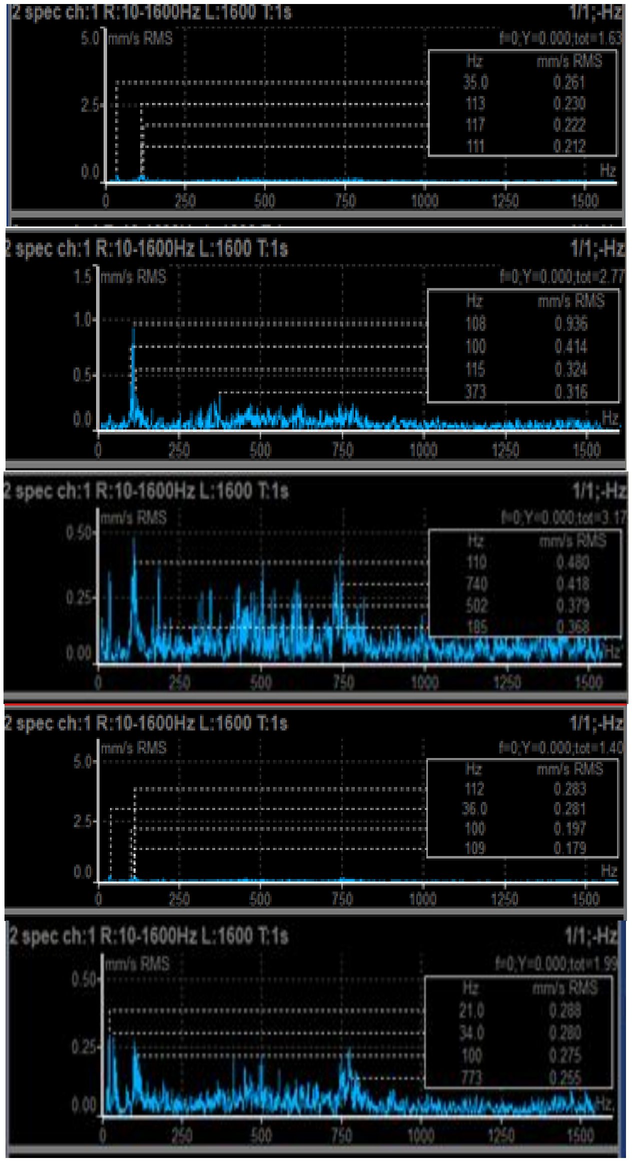

Fig. 14 Frequency domain plot of vibration signals of GFHB at various loads

The gear fracture vibration and healthy bearing conditions under different loads show differences in the amplitude of the Gear Mesh Frequency (GMF). The rationale for this sudden rise is the high severity of the fracture fault, which causes occasional loss of contact and impact loading between gear teeth. This action indicates that gear fracture faults are highly load-sensitive and cause sudden changes in the vibration amplitude of the gear transmission system compared with other fault conditions. Figure 14: Frequency Domain Plot of Vibration Signals of GFHB at Various Loads.

Case IV: Gear Pitting and Healthy Bearing

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.0416	0.1064	0.1337	0.1468	0.1994

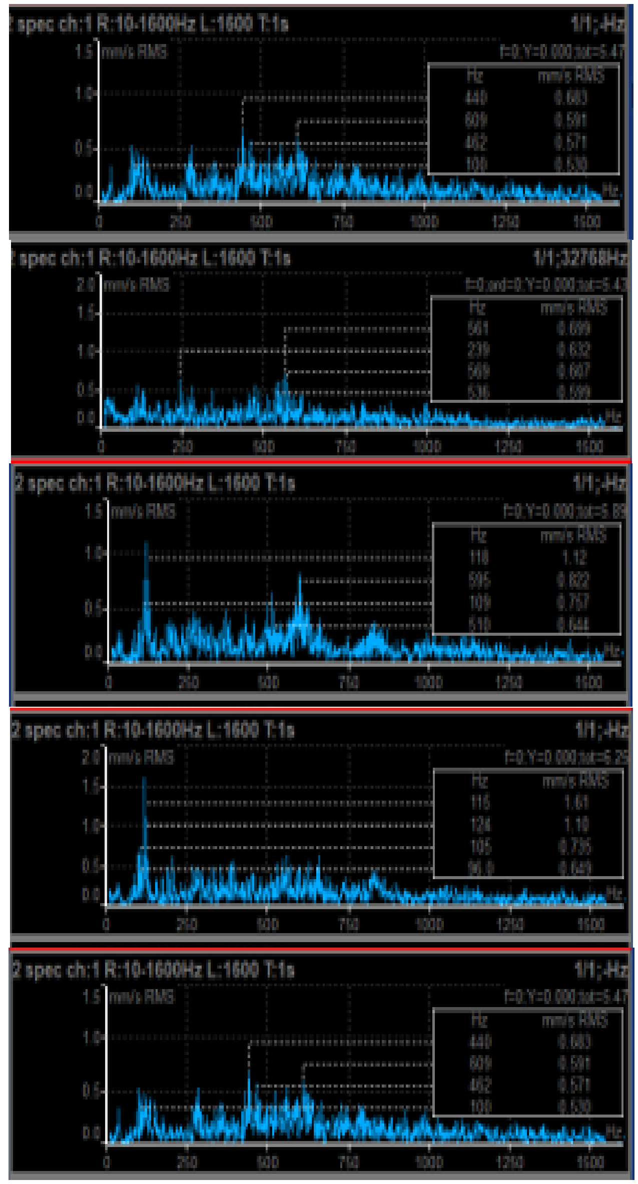

Fig. 15 Frequency domain plot of vibration signals of GPHB at various loads

The increase in amplitude shows that surface discontinuities, such as pitting, result from local faults that worsen under load. The increased peak intensity and modulation effects are also evident in the frequency spectra, which are caused by repeated contact on pitted surfaces. This activity validates that gear pitting results in a vibration response associated with the load, and that the response signal increases moderately over the life of the gear, but is clearly distinguishable from both healthy and severe fault conditions.

Case V: Gear Wear and Healthy Bearing

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.0158	0.0491	0.0848	0.0859	0.0909

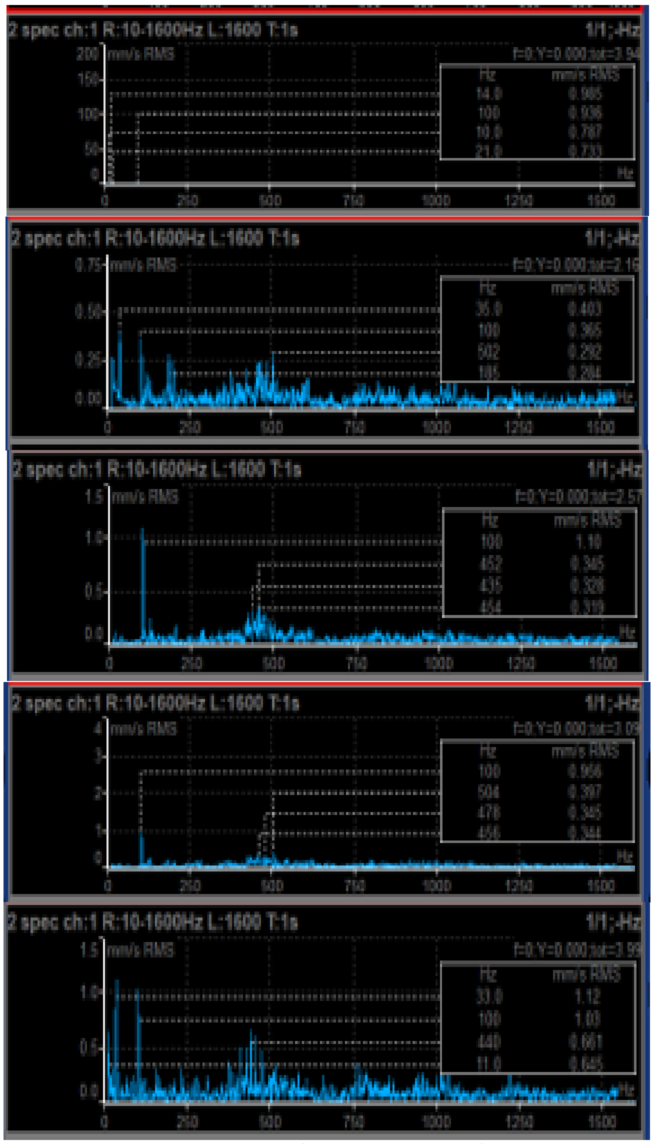

Fig. 16 Frequency domain plot of vibration signals of GWHB at various loads

The gear wear condition and healthy bearing condition under three different load conditions are shown here from the vibration analysis, and it is observed that the amplitude of the Gear Mesh frequency (GMF) gradually increases as the load increases.

The frequency spectrum shows elevated peaks relative to the healthy case, with no impulsive or irregular behavior, indicating that the wear is mild and progressive. This is because wear builds up gradually and causes low-intensity vibrations compared to other fault conditions.

Case VI: Healthy Gear and Bearing Wear

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.060	0.110	0.123	0.117	0.231

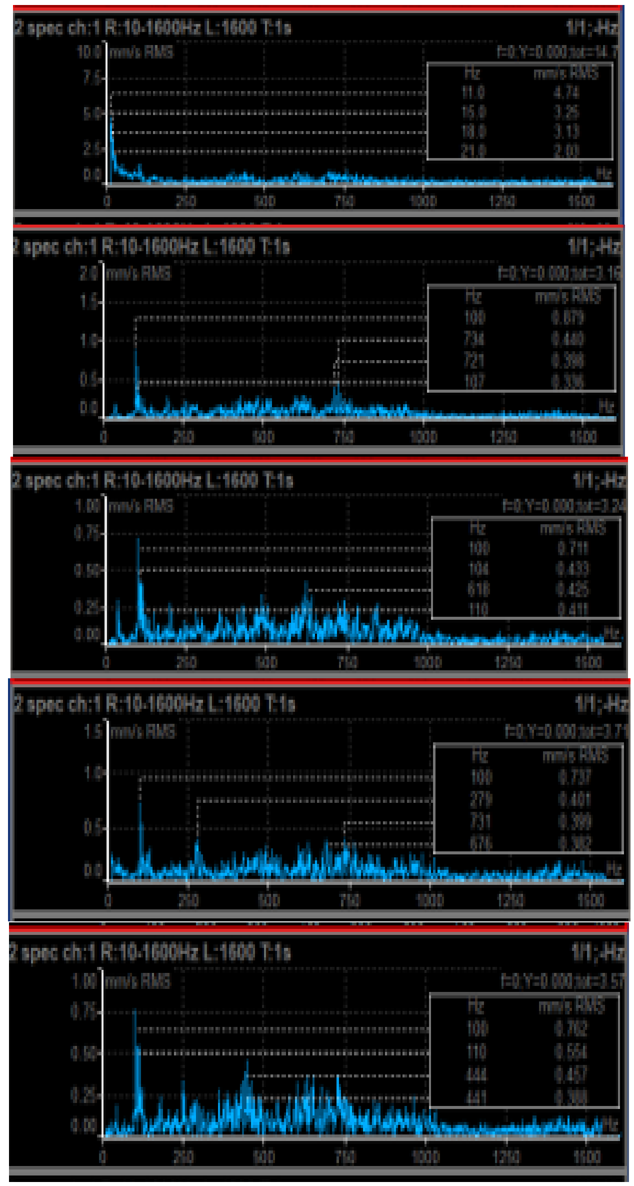

Fig. 17 Frequency domain plot of vibration signals of HGBW at various loads

The greater the amplitude, the more evident it becomes that the components' wear behaviour substantially impacts the system's overall vibration response. The higher noise level and wider peaks in the frequency spectra than in the healthy situation result from non-uniform interaction during wear.

This behavior shows increased vibration levels due to bearing wear and exhibits an apparent load-dependent response, even though the gear is in a healthy condition.

Case VII: Healthy Gear and Bearing Pitting

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.0137	0.0214	0.0544	0.9220	2.4630

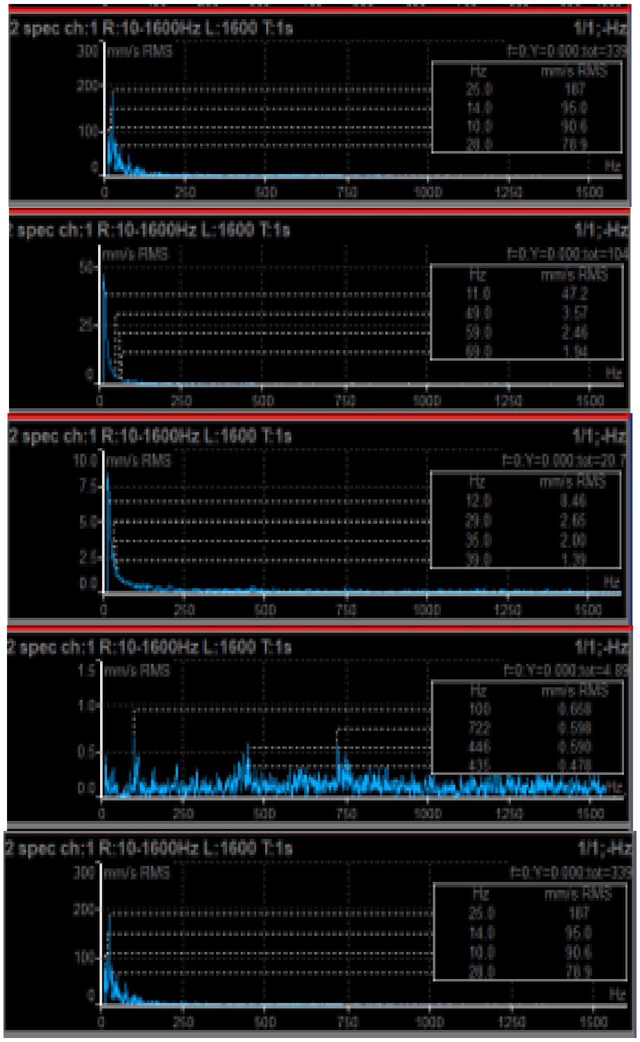

Fig. 18 Frequency domain plot of vibration signals of HGBP at various loads

There is relatively low amplitude at low loads, which rises from 0.0137 mm/s at 20N to 0.0544 mm/s at 60N. However, with an increase in load, a steep and drastic increase is seen at higher loads: 0.9220 mm/s at 80 N, increasing to 2.4630 mm/s at 100 N. Localized pitting defects on the bearing raceways give rise to high impact forces as the rolling elements travel over the defect area, and this is believed to cause this behavior. There are also distinct peaks in the frequency spectra, accompanied by enhanced noise, which signify strong modulation and activity associated with the defects. This behaviour indicates that bearing pitting is a serious fault, as it is characterized by a rapidly increasing vibration amplitude at higher loads, making it readily distinguishable from other fault types.

Case VIII: Gear Fracture and Bearing Pitting

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.0595	0.0658	0.2417	0.3020	0.3153
Amplitude(Bearing)(mm/s)	0.0113	0.0199	0.0439	0.0665	0.1608

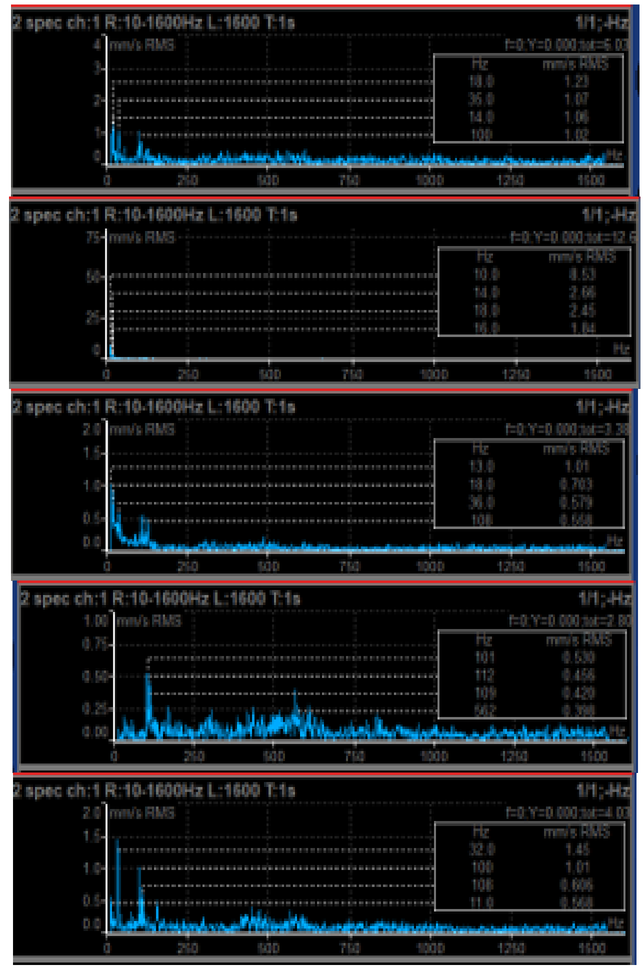

Fig. 19 Frequency domain plot of vibration signals of GFBP at various loads

The gear fracture condition under varying loads (20N to 100N) has been analysed, and notable vibration responses for the severe gear fault condition have been obtained, as well as for severe bearing faults. The amplitude of the Gear Mesh Frequency (GMF) increases with increasing load, from 0.0595 mm/s to 0.3153 mm/s, due to the presence of impact and intermittent contact forces, which can lead to gear fracture. However, the corresponding amplitude for the bearing also increases from 0.0113 mm/s to 0.1608 mm/s, suggesting the influence of localized pitting defects on the bearing. The spectra have prominent peaks (modulation) generated by the interaction between the gear and bearing defect frequencies. With combined faults, the amplified and complex vibrations required less identification, making the vibrations more obvious at higher loads.

Case IX:- Gear Fracture and Bearing Wear

Load(N)	20	40	60	80	100
Amplitude(GMF)(mm/s)	0.1168	0.1708	0.2417	0.3182	0.4320
Amplitude(Bearing)(mm/s)	0.0171	0.0192	0.0244	0.0497	0.0667

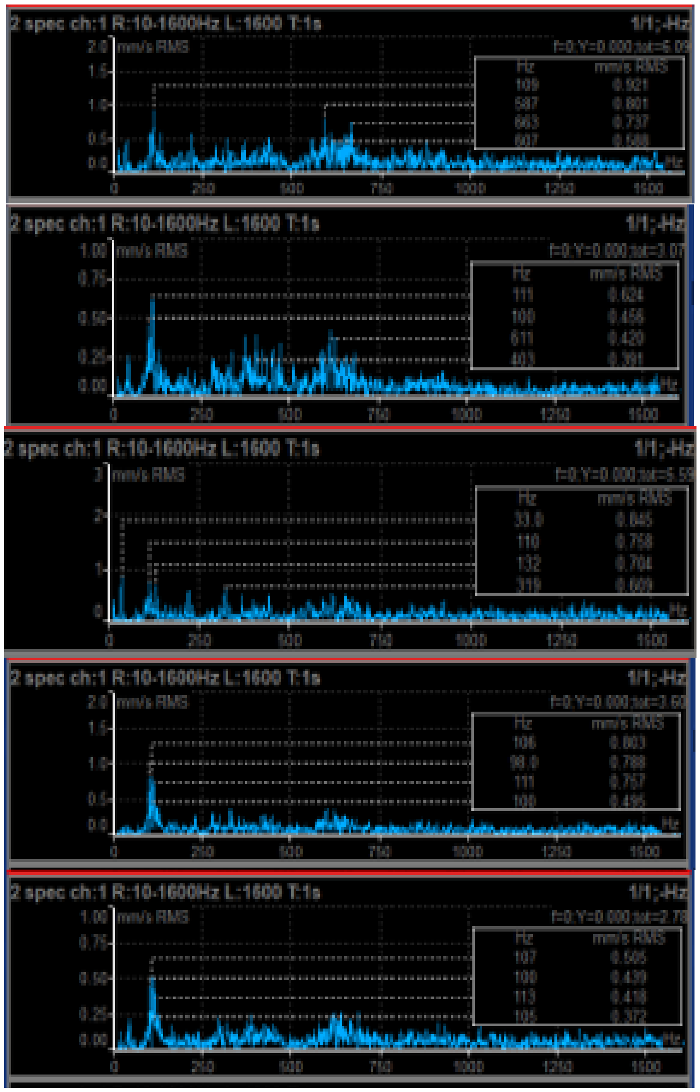

Fig. 20 Frequency domain plot of vibration signals of GFBW at various loads

The amplitudes of both the Gear Mesh Frequency (GMF) and the bearing-related amplitudes have increased consistently and significantly with load from 20 N to 100 N, as indicated by the vibration analysis of the gear fracture and bearing wear conditions. The GMF amplitude increases as the load rises from 20 N to 100 N, from 0.1168 mm/s to 0.4320 mm/s, indicating that gear fracture is the dominant factor, resulting in impact loading due to intermittent gear contact. At the same time, the bearing amplitude smoothly changes from 0.0171 mm/s to 0.0667 mm/s, which is caused by distributed surface wear on the bearing raceways. Bearing wear causes a smoother, gradual increase in vibration levels, whereas bearing pitting produces sharp impulses. The combined effect produces high-amplitude vibrations that grow at relatively constant levels without any sudden peaks. The frequency spectra show higher peak intensities due to gear fracture and broader spectral components due to bearing wear. The condition indicates that the gear fracture is the dominant vibration source, while bearing wear contributes to overall vibration amplification, indicating it is moderately severe but stable.

3.2.1. Influence of Load on Vibration Amplitude

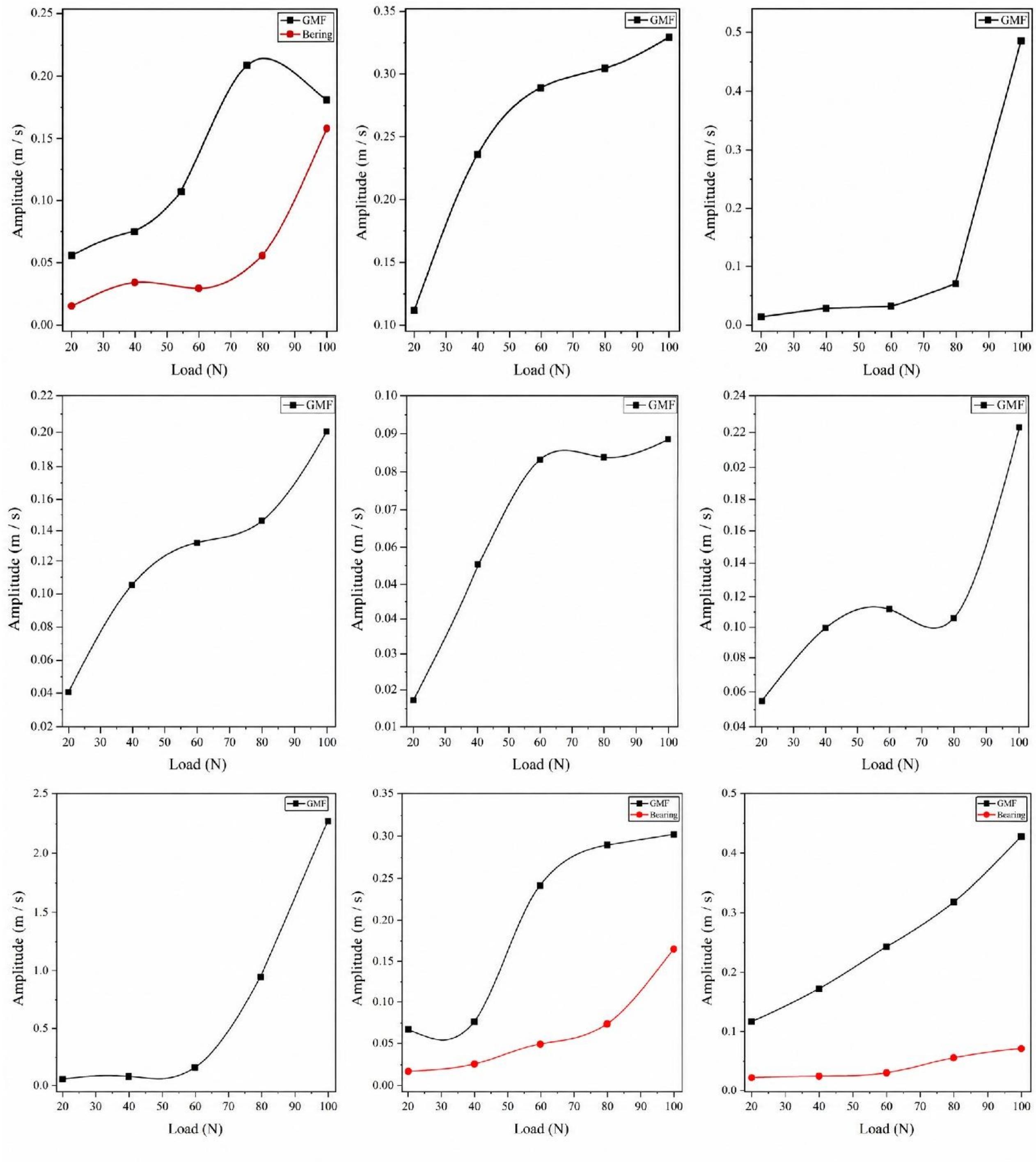

Fig. 21 Graphical representation of amplitude values for frequency domain at various loads (experimental)

Figure 21 shows the experimental amplitude graph (in the frequency domain) for different loading cases. As can be seen in the graphs, the amplitude response varies significantly over a range of load and frequency. In most cases, the amplitude increases slowly at the lower frequencies and sharply at the higher frequencies, and this represents more vibration motion behavior in close regard to the resonant areas. The experimental responses, indicated by the black curves, are compared with the remaining curves, indicated by the red curves, to assess comparability, as required by the task. Several of the graphs showed nonlinear trends, which were thought to be the result of damping and stiffness variations and/or structural changes during operation. Overall, the results show that under increased load, vibration amplitudes and their patterns change, thereby influencing the system's dynamic performance and stability.

4. Frequency-Domain Behavior and Amplitude-based Diagnostic Trends

The frequency domain analysis performed in this experiment clearly showed relationships between fault conditions and the vibration response characteristics of the rotor-bearing-gear system, with operating parameters. The FFT spectra under various operating conditions indicated that vibrations increased considerably in both the amplitude at the Gear Meshing Frequency (GMF) and the amplitudes at the bearing frequencies as the fault increased and as rotational speed and load increased. Changes in spectral characteristics are good indicators for fault diagnosis and condition monitoring. They remained stable and well-defined under healthy operating conditions, with sharp peaks at the GMF (group minor frequencies) and bearing frequencies.

The amplitude of vibration increases gradually with running speed and load, with almost linear relationships, indicating that they are statically stable and that the meshing action is in order. There were no additional harmonics, sidebands, or irregular spectral components observed, as would be expected to indicate the failure of the gear and bearing elements. The frequency-domain response was significantly affected by the gear defects. This caused moderate increases in vibration signal amplitude due to surface roughness and material erosion resulting from gear corrosion and wear. These faults resulted in smoother spectral abnormalities and minimal harmonic activity, with distributed fault behavior. On the other hand, gear pitting created local discontinuities on the tooth surface, leading to localized stress impacts during meshing.

The FFT spectra revealed broadened peaks and sidebands around the GMF, which were attributed to modulation effects due to repeated contact at pitted areas. The most severe spectral response was observed when the gear fractured. High-speed oscillation and impact excitation, influenced by intermittent tooth contact, led to a significant increase in vibration amplitude with speed and load. The frequency spectra exhibited high-amplitude peaks, harmonics, broadened bands, and elevated noise levels, all of which were associated with high dynamic instability. The vibration amplitude was highly nonlinear, with greater nonlinearity at higher operating speeds and loads. There was also characteristic behavior in the spectrum due to bearing defects. After a period of time, the vibration amplitude rose gradually, and the noise was also slightly higher, which was attributed to vibration caused by bearing wear due to progressive distributed surface degradation and increased friction. This is mainly attributable to the localized defects on the raceways and rolling elements, which caused strong impulsive vibration responses due to bearing pitting. The increased peak amplitudes, spectral broadening, and spectral modulation caused by repeated impacts during the bearings' operation were observed in the spectra.

The frequency spectra for all fault conditions were highly complex, and the vibrations under combined fault conditions exhibited high amplitudes (concurrent gear fracture and bearing pitting, bearing wear and gear fracture). Several harmonics, sidebands, and higher noise levels were noticed as a result of simultaneous gear and bearing excitations. In all cases, the highest measured vibration amplitudes and the most unstable spectral behavior were observed under conditions of gear fractures and bearing pitting. Experimental investigation also revealed that vibration magnitude is significantly affected by rotational speed. Increasing the speed, meshing frequency, and vibration energy of impacts, simultaneously with increasing vibration repetition rate, thus increasing the vibration energy and showing more pronounced spectral components.

Also, the vibration amplitude and fault signature increased with increased loading. Localized faults (fracture and pitting) were found to be more responsive to changes in loading and speed than distributed faults (wear and corrosion). In conclusion, the experimental frequency-domain analysis validated the effectiveness and reliability of FFT-based vibration analysis for detecting and differentiating various gear and bearing faults in rotor-bearing-gear systems. The characteristics observed in the spectrum, such as amplitude growth, harmonics, sidebands, and modulation information, provide a good indication of the machine's condition and can be used in predictive maintenance applications.

4.1. Comprehensive Benchmarking for Proposed Methodology

Many vibration-based signal processing and artificial intelligence techniques have been developed for fault diagnosis of vibrating devices in rotating machinery. Many traditional methods are still used: the Fast Fourier Transform (FFT) analysis is one of the most widely adopted techniques due to its computational efficiency and correspondence with machine dynamics. On the other hand, recently developed diagnostic techniques such as Wavelet Transform (WT), Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and hybrid deep learning have shown promising diagnostic performance for complex rotating machinery applications. These techniques tend to achieve higher classification accuracy on benchmark datasets that can be easily controlled. Still, in general, they require significantly more computational resources and a large number of well-labeled datasets to train the model accurately.

The proposed methodology is a hybrid approach that integrates experimentally extracted FFT-based frequency-domain features with supervised machine learning algorithms to ensure accurate fault classification while maintaining the physical interpretation of vibration signatures. The extracted features are not necessarily sensible in an end-to-end deep learning method.

Still, they are also directly linked with the motor characteristic frequencies: Gear Meshing Frequency (GMF), Bearing Characteristic Frequencies, or harmonic components and modulation sidebands, which enable the maintenance engineer to correlate the decisions made with the respective motor failure mechanisms. This property plays a major role in the ease of system interpretability and engineering decision-making during condition monitoring.

FFT is easier to implement, has a significantly lower computational cost, and offers no choices for mother wavelets, decomposition levels, or reconstruction parameters, unlike wavelet-based signal processing techniques, which affects diagnostic capability. Likewise, the decomposition methods (EMD, VMD) require iterative decomposition of the signal, which increases computational complexity, especially for continuous online monitoring applications. Unlike FFT, however, FFT can be used to obtain a fast spectral representation of vibration signals and to extract characteristic frequencies appropriate for real-time implementation efficiently.

Large-scale benchmark datasets are well known for their classification performance, with deep learning models such as CNNs, LSTM networks, and Transformer architectures exhibiting impressive results. However, these methods are often “black-box”; that is, the connection between extracted features and actual machine behaviour is not clearly evident.

Moreover, they generally demand substantial computational resources and large labeled training sets, both of which are rarely available in industrial applications. To address these limitations, the proposed methodology utilizes physically meaningful frequency-domain features derived from experimentally measured vibration signals, thereby reducing the computational cost while retaining diagnostic clarity and engineering interpretability.

Furthermore, the methodology proposed in this study is experimentally investigated under nine operating conditions: healthy, single gear defect, single bearing defect, and simultaneous gear-bearing defect, with variable external load and rotational speed.

The proposed experimental framework can be seen as a three-pronged approach that not only enables comprehensive experimental validation but also extracts physically interpretable features in the frequency domain and applies supervised machine learning to perform diagnosis of working conditions relevant to predictive maintenance of rotating machinery under realistic industrial conditions.

4.1.1. Comparative Benchmarking with State-of-the-Art Diagnostic Techniques

Table 4. Comparison table of proposed method with diagnostic techniques

Method	Advantages	Limitations	Comparison with Proposed Method
FFT	Simple, fast, physically interpretable, suitable for real-time monitoring	Limited for highly non-stationary signals	The proposed method enhances FFT using supervised ML for automatic fault classification.
Wavelet Transform (WT)	Excellent time-frequency localization	Requires wavelet selection and higher computational effort	Proposed method is simpler and easier to implement in industry
EMD / VMD	Effective for non-linear and non-stationary signals	Computationally intensive and sensitive to parameter settings	Proposed method requires lower computational resources
CNN	High classification accuracy with large datasets	Requires extensive labelled data and GPU-based training	The proposed method performs well using experimentally extracted features and conventional ML
LSTM	Suitable for sequential vibration data	Long training time and high computational complexity	The proposed method offers faster implementation and better interpretability
Proposed FFT + ML	Experimentally validated, interpretable, low computational cost, suitable for combined gear-bearing faults.	Performance depends on the quality of extracted frequency features	Provides an efficient balance between accuracy, computational cost, and industrial applicability

Table 4 shows a qualitative comparison of the proposed framework for fault diagnosis that is based on FFT and other state-of-the-art methods that have been widely reported in the literature. Deep learning approaches, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are typically very accurate at classification if a large labeled dataset exists. However, both these methods suffer from the requirement of significant computational resources, long training times, and expensive computing equipment and can be somewhat difficult to apply in an industrial online monitoring system. In a similar way, the signal decomposition methods like Wavelet Transform (WT), Empirical Mode Decomposition (EMD), and Variational Mode Decomposition (VMD) have the ability to obtain a good time-frequency representation for non-stationary vibration signals, but they require more complicated computation and parameter tuning than FFT analysis.

On the contrary, the proposed method extracts features based on FFT in the frequency domain from the experiments and fuses the features with the traditional supervised machine-learning diagnostic methods to realize reliable fault diagnosis under low complexity and high interpretability. The proposed framework validates experimentally nine operating conditions, such as simultaneous gear-bearing faults, under a combination of different speed and load levels, while many of the existing research addressing the diagnosis of gear and bearing faults are focused on testing only one type of fault at a time.

The extracted features are directly related to the gear meshing frequency, bearing characteristics frequencies, harmonics, and sidebands, which allows maintenance engineers to understand the state of the gear condition without resorting to black box models. Hence, the proposed approach offers an effective balance among good diagnosis accuracy, computation speed, interpretation and industrial applicability.

4.2. Industrial Applicability and Scalability

The possible diagnostic method has been designed with respect to the practical implementation in the industry. Extremes in operating speeds, mechanical loading, and environmental conditions are common in industrial rotating machinery and can affect their vibration characteristics. The experimental study in the present research demonstrates that the proposed methodology is sufficiently robust for practical condition monitoring across different operating conditions. Another major advantage is the relatively low computational complexity of FFT-based feature extraction, thereby allowing the solution to be rolled out in real time with off-the-shelf vibration monitoring technology, using neither specialized graphics processing units nor cloud computational power.

To be deployed in industry, the positioning of the sensors, the periodic calibration of the sensors, and appropriate noise suppression techniques are necessary; however, if successful. Accelerometers should be installed as close as possible to bearing housings and gearbox casings to maximize sensitivity to mechanical fault excitations and minimize structural attenuation. Frequency-domain analysis should be preceded by appropriate anti-aliasing filters and/or signal conditioning to minimize electrical and environmental noise. Due to the relatively low computational time required for the FFT, it is also possible to incorporate the methodology into an online condition monitoring system that continuously monitors machine condition and supports predictive maintenance scheduling. These properties make the proposed method a viable option for industrial rotating machinery when service conditions vary.

4.3. Practical Considerations for Industrial Deployment

The machine learning framework proposed here is shown to be effective for fault diagnosis in a controlled laboratory setting, but there are many practical considerations that need to be taken into account to make it work in an industrial setting. In the industrial rotating machinery, variable loading, variable rotational speeds, severe environmental background, and electromagnetic interference are common conditions, which can affect the quality of the vibration signal and the performance of vibration diagnostics. This implies appropriate signal acquisition, sensor installation and computational optimization to ensure reliable real-time implementation.

The position of the sensor can have the greatest influence on the accuracy of the measurement. The ideal placement for accelerometers is to attach them as close to the bearing housing and housing of the gearbox as possible to give the best sensitivity to vibrations caused by the faults and capture while minimizing structural attenuation and external disturbances. However, correct orientation of the sensors, tie-ins for each install, and regular calibration are also required to guarantee repeatable and reliable measurements over time.

The other practical issues are environmental & measurement noise from nearby equipment, structural vibrations, electrical interference and varying operating conditions. For the best vibration-acoustic signal quality, signal conditioning methods such as the appropriate choice of anti-aliasing filters, noise filtering and proper sampling frequency should be used along with the vibration measure. These steps reduce the impact of normalisation in a preprocessing phase to extract the characteristic fault frequencies and to make the machine learning classification more robust.

An additional key challenge for the industrial deployment is computational efficiency. The proposed method is based on features extracted by FFT and applies conventional supervised machine learning algorithms, which are easy to implement with moderate computational complexity, compared to deep learning techniques that demand a large number of labeled examples, massive amounts of data, and powerful GPUs. Thus on-line condition monitoring could be continuously executed on embedded monitoring systems, industrial Programmable Logic Controller (PLC) or basic edge computing devices without depending on cloud-based processing.

Maintenance-wise, the proposed methodology can be incorporated into a predictive maintenance scheme and can be adopted to continuously track the vibration behavior to capture abnormal operating conditions, which eventually lead to catastrophic failure. Identifying problems early allows the maintenance engineer to plan the repair in advance, minimize equipment downtime due to failure, minimize maintenance costs, and ensure optimum reliability and safety of the machine during operation.

The presented experimental work might allow promising results, but future studies should be devoted to the validation of the proposed framework with long-term time series industrial datasets involving various rotating machine structures operating in different environments. Moreover, the combination of Wireless Sensor Networks (WSN), Industrial Internet of Things (IIoT) and Cloud-based Asset Management (CAM) would further improve the scalability and feasibility of the proposed diagnostic approach for Industry 4.0 applications.

5. Machine Learning-based Fault Classification

5.1. Introduction

Vibrating measurement signals enable fault signals to be captured, and machine learning techniques are extremely important in rotating machine diagnostics. Conventional vibration analysis methods require expert interpretation of frequency spectra, whereas machine learning algorithms can classify machine conditions more efficiently and accurately. Experimentally obtained FFT data were combined with machine learning models to enhance the capability of machine learning and vibration signals in the frequency domain for fault diagnosis of the rotor-bearing-gear system. A vibration spectrum and the amplitude values derived from this were used for fault classification and condition monitoring when varying the speed and load parameters [16, 17].

5.2. Experimental Data Preparation

The machine learning dataset was created from vibration data measured in the frequency domain during an experimental investigation at various operating speeds and loading conditions. A Fast Fourier Transform (FFT) spectrum was created from each experimental observation and examined for fault-sensitive spectral components representing the Gear Meshing Frequency (GMF) of the gears, Bearing Characteristic Frequencies (BCF), harmonic components, and modulation on the sideband. These frequency-domain characteristics were tabulated in a structured feature matrix for each healthy operating condition, each gear defect, each bearing defect, and each combined gear/bearing fault condition. Steps taken before model development included checking extracted features for consistency and aberrant measurements to reduce the impact from experimental noise and measurement uncertainty. The resulting data set thus provides a complete description of the experimental gearbox system's operation across the entire tested operating range.

5.3. Machine Learning Model Development

Several supervised classification methods were tested to determine their ability to classify faults in the frequency domain. The classifiers, such as Decision Tree, Random Forest, Support Vector Machine, Naïve Bayes, and K-Nearest Neighbour, were chosen due to their extensive use in rotating machinery diagnostics and their ability to model nonlinear engineering data sets with low computational complexity.

A set of frequency-domain features was experimentally extracted from each, and the same feature sets were retained throughout the training process to ensure the models were as fair and balanced as possible. The aim of using more than one classifier was to identify the most suitable classification algorithm from the vibration characteristics measured under actual operating conditions to separate the healthy operating range, the individual defect range, and the range of the coexistence of the gear and bearing fault.

5.4. Performance Evaluation and Statistical Validation

The performance of the classification models was evaluated using multiple performance metrics, including accuracy, precision, recall, and F1-score. Accuracy represents the proportion of correctly classified observations, while precision measures the proportion of predicted fault conditions that were correctly identified. Recall evaluates the ability of the classifier to identify the actual fault conditions, and the F1-score provides a combined measure of precision and recall. These metrics were selected because classification performance cannot be adequately represented by accuracy alone when different fault classes may exhibit similar spectral characteristics.

The classifiers were evaluated using the experimental dataset after separation into training and independent testing data. The same FFT-derived feature representation was supplied to all classifiers to provide a consistent basis for comparison. The independent test set was not used for model fitting and was used to evaluate classification performance on observations outside the training data.

5.5. Analysis of Model Generalization and Overfitting

Model generalization was considered by evaluating the trained classifiers on an independent test dataset that was not used during model training. The purpose of this evaluation was to determine whether the frequency-domain features learned from the training observations retained their diagnostic capability for observations outside the training data.

Overfitting is a potential concern in machine-learning-based fault diagnosis when a classifier learns patterns specific to the training observations rather than general fault characteristics. In the present study, this risk was addressed by using a common, physically interpretable FFT-derived feature set and by evaluating the trained models using independent test data.

The selected features correspond to mechanically meaningful characteristics, including gear-meshing frequency, bearing characteristic frequencies, harmonics, and sideband behaviour, rather than a large number of arbitrary spectral variables.

However, the present study did not employ repeated k-fold cross-validation or statistical significance testing between classifiers. Therefore, the reported results should be interpreted as performance estimates for the investigated experimental dataset rather than as definitive evidence of the statistical superiority of one classifier over another. Further validation using larger datasets, repeated cross-validation, and independent external datasets is required to establish stronger evidence of generalisation.

5.6. Proposed Diagnostic Model

The proposed diagnostic methodology preserves the engineering meaning of all selected features, unlike many deep learning models that extract latent features without engineering interpretation. Higher deviations from normal gear meshing behaviour are indicated by a larger vibration amplitude at the Gear Meshing Frequency, and higher bearing characteristic frequencies are associated with defects in assembly areas such as rolling elements or bearing raceways. On the other hand, harmonic generation and sideband modulation also provide further evidence of localized mechanical damage and defect growth. As a result, any machine learning prediction can be immediately correlated with tangible changes in the vibration spectrum so that the maintenance engineer can draw their diagnostic conclusions based more confidently and implement them in the real industrial predictive maintenance system easily.

5.7. Frequency Domain Analysis Performance

5.7.1. Performance under Speed Variation

Different classification models were created with the training dataset by applying Decision Tree, Random Forest, Support Vector Machine, Naïve Bayes, and KNN.

Table 5. Performance summary for frequency domain (speed variation)

Sr.No.	Model	Accuracy	Precision	Recall	F1-Score
01	Random Forest	0.8351	0.8467	0.8351	0.8334
02	SVM	0.8269	0.8994	0.8269	0.8592
03	Naïve Bayes	0.8012	0.8581	0.8012	0.8885
04	Decision Tree	0.8096	0.8312	0.8096	0.8086
05	KNN	0.8334	0.8592	0.8334	0.8163

5.7.2. Performance under Load Variation

Different classification models were created with the training dataset by applying Decision Tree, Random Forest, Support Vector Machine, Naïve Bayes, and KNN.

The experimental results showed that machine learning models can effectively classify vibration signatures associated with different fault conditions using frequency-domain data.

Table 6. Performance summary for frequency domain (load variation)

Sr.No.	Model	Accuracy	Precision	Recall	F1-Score
01	Random Forest	0.8751	0.8967	0.9351	0.9334
02	SVM	0.8869	0.8394	0.9269	0.9592
03	Naïve Bayes	0.8512	0.7881	0.9012	0.8785
04	Decision Tree	0.8996	0.9112	0.9096	0.8586
05	KNN	0.9334	0.8512	0.8334	0.9163

5.8. Discussion of Classification Performance

The machine learning results demonstrate that experimentally extracted frequency-domain features provide effective discrimination among healthy, individual-fault, and combined-fault operating conditions. The classifiers successfully utilised Variations in gear meshing frequency amplitude, bearing characteristic frequencies, Harmonic components, and spectral modulation behaviour to identify the corresponding mechanical condition. The observed classification performance confirms that frequency-domain vibration Characteristics contain sufficient diagnostic information for reliable fault identification. Furthermore, the integral ratio of FFT-based feature extraction with supervised machine learning reduces dependence on subjective spectrum interpretation while maintaining direct correspondence between measured vibration behaviour and physical fault mechanisms. These characteristics demonstrate the suitability of the proposed methodology for intelligent condition monitoring of rotating machinery operating under variable speed and loading conditions.

5.9. Receiver Operating Characteristic Curve

The Receiver Operating Characteristic (ROC) curve obtained for various Machine Learning classifiers using Frequency Domain vibration features extracted from FFT analysis is shown in the figure. Under all the operating conditions of the rotor-bearing-gear system, the various machine learning models are analyzed by applying the ROC analysis technique to classify rotor-bearing-gear fault types. The ROC curve is a graph of the True Positive Rate (TPR) versus the False Positive Rate (FPR) across various cut-off values for the classifier. The classifier's position towards the upper left indicates its effectiveness at discriminating between faults, and the better; the dashed line down the middle is a random classifier.

The KNN model also gave the highest AUC value of 0.65 among other classifiers, and the second highest AUC value was obtained with the RF model of 0.64. Compared to FFT-based vibration features, these classifiers performed well in discriminating the patterns of these faults in comparison to the other classifiers. The Support Vector Machine (SVM) classifier, Naïve Bayes, and Decision Tree classifiers had relatively low AUC value indicating moderate classification performance of these classifiers. The classification accuracy is low due to the close relationship between vibration signals from different fault types, especially when combined fault signals from gears and bearings occur under different speed/load conditions.

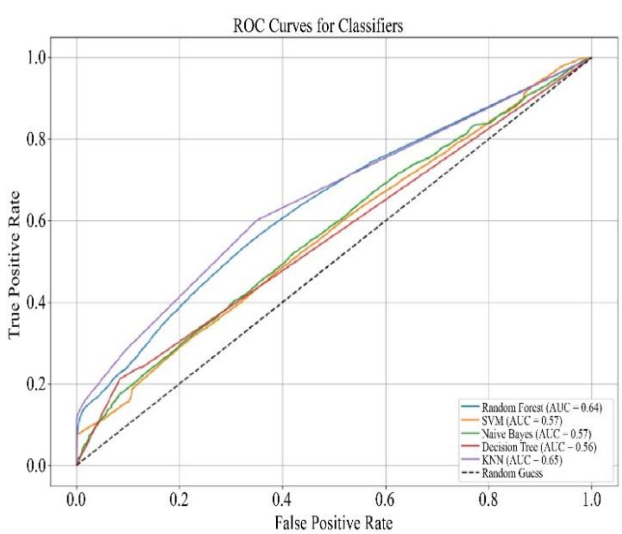

Fig. 22 ROC curve frequency domain

The vibration parameters obtained from the FFT spectrum in the frequency domain are rich in information about the machine's state of health, as revealed by ROC analysis, and are used for an effective machine learning-based fault diagnosis method. However, a medium AUC indicates that using a more sophisticated feature extraction method, optimizing feature selection, expanding the experimental data set, and employing deep learning-based classification methods can yield higher classification accuracy. The overall results demonstrate that integrating frequency-domain vibration analysis with machine learning is a feasible approach for developing a condition monitoring and predictive maintenance system for rotating machinery.

5.10. Limitation and Future Validation using Public Benchmark Datasets

A limitation of the present study is that the proposed FFT-based feature extraction and machine-learning framework has not yet been evaluated using an independent public benchmark dataset. The current investigation was conducted using a dedicated rotor-bearing-gear experimental test rig designed to investigate individual and combined gear-bearing faults under controlled variations in rotational speed and load. The experimental programme, therefore, provides controlled validation of the proposed methodology within the investigated test system. Public benchmark datasets, such as the Case Western Reserve University bearing dataset, provide valuable opportunities for independent evaluation. However, such datasets primarily represent bearing-fault conditions and do not reproduce the complete combined gear-bearing configuration investigated in the present study. Consequently, their absence from the current experimental evaluation is acknowledged as a limitation rather than evidence that the proposed framework has been generally validated across different machines. Future work will apply the same FFT-based feature-extraction and machine-learning framework to suitable public benchmark datasets and evaluate its performance under different machines, fault types, operating conditions, and sensor configurations. Such cross-dataset evaluation will provide stronger evidence regarding the generalization and robustness of the proposed diagnostic approach.

5.11. Error Analysis and Explainability

The proposed methodology yields physically explainable fault diagnosis since the extracted frequency-domain features are associated with known mechanical phenomena. Higher GMF amplification is associated with degradation of gear meshing behaviour; higher amplification of the bearing characteristic frequency is associated with localised bearing defects. The higher-order harmonics (sidebands around the GMF) indicate increased fault severity. The proposed framework is based on FFT, which can provide direct interpretation of vibration signatures, thereby enhancing the certainty of maintenance decision-making. In contrast, black-box deep learning models are difficult for maintenance engineers to interpret and to understand the relationships between vibration signatures and mechanical faults.

5.12. Limitations of the Study

While the proposed methodology showed good performance in experimental fault diagnosis of a rotor-bearing-gear system, some limitations should be recognised. An experimental investigation was conducted on a single-stage straight-bevel gearbox in a controlled laboratory setting. It is, therefore, important to note that the resulting vibration responses can vary for industrial machines under changing environmental conditions and loading/excitation conditions. The experimental programme of the present investigation was focused on the experimental generation of gear corrosion, gear wear, gear pitting, gear fracture, bearing wear and bearing pitting only, with no attempt being made to account for other fault mechanisms within the scope of this investigation; these include lubrication degradation, shaft misalignment, rotor imbalance and looseness.

Moreover, modeling of the machine learning models was performed based on experimentally measured features in the frequency domain from a developed laboratory test rig. Results have shown the potential of the proposed approach under controlled conditions, but validation on publicly available benchmark datasets and measurements from industrial settings would increase confidence in its generalisation capabilities. Statistical validation is another limitation of the present investigation. Although accuracy, precision, recall and F1-score were used to evaluate the classifiers and an independent test set was considered for assessing generalisation, repeated cross-validation and formal statistical significance testing were not performed. Consequently, differences between classifier performance should not be interpreted as statistically significant without further repeated validation. Future work will therefore incorporate repeated cross-validation, confidence intervals, and appropriate statistical comparison of classifier performance using larger experimental and independent datasets.

5.13. Ethical and Data Transparency

The present study is based on the characteristics of the rotor, bearings, and gear tested under controlled laboratory conditions using a rotor-bearing-gear test rig developed for the study. Calibrated instrumentation and consistent experimental procedures were used for all vibration measurements to avoid inconsistencies, lack of repeatability, and unreliable data collection. Artificial gear and bearing defects were added in a controlled manner to represent typical gear and bearing conditions in the tests, with the same operating conditions maintained across all tests to enable comparison.

The vibration signals were measured experimentally without modification of the original data and subsequently analyzed and classified without alteration by using data processing, frequency-domain analysis, and machine-learning classification. The acquired FFT spectra were directly obtained from the extracted frequency-domain features, which were achieved based on the established signal-processing procedure. The reported values are the actual experimental results obtained under the conditions used in the tests. All efforts are made to ensure transparency and to create experimental procedures, feature extraction processes, and performance evaluations that can be reproduced by end users in similar experimental facilities using the same methodology. The authors confirm that no manipulation or selective reporting of data was carried out in preparing the results shown.

6. Conclusion

This experimental investigation identified faults in the rotor-bearing-gear system in the frequency domain at variable operating speeds and loads. The Fast Fourier Transform was employed to analyze vibration signals from a specially designed bevel gearbox test rig to detect characteristic spectral features associated with healthy conditions, individual gear deterioration, individual bearing deterioration, and combined fault conditions.

Measurable increases in vibration amplitude, in harmonic generation behavior at the Gear Meshing Frequency, and also in the harmonic modulation behavior at both the Gear Meshing Frequency and the bearing characteristic frequency were found as a result of experimental observations for increasing defects. Results under combined fault conditions showed more complex spectral responses than those under single-fault conditions, enabling frequency-domain analysis of interacting fault mechanisms. Finally, we used frequency-domain features extracted from experiments for supervised machine-learning-based classification with different algorithms. The classification results achieved in this work indicate that features derived from FFT analysis, which can be physically interpreted, are sufficiently useful for classifying the various operating conditions of a gearbox with relatively low computational complexity. The proposed methodology maintains the causality between measured vibration characteristics and actual mechanical fault mechanisms, is less computationally intensive than deep learning techniques, and enhances engineering interpretability and maintenance's ability to make reasoned decisions. In the context of the current state of research, this investigation is crucial because it combines complete experimental validation, frequency-domain feature extraction, and machine-learning classification within a common diagnostic framework.

This methodology balances diagnostic accuracy, computational efficiency, and practical applicability, making it suitable for predictive maintenance of rotating machines operating under variable service conditions. In the future, the proposed methodology will be validated on publicly available benchmark datasets to further enhance the robustness and applicability of the diagnostics for industrial applications, using advanced intelligent learning frameworks in industrial operating contexts.

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