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Vibration-Based Experimental Analysis For Fault Detection In Deep Groove Ball Bearings

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Abstract—Crankshaft supporting bearings in internal combustion (IC) engines are critical for maintaining structural integrity, reducing friction, and ensuring smooth operation, especially at high engine speeds. However, premature wear of these bearings can lead to increased noise, vibration, and potential engine failure, posing significant challenges in automotive engine reliability. This research investigates the causes of whining noise and vibration issues observed in 160cc motorcycle engines which are attributed to defects in the crankshaft bearings. The primary objective is to analyze and identify bearing defects through vibration analysis, comparing faulty bearings with healthy counterparts. The study explores the development and progression of bearing defects over time, focusing on common failure modes such as damage to rolling elements, inner races, outer races, and cages. The research aims to establish methodologies for early detection and diagnosis of bearing faults. By pinpointing the root causes of bearing degradation and providing diagnostic solutions, this work contributes to improving thedurability and performance of motorcycle engines. The findings are expected to enhance engine reliability, reduce warranty costs, and offer a better user experience by addressing complaints related to bearing-related noise from engine and vibration issues.

Index Terms - Rolling Element Bearing, Bearing Defect, Vibration Measurement

1.Introduction

The bearing is a crucial component in all rotating machinery, serving the purpose of supporting the machines and facilitating the rotational movement of the shaft relative to a stationary structure. Over 90% of machines utilize rolling element bearings, and their malfunction can result in the failure of the entire machine. Consequently, these bearings are regarded as some of the most vital elements in industrial settings. The reliability and durability of bearings are therefore paramount for the overall condition of a machine. During operation, bearings endure substantial and dynamic loads produced by the machines, which are transmitted through the components of the rolling element bearings. As such, the state of the bearings is critical in high production volume systems, where numerous rotating machines play a significant role in the production process. Timely identification of any defects in the bearings is essential to prevent increased downtime, extended production periods, and potential catastrophic failures of the machinery. Therefore, the detection of these defects is crucial for effective condition monitoring and quality assessment of bearings. Various methods exist for diagnosing defects in bearings, including acoustic measurement, temperature monitoring, wear debris analysis andvibration measurement. Among these, vibration monitoring is a widely employed and cost-effective technique [1-2] for identifying, locating, and differentiating defects in rolling element bearings. Bearings generate noise and vibration due to variations in compliance or the presence of defects. Even geometrically perfect bearings produce vibrations when subjected to radial loads. The existence of defects leads to a marked increase in vibration levels. Numerous techniques have been developed for defect diagnosis in bearings through vibration and acoustic measurements, including time domain analysis, frequency domain analysis, time-frequency domain analysis, shock pulse methods, and acoustic emission techniques.

1.1 Defects in Bearing

Even a properly functioning bearing can produce vibrations however, the presence of defects can lead to a substantial increase in these vibration levels. Numerous factors contribute to premature bearing failures, with the most prevalent being fatigue, wear, plastic deformation, corrosion, brinelling, inadequate lubrication, improper installation, and flawed design. Recognizing these defects and the vibrations they generate is crucial for effective condition monitoring of bearings. Bearing defects can be categorized into two main types: distributed defects and localized defects.

1.1.1 Distributed Defects: These defects encompass issues such as surface roughness, waviness, misaligned races, and incorrectly sized rolling elements [9]. The primary causes of distributed defects include manufacturing errors, abrasive wear, and improper installation [2]. In cases of distributed defects, the contact forces between rolling elements and raceways fluctuate, leading to vibration. The vibration response associated with distributed defects is primarily utilized for quality inspection and condition monitoring of bearings.

1.1.2 Localized Defects: This classification of defects encompasses pits, cracks, and spalls that can form on the rolling surfaces. Among these, spalling is the most prevalent mode of failure. In fact, fatigue cracks initiate beneath the surface and extend towards the exterior until the material ultimately fails, resulting in localized defects. Bentley [10] demonstrated in his research that 90% of all bearing faults are associated with damage to the inner ring, outer ring, and rolling elements as a result of localized defects.

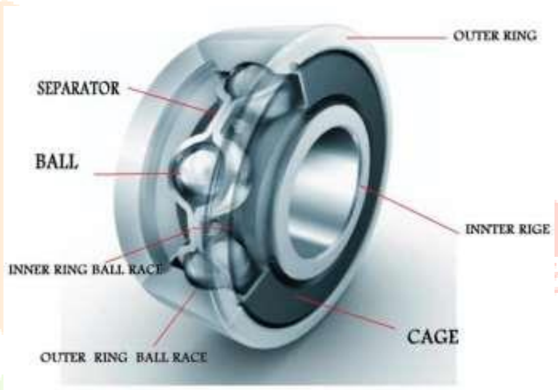

Figure1. BallBearingParts[12]

The elements of rolling contact bearings, including the inner raceway, outer raceway, rolling elements, and cage, interact through a combination of rolling and sliding motions, resulting in intricate vibration patterns. The level of vibration is influenced by several factors, including the energy of impact, the measurement location of the vibration, and the design of the bearing.

Identifying faults in rolling element bearings is a critical task for vibration analysts and is also a top priority for maintenance engineers aiming for early-stage detection. When lubrication is insufficient, it typically results in an increase in high-frequency “noise” levels. This increase doesn’t correspond to one specific frequency but varies based on the structural characteristics of the machine. Importantly, this noise occurs at frequencies far beyond the audible range of human hearing. As lubrication deteriorates further, both the intensity and the character of the noise change. While the noise level rises, its frequency tends to shift from very high to moderately high ranges. Although lower frequencies may also show signs of change, the higher frequency range offers a more distinct indication of poor lubrication. In the absence of an adequate lubricant film, direct metal-to-metal contact becomes more frequent. This contact generates energy impulses known as stress waves or shock pulses, which resemble ripples spreading from the point of contact. These waves propagate at the speed of sound and occur almost instantaneously. Over time, the extreme internal forces within the bearing can lead to localized subsurface damage, such as at the base of the outer race. Noise generated from poor lubrication is generally random and non-periodic. However, once a structural defect like a spall or crack emerges, it introduces periodic vibrations linked to specific bearing defect frequencies. For instance, if damage is present on the outer race, every time a rolling element passes the defect site, it creates a measurable vibration spike. When the damaged area lies between rolling elements, the vibration response lessens. The good news is that we can calculate the frequency of this vibration (we can determine how often the rolling element will pass that point). The challenge, however, lies in the fact that such vibrations have extremely low amplitude, necessitating the use of advanced diagnostic tools for effective detection.

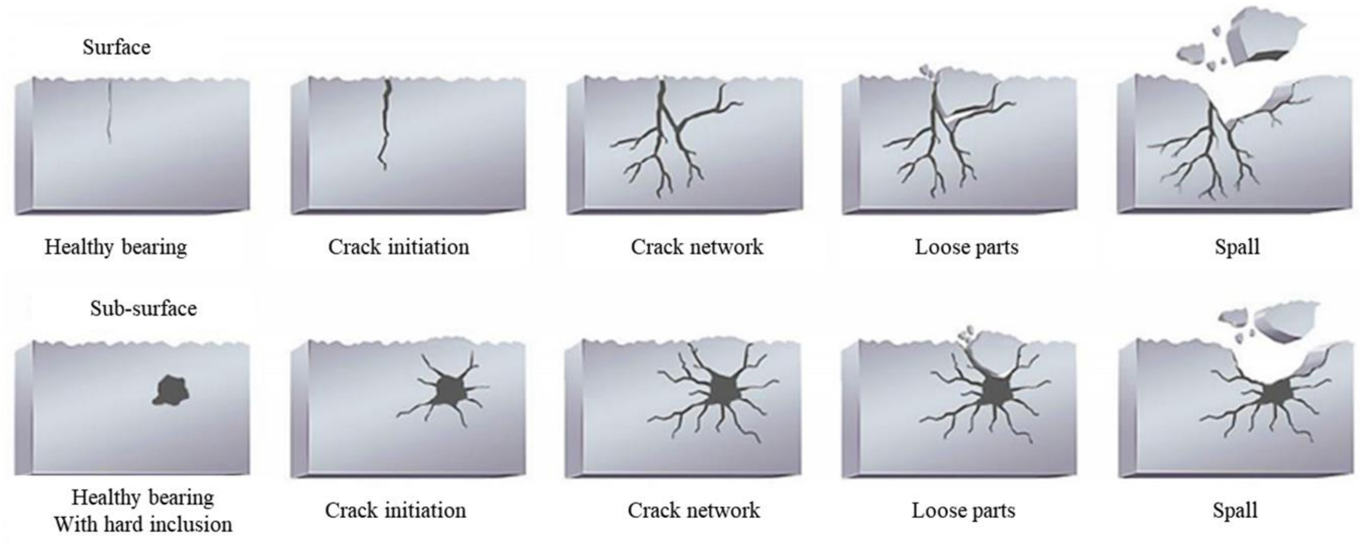

Figure 2. Crack and spall development [8]

1.2. Vibration Response due to Localized Defect

The interaction between a localized defect on a component and its mating surface leads to a sudden alteration in contact stresses, resulting in short-duration pulses. These pulsesgenerate vibrations that can be monitored. The vibration signal produced by a defective bearing can be analysed using time domain, frequency domain, or a combination of both.

1.2.1 Time Domain Approach: The time domain analysis represents the most straightforward method for detecting faults in bearings. This technique typically employs scalar indices to assess the condition of the bearing. In time domain analysis, the signal is evaluated through temporal vibrational data, allowing for an estimation of the bearing's condition based on its values. A fundamental approach in this domain involves measuring the overall root-mean-square (RMS) level and the crest factor, which is the ratio of the peak value to the RMS value of acceleration. The resulting RMS values are then compared against established benchmarks to ascertain the bearing's condition [11]. The third statistical moment, normalized by the cube of the standard deviation, is referred to as the coefficient of skewness. Dyer et al. [9] introduced kurtosis, the fourth moment, which is normalized by the fourth power of the standard deviation. For a healthy bearing, the kurtosis value is typically 3; a value exceeding 3 suggests the presence of defects. However, a notable limitation of kurtosis is that, as damage progresses, its value may decrease to that of an undamaged bearing. This occurs because kurtosis is sensitive to the pulse responses generated by defects in the vibration signal. As the nature of the damage evolves, the vibrational signals tend to become increasingly random, leading to reduction in kurtosis values to those characteristics of a normalbearing. Oack and Lapora [10] also addressed this phenomenon in their research. Consequently, kurtosis has not gained widespread acceptance in industrial applications.

1.2.2 Frequency Domain or Spectral Analysis: It is the predominant method employed for diagnosing faults in bearings. This approach involves transforming time-domain vibration signals into discrete frequency components through the application of a fast Fourier transform (FFT). The examination of raw vibration signals in the frequency domain can be
accomplished using both the Discrete Fourier Transform (DFT) and the Fast Fourier Transform (FFT). DFT is a straightforward mathematical technique which is less efficient compared to FFT. To provide a more accessible and effective means of obtaining narrow band spectra FFT is better tool. Additionally, some researchers [3, 8] have identified the high frequency range of the spectrum as a valuable tool for predicting the condition of rolling element bearings. When defects occur in rolling element bearings, they generate pulses of very short duration, which in turn excite the natural frequencies of the bearing elements and housing structures, leading to an increase in vibrational energy at these elevated frequencies.

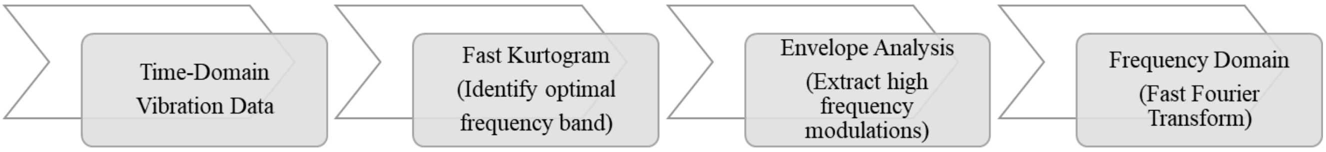

Figure 3. Processing Flow of Data

2. Objectives and Motivations

The Crankshaft bearings are critical for the proper functioning of internal combustion (IC) engines, as they directly influence the engine's noise, vibration, and overall durability. Recent warranty analyses indicate that premature bearing wear in motorcycles, particularly 160cc engines, is causing increased whining noise and increased vibrations. This leads to higher warranty claims and significant repair costs for manufacturers.

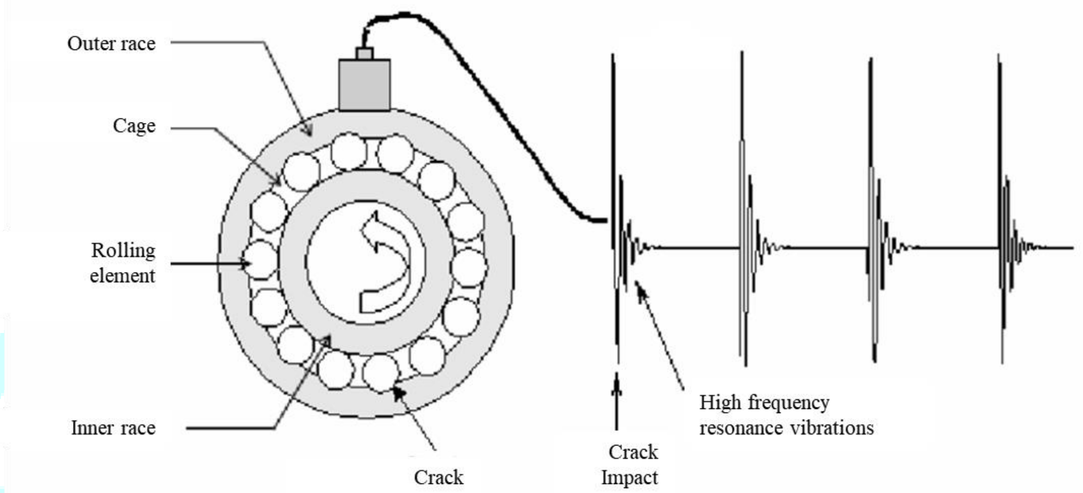

Figure 4. The typical time waveform due to a crack on the outer race of a rolling element bearing [7]

The underlying causes of the vibration could include improper lubrication, wear, misalignment, or manufacturing defects in the bearings. Addressing these issues will improve engine performance, reduce noise, and enhance the overall user experience while providing manufacturers with cost-effective solutions and more reliable bearing designs. The objectives of this study are to investigate and identify defects in crankshaft supporting bearings by comparing their performance with that of healthy bearings using vibration analysis. The project also aims to study the development of bearing defects over time, develop early detection methodologies, and ensure the consistency of bearing performance across varying RPMs.

3. Materials and Methods

The experimental setup for vibration analysis of ball bearings is meticulously designed to replicate real-world operating conditions and gather accurate data for identifying bearing defects. An AC motor (½ HP, Make-SAJ) serves as the power source, delivering rotational energy to the system. The motor’s speed is precisely controlled using an ACS Series speed control unit, enabling tests across various RPMs, while a tachometer (0-9000 RPM range) ensures consistent monitoring of rotational speed. The ball bearing under test is mounted in a robust SKF bearing housing, and axial loads are applied using a trapezoidal-thread power screw. The load applied is measured with a UNIS load cell capable of handling up to 500 N, ensuring accurate and reliable force measurement. To monitor vibrations within the bearing, a triaxial accelerometer (B&K) is strategically positioned vertically on the outer race of the bearing, while the inner race is rotated by the motor. This arrangement allows the accelerometer to capture precise vibration data in three axes, reflecting the dynamic responses of the bearing under various load and speed conditions. The system is stabilized using support fixtures mounted on a surface plate to eliminate external disturbances during testing. The vibration signals recorded by the accelerometer are transmitted to a B&K data acquisition unit, which processes the data for real-time analysis.

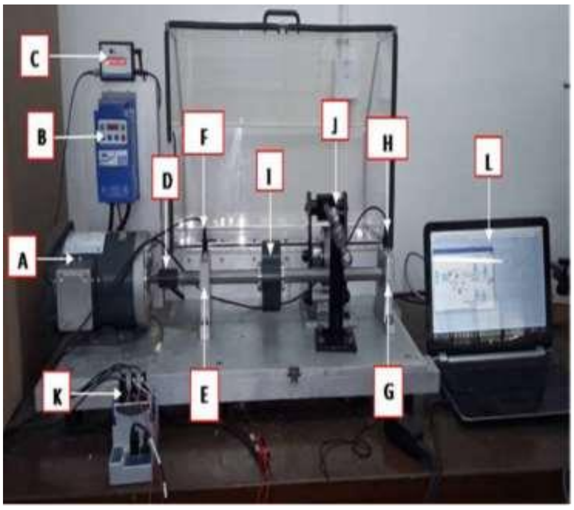

Figure 5. Experimental Setup

Deep groove ball bearing (Designation-6306) roller bearing supports the crankshaft assembly in an internal combustion engine are taken for vibration measurements. The first digit,6 signifies that it is a deep groove ball bearing, designed for smooth operation while supporting both radial and axial loads. The second digit, 3 indicates a medium-duty bearing, making it suitable for applications with moderate load requirements. The final two digits represent the bore diameter, which is determined by multiplying the number by 5, resulting in an inner diameter of 30mm.

Table 1. Description of Test Setup Components

Sr. no.	Equipment	Specification
A	AC motor	½ HP, Make-SAJ
B	Speed control unit	ACS series drives
C	Tachometer	0-9000 RPM
D	Coupling	Flexible coupling
E	Bearing	SKF make- 6306
F	Load cell	0-500 N, Make-UNIS
G & H	Support fixture	Surface Plate
I	Accelerometer	Piezoelectric Triaxial (B & K)
J	Power screw	Trapezoidal thread
K	Data acquisition unit	B & K (Bruel and Kjaer)
L	Laptop	Dell Technologies

A triaxial accelerometer is a sensor that measures vibrations. Accelerometers operate based on the principle of converting mechanical vibrations or forces (acceleration) into proportional electrical charges using piezoelectric materials. When a mechanical device is stationary, accelerometers can measure static acceleration (continuous gravitational force from the Earth) and analyze the device's tilt angle relative to the Earth. During device operation, accelerometers can measure dynamic acceleration (vibration or rotation) and analyze the device's displacement and vibration frequency. There are single-axis accelerometers and triaxial accelerometers depending on the measurement direction. Single-axis accelerometers measure vibration along a single axis, while triaxial accelerometers can measure vibration along three mutually perpendicular axes—typically labelled as X, Y, and Z axeswhich allows the accelerometer to capture the complete motion of theobject or system being tested.For mounting the accelerometer on the stationary outer race of the bearing, we are using the adhesive method, which ensures a reliable connection and supports a frequency range up to 2500 to 4000 Hz.

Table 2. Frequency limit for accelerometer measurements based on mounting methods

Mounting Method	Frequency Limit (Hz)
Hand Held	500
Magnet	2000
Adhesive	2500 – 4000
Stud	6000 – 10,000

Figure 6. Triaxial Accelerometer (Piezoelectric type)

Bearings are primarily designed to support loads acting in the radial direction, which results in most of the dynamic forces and associated vibrations being concentrated in the radial plane. This makes vibrations along the radial axes the most representative and significant for condition monitoring and fault diagnosis. Radial vibrations occur in the X and Z directions, representing the deflection of the shaft perpendicular to its axis of rotation. Vertical deflection is measured up and down relative to the crankshaft's axis, typically when the engine is positioned vertically. Horizontal deflection, on the other hand, measures side-to-side movement across the crankshaft's axis, commonly performed when the engine is in a horizontal orientation. In addition to radial vibrations, axial vibrations, measured in the Y direction, represent deflections along the length of the crankshaft.

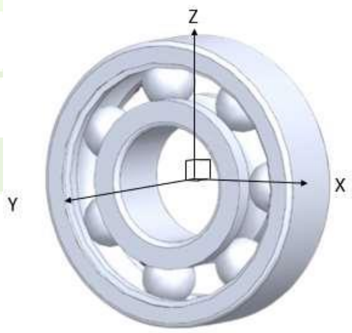

Figure 7. Ball Bearing Vibration Measurement Directions

4. Testing and Experimentation

The research focuses on defect identification in ball bearings using advanced vibration analysis techniques and experimental setups. The methodology involves studying the fundamentals of signal processing, including Fast Fourier Transform (FFT), envelope analysis, and kurtosis techniques, while employing software tools like Pulse-Lab Shop, Pulse Reflex, MATLAB, and BK Connect for efficient data analysis. Data acquisition was conducted using a specially designed jig for vibration testing, with signals captured across multiple axes via triaxial accelerometers. Time - domain vibration data was recorded in Pulse-Lab Shop and converted to .wav format using Pulse Reflex for further processing. The progression of defects on bearing surfaces and their impact on frequency signatures were analysed, with high-frequency resonances triggered by rolling elements striking faults being a key focus. Critical excitation frequencies and their harmonics, essential for detecting defects, were calculated manually or obtained from SKF catalogues, enabling precise identification and diagnosis of bearing faults.Faults in any of the four bearing components will generate specific frequencies dependent upon the bearing geometry and rotating speed. These four fault frequencies are commonly termed: BPFO - Ball Pass Frequency, Outer Race BPFI - Ball Pass Frequency, Inner Race BSF - Ball Spin Frequency FTF - Fundamental Train Frequency.If frequencies are detected at these critical frequencies, the fault can be associated with that component.

BPFI (Ball Pass Frequency of Inner race):The inner race rotates with the shaft. Each ball hits the inner race more often because the contact point keeps moving. Therefore, the defect on the inner race creates more frequent impacts. That's why BPFI is highest —more contacts per second.

BPFO (Ball Pass Frequency of Outer race):The outer race is fixed (doesn't rotate).The balls roll over it, but since the race is stationary, contacts are less frequent. Resulting fault frequency is lower than BPFI.

BSF (Ball Spin Frequency):This is the frequency at which the ball spins around its own axis, not around the bearing. It's affected by sliding and skidding, and usually lower than BPFI and BPFO.

FTF (Fundamental Train Frequency):It is the rate at which the cage (or retainer) of the bearing rotates. It's also called Cage Frequency. The cage rotates slower than the shaft and the balls — its job is just to hold and space the balls. Imagine the balls rolling around the bearing — the cage just guides them. It makes one rotation for every few shaft revolutions, depending on bearing geometry. So, it appears at a fraction of the shaft frequency.

Here the motor shaft runs at a rotational speed of 1500 RPM, its shaft frequency is:1500 RPM / 60 = 25 Hz. This is considered the 1st order.2nd order = 2 × 25 Hz = 50 Hz. 3rd order = 3 × 25 Hz = 75 Hz. n-th order = n × shaft frequency

Table 3.Critical Frequencies of Bearings

Fault Type	Full Form	Frequency order (From Formula)	Frequency (From Catalogue)
FTF	Fundamental Train Frequency	0.38172 Orders	9.5Hz (Lowest)
BSF	Ball Spin Frequency	1.995 Orders	49.9Hz (Mid)
BPFO	Ball Pass Frequency Outer Race	3.05364 Orders	76.3Hz (High)
BPFI	Ball Pass Frequency Inner Race	4.9464 Orders	123.6Hz (Highest)

4.1 Advanced Data Processing Techniques

Advanced data processing and visualization techniques played a pivotal role in the analysis of vibration signals to detect and diagnose ball bearing defects with precision. The Fast Kurtogram technique was utilized to isolate the sharpest frequency ranges, significantly enhancing the clarity of defect signals by filtering out noise. This method effectively pinpointed the high-frequency resonances associated with localized faults. To further refine the analysis, envelope analysis was employed to extract modulation frequencies from the time-domain signals. This approach outperformed traditional FFT in identifying defect frequencies, as it mitigated theinfluence of noise and highlighted critical frequency components more effectively.For data analysis and visualization, vibration data from each axis was processed individually, and the results were systematically stored in Excel for structured evaluation. FFTs and envelope spectra of band-passed data were plotted to identify and analyse critical defect frequencies. To streamline this process, an in-house MATLAB code was developed, automating key tasks such as envelope extraction, FFT of envelope spectra, and defect frequency detection. The code also included features for defining user-specified critical frequency ranges and visualizing overlaps between critical frequencies and the envelope spectrum. This ensured accurate defect identification and simplified the diagnostic process, making it highly efficient and reliable.Time-domain vibration data is initially acquired using Pulse-Lab Shop, and the raw data is converted into a .wav file (Waveform Audio File Format) using Pulse Reflex for further processing.Raw time-domain vibration data, particularly when acquired from bearings, is often noisy due to environmental interference, sensor inaccuracies, and random fluctuations in system performance. This noise can obscure important fault signals, making it challenging to detect defects. To mitigate this, signal processing techniques like filtering, envelope analysis, and Fast Fourier Transform (FFT) are employed to extract meaningful features. These methods help isolate defect frequencies by removing unwanted noise and enhancing the signal, thereby improving the reliability of diagnostic results.

To generate the Fast Kurtogram plot, the vibration data from each axis is processed separately, with the processed data manually stored in an Excel sheet for analysis. Each axis is individually analysed, and the corresponding Kurtogram data is entered manually. During the Fast Fourier Transform process, a 0.5-second band-pass signal is lost due to filtering. Similarly, for envelope analysis, only 500 milliseconds of envelope data is utilized to focus on the most critical aspects of the vibration signal. This stepwise approach ensures precise data extraction and preparation for defect diagnosis.

Figure 8 and 9 displays the time domain rawdata of the healthy bearing and defective bearing SKF-6306 rotating at 1500rpm machine operating at 25 Hz.

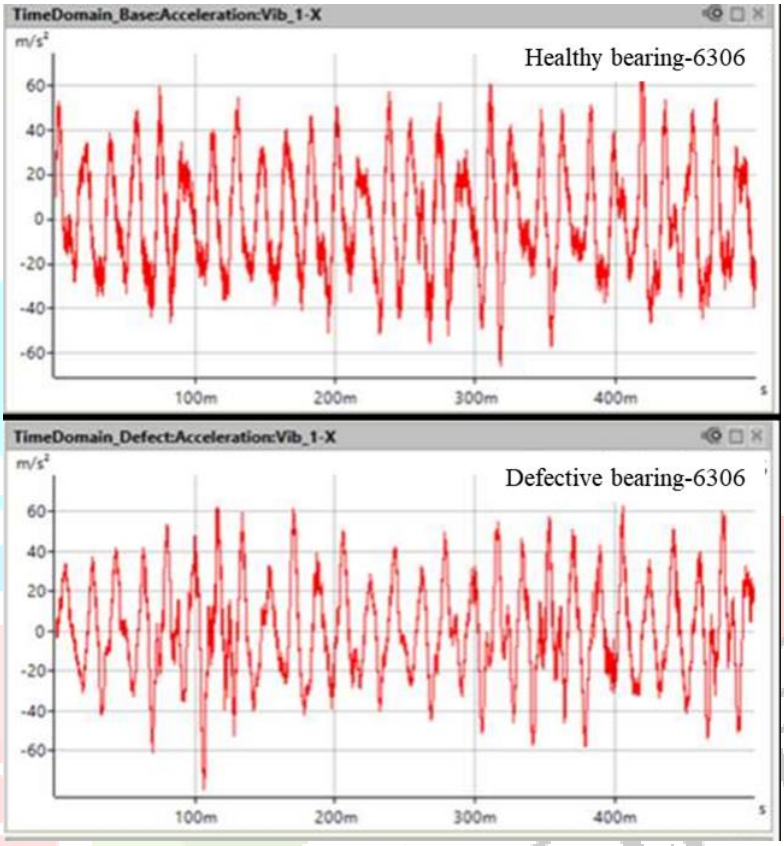

Figure 8. Healthy versus Defective Bearing Time Raw Data (X-direction)

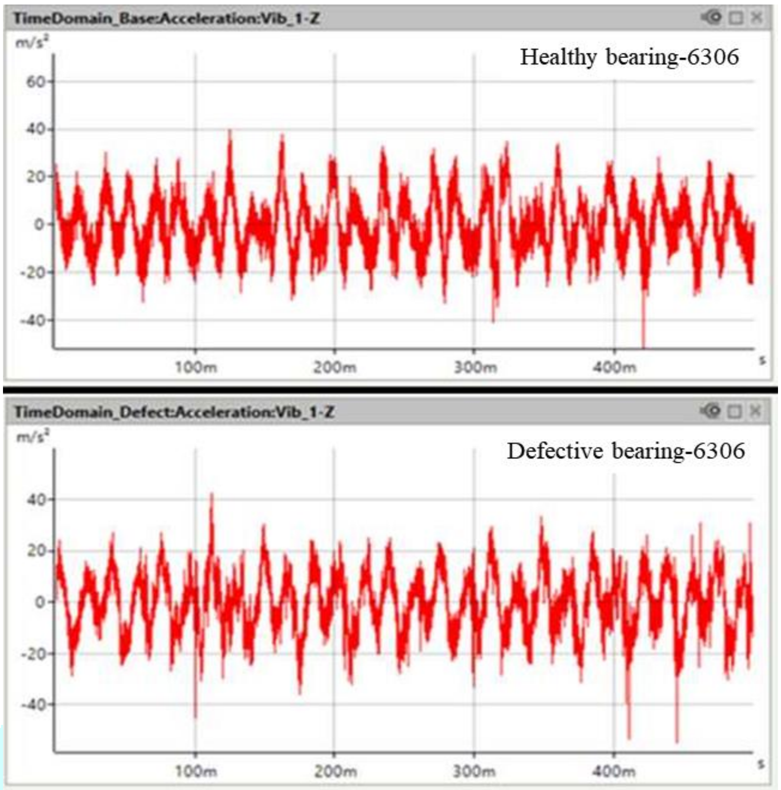

Figure 9. Healthy versus Defective Bearing Time Raw Data (Z-direction)

4.2 Data Visualization and Analysis Technique

Advanced data visualization and analysis techniques were essential to accurately detect and quantify bearing defects, leveraging the strengths of signal processing methods like Tone-to-Noise Ratio (TNR), normalization, and matched filter RMS. The TNR, a critical metric in vibration analysis, quantifies the clarity of a signal by comparing its strength (the "tone") against background noise. A higher TNR indicates a stronger and more distinguishable signal, enabling precise identification of defect related frequencies, even amidst significant noise interference

The systematic process to calculate defect indices began with identifying peak values within a narrow 3 Hz bandwidth around critical frequencies, ensuring high sensitivity to tonal components. To account for noise, an average value was calculated within a broader 10 Hz bandwidth, and the TNR was computed as the ratio of these two values. This ensured that defect-related peaks were highlighted relative to their noise environment. To further refine results and mitigate the effects of harmonics, the calculated TNR values were normalized by dividing them by the TNR of the shaft frequency, isolating the true defect frequencies from secondary interference.

Normalization techniques played a pivotal role in ensuring consistency and comparability across datasets. By normalizing defect indices to unity, variations arising from sidebands or multiple defects were minimized, allowing for direct comparison between defective and healthy bearings. The matched filter RMS method provided additional granularity, enabling a logarithmic comparison that specifically emphasized critical frequency defects. This approach effectively reduced the influence of sidebands and non-defective components, providing a focused and robust measure of defect severity. The data visualization techniques implemented were equally crucial. Envelope spectra were generated from time-domain signals using Fast Kurtogram and envelope analysis, which effectively filtered out noise and enhanced the visibility of defect frequencies. FFTs of these envelope spectra provided clear and interpretable graphs, where critical frequencies and their indices could be visualized. The in-house MATLAB code automated much of this process, streamlining envelope extraction, FFT generation, and defect detection. Features such as user-defined frequency ranges, overlap visualization, and automated results exportation to Excel made the analysis more efficient and reproducible. Together, these methods—TNR calculations, normalization, matched filter RMS, and enhanced visualization techniques—provided a robust framework for defect detection.

Figure 10 displays the FFT results of the healthy bearing SKF-6306 rotating at 1500rpm i.e. operating at 25 Hz.

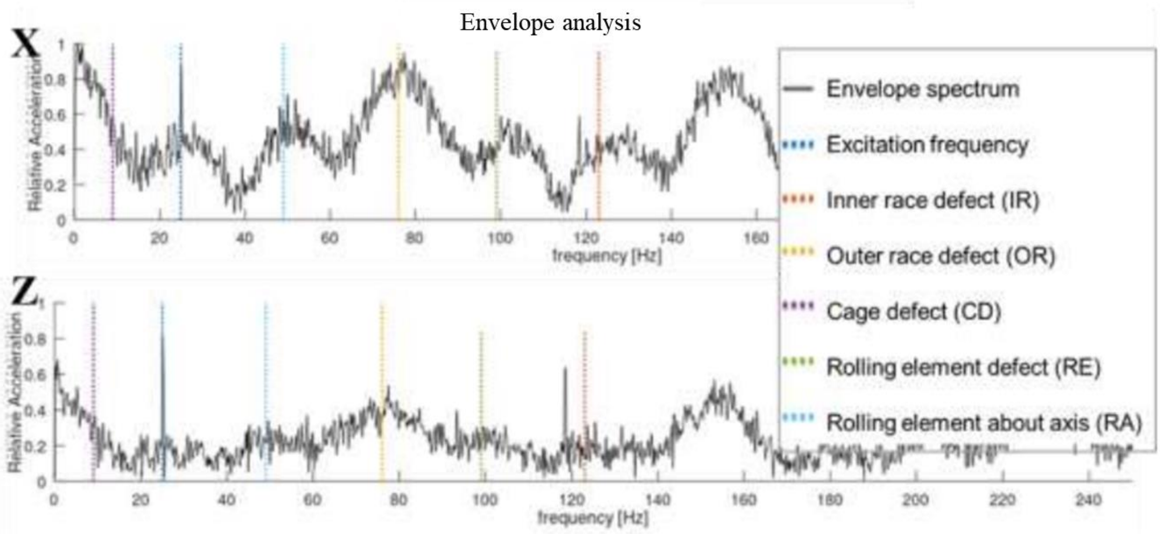

Figure 10. Amplitude Spectrum of Squared Envelope of Healthy Bearing

Table 4. Healthy Bearings Defect Indices

Sr.no.	Parameter	Frequency	X-direction	Z-direction
	1X - Machine Running Speed 1500rpm	25.0Hz	1	1
1	BPFO - Ball Passing Frequency of Outer Race	BPFO_76.3Hz	0.59	0.30
2	BPFI - Ball Passing Frequency of Inner Race	BPFI_123.6Hz	0.76	0.40
3	FTF - Fundamental Train Frequency	FTF_9.5Hz	0.71	0.36
4	BSF - Ball Spin Frequency	BSF_49.9Hz	0.70	0.32

Figure 12 displays the FFT results of the healthy bearing SKF-6306 rotating at 1500rpm i.e. operating at 25 Hz.

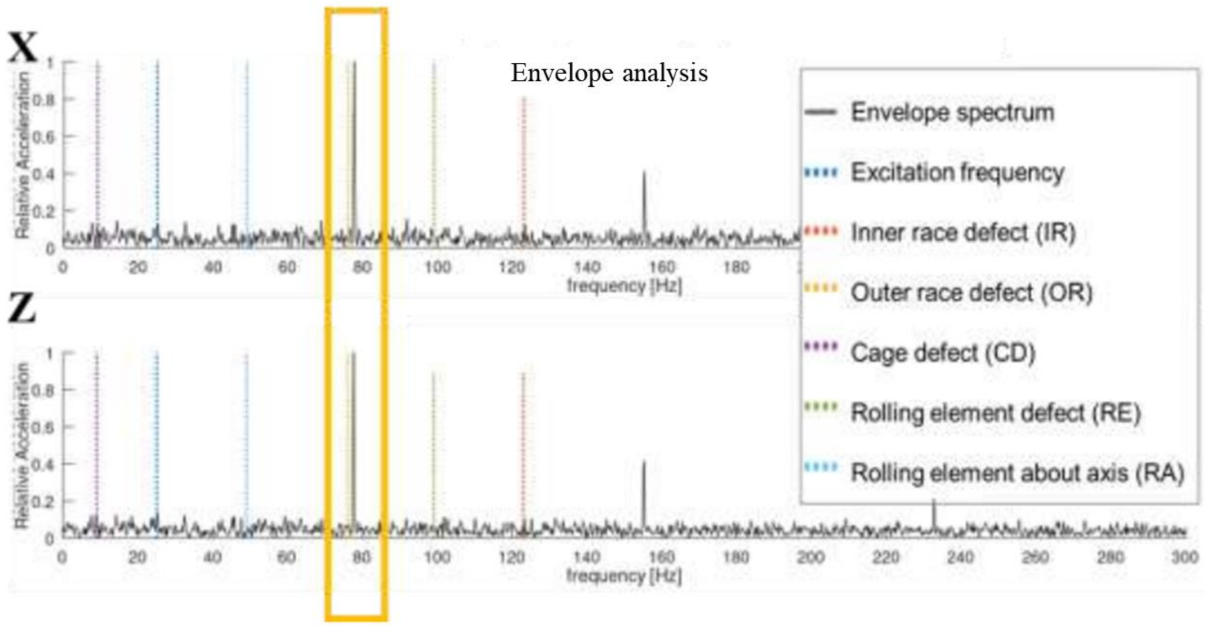

Figure 12. Amplitude Spectrum of Squared Envelope of Defective Bearing

Table 5.DefectiveBearings Defect Indices

Sr.no.	Parameter	Frequency	X-direction	Z-direction
	1X - Machine Running Speed 1500rpm	25.0Hz	1	1
1	BPFO - Ball Passing Frequency of Outer Race	BPFO_76.3Hz	4.42	4.76
2	BPFI - Ball Passing Frequency of Inner Race	BPFI_123.6Hz	1.02	0.94
3	FTF - Fundamental Train Frequency	FTF_9.5Hz	0.94	0.99
4	BSF - Ball Spin Frequency	BSF_49.9Hz	1.04	1.03

5. Results and Conclusions

The experimental analysis effectively distinguished between healthy and defective ball bearings using advanced vibration signal processing techniques. Component-level testing has proven to be sufficiently accurate for the diagnosis of bearing defects, offering a reliable method for identifying faults without the complexities of full-system evaluation. Healthy bearings consistently exhibited frequency spectra with indices below 1, indicating the absence of significant defects. In contrast, defective bearings demonstrated indices exceeding 4, with prominent peaks aligning with critical defect frequencies. These observations confirmed the presence of damage, specifically in the outer race of the defective bearings.

The integration of envelope analysis, kurtosis, and Tone-to-Noise Ratio (TNR) calculations proved highly effective in isolating defect frequencies from noise and harmonics, ensuring precise detection and quantification. The normalized defect indices, calibrated to unity for comparative analysis, provided a clear and reliable measure of defect severity, allowing for straightforward differentiation between healthy and faulty bearings. The Fast Kurtogram and envelope spectrum further enhanced the clarity of defect identification by focusing on sharp, high-frequency components associated with bearing faults.By utilizing the Tone-to-Noise Ratio (TNR) of defect frequencies and comparing it against the noise amplitudes in the vibration data, an effective severity index for bearing defects can be developed. This index allows for the detection of faults by highlighting the differences between healthy and defective bearings.

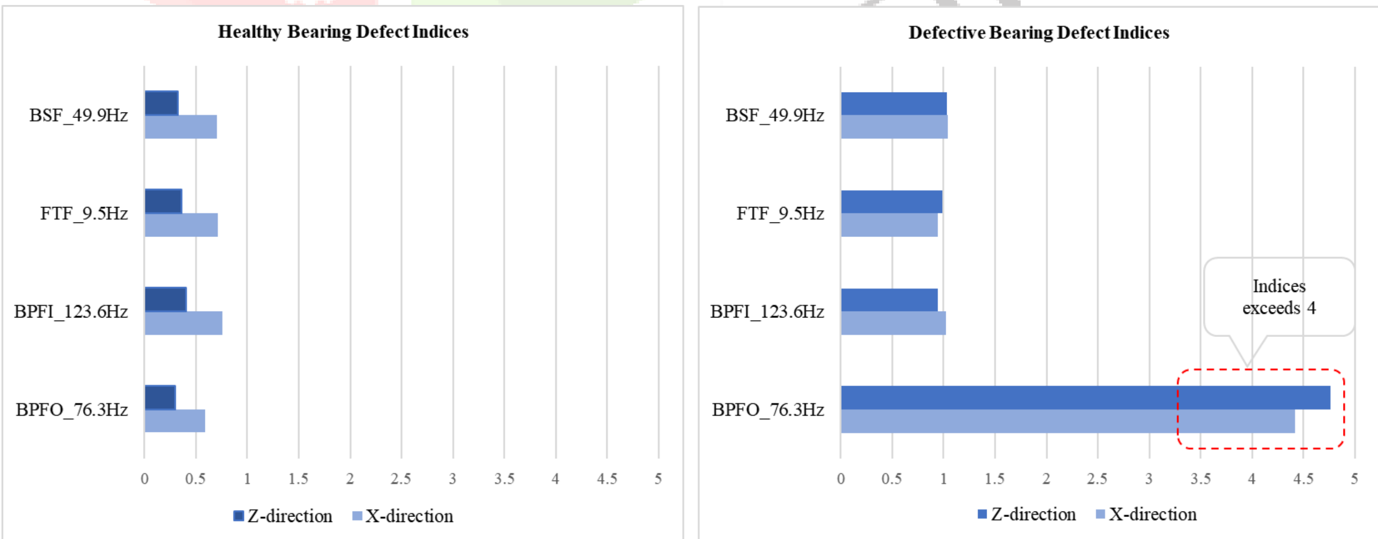

Figure 13.Bearings Defect Indices Comparison

When the defect indices of bearing exceed the threshold values observed in healthy bearings, it becomes possible to identify and diagnose potential faults even at early stages. This method enables proactive maintenance and more accurate fault detection, ensuring the reliability and longevity of machinery by addressing issues before they lead to catastrophic failures.The results validated the robustness of the proposed methodology in identifying bearing defects with high accuracy. The approach is particularly effective for early fault detection, as it leverages critical frequency analysis and advanced filtering techniques to minimize the influence of sidebands and harmonics. The insights gained from this study offer a systematic and scalable method for bearing health monitoring, contributing to improved reliability and reduced maintenance costs in practical applications.

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