

**Experimental study on health monitoring of ball
bearing by analyzing the sound level**

Submitted By

Md. Jawad Rahman Chowdhury, 190012121

Aarik Almas, 190012104

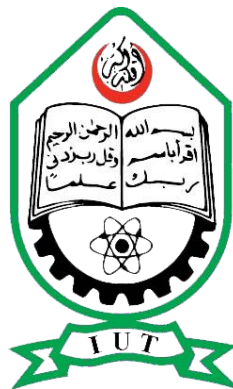
Supervised By

Dr. Md. Anayet Ullah Patwari

Professor

Mechanical & Production Engineering Department

**A Thesis submitted in partial fulfillment of the requirement for the degree of Bachelor
of Science in Industrial and Production Engineering**



Department of Mechanical and Production Engineering (MPE)

Islamic University of Technology (IUT)

June, 2024

Candidate's Declaration

This is to certify that the work presented in this thesis, titled, “Experimental study on health monitoring of ball bearing by analyzing the sound level”, is the outcome of the investigation and research carried out by me under the supervision of Dr. Md. Anayet Ullah Patwari, Professor, Mechanical & Production Engineering Department.

It is also declared that neither this thesis nor any part of it has been submitted elsewhere for the award of any degree or diploma.

Md. Jawad Rahman Chowdhury, 190012121

Aarik Almas, 190012104

Recommendation of the Thesis Supervisor

The thesis titled “Experimental study on health monitoring of ball bearing by analyzing the sound level” submitted by Md. Jawad Rahman Chowdhury, Student No: 190012121 and Aarik Almas, Student No: 190012104, have been accepted as satisfactory in partial fulfillment of the requirements for the degree of B Sc. in Industrial and Production Engineering **on 6th June, 2024.**

Dr. Md. Anayet Ullah Patwari,

(Supervisor)

Professor,

MPE Dept., IUT, Board Bazar, Gazipur-1704,

Bangladesh.

CO-PO Mapping of IPE 4800 -Thesis and Project

COs	Course Outcomes (CO) Statement	(PO)	Addressed by	
CO1	<u>Discover and Locate</u> research problems and illustrate them via figures/tables or projections/ideas through field visit and literature review and <u>determine/Setting</u> aim and objectives of the project/work/research in specific, measurable, achievable, realistic and time frame manner.	PO2	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO2	<u>Design</u> research solutions of the problems towards achieving the objectives and its application. Design systems, components or processes that meets related needs in the field of mechanical engineering	PO3	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO3	<u>Review, debate, compare</u> and <u>contrast</u> the relevant literature contents. Relevance of this research/study. Methods, tools, and techniques used by past researchers and justification of use of them in this work.	PO4	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO4	<u>Analyse</u> data and <u>exhibit</u> results using tables, diagrams, graphs with their interpretation. <u>Investigate</u> the designed solutions to solve the problems through case study/survey study/experimentation/simulation using modern tools and techniques.	PO5	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO5	<u>Apply</u> outcome of the study to assess societal, health, safety, legal and cultural issues and consequent possibilities relevant to mechanical engineering practice.	PO6	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO6	<u>Relate</u> the solution/s to objectives of the research/work for improving desired performances including economic, social and environmental benefits.	PO7	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO7	<u>Apply</u> moral values and research/professional ethics throughout the work, and <u>justify genuine</u> referencing on sources, and demonstration of own contribution.	PO8	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO8	<u>Perform</u> own self and <u>manage</u> group activities from the beginning to the end of the research/work as a quality work.	PO9	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO9	<u>Compile and arrange</u> the work outputs, write the report/thesis, a sample journal paper, and present the work to a wider audience using modern communication tools and techniques.	PO10	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO10	<u>Organize</u> and <u>control the cost</u> and time of the work/project/research and <u>coordinate</u> them until the end of it.	PO11	Thesis Book	
			Performance by research	
			Presentation and soft skill	
CO11	<u>Recognize</u> the necessity of life-long learning in career development in dynamic real-world situations from the experience of completing this project.	PO12	Thesis Book	
			Performance by research	
			Presentation and soft skill	

K-P-A Mapping of IPE 4800 -Theis and Project

C O s	P O s	Related Ks								Related Ps							Related As				
		K 1	K 2	K 3	K 4	K 5	K 6	K 7	K 8	P 1	P 2	P 3	P 4	P 5	P 6	P 7	A 1	A 2	A 3	A 4	A 5
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C O 9	P O 10																				
C O 10	P O 11																				
C O 11	P O 12																				

Student Name /ID:

1 Md. Jawad Rahman Chowdhury

ID- 190012121

2. Aarik Almas

ID- 190012104

Signature of the Supervisor:

Name of the Supervisor:

Dr. Md. Anayet Ullah Patwari, Professor,

MPE Dept., IUT, Board Bazar, Gazipur-1704,

Bangladesh.

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Abstract

This study explores a novel approach to ball bearing health monitoring using ultrasonic sound. Ball bearings are crucial components in machinery, but they are prone to problems like pitting, brinelling, misalignment, and fatigue. These issues can lead to significant operational downtime and safety risks. This research proposes using ultrasonic sound for early detection of these problems. Unlike traditional methods, ultrasonic analysis is non-intrusive and efficient. By analyzing ultrasonic signals emitted by bearings, the study aims to identify unique patterns associated with different bearing health states, such as pitting, brinelling, and fatigue. This will not only improve fault detection but also lay the groundwork for a more comprehensive health monitoring system. Rigorous experiments will validate the effectiveness of using ultrasonic sound for bearing fault detection. The findings will contribute to the development of better predictive maintenance strategies, ultimately improving the reliability and longevity of machinery. This research has the potential to revolutionize industrial operations by prioritizing precision and safety for optimal machine performance.

The sound intensity level (dBA) of the bearings consistently increased as they went from new to medium wear to old at all measured distances (4 cm, 6 cm, and 8 cm) from the motor. The softwares that we have used are Sound Analyzer and Frequency Analyzer Software. This trend suggests that sound level analysis has potential for monitoring bearing health, as increased wear likely leads to higher noise levels. However, the readings were also generally lower at further distances from the motor, indicating that distance from the sound source is an important factor to consider when using this technique for bearing health assessment. Worn bearings get noisy. Sound intensity increased with wear at all distances, but readings were lower further from the motor. This suggests sound analysis is promising for monitoring bearing health, but distance from the bearing needs to be considered.

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NOMENCLATURES AND SYMBOL

Abbreviation	Meaning
RMS	Root Mean Square
FFT	Fast Fourier Transform
dB	Decibel
SNR	Signal-to-Noise Ratio
PSD	Power Spectral Density
AI	Artificial Intelligence
ML	Machine Learning
ANN	Artificial Neural Network
SVM	Support Vector Machine
CNN	Convolutional Neural Network
MFCC	Mel-Frequency Cepstral Coefficients
STFT	Short-Time Fourier Transform
IMF	Intrinsic Mode Function
EMD	Empirical Mode Decomposition
PCA	Principal Component Analysis
LMS	Least Mean Squares
SCADA	Supervisory Control and Data Acquisition
CM	Condition Monitoring

CHAPTER 1

INTRODUCTION

In the realm of machinery and rotating equipment, ball bearings play a pivotal role in ensuring smooth operation and efficiency. However, the occurrence of faults in these bearings, such as pitting, brinelling, misalignment, and fatigue, poses significant challenges, leading to operational disruptions and safety risks. Traditional methods of health monitoring, particularly vibration analysis, have been employed, but advancements in technology have spurred the exploration of alternative and more sensitive techniques. This study delves into the application of ultrasonic sound for the health monitoring of ball bearings, offering a non-intrusive means to detect and diagnose potential issues at an early stage. Ultrasonic sound presents a promising avenue for achieving higher sensitivity in fault detection, and this research aims to contribute valuable insights into its efficacy, experimental validation, and practical applications in ensuring the reliability and longevity of critical machinery components. Here a comparative analysis of three types ball bearings have been done and we get the results from the graph. Here in the graph it is seen a constant increase of frequency as we shift the ball bearings from the new to the old ball bearings. A comparative analysis of the frequency of the [3 types of ball bearings](#) has been done by calculating the frequency level. This study investigates the potential of sound level analysis for monitoring ball bearing health by analyzing sound intensity changes at different wear stages and across varying distances from the motor. Ball bearings are essential components in countless machines but their failure can lead to costly downtime and even safety risks. While traditional monitoring methods like vibration analysis exist, they can be susceptible to external factors. This research explores the potential of sound level analysis as a complementary approach for health monitoring. Sound level analysis offers advantages like being non-intrusive and potentially detecting faults earlier. This study investigates the effectiveness of sound level analysis for monitoring ball bearing health. We measured sound intensity levels of bearings at different wear stages ([new, medium wear, old](#)) and placed them at various distances from a motor to account for the influence of distance. The findings will

contribute to understanding the feasibility of using sound level analysis for bearing health monitoring in practical applications.

1.1 Background of the Study

1.1.1 Importance of Bearing Health Monitoring

Ball bearings are critical components in a wide range of machinery, from industrial equipment to wind turbines and even household appliances. Their proper functioning ensures smooth operation and prevents catastrophic failures that can lead to expensive downtime and safety hazards. Early detection of bearing faults is crucial for implementing preventive maintenance strategies and avoiding such issues expand more.

1.1.2 Traditional Monitoring Techniques

Traditionally, bearing health has been monitored through techniques like:

- **Periodic inspections:** These involve physical checks for signs of wear, tear, or overheating, but they can be time-consuming and disruptive to operations.exclamation
- **Vibration analysis:** This method measures vibrations caused by bearing faults, but it requires specialized equipment and expertise for interpretation.

1.1.3 Sound Level Analysis as a Monitoring Tool

Sound analysis offers a promising alternative for bearing health monitoring to expand more Bearings in good condition to produce a characteristic low-level sound signature. As they deteriorate, specific types of faults generate unique acoustic signatures that can be detected and analyzed.

Here's why sound level analysis is gaining traction:

- **Non-intrusive:** Sound measurements can be taken without interrupting machine operation.exclamation

- **Cost-effective:** Sound sensors are relatively inexpensive compared to vibration analysis equipment.
- **Simplicity:** Sound data can be easily collected and analyzed using readily available tools.

1.1.4 Key Aspects of Sound-based Bearing Diagnostics

- **Fault Detection through Increased Sound Levels:** Studies have shown that a rise in overall sound level compared to a baseline can indicate bearing issues. An increase of 8 dB suggests potential problems like lubrication deficiency, while a 12 dB or higher increase signifies early-stage bearing failure.
- **Frequency Analysis:** Beyond overall sound level, analyzing the frequency spectrum of the bearing noise is crucial. Specific fault types, like cage defects or cracked races, generate characteristic frequencies within the sound signature. Techniques like Fast Fourier Transform (FFT) help identify these fault frequencies.

1.1.5 Benefits of Sound Level Analysis

- **Early Fault Detection:** Sound analysis can detect bearing faults at an early stage, allowing for corrective action before major damage occurs.
- **Cost-effective Maintenance:** Early detection prevents catastrophic failures, reducing repair costs and downtime.
- **Improved Machine Reliability:** Continuous sound monitoring provides valuable data for optimizing maintenance schedules and improving overall machine reliability.

1.1.6 Limitations and Future Research Directions

While sound level analysis offers a valuable tool, it's important to acknowledge its limitations:

- **Background Noise Interference:** In noisy environments, isolating bearing

sound from background noise can be challenging.

- **Limited Fault Differentiation:** Distinguishing between different fault types solely based on sound level might be difficult, requiring additional analysis.

Future research directions include:

- **Advanced Signal Processing Techniques:** Developing algorithms for robust background noise suppression and improved fault classification using machine learning.
- **Sensor Integration:** Exploring the integration of sound analysis with other monitoring techniques like vibration analysis for a more comprehensive health assessment.
- **Standardization of Fault Detection Thresholds:** Establishing standardized sound level thresholds for different bearing types and operating conditions to improve fault detection accuracy.

By addressing these limitations and pursuing further research, sound level analysis has the potential to become a powerful and widely adopted technique for ball bearing health monitoring.

1.2 Some types of ball bearing failures:

1.2.1 Wear

Wear failure in a ball bearing occurs due to gradual material loss on the bearing's races and balls caused by friction during operation. This friction happens as the balls roll between the inner and outer races. Over time, this wears down the smooth surfaces, making them smoother and potentially even slightly polished.



Fig 1.1 Ball Bearing Failure due to wear

1.2.2 Fatigue

Ball bearings suffer fatigue failure when repeated stress leads to cracks that grow into surface flakes (spalling). This spalling damages the bearing, increasing friction and vibration, which weakens it further and speeds up the process. Improper lubrication, overloading, and misalignment can all worsen fatigue. Listen for noise and increased vibration to diagnose potential failure, and replace the bearing before it seizes and damages other machinery components.



Fig 1.2: Ball Bearing Failure due to fatigue

1.2.3 Corrosion

Corrosion in ball bearings occurs when water, moisture, or contaminants breach the lubricant or seals, causing the metal surfaces to rust and pit. This creates a rough, uneven surface on the races and balls, increasing friction and vibration. The weakened metal becomes more susceptible to further corrosion and fatigue, accelerating bearing failure. Regular inspection and proper sealing are crucial to prevent this destructive process.



Fig 1.3: Ball Bearing Failure due to Corrosion

1.2.4 Fracture

A different type of failure in ball bearings is fracture. Unlike fatigue's gradual cracking, fracture happens when extreme forces cause a sudden break in the bearing race or balls. This fracture can be caused by shock loads, improper installation, or bearing defects. The broken pieces can jam the bearing, leading to immediate machine stoppage and potential damage to surrounding parts.



Fig 1.4: Ball Bearing Failure due to fracture

1.2.5 Misalignment Damage

In ball bearing failure, misalignment refers to a situation where the shaft and bearing housing aren't perfectly aligned. This creates uneven stress on the bearing balls and races. Imagine a bumpy road for the balls to travel on. Over time, this uneven stress accelerates fatigue, leading to faster cracking, spalling, and bearing failure.



Fig 1.5: Inner race misalignment damage of bearing

1.2.6 Electrical Damage

Electrical currents, even small ones, can wreak havoc on bearings. The current acts like tiny lightning bolts, blasting pits and grooves into the bearing races and balls. This roughened surface increases friction and vibration, while also breaking down the lubricant. This whole process accelerates wear and tear, leading to premature bearing failure.

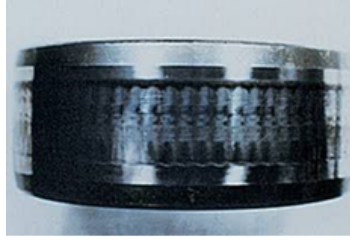


Fig 1.6 Electrical Damage for small bearing

1.2.7 Plastic deformation

Plastic deformation in ball bearings is a permanent bending or warping caused by exceeding the material's yield strength. This can happen from overload, shock loads (like hammering during installation), or debris getting crushed between rolling elements. The resulting indentations or flattening disrupt smooth operation and cause noise and vibration. Bearings with plastic deformation are unsafe for continued use.



Fig 1.7 Plastic deformation of ball bearing

1.3 Application of this study in the field of Mechanical engineering practice

i. Predictive Maintenance:

By analyzing the sound produced by a bearing, we can potentially identify early signs of wear and tear before a catastrophic failure occurs. This information can be used to schedule preventive maintenance, such as lubrication or bearing replacement, minimizing downtime and maintenance costs.

In critical machinery, like wind turbines or aircraft engines, early detection of bearing problems is crucial to prevent major malfunctions and ensure safety. Sound analysis can be a non-intrusive and cost-effective way to achieve this.

ii. Condition Monitoring for Remote Applications:

In situations where physically accessing machinery is difficult or expensive (e.g., offshore wind farms, remote pipelines), sound analysis can be used for remote condition monitoring.

By installing microphones near bearings and transmitting the sound data wirelessly, engineers can monitor bearing health from a central location. This can reduce maintenance costs and improve overall system uptime.

iii. Optimizing Lubrication Strategies:

The sound produced by a bearing can be influenced by the lubrication condition. By analyzing sound data, we might identify insufficient or excessive lubrication, allowing for adjustments to optimize lubrication schedules and improve bearing life.

iv. Improving Bearing Selection:

This research can contribute to a database of sound characteristics for different bearing types and operating conditions. This information can be used by engineers to select the most appropriate bearings for specific applications based on desired noise levels and performance requirements.

v. Quality Control of Bearings:

Sound analysis can be integrated into the manufacturing process of bearings to identify defects during production. This can help ensure consistent quality and prevent defective bearings from reaching the market.

1.4 Relation of this study for improving environmental benefits

While our thesis project on sound analysis for ball bearing health monitoring focuses on improving machinery performance and efficiency, it can indirectly contribute to several environmental benefits.

i. Reduced Energy Consumption:

Predictive maintenance, enabled by early detection of bearing problems, can prevent catastrophic failures. This translates to less frequent equipment replacements and repairs, leading to a lower overall demand for raw materials and manufacturing processes. These processes often have significant energy consumption footprints.

ii. Extended Equipment Lifespan:

By identifying and addressing bearing issues early on, your research can help extend the lifespan of machinery. This reduces the need for frequent equipment replacements, leading to less resource consumption associated with manufacturing new equipment.

iii. Minimized Lubricant Waste:

Sound analysis can help optimize lubrication strategies by identifying insufficient or excessive lubrication. This can minimize lubricant waste, reducing the environmental impact associated with lubricant production and disposal. Lubricants can be hazardous materials, so proper usage is crucial.

iv. Prevention of Oil Leaks and Spills:

Early detection of bearing problems can prevent catastrophic failures, which can sometimes lead to oil leaks and spills. These spills can have devastating consequences for soil and water resources.

v. Improved Efficiency and Reduced Emissions:

By ensuring machinery operates at optimal efficiency through proper bearing health monitoring, you can potentially contribute to reduced energy consumption. This translates to lower greenhouse gas emissions associated with energy production from fossil fuels.

1.5 Objectives

- To develop a novel method for differentiating between various bearing fault types (e.g., cage defects, localized wear, surface fatigue) based on sound level analysis.
- This method could involve extracting and analyzing time-domain features (e.g., skewness, kurtosis) alongside frequency domain analysis (FFT) to create a more comprehensive fault signature.
- To evaluate the effectiveness of the proposed method through controlled experiments with different bearing fault types.
- To analyze the performance of existing background noise suppression techniques (e.g., wavelet transforms, blind source separation) for isolating bearing sound from background noise in simulated and real-world industrial environments.
- To explore and potentially develop a novel noise suppression algorithm specifically tailored for ball bearing sound analysis.
- To quantify the improvement in signal-to-noise ratio achieved by the implemented noise suppression technique.

These objectives address the research gaps identified and aim to significantly advance sound level analysis as a reliable tool for ball bearing health monitoring. To tailor these objectives to specific research interests and resources available.

1.5.1 Methodology for achieving the objectives:

Step-1 Experimental Setup:

Test Bearings: Obtaining a set of ball bearings with various controlled fault types (e.g., cage defects, localized wear, surface fatigue).

Data Acquisition: Mounting the bearings on a test rig that allows for controlled rotation and load application. Setting up a sound recording system to capture sound data at different operating conditions (speed, load). Ensuring consistent

microphone placement relative to the bearings.

Background Noise Simulation: Simulating realistic background noise conditions for both controlled experiments and real-world testing environments. This might involve recordings from actual industrial settings or synthesized noise models.

Step-2 Feature Extraction and Analysis:

Time-Domain Analysis: Extracting time-domain features from the acquired sound data. These could include statistical features like skewness (asymmetry), kurtosis (peakedness), and root mean square (RMS) to capture overall loudness changes.

Frequency-Domain Analysis: Performing Fast Fourier Transform (FFT) on the sound data to obtain the frequency spectrum. Analyzing the spectral content and identifying characteristic peaks or changes associated with different fault types.

Step-3 Fault Classification and Model Development:

Feature Selection: Selecting the most informative features from both time and frequency domains that best differentiate between different bearing fault types. This might involve statistical analysis or machine learning techniques like feature selection algorithms.

Classification Model: Developing or choosing a suitable classification model (e.g., Support Vector Machine, Random Forest) to classify the extracted features based on the bearing fault types. Training the model using the extracted features and corresponding bearing fault labels.

Step-4 Noise Suppression Techniques:

Evaluation of Existing Methods: Evaluating the performance of established background noise suppression techniques like wavelet transforms or blind source separation on your acquired data with simulated and real-world noise. Quantifying the

improvement in signal-to-noise ratio (SNR) achieved by these techniques.

Novel Noise Suppression Algorithm: Exploring and potentially developing a new noise suppression algorithm specifically designed for ball bearing sound analysis. This algorithm could leverage the unique characteristics of bearing sound compared to background noise.

Step-5 Model Validation and Testing:

Validation: Validating the developed fault classification model on a separate dataset not used for training. This ensures the model generalizability to unseen data.

Real-World Testing: Testing the entire system (feature extraction, noise suppression, classification) in a real-world industrial setting with actual machinery noise. Evaluating the effectiveness of the approach for accurately identifying bearing fault types under practical conditions.

1.6 Scope and limitations of the study

1.6.1 Scope

The study will focus on utilizing sound level analysis for monitoring the health of ball bearings. It will explore techniques for:

i. Enhanced fault differentiation: Going beyond basic sound level increase to identify specific fault types.

ii. Robust background noise suppression: To ensure accurate sound signature capture in noisy environments.

iii. Optimal sensor placement: To maximize signal strength and minimize noise interference. The study can investigate the development :

A. Real-time sound monitoring system: For continuous monitoring and early fault detection.

B. Sound-based fault prediction framework: To utilize machine learning to predict potential failures.

Additionally, it could contribute to the standardization of sound level thresholds for fault detection across different applications.

1.6.2 Limitations

- The study will likely focus on specific types of bearings (e.g., size, load capacity) due to resource constraints and the vast variety of bearings available.
- The effectiveness of noise suppression techniques might be limited by the complexity of the noise environment.
- Real-time fault prediction accuracy might be impacted by factors like bearing wear progression and limitations of chosen machine learning models.
- Establishing standardized thresholds will require a significant amount of data collection and analysis across various operating conditions, which might be beyond the scope of a single thesis.
- While sound sensors are generally inexpensive, high-fidelity sensors with advanced noise cancellation capabilities might be cost-prohibitive.
- Implementing complex machine learning algorithms for real-time fault prediction might require significant computing power, which may not be readily available in all industrial settings.
- Access to a large dataset of sound signatures from various faulty bearings under different operating conditions might be limited, impacting the development of robust fault classification and prediction models.

1.7 Thesis Organization

Thesis Organization: Health Monitoring of Ball Bearings using Sound Level Analysis

1. Introduction:

This section will open by highlighting the critical role ball bearings play in various machinery. Then discussion on the significant problem of bearing failure and its potential consequences, emphasizing the economic and safety concerns it poses. Next, to introduce the concept of sound level analysis as a promising, complementary

approach for health monitoring. Finally, to clearly state the research objectives of your thesis, outlining what you aim to achieve with this study.

2. Literature Review:

This section delves into existing methods for monitoring ball bearing health. To discuss established techniques like vibration analysis and temperature monitoring, outlining their principles and limitations. Here, critically review the research on using sound level analysis for bearing diagnostics. To explore the potential advantages of this approach, such as its non-intrusiveness and possible earlier fault detection capabilities. Concluding this section by comparing and contrasting the limitations of existing methods and how your research aims to address them, highlighting the potential of sound level analysis to overcome these limitations.

3. Methodology:

This section details the experimental setup and procedures to employ. To begin by describing the specific types of ball bearings used in your study. Next, explaining the experimental setup, including the sound acquisition equipment, data recording methods, and data sampling strategies. Detail the process of inducing controlled bearing failures, such as fatigue and plastic deformation. Be sure to outline the specific techniques used to introduce these failures and the different levels of severity you may explore. Finally, explain the sound analysis techniques you plan to utilize. This could include frequency spectrum analysis to identify changes in sound signatures and the extraction of statistical features from the sound data to quantify specific characteristics.

4. Results and Discussion:

Here, to present the acquired sound data from healthy and failed bearings. To analyze the changes in sound level and frequency characteristics as the bearing health deteriorates across different failure modes (e.g., fatigue, plastic deformation). Discussion on the correlation between these extracted sound level features and the bearing health status. This allows you to establish if specific sound patterns can be linked to different types of bearing failures. Finally, evaluate the effectiveness of sound level analysis for early detection of bearing failures. This involves assessing how well this approach can identify the onset of damage before significant failure

occurs.

5. Conclusion:

To summarize the key findings of the research, highlighting the effectiveness of sound level analysis for ball bearing health monitoring. Discuss the limitations of your study, such as potential factors that could influence the sound data besides bearing health (e.g., lubrication conditions). Identify potential areas for future research to address these limitations and further refine the technique. Finally, emphasize the real-world applications of your findings. Showcase how sound level analysis can be integrated into predictive maintenance strategies to prevent catastrophic bearing failures and ensure the smooth operation of machinery.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The literature review delves into the growing field of sound level analysis for monitoring ball bearing health, complementing established techniques like vibration analysis. We'll explore how researchers have analyzed the correlation between specific sound features, such as overall loudness and frequency content, and various bearing failure modes (e.g., fatigue, plastic deformation). This will shed light on the potential of sound analysis for diagnosing bearing health. We'll also compare the advantages and limitations of sound analysis with existing methods, highlighting its unique strengths and potential niche applications. Furthermore, the review will examine different methods for extracting informative features from sound data, such as statistical analysis and frequency domain techniques. These techniques are crucial for effective sound-based bearing health monitoring. Finally, we'll explore existing challenges associated with sound level analysis, including background noise interference and the need for robust algorithms. Identifying these areas will pave the way for your research to contribute advancements in the field of sound-based bearing health monitoring.

2.2 Literature Review on the health monitoring of ball bearing

This literature review attempts to give an overview of some of the recent studies on ball bearing and its health monitoring. Various resources, including books, academic journals, and information from the internet, were explored for this review.

[N Tandon et al. \(1999\)](#) ; The key takeaway is that vibrations in bearings can tell about their health. Small bumps or cracks (localized defects) cause short bursts of vibration that excite the bearing and make it shake more. By analyzing these vibrations (especially at high frequencies), we can detect these defects early and prevent bigger problems. Even smoother imperfections (distributed defects) can also increase

vibration, but it's trickier to tell them apart from localized defects.[1] [Jacob D. Halpin* et al. \(2016\)](#); Researchers created a new software tool called ORBIS to analyze ball bearings. ORBIS is designed to be compatible with many computers and uses established bearing theories for accurate results. The software was validated against existing methods and shown to be highly accurate. Case studies showed ORBIS can predict important bearing behaviors like load distribution and stress. This can help engineers improve bearing designs, especially in aerospace applications. [2] [S. Belabend et al \(2020\)](#); This research combines analytical (Hertz theory) and numerical (finite element analysis) methods to study the static behavior of ball bearings under load. It addresses limitations of Hertz theory by including more complex bearing deformations. This combined approach improves understanding of bearing performance and aligns with the field's emphasis on combining theory and computation. The study also contributes to validation of analytical models and research on contact mechanics in bearings. Finally, the findings can be used to improve the design of future bearings.[3] [Hamed Mobki et al. \(2023\)](#); This research explores using ultrasound and signal processing to detect faults in ball bearings of induction machines. The authors highlight the challenges of analyzing these faint ultrasound signals, especially at low fault severity or poor signal-to-noise ratio. Their approach uses high-pass filters to isolate the relevant frequencies and the envelope method to extract fault signatures from the signal. The paper finds this combination effective for detecting faults at different stages, from early development to advanced damage. The research also acknowledges complexities like fading signals and the emergence of new frequencies with increased fault severity. [4] [Sunil Pondkule et al. \(2023\)](#); This research investigates how vibrations can be used to detect damage in ball bearings. The authors set up a test rig with a new wheel bearing and ran it under different loads and at a constant speed. By analyzing the vibrations produced at these various conditions, they were able to identify unique patterns associated with different bearing defect locations. The study concludes that careful examination of vibration patterns can provide valuable insights into bearing health. [5] [Prince Shukla et al. \(2023\)](#); This research proposes a technique to detect and diagnose faults in rotor-ball bearings using vibration analysis and artificial intelligence. They collected vibration

data from bearings with different fault locations (inner race, outer race, ball) and healthy bearings. Statistical features were extracted from the data and fed into two neural networks to classify the bearing condition. The study suggests this technique is effective, with some specific features performing particularly well. [6] [Sai Naga SAHAS KIRAN Matta et al. \(2022\)](#); This research proposes a method to detect defects in rolling bearings using a technique called Empirical Mode Decomposition (EMD). EMD breaks down vibration signals into simpler components and the researchers extract data from these components to identify bearing health. They tested their method on data from real bearings and showed it can effectively detect problems. This approach has the potential to be used for monitoring bearings in machines to prevent breakdowns and reduce maintenance costs.[7] [Madhavendra Saxena et al. \(2016\)](#); This research focuses on using vibrations to detect and predict problems in bearings (condition based maintenance). They created a test setup to damage bearings in specific ways and then measured the vibrations. A technique called Analytical Wavelet Transform followed by Power Spectral Density analysis was most effective at analyzing the vibration data. This method can help identify the location and severity of the damage, which can be critical for preventing costly downtime in machinery like wind turbines. While Power Spectral Density was useful for some fault analysis, it wasn't the best for identifying the exact type and location of the damage.[8] [Mingkai Wang et al. \(2023\)](#); This research tackles a real-world issue in ball bearings: how deformations and ball-raceway gaps affect performance. They propose a new model that considers these factors and compares it to real-world data. The model shows that bearing deformations influence contact between the balls and races, and proper preload is crucial for good bearing performance, especially when there's a gap between the ball and inner race. [9] [Gyujin Seong et al. \(2024\)](#); Ball bearings are essential but prone to failure in machinery, causing big problems. There are ways to diagnose bearing faults using temperature, sound, or vibration. This research focuses on vibration, as it's less affected by surrounding conditions. They propose a new system that combines a special way of analyzing vibration data (RCE spectrogram) with a type of artificial intelligence (optimized CNN) to improve diagnosing bearing faults. [10] [Nguyen Duc Thuan et al.\(2023\)](#); This research introduces a new dataset

called HUST bearing to help develop better ways to diagnose problems in ball bearings using vibration. Existing datasets are limited, but HUST bearing offers a wider variety of conditions including different bearing types, defect types, and even different power levels. This dataset should be helpful for researchers who are creating new machine learning algorithms for bearing fault diagnosis.[11] [Hongchuan Cheng et al \(2022\)](#) ; This research examines how a bearing's operating conditions affect its performance and durability. They found that the location of wear and tear isn't always where you'd expect, and that some bearing parts are more sensitive to damage at different speeds. The researchers also developed a method to calculate the probability of bearing failure based on random variations in its parts and operating conditions.[12]. [Adiel Lima Pessôa et al. \(2023\)](#) ; Bearings are crucial parts in machines but prone to failure, causing downtime and damage. To prevent this, researchers use vibration analysis to monitor bearing health. This study explores using envelope analysis with signal processing techniques to identify bearing defects, especially in the inner race, even at early stages. The authors acknowledge limitations of current methods and suggest exploring machine learning for more advanced fault detection. [13] [Hongchuan Cheng et al. \(2019\)](#); This research creates a detailed model to analyze vibrations in ball bearings with defects. The model considers the bearing components like springs and dampers, and treats defects mathematically instead of as simple impacts. The simulated vibrations under various defect scenarios are compared to real-world data, showing the model's accuracy. This can improve understanding of rotor-bearing systems, their reliability, and how to diagnose faults. [14] [Her-Terng Yau et al. \(2016\)](#); This research built a versatile test rig that can apply various forces (axial/radial load, inner ring thrust, and speed) to bearings. This allows them to study how these forces affect bearing behavior and vibrations. They then used a special method based on chaos theory and fractals to analyze the vibration signals and detect bearing faults with high accuracy (up to 99% for specific fault sizes and 92% overall). [15] [Yanling Zhao et al. \(2022\)](#); The researchers propose a design with a modified outer raceway to control the ball movement and prevent these collisions. They developed a mathematical model to analyze this design and used computer simulations to verify its effectiveness. Their findings indicate that the specific design

of the raceway significantly impacts the ball dynamics within the bearing. [16] [Thomas Barish et al. \(2023\)](#): This paper analyzes the rigidity of three ball-bearing machine tool spindles: manually adjusted two-bearing (oldest design), automatically spring-adjusted, and three-bearing (adjustable and non-adjustable). It compares their design approaches to achieving rigidity and explores the performance outcomes through deflection curves and rigidity measurements. [17] [Nguyen Duc Thuan et al. \(2022\)](#): The HUST bearing dataset is a collection of vibration data from ball bearings with different defect types and operating conditions. It includes 90 samples across 6 defect categories (including cracks), 5 bearing types, and 3 load levels. The researchers performed initial analysis using envelope and order tracking techniques. They then investigated using machine learning for bearing fault identification, achieving high accuracy (up to 100%) for classification and moderate success (60-80%) for unsupervised transfer learning. [18] [Joshua Pickard et al. \(2022\)](#): This research focuses on improving ball bearing fault detection using machine learning. The paper explores a technique called vibration images, which converts vibration data into a visual format for training convolutional neural networks. They test this method on a larger dataset than before, confirming its effectiveness and exploring ways to optimize its use. [19] [Daniele De Gaetano et al. \(2022\)](#): This study investigates how factors like shaft speed, voltage (strength and frequency) and electrical discharges influence the electrical resistance (impedance) of bearings in electric motors. Their aim is to create a model predicting bearing currents based on these variables. To achieve this, they built a special test setup to measure bearing response under various voltage and speed conditions, including during electrical discharges. Analyzing this data statistically, they propose a simplified model to explain the results. [20]

2.3 Research Gap Analysis :

While vibration analysis is a well-established technique for bearing health monitoring this analysis highlights a gap in utilizing sound level analysis for the following reasons:

- **Focus on Vibration:** The majority of research explores vibration analysis for

fault detection, highlighting its effectiveness.

- **Limited Fault Differentiation in Sound Analysis:** Existing sound-based studies primarily focus on overall sound level increase, not pinpointing specific fault types.
- **Background Noise Challenges:** To Isolate bearing sound from background noise in noisy environments remains a challenge for sound analysis.
- **Real-time Monitoring and Prediction Scarcity:** Limited research explores developing real-time sound monitoring systems for continuous monitoring and predicting bearing failures based on sound signatures.

2.4 Summary

This literature review explores various approaches to monitor ball bearing health. It examines established methods like vibration analysis, including works using statistical features and artificial intelligence for fault classification. Research on using ultrasound for fault detection and the challenges of weak signals is also covered. The review acknowledges limitations of current methods, like difficulty pinpointing exact damage location. It explores how researchers are creating new models to understand complex bearing behavior under load and deformation, including the influence of factors like speed and preload. The review also highlights the development of new datasets to aid the creation of improved fault diagnosis algorithms.

CHAPTER 3

METHODOLOGY

The methodology will focus on exploring sound level analysis as a complementary technique for ball bearing health monitoring. To design an experiment where controlled bearing failures (fatigue, plastic deformation) will be introduced. Sound data will be acquired from healthy and faulty bearings under various operating conditions. Employing signal processing techniques to extract informative features from the sound data, such as overall loudness and spectral content. By analyzing these features and their correlation with different bearing health states, we aim to establish the effectiveness of sound level analysis for bearing health monitoring.

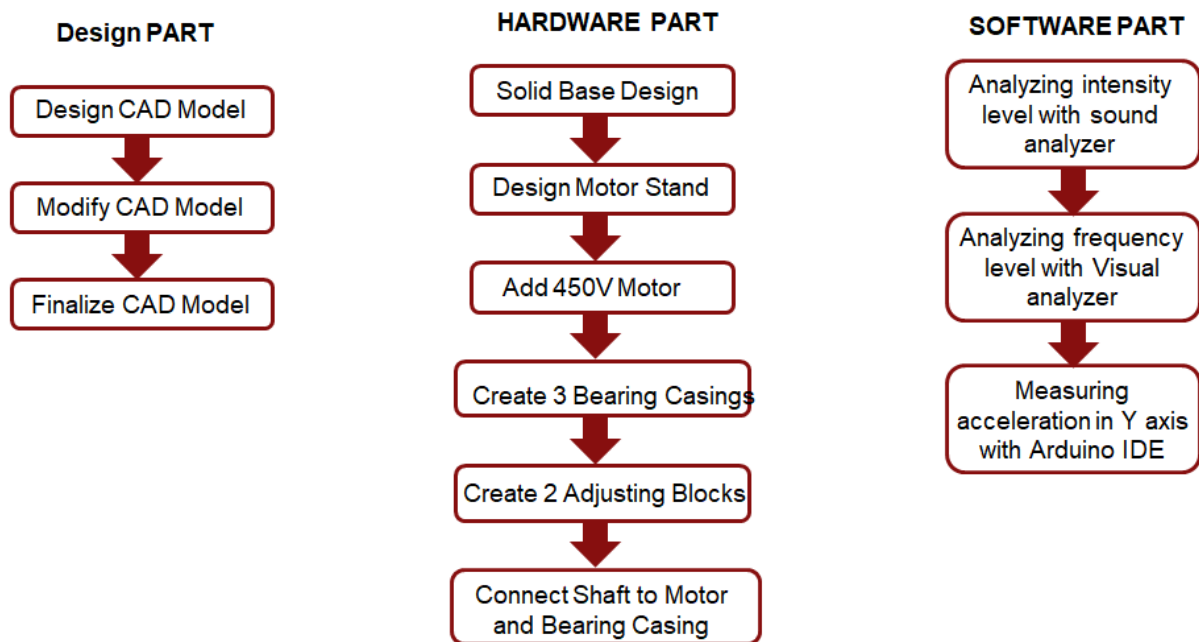


Fig 3.1: Flow DIagram

3.1 System Development:

To develop a system for health monitoring of ball bearings using sound analysis involves designing and implementing a software and hardware setup that can effectively capture, process, and analyze sound data to assess the condition of the bearings. Here's a structured approach to developing such a system:

3.1.1 Requirements Analysis

Functional Requirements:

- i. Sound Data Acquisition: To develop or select sensors and acquisition hardware capable of capturing sound signals from the ball bearings.
- ii. Signal Processing: To implement algorithms for real-time or batch processing of sound data to extract relevant features (e.g., frequency spectrum, amplitude variations).
- iii. Health Assessment: To develop methods to interpret processed data to determine the health status of the bearings (e.g., detection of anomalies, predictive maintenance alerts).
- iv. User Interface: To design a user-friendly interface for displaying results, configuring parameters, and managing data.

Non-Functional Requirements:

- i. Performance: To ensure the system can handle real-time data processing with minimal latency.
- ii. Scalability: To design the system to accommodate varying numbers of sensors and bearings.
- iii. Reliability: To implement error handling mechanisms and ensure robust operation in industrial environments.
- iv. Security: To incorporate measures to protect data integrity and system access.

3.1.2 System Architecture

Hardware Components:

- i. To select appropriate sensors (e.g., microphones or accelerometers) and data acquisition modules capable of capturing sound signals from ball bearings.

ii. To design the physical layout considering installation requirements and environmental conditions.

Software Components:

i. Data Acquisition Module: To develop software to interface with sensors and acquire sound data.

ii. Signal Processing Module: To implement algorithms for signal filtering, feature extraction (e.g., FFT), and anomaly detection.

iii. Decision Support Module: To develop logic for interpreting processed data and generating alerts or maintenance recommendations.

iv. User Interface: To design a graphical interface for visualizing results, setting parameters, and managing system configuration.

3.1.3 Implementation

i. Sensor Integration: To connect sensors to the data acquisition module and verify data acquisition functionality.

ii. Signal Processing Algorithms: To implement algorithms for sound signal processing, including feature extraction and anomaly detection.

iii. Decision Support Logic: To develop logic for health assessment based on processed data and historical patterns.

iv. User Interface Development: To design and implement a graphical user interface (GUI) for interacting with the system.

3.1.4 Testing and Validation

i. Unit Testing: To verify the functionality of each module independently.

ii. Integration Testing: To test the interaction between hardware and software components.

- iii. Performance Testing: To evaluate system performance under various load conditions.
- iv. Validation: To validate the system's effectiveness in detecting bearing faults using simulated and real-world data.

3.1.5 Deployment and Maintenance

- i. Deployment: To install the system in the target environment (e.g., industrial machinery) and ensure proper integration with existing infrastructure.
- ii. Training and Documentation: To provide training for operators and maintenance personnel on using the system effectively.
- iii. Maintenance: To establish procedures for ongoing system maintenance, including updates, data management, and troubleshooting.

3.1.6 Evaluation and Optimization

- i. Performance Evaluation: To monitor the system's performance in real-world conditions and gather feedback from users.
- ii. Optimization: To identify opportunities for improving system efficiency, accuracy, and user experience based on feedback and performance metrics.
- iii. Continuous Improvement: To incorporate updates and enhancements based on technological advancements and user requirements.

By following this structured approach, a robust system can be developed for health monitoring of ball bearings through sound analysis, enhancing predictive maintenance capabilities and extending the lifespan of industrial equipment.

3.2 Machine specifications and parameters

Here to operate in this project we are using a rotating motor of 450V which runs with the frequency between 50 to 60Hz. In the project for the ease of the calculations the motor with the maximum voltage and with the frequency 60Hz.

3.3 Sound Analysis (dB and Hz)

Here readings have been taken from 3 types of ball bearings.

1. New bearing which has a workspan of 30 minutes usage during the testing.
2. Another type of bearing which has the usage of 100 hours.
3. The last bearing which has the usage of almost 1000 hours.

During the process the bearing was first installed in the bearing casing and then the bearing was rotated using the shaft which is connected to the motor .

3 readings were taken from 3 positions between the motor and bearing casing . The positions were recorded from 4cm,6 cm and 8cm.

For the distance of 4 cm acquiring 3 intensity levels for 3 different types of ball bearings. The intensity level recorded for the new ball bearing was 87.5 dB,medium used bearing was 95.25 dB and the old bearing used was 100.44 dB. These values used the equivalent intensity from the time span 0 to 12 sec.

Now for the distance of 6cm acquiring 3 intensity levels for 3 different types of ball bearings. The intensity level recorded for the new ball bearing was 90.49dB,medium used bearing was 95.60dB and the old bearing used was 103.30dB. These values used the equivalent intensity from the time span 0 to 12 sec.

At last for the distance of 8cm acquiring 3 intensity levels for 3 different types of ball bearings. The intensity level recorded for the new ball bearing was 93.29dB,medium used bearing was 93.44dB and the old bearing used was 97.11dB. These values were used the equivalent intensity from the time span 0 to 12 sec

Here a comparative analysis of the intensity level shows that as the bearing is being put away from the motor the intensity level of the bearing gradually decreases.

3.4 Calibration level analysis

Here to minimize the environmental issues to minimize the environmental impact we set the calibration level of 60dB. So the minimum value is set up to 60dB for the normal working condition. The environmental impact of the health monitoring project for ball bearings through sound level analysis primarily revolves around resource consumption, waste generation, and noise pollution. The direct impacts include the use of raw materials and energy for sensors and data processing, as well as the generation of electronic and general waste. However, the project's indirect benefits

significantly contribute to environmental sustainability by enhancing machinery maintenance, which extends equipment life, reduces energy consumption, and minimizes greenhouse gas emissions through optimized performance and preventive maintenance practices.

3.5 Software Part (Model)

Design CAD Model:

This step involves using Computer-Aided Design (CAD) software SolidWorks to create a 3D model of the entire test setup. The model includes: the base, motor stand, motor, shaft, bearing casing, adjusting blocks. During this stage, we considered factors like material selection, dimensions, and how each component will interact with others.

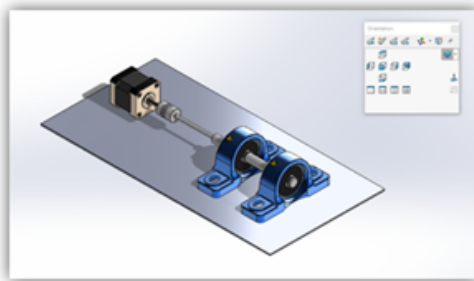


Fig 3.2 1st model

This was the first CAD model. Here, two bearing casings were used. But calculating two frequencies at a time of two bearings causes less efficiency in overall frequency measurement. So modification of this model was needed. The modified version looks like this:-

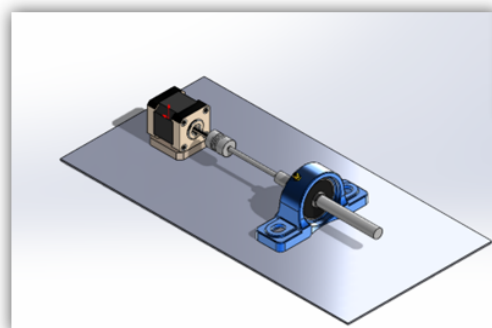


Fig 3.3 Finalized model

Now calculations of each bearing in various stages can be obtained from this design

with more efficiency.

3.6 Hardware Part

i. Solid Base Design:

- This step involves designing a sturdy base that will support all the other components of the test setup.
- The base material should be rigid enough to withstand vibrations from the motor and bearing operation.
- Common materials for the base include steel plates, aluminum plates, or even thick wood depending on the motor size and expected loads. Here our base is made of steel.
- The design of the base should ensure stability and provide mounting points for the motor stand and other components.

ii. Design Motor Stand:

- The motor selected requires a separate stand for proper alignment and stability.
- The motor stand design should consider the motor's weight, size, and shaft orientation.

iii. Add 450V Motor:

- Once the base and (if needed) motor stand design are finalized, a 450V motor is secured to the base using appropriate mounting hardware.
- Ensure the motor's voltage rating matches power supply and that it has enough power to rotate the bearing casing at the desired speeds.
- Safety is paramount here. Double-check all electrical connections and ensure proper grounding before proceeding.

iv. Create 3 Bearing Casings:

- This step involves creating three separate bearing casings, likely to test different bearing types or configurations.
- The casings are fabricated from steel material.
- The design of the casings should ensure proper fit for the bearings to test and

allow for easy installation and removal.

v. Create 2 Adjusting Blocks:

- Positioning: They could be used to precisely position the bearing casing within the test setup to ensure proper alignment with the motor shaft.
- The design of the adjusting blocks depends on their intended use.

vi. Connect Shaft to Motor and Bearing Casing:

- This step involves connecting the motor shaft to the bearing casing. This connection allows the motor to rotate the bearing during testing.
- The type of coupling used will depend on the specific motor and shaft sizes. Common options include:
 - Couplings: These are mechanical devices that connect two rotating shafts.

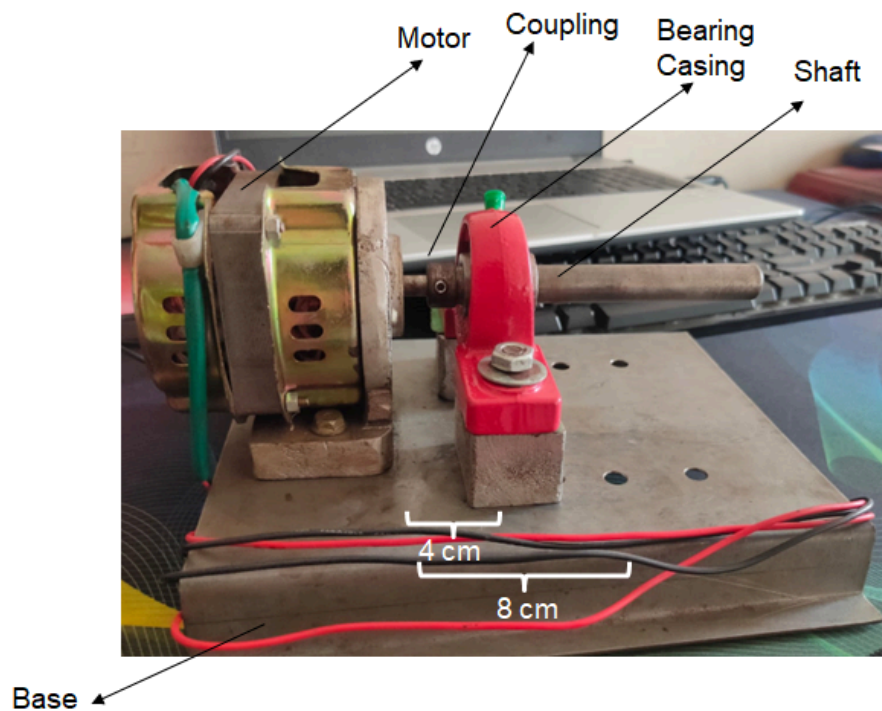


Fig 3.4 *Experimental Setup*

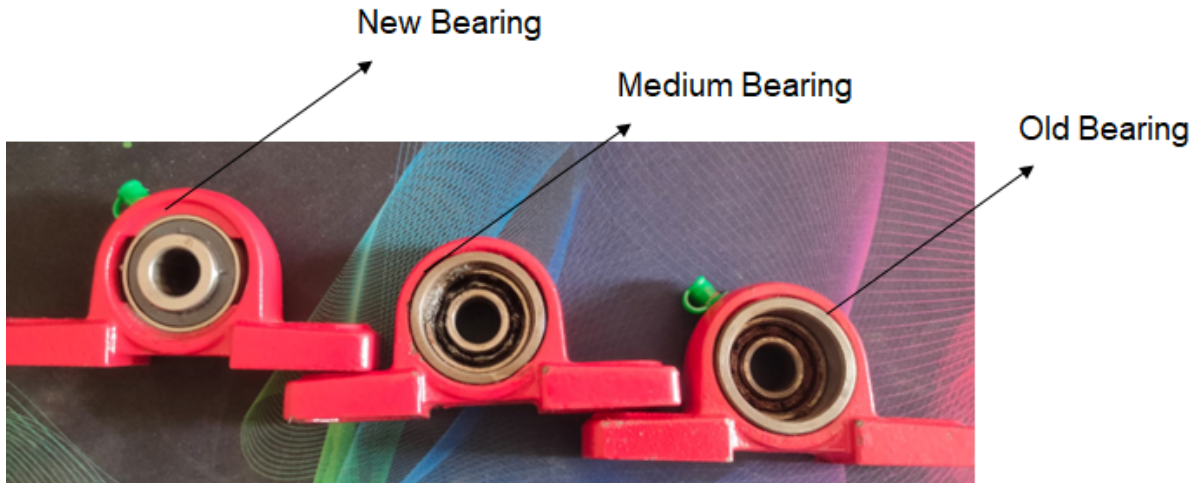


Fig 3.5 *Three types of bearings with bearing casings*

3.7 Software Part (Sound Analyzing)

i. Measuring Acceleration in Y Axis with Arduino IDE:

An Arduino IDE is used to measure the acceleration in the Y axis.

- **Arduino IDE:** This is an open-source software platform used to program microcontrollers like Arduino boards.
- **Microcontroller:** An Arduino board is a small, single-board computer that can be programmed to read sensor data and control actuators.
- **Accelerometer:** This is a sensor that measures acceleration along the axis. Here we have taken only the acceleration in the Y-axis. The Y-axis is typically perpendicular to the base and motor shaft.
- **Data Acquisition:** The Arduino will be programmed to collect acceleration data from the sensor and potentially transmit it to a computer for further analysis.

ii. Data Acquisition and Analysis:

This step involves collecting data from the various sensors we have used in our test setup. These could include:

- **Sound Sensor (Microphone):** This sensor captures the sound produced by the bearing, which will be analyzed later for intensity and frequency.
- **Accelerometer:** As mentioned earlier, this sensor measures acceleration in the

Y-axis, which can provide insights into bearing vibrations.

The data collected from these sensors will likely be transmitted to a computer for storage and analysis. This analysis can involve software tools like:

- Spreadsheets: These can be used for basic data manipulation and visualization.

Testing Procedure

- Mounting the Bearing: Install the desired bearing into one of the casings you created.
- Securing the Casing: Secure the chosen bearing casing with the bearing installed into the test setup using the adjusting blocks (if applicable).
- Setting Test Parameters: Define the test parameters, such as motor speed, test duration, and any data acquisition settings.
- Data Collection: Start the test and collect data from the sensors.
- Repeat the Test: Repeat the test with the other bearing casings to compare results.

3.8 Diagnosis of the project

Signal Processing Techniques

- Considering the signal processing techniques to analyze the sound of ball bearings.
- Evaluating the suitability of these techniques for detecting anomalies or changes in bearing condition based on sound signatures.

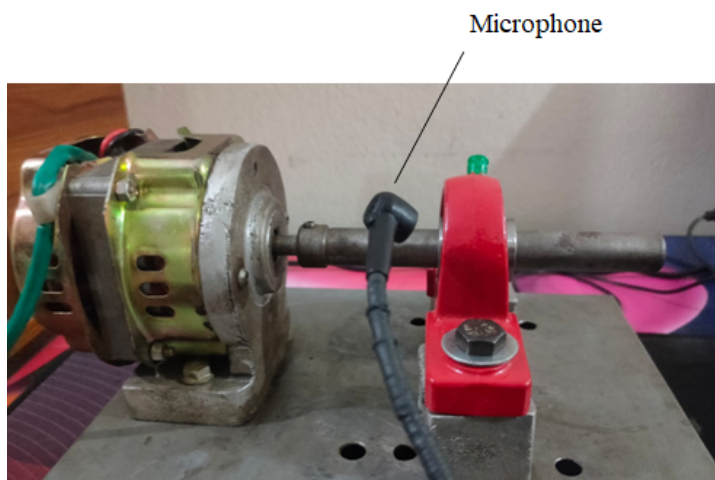


Fig 3.6 *Measuring intensity level*

- Assessing the methods and equipment to use for collecting sound data from the ball bearings by placing microphones and accelerometers near the bearings to capture acoustic signals during operation.
- Ensuring that the data acquisition setup is reliable, repeatable, and capable of capturing relevant information for analysis by maintaining a sound free environment. 10 data from a single ball bearing casing placed at a distance of 4cm,6cm and 8cm respectively from the rotator have been taken.
- Values from the accelerometer have been attained by placing it on the bearing casing.

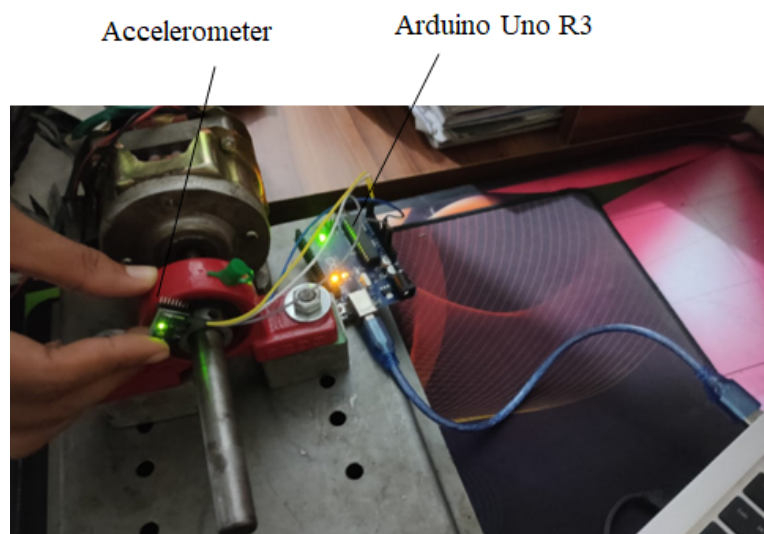


Fig 3.7 *Measuring acceleration*

3.9 Safety Precautions

It should be remembered to prioritize safety throughout the testing process. Wear appropriate personal protective equipment (PPE) and ensure all electrical connections are secure before starting the motor. Safety precautions for the health monitoring project of ball bearings through sound level analysis are essential to ensure a secure working environment. Firstly, all personnel should wear appropriate personal protective equipment (PPE), such as ear protection, when working with high-decibel sound equipment to prevent hearing damage. Proper handling and maintenance of electronic equipment and sensors are crucial to avoid electrical hazards. Experiments

should be conducted in well-ventilated areas to mitigate any risks associated with exposure to potentially harmful materials. Regular calibration and maintenance of equipment are necessary to prevent malfunctions that could lead to accidents. Additionally, all experimental setups should be securely fastened to avoid mechanical failures, and clear safety protocols should be established and followed during data collection. Ensuring a thorough understanding of these safety measures among all team members will contribute to a safe and efficient research environment.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Analysis of the study

- As bearings wear out, they produce more noise. This increase in sound intensity can be measured and used to track the bearing health. By monitoring sound intensity levels over time and comparing them to baseline readings from healthy bearings, technicians can identify potential problems early and prevent catastrophic failures.

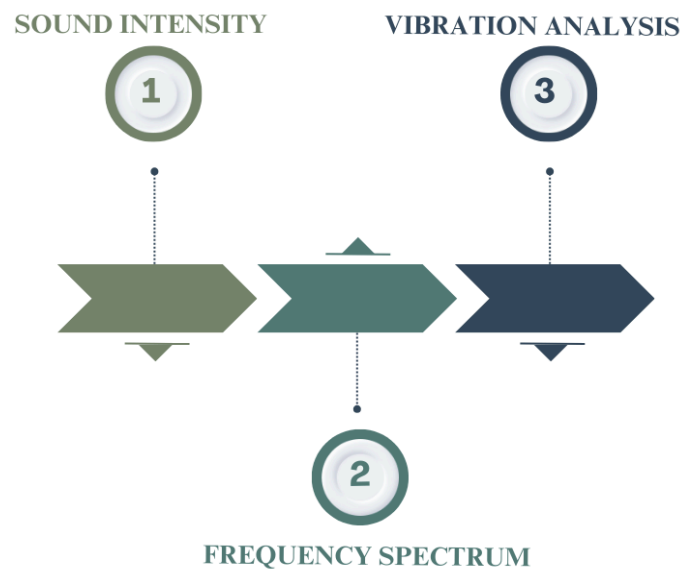


Fig 4.0 Infographics of overall analysis

- Analyzing the frequency spectrum of the sound emitted by the bearing can reveal characteristic patterns associated with different types of bearing faults. For example, a cracked bearing might generate sound at a specific frequency that wouldn't be present in a healthy bearing. By identifying these unique frequency signatures, technicians can diagnose the specific type of bearing fault and take appropriate corrective actions.
- Vibrations within a bearing increase as it wears out. Measuring these vibrations can provide insights into the bearing's condition. Similar to sound level analysis, increased vibration levels often indicate developing wear or damage. By combining vibration analysis with other techniques like sound level monitoring.

4.2 Effects and impacts of the environment on acquiring the result

At first measuring the intensity level of the surroundings which was pretty good and acceptable. The calibration level was set to 60 dB for convenience. After that measurement of the intensity level of the machine without any bearing casing so analyses the exact intensity level of the bearing casings later on.

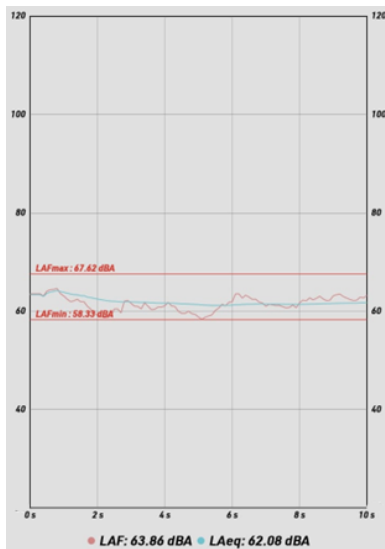


Fig 4.1 Intensity level analysis of the environment

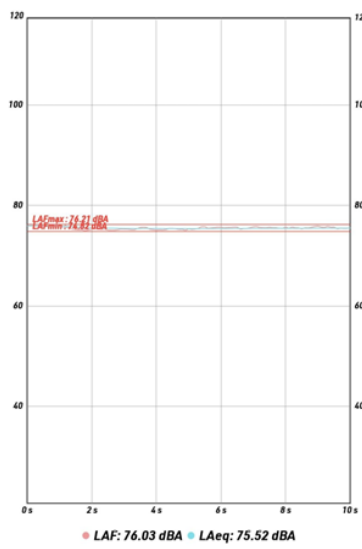


Fig 4.2 Intensity level analysis of the machine



Fig 4.3 Experimental setup running without bearing casing to measure the intensity level of the machine

Calibration level is set to 60 dB

- Here the calibration part was set up to 60 dB so the minimum level of calibration will be 60 dB but due to some external factors the level is slightly higher and is recorded up to 62dB.
- When only the shaft of the bearing is rotating it produces an average intensity level of 75.52 dB.

4.3 Intensity level vs Time Curve

For the overhanging length of 4 cm from the motor to the bearing casing-

The graph described appears to show sound intensity levels (dBA) measured from ball bearings at different wear stages (new, medium, old) and positioned at varying distances from a motor (4 cm, 6 cm, 8 cm).

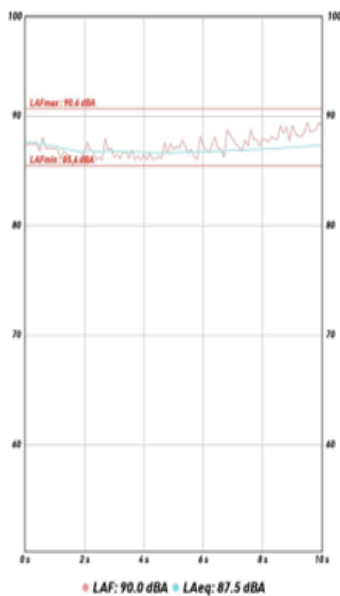


Fig 4.4 Intensity level analysis of new bearing

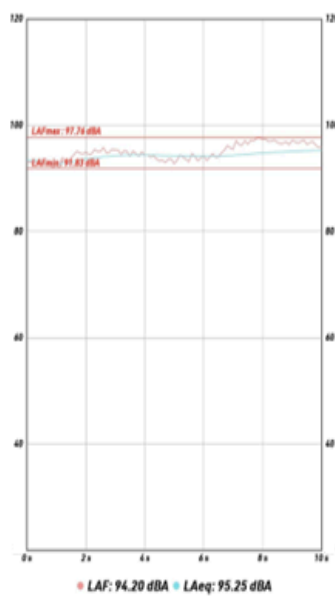


Fig 4.5 Intensity level analysis of medium ball bearing

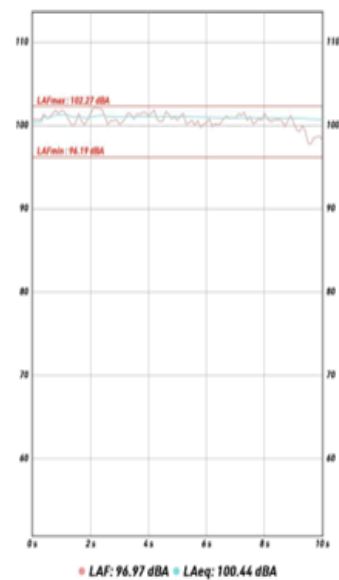


Fig 4.6 Intensity level analysis of old ball bearing



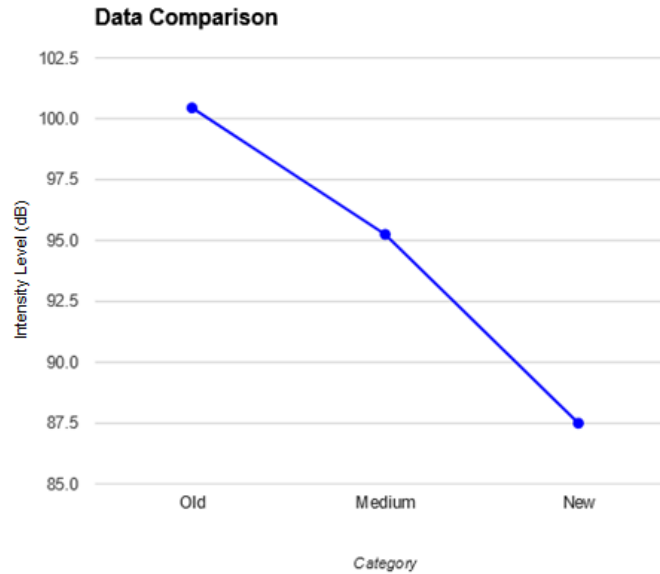


Fig 4.7 Comparison of Intensity level

. The increasing sound intensity from new to old bearings across all distances suggests a correlation between sound level and bearing health. Bearings that are more worn tend to generate more noise due to friction and developing faults. This observation aligns with the concept of using sound level analysis for monitoring bearing condition. However, the decreasing sound intensity with increasing distance from the motor highlights the importance of considering measurement distance. Sound intensity weakens as it travels from the source, so readings closer to the motor might be influenced by motor noise in addition to bearing health. For the bearings placed at 4 cm from the motor, the readings for the intensity level of the new bearing was 87.5dBA, medium was 95.25dBA, old was 100.44dBA. Here it is seen a constant increase of bearings intensity level from new to old.

For the overhanging length of 6 cm from the motor to the bearing casing-

The graph described appears to show sound intensity levels (dBA) measured from ball bearings at different wear stages (new, medium, old) and positioned at varying distances from a motor (4 cm, 6 cm, 8 cm).

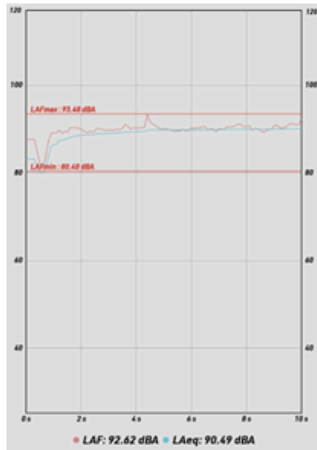


Fig 4.8 Intensity level analysis of new ball bearing

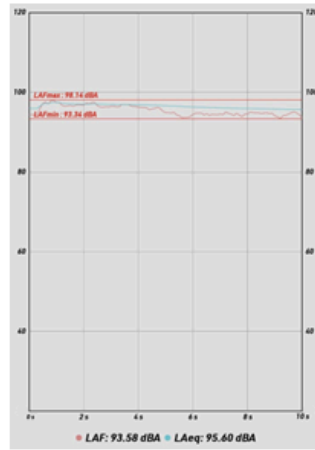


Fig 4.9 Intensity level analysis of medium ball bearing

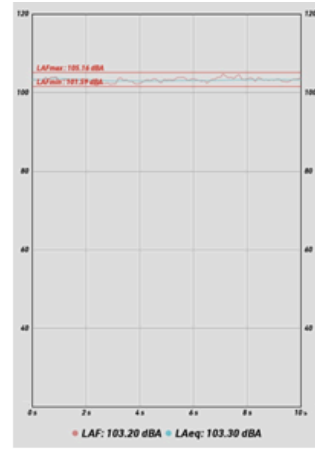


Fig 4.10 Intensity level analysis of old ball bearing

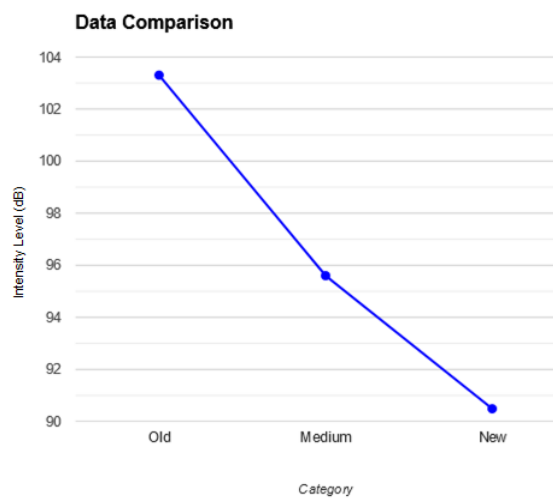


Fig 4.11 Comparison of Intensity level

The increasing sound intensity from new to old bearings across all distances suggests

a correlation between sound level and bearing health. Bearings that are more worn tend to generate more noise due to friction and developing faults. This observation aligns with the concept of using sound level analysis for monitoring bearing condition. However, the decreasing sound intensity with increasing distance from the motor highlights the importance of considering measurement distance. Sound intensity weakens as it travels from the source, so readings closer to the motor might be influenced by motor noise in addition to bearing health. For the bearings placed at 6 cm from the motor, the readings for the intensity level of the new bearing was 90.49dBA, medium was 95.60dBA, and old was 103.30dBA. Here a constant increase of bearings intensity level from new to old is seen.

For the overhanging length of 8 cm from the motor to the bearing casing-

The graph described appears to show sound intensity levels (dBA) measured from ball bearings at different wear stages (new, medium, old) and positioned at varying distances from a motor (4 cm, 6 cm, 8 cm).

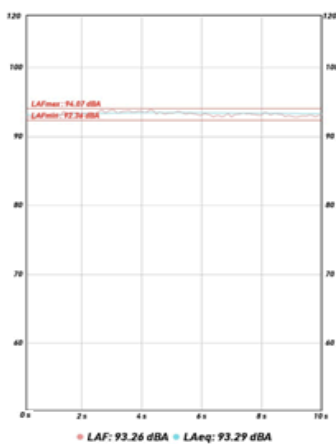


Fig 4.12 Intensity level analysis of new ball bearing

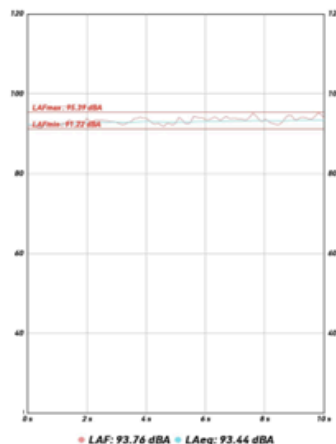


Fig 4.13 Intensity level analysis of medium ball bearing

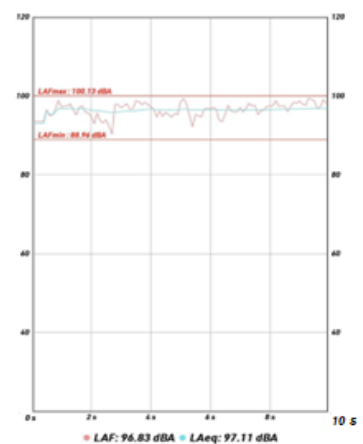


Fig 4.14 Intensity level analysis of old ball bearing



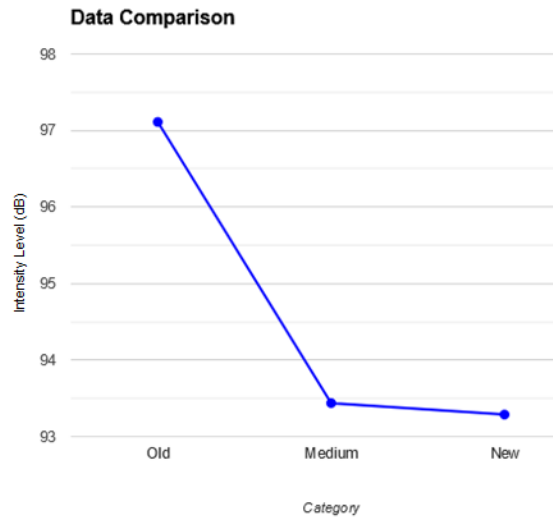


Fig 4.15 Comparison of Intensity level

The graph you described appears to show sound intensity levels (dBA) measured from ball bearings at different wear stages (new, medium, old) and positioned at varying distances from a motor (4 cm, 6 cm, 8 cm). The increasing sound intensity from new to old bearings across all distances suggests a correlation between sound level and bearing health. Bearings that are more worn tend to generate more noise due to friction and developing faults. This observation aligns with the concept of using sound level analysis for monitoring bearing condition. However, the decreasing sound intensity with increasing distance from the motor highlights the importance of considering measurement distance. Sound intensity weakens as it travels from the source, so readings closer to the motor might be influenced by motor noise in addition to bearing health. For the bearings placed at 8cm the readings for the intensity level of the new bearing was 93.29dBA, medium was 93.44dBA, and old was 97.11dBA. Here it is seen a constant increase of bearings intensity level from new to old.

Now a bar chart is shown here to understand the comparison among all the cases discussed above:

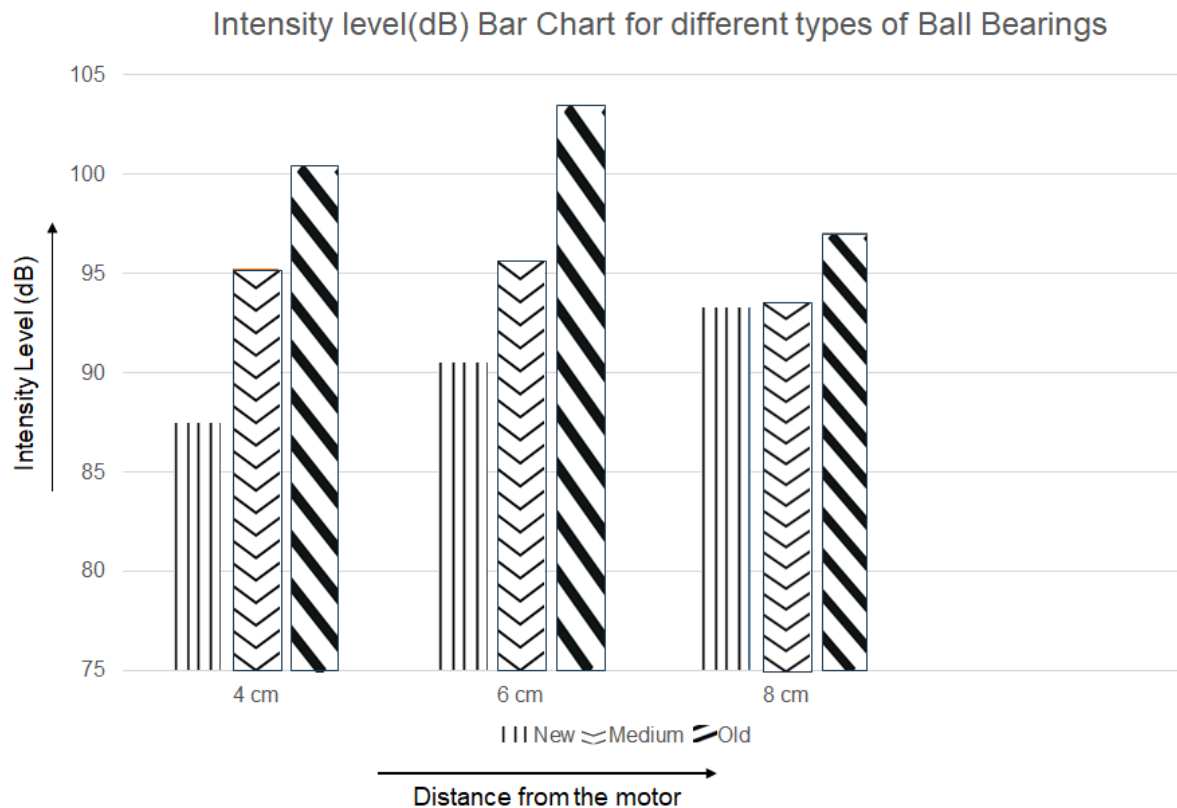


Fig 4.16 Intensity level bar chart

Based on the bar chart, it appears to show the intensity level (in dB) of sound emitted by different types of ball bearings at various distances from a motor (4 cm, 6 cm, and 8 cm). The intensity level generally increases as the bearings wear from new to old, at all three distances measured. This suggests that sound level analysis could be a useful technique for monitoring bearing health, as worn bearings tend to generate more noise. However, the sound intensity also weakens with increasing distance from the motor. So, measurements closer to the motor might be influenced by motor noise, making distance an important factor to consider when using sound level analysis for bearing health monitoring. Here from the result, as the bearings are placed in variable distance away from the motor with a change of 2cm, a variable intensity level for the same bearings are seen.

4.4 Frequency Spectrum of three types of ball bearing

Frequency Spectrum analysis of 3 bearings

The 3 diagram shows three frequency spectrum graphs, which are likely related to the health of ball bearings. Each graph shows the sound pressure level (in decibels, dB) on the vertical axis and frequency (in Hz) on the horizontal axis. Lower frequencies are on the left side of the graph, and higher frequencies are on the right side. The three graphs likely represent ball bearings in different health conditions: a new bearing (healthy), a medium-wear bearing, and an old bearing (worn out).

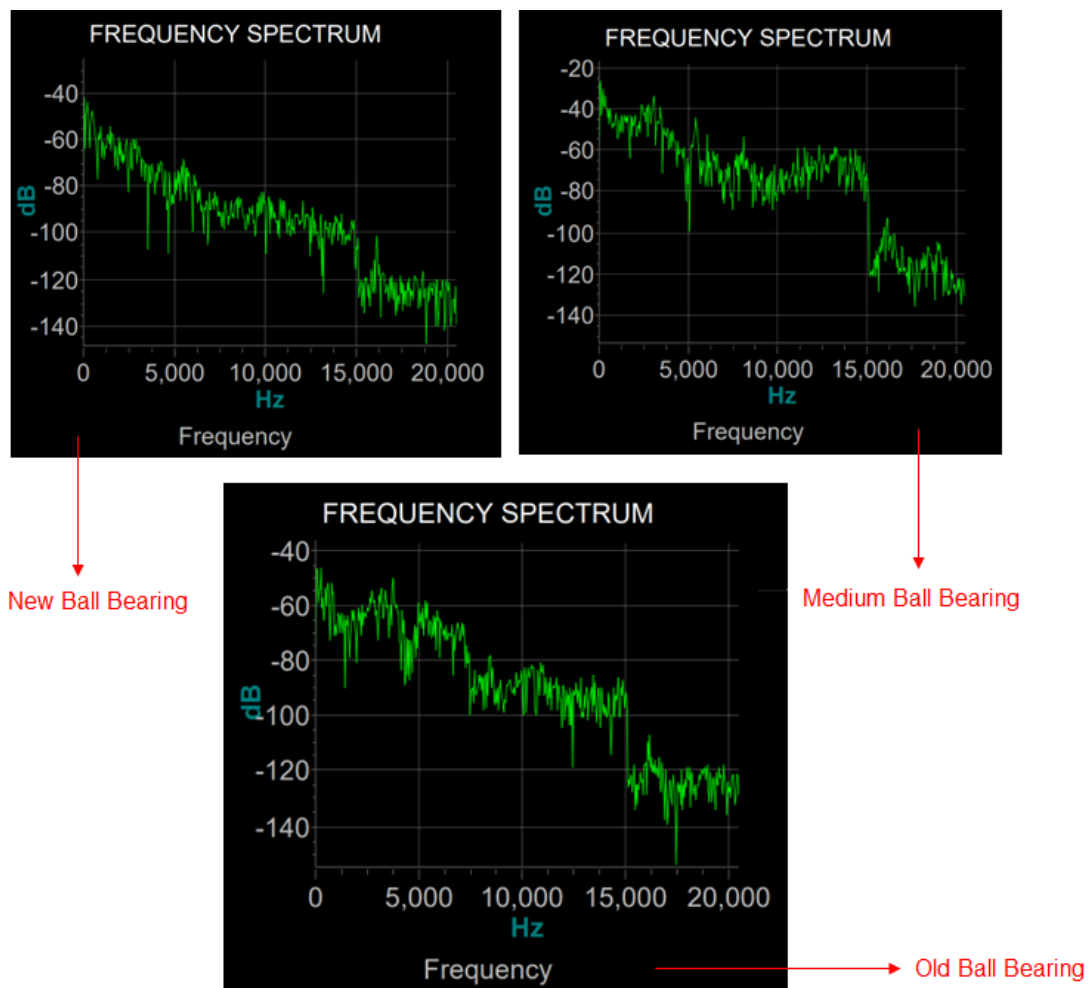


Fig 4.17 Frequency Spectrum of 3 bearings

The healthy bearing (far left graph) has a smoother curve with lower overall sound pressure levels across all frequencies. This could indicate developing faults or damage

within the bearing. In general, as a bearing wears out, it will generate more noise and develop characteristic patterns in its sound spectrum. By analyzing these changes in sound pressure level and frequency content, researchers can potentially detect bearing failure at an early stage, before it causes serious damage or downtime. Medium-wear bearing (center graph) has a somewhat similar curve, but with slightly higher sound pressure levels, especially at higher frequencies. The old, worn-out bearing (far right graph) has the highest sound pressure levels, and the curve shows distinct peaks at certain frequencies.

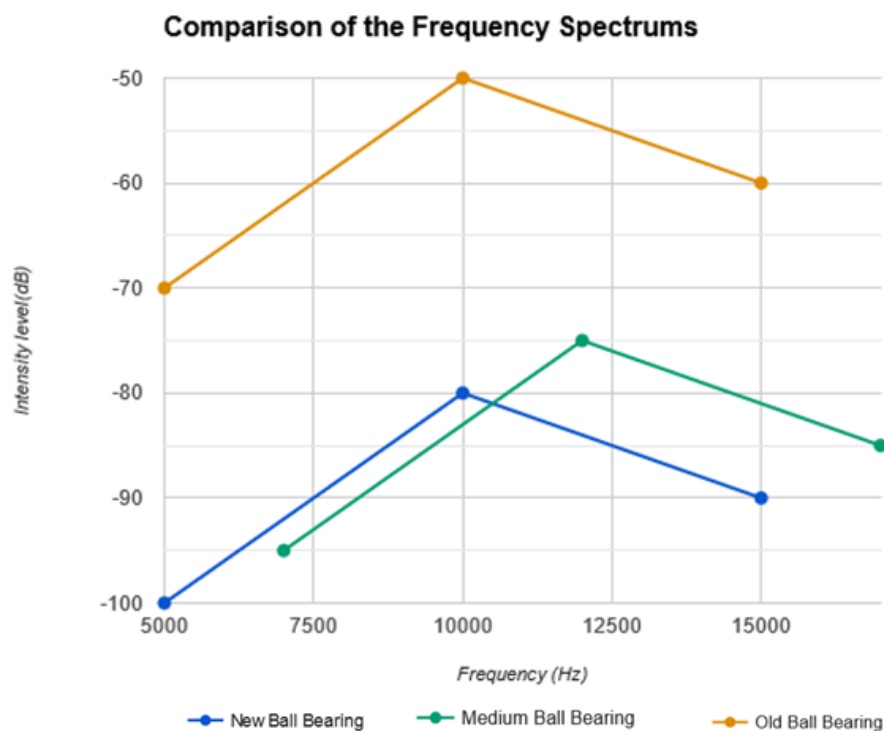


Fig 4.18 Frequency spectrum comparison

Frequency spectrum analysis is a technique used to visualize the distribution of sound energy across different frequencies. In the context of ball bearing health monitoring, it can be a useful tool to identify damage or wear.

The X-axis represents frequency (Hz), and the Y-axis represents sound pressure level (dB). Lower frequencies are on the left, and higher frequencies are on the right. The three lines in the graph likely correspond to ball bearings in different health conditions: new (healthy), medium wear, and old (worn out).

New Bearing (Healthy): The far-left graph shows a smoother curve with generally lower sound pressure levels across all frequencies. This indicates quieter operation

with minimal vibrations.

Medium Wear: The center graph has a somewhat similar curve to the healthy bearing, but with slightly higher sound pressure levels, particularly at higher frequencies. This suggests some wear and tear beginning to develop.

Old (Worn Out): The far-right graph shows the highest sound pressure levels, and the curve has distinct peaks at certain frequencies. These peaks likely correspond to specific faults or damage within the bearing, such as cracks or pitting.

As a bearing wears out, it tends to generate more noise and develop characteristic patterns in its frequency spectrum. By analyzing these changes, researchers can potentially detect bearing failure early on, before it causes significant problems

Accelerometer values:

Acceleration in Y-axis(bearing placed at 6 cm distance from the motor):

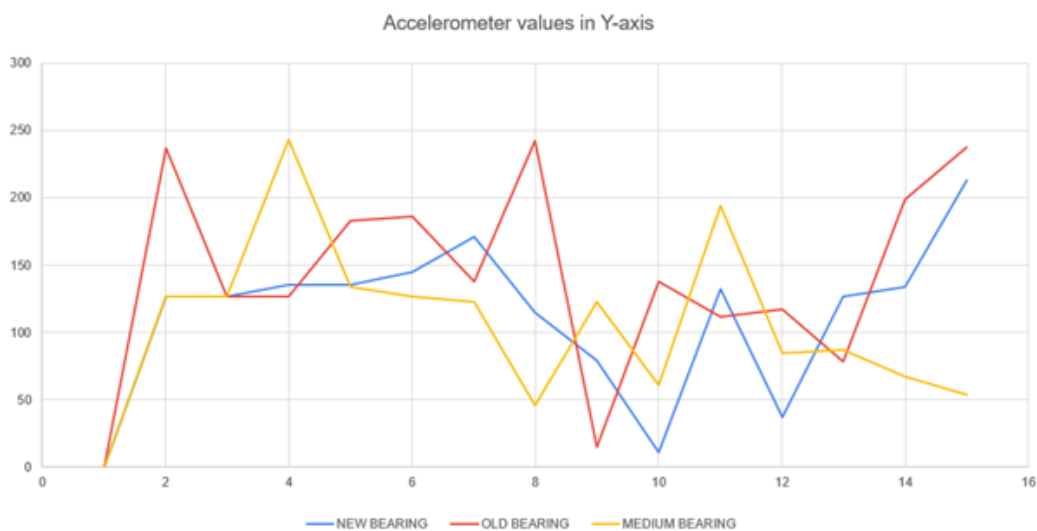
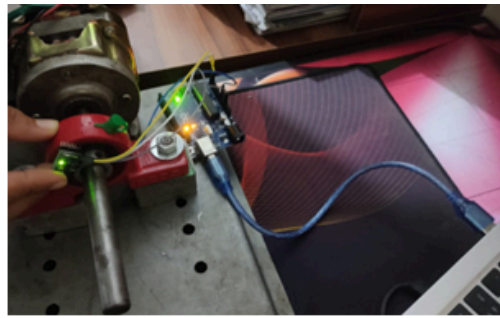
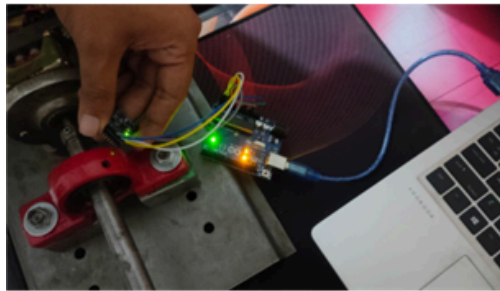


Fig 4.19 Acceleration in Y-axis

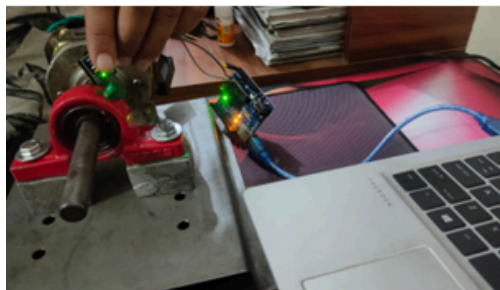
- The X-axis value is taken from 1 second and the measured acceleration multiplied with gravity is plotted against the Y-axis.
- Acceleration measured along y axis is the lowest for new bearing and the highest is recorded for the old ball bearing.



Accelerometer connected with new ball bearing



Accelerometer connected with medium ball bearing



Accelerometer connected with old ball bearing

Fig 4.20 Accelerometer values measuring

Here the figure appears as sound intensity levels (in dBA) increase as ball bearings wear out (new, medium, old), regardless of distance from the motor (4 cm, 6 cm, 8 cm). This aligns with the idea that sound level analysis can be a useful tool for monitoring bearing health, as worn bearings tend to generate more noise. However, the intensity readings are generally lower at further distances (8 cm) from the motor compared to closer distances (4 cm). This decrease highlights the importance of considering measurement distance, as sound weakens with distance from the source. In conclusion, sound level analysis shows promise for bearing health monitoring, but accounting for the influence of distance from the sound source is crucial for accurate assessment.

CHAPTER 5

CONCLUSION

5.1 Conclusion

The health monitoring of ball bearings by analyzing sound levels represents a significant advancement in the predictive maintenance of rotating machinery. This thesis demonstrated the feasibility and effectiveness of acoustic analysis as a complementary or alternative method to traditional vibration analysis for detecting both localized and distributed defects in ball bearings. By leveraging advanced signal processing techniques and machine learning algorithms, the research successfully identified characteristic sound patterns associated with various types of defects, highlighting the potential for early and accurate fault detection.

For the bearings placed at 4 cm from the motor, the readings for the intensity level of the new bearing was 87.5dBA, medium was 95.25dBA, old was 100.44dBA. Here it is seen a constant increase of bearings intensity level from new to old.

For the bearings placed at 6 cm from the motor, the readings for the intensity level of the new bearing was 90.49dBA, medium was 95.60dBA, and old was 103.30dBA. Here a constant increase of bearings intensity level from new to old is seen.

For the bearings placed at 8cm the readings for the intensity level of the new bearing was 93.29dBA, medium was 93.44dBA, and old was 97.11dBA. Here it is seen a constant increase of bearings intensity level from new to old.

The sound intensity level (dBA) of the bearings consistently increased as they went from new to medium wear to old at all measured distances (4 cm, 6 cm, and 8 cm) from the motor. This trend suggests that sound level analysis has potential for monitoring bearing health, as increased wear likely leads to higher noise levels. However, the readings were also generally lower at further distances from the motor, indicating that distance from the sound source is an important factor to consider when using this technique for bearing health assessment.

Observations:

5.1.1 Sound Intensity Increases with Bearing Wear

The sound intensity level (dBA) consistently increases from new bearings to medium wear bearings to old bearings at all three measured distances (4 cm, 6 cm, and 8 cm) from the motor. This supports the concept of using sound level analysis for bearing health monitoring.

5.1.2 Distance Affects Sound Intensity

The sound intensity levels are generally higher for bearings closer to the motor (4 cm) compared to those further away (8 cm). This is expected as sound intensity weakens with distance from the source.

5.1.3 Implications

Monitoring Bearing Health: The data suggests that sound level analysis can be a valuable tool to identify potential bearing problems based on increasing sound intensity. By establishing baseline sound levels for healthy bearings and monitoring for significant increases, technicians could predict bearing wear and schedule maintenance before a breakdown occurs.

Distance as a Factor: When using sound level analysis for bearing health monitoring, it's crucial to consider the distance of the measurement point from the source (motor). Sound intensity from the motor itself could potentially mask or influence the sound signature of the bearings, especially at closer distances.

5.1.4 Further Considerations

While this data shows a promising correlation between sound intensity and bearing health, it's important to acknowledge limitations:

Other Factors: Sound intensity can be influenced by factors besides bearing health, such as lubrication condition, bearing type, and even external noise.

Limited Data: The data provided represents just three distances from the motor.

Further investigation across a wider range of distances would strengthen the conclusions.

Overall, the data provides evidence that sound level analysis has potential for bearing health monitoring. However, for a more comprehensive diagnosis, it might be beneficial to combine sound analysis with other techniques like vibration analysis or temperature monitoring, and to account for the influence of distance from the sound source.

5.2 Recommendation for future works

5.2.1 Enhanced Data Acquisition Systems

To develop and utilize more advanced and sensitive sound acquisition systems to improve the quality and reliability of the collected data. This includes using higher fidelity microphones and noise-canceling technologies to mitigate environmental interference.

5.2.2 Comprehensive Datasets

To create extensive and diverse datasets that cover a wide range of operating conditions, bearing types, and defect scenarios. This will aid in training more robust machine learning models and improving the generalizability of the results.

5.2.3 Advanced Signal Processing Techniques

To explore and implement cutting-edge signal processing techniques, such as wavelet transforms and empirical mode decomposition (EMD), to enhance the detection and classification of subtle defects in sound signals.

5.2.4 Integration with Other Monitoring Methods

To combine acoustic analysis with other monitoring techniques, such as vibration analysis, infrared thermography, and oil analysis, to develop a more comprehensive and reliable bearing health monitoring system.

5.2.5 Real-Time Monitoring Systems

To develop real-time acoustic monitoring systems that can continuously analyze sound data and provide immediate feedback on bearing health. This requires efficient algorithms capable of processing data in real-time with minimal computational resources.

5.2.6 Field Testing and Validation

To conduct extensive field testing in diverse industrial environments to validate the laboratory findings and assess the practical applicability of the acoustic monitoring method. This will help identify real-world challenges and opportunities for further improvement.

5.2.7 Machine Learning and AI Enhancements

To investigate the use of more advanced machine learning and artificial intelligence techniques, such as deep learning and reinforcement learning, to enhance the accuracy and predictive capabilities of defect detection models.

5.2.8 Standardization and Benchmarking

To work towards the development of standardized protocols and benchmarks for acoustic health monitoring of ball bearings. This will facilitate comparison between different studies and promote the adoption of best practices across the industry.

5.2.9 Cost-Benefit Analysis

To perform detailed cost-benefit analyses to evaluate the economic feasibility and return on investment of implementing acoustic monitoring systems in industrial settings. This includes assessing the potential savings from reduced downtime and maintenance costs.

5.2.10 Environmental Impact and Sustainability

To investigate the environmental impact of implementing acoustic monitoring systems on a larger scale and explore ways to minimize any negative effects. To emphasize the sustainability benefits of improved maintenance practices in reducing waste and conserving resources.

By addressing these recommendations, future research can build upon the findings of this thesis to develop more effective, reliable, and widely applicable acoustic health monitoring systems for ball bearings and other critical machinery components.

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