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Condition Monitoring and Predictive Analytics of Electric Motor by using Machine Learning.

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Abstract: *This research paper addresses the crucial issue of early bearing failure within electric motors, a common problem impacting industrial operations. It begins with a thorough problem identification and historical study of asset failures to pinpoint strategic sensor placement on the motor casing, specifically targeting the bearing area. Time series data acquisition captures the dynamic motor behavior, with LabVIEW software facilitating visualization through frequency plots and spectral graphs. Subsequent preprocessing involves modifying data structure and computing vibration metrics like RRMS and IRRMS to quantify vibration levels. The processing stage consists of condition monitoring using structured supervised datasets transformed into the frequency domain in MATLAB. Interpretation of results enables bearing health assessment and identification of dominant frequency components. Additionally, the remaining useful life of the bearing is estimated using the Support Vector Classifier algorithm, supplemented by RRMS and IRRMS to enhance prediction accuracy. A machine learning model, developed in Python and trained on bearing datasets, predicts the remaining useful life based on sensor-collected data. This comprehensive methodology aims to provide insights into bearing health, facilitating proactive maintenance and optimizing industrial operations*

Keywords: Predictive maintenance, Electric motor bearings, Accelerometer sensors, Vibration analysis, Industrial efficiency

I. INTRODUCTION

Electric motors are essential components in industrial applications, and the reliable operation of these motors is crucial for maintaining production efficiency. Bearings play a critical role in supporting the rotating shaft of electric motors, and their failure can lead to significant downtime and maintenance costs. Traditional maintenance approaches often rely on reactive strategies, where repairs are conducted after a failure occurs. However, predictive maintenance techniques offer a proactive solution to monitor bearing health and detect potential faults before they escalate. This paper investigates the implementation of predictive maintenance techniques for electric motor bearings to enhance industrial efficiency and reliability.

II. LITERATURE REVIEW

Previous studies have emphasized the importance of monitoring bearing conditions in electric motors to prevent unexpected failures 5. Accelerometer sensors have been widely used to detect early signs of bearing wear by analyzing vibration patterns 3. By implementing proactive monitoring approaches and utilizing power spectra analysis, maintenance teams can identify potential faults in bearings and take timely corrective actions to avoid unplanned downtime and costly repairs. The use of advanced prediction tools, such as machine learning algorithms, has shown promise in enhancing the accuracy of fault detection and prediction.

Machine learning (ML) is a type of artificial intelligence (AI) that allows computers to learn without being explicitly programmed. In the context of predictive maintenance, ML algorithms can be used to analyse data from sensors on machines to identify patterns that can predict when a machine is about to fail. This information can then be used to schedule maintenance before the machine fails, which can help to avoid costly downtime and repairs.

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III. METHODOLOGY

The research methodology involves the installation of accelerometer sensors on electric motors to monitor vibration patterns and collect data on bearing conditions. Power spectra analysis is conducted on the collected data to identify anomalies indicative of bearing wear and potential failures. Proactive maintenance strategies are employed to optimize maintenance schedules and minimize downtime in industrial processes.

The project methodology begins with identification and definition of the problem then the historical study of asset and its failure is done to identify the strategic placement of a sensor on the motor casing, specifically targeting the area where the motor bearing is situated. Time series data acquisition is then carried out, capturing the dynamic behavior of the motor over time. LabVIEW software is employed to visualize the data, presenting frequency plots and spectral graphs for enhanced analysis. Subsequently, the data undergoes pre-processing, where its structure is modified, and metrics such as RRMS (Root Mean Square of Raw Data) and IRRMS (Integrated Root Mean Square) are computed to quantify the vibration levels. RRMS is calculated for discrete datasets, providing insights into the severity of vibration. 8 The processing stage comprises two primary components. Firstly, condition monitoring is conducted using structured supervised datasets of time and acceleration values.

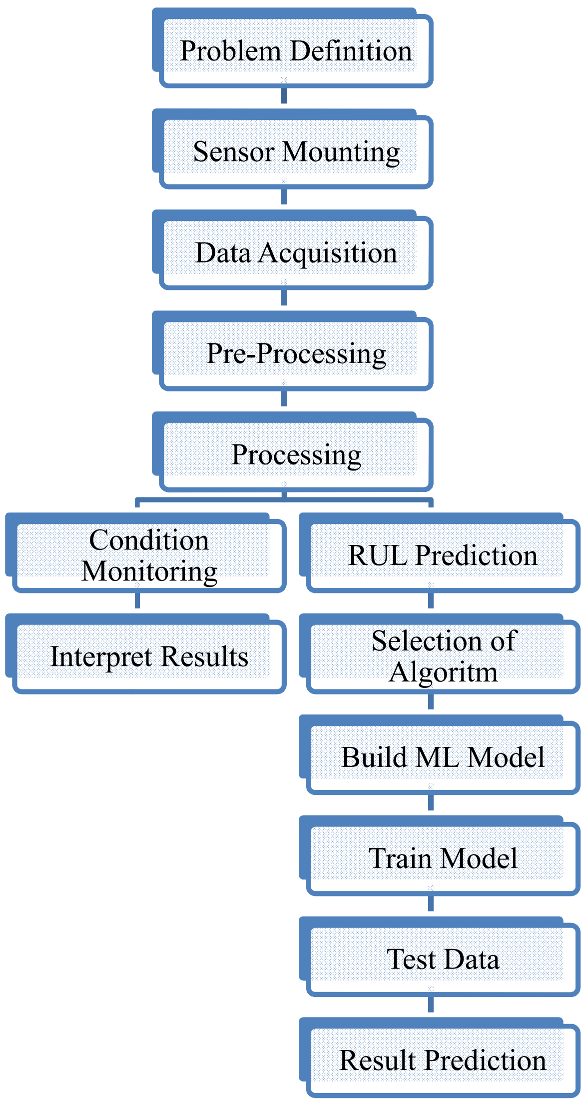

Fig. 1. Methodology

Data is transformed into the frequency domain, and MATLAB software generates condition monitoring graphs. Through interpretation of the results, the health of the bearing is assessed, and the dominant frequency components affecting the bearing are identified. Secondly, the remaining useful life of the bearing is estimated. Initially, an algorithm selection process is undertaken, with the Support Vector Classifier (SVC) algorithm chosen for its effectiveness. To minimize deviations and ensure smoother predictions, RRMS and IRRMS are mathematically utilized. A machine learning model is then constructed using Python programming, trained on a dataset of bearings. Subsequently, sensor-collected data is fed into the model for testing, yielding predictions regarding the remaining useful life of the bearing.

IV. OBJECTIVES

- To implement model for condition monitoring method to enhance equipment reliability and minimize downtime.
- To develop a machine learning model to predict failure and remaining useful life of the asset.

V. PROBLEM DEFINITION

The problem at hand revolves around addressing the inherent challenges associated with maintaining the reliability and performance of induction motors, particularly focusing on the critical component of motor bearings. The initial failure often observed in motors occurs within the bearings. These critical components support the rotating shaft, facilitating smooth operation. Unfortunately, bearings are prone to wear, degradation, and eventual failure due to the constant stress and friction they endure. This early failure can disrupt motor performance, leading to unplanned downtime, reduced efficiency, and increased maintenance costs. Recognizing the significance of addressing bearing failures promptly, predictive maintenance strategies are essential to mitigate these risks and ensure the reliable operation of industrial machinery.

Manual inspections and periodic maintenance schedules are often inefficient, costly, and prone to human error, necessitating a more proactive approach to maintenance. Our project aims to tackle this challenge by implementing a predictive maintenance system leveraging accelerometer sensors mounted on motor casings.

The specific problem we aim to address includes:

1. Detecting early signs of bearing wear and degradation through continuous condition monitoring.
2. Collecting and analyzing relevant data from sensors installed on induction motor casings.
3. Utilizing machine learning algorithms to identify patterns, anomalies, and subtle changes in motor behavior indicative of potential faults.
4. Developing predictive algorithms capable of forecasting performance degradation in motor bearings and estimating the remaining useful life of the bearings.

By solving these key challenges, our project endeavors to enhance the reliability, efficiency, and lifespan of induction motors, ultimately reducing unplanned downtime and maintenance costs for industrial applications.

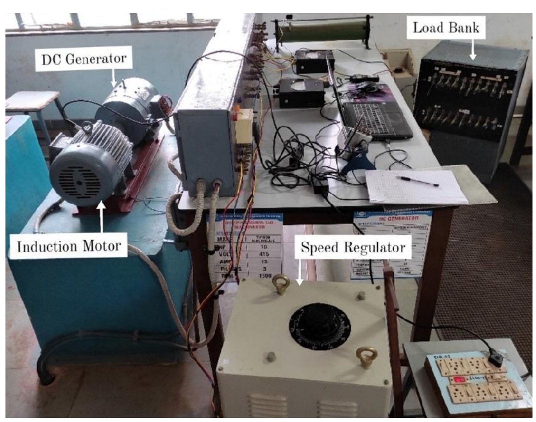

Fig. 2. Experimental Setup

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VI. RESULTS AND DISCUSSION

In this experiment, the motor was running at constant voltage and the load was varied by varying the load on the DC generator by using load bank. The readings were taken at five different load conditions.

For all five readings, the generator load voltage is 200 volts and the motor rated volt is 415 volts. The rated amps vary across all the readings, ranging from 1.5 to 4.83 amps. The load amps increase as the motor's rated amps increase. The speed of the motor decreases slightly as the load on the generator increases.

TABLE I: Experimental Values

Sr. No.	Motor Rated (V)	Motor Rated (A)	Load (V)	Load (A)	Motor (rps)
1	415	1.5	200	0	25
2	415	1.50	200	0.4	24.90
3	415	2.15	200	1.9	24.16
4	415	3.11	200	3.4	24.63
5	415	4.83	200	5.8	23.94

For 1st power spectrum graph, the speed of the motor is 25 rps i.e. 1500 rpm. The motor rated ampere is 1.5 at zero loading and the graph indicate the highest peak of 1x leading towards unbalance at around 500 Hz.

In the power spectrum 2, the motor rated ampere is 1.5 A at loading of 0.4 A and the graph come with the peaks ranging at 0.004 on y-axis around 500 Hz leading towards misalignment, the speed of the motor decreases as load increase and it comes out to be is 24.90 rps i.e. 1494 rpm.

For power spectrum graph 3, the speed of the motor is 24.16 rps i.e. 1499 rpm. The motor rated ampere is 2.15 A at 1.9 A loading of the generator and the graph indicate the highest peak of 1x leading towards misalignment at around 500 Hz and other peak of 2x indicated misalignment.

For 4th power spectrum, the speed of the motor is 24.63 rps i.e. 1477rpm. The motor rated ampere is 3.11 A at 3.4 A loading and the graph indicate the highest peak of 1x leading towards misalignment at around 500 Hz and other peak of 2x indicated misalignment at around 50 Hz.

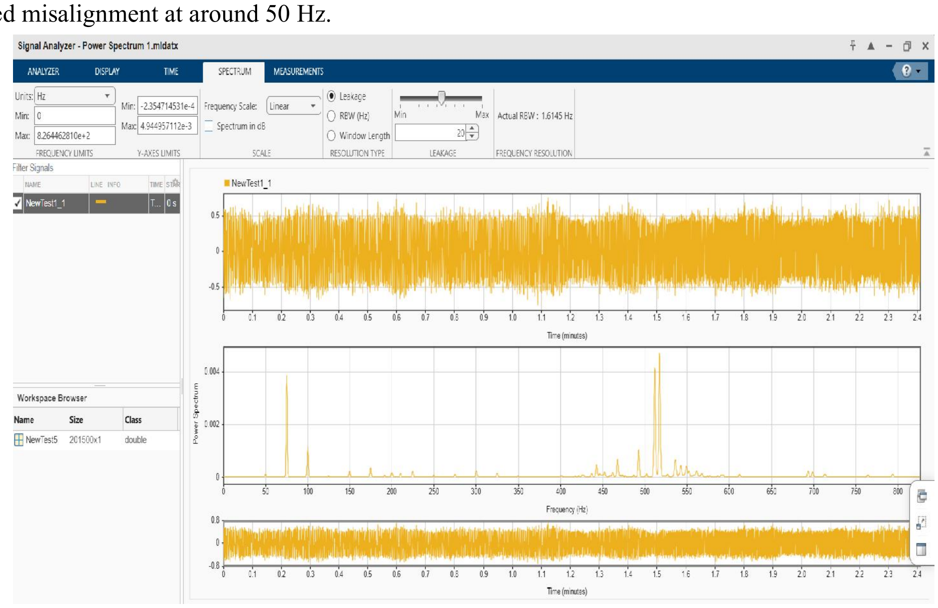

Fig. 3 Power Spectrum 1

For power spectrum 5, the motor rated ampere is 4.83 A at loading of 5.8 A and the graph come with the peaks ranging at 0.002 on y-axis around 500 Hz leading towards unbalance and at around 100 Hz for misalignment, the speed of the motor decreases as load increase and it comes out to be is 23.94 rps i.e. 1436 rpm.

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In conclusion, the application of condition monitoring techniques for motors, particularly focusing on the theoretical calculations of Bearing Fault Frequencies (BPFI, BPFO, and BDF), is vital for predictive maintenance and ensuring operational efficiency.

The theoretical values obtained for BPFI, BPFO, and BDF at 116.94Hz, 75.05Hz, and 104.76Hz, respectively, provide crucial insights into the potential fault frequencies within the motor system.

The alignment of these theoretical frequencies with the observed power spectrum graph reinforces the significance of employing condition monitoring methodologies. Notably, the observation that the fifth harmonic of the BDF aligns with the highest peak in the power spectrum graph underscores its relevance as a potential indicator of bearing faults.

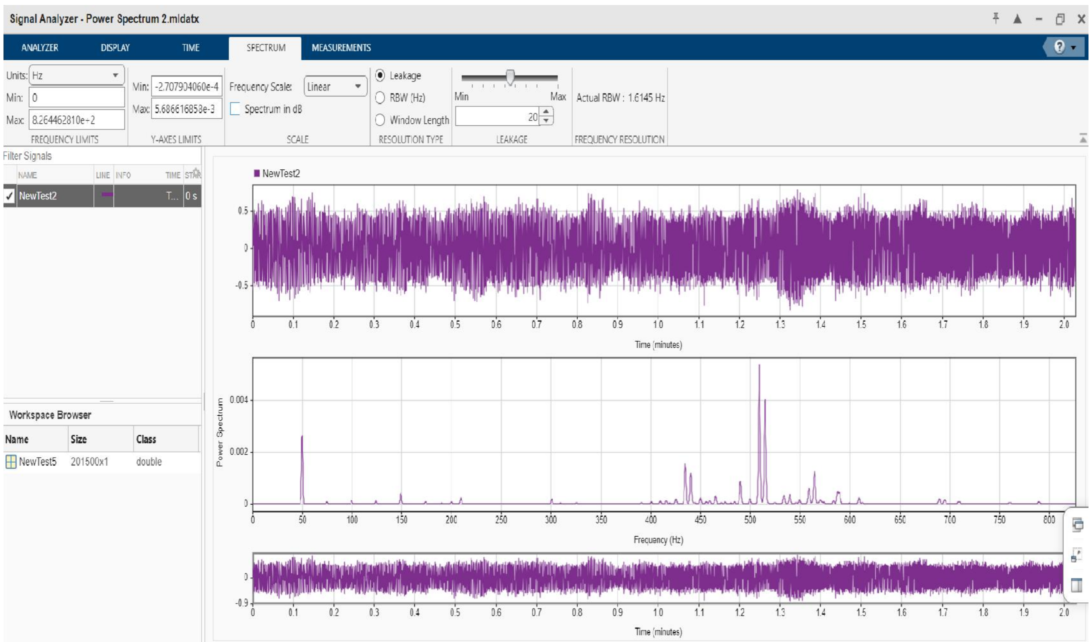

Fig. 4 Power Spectrum 2

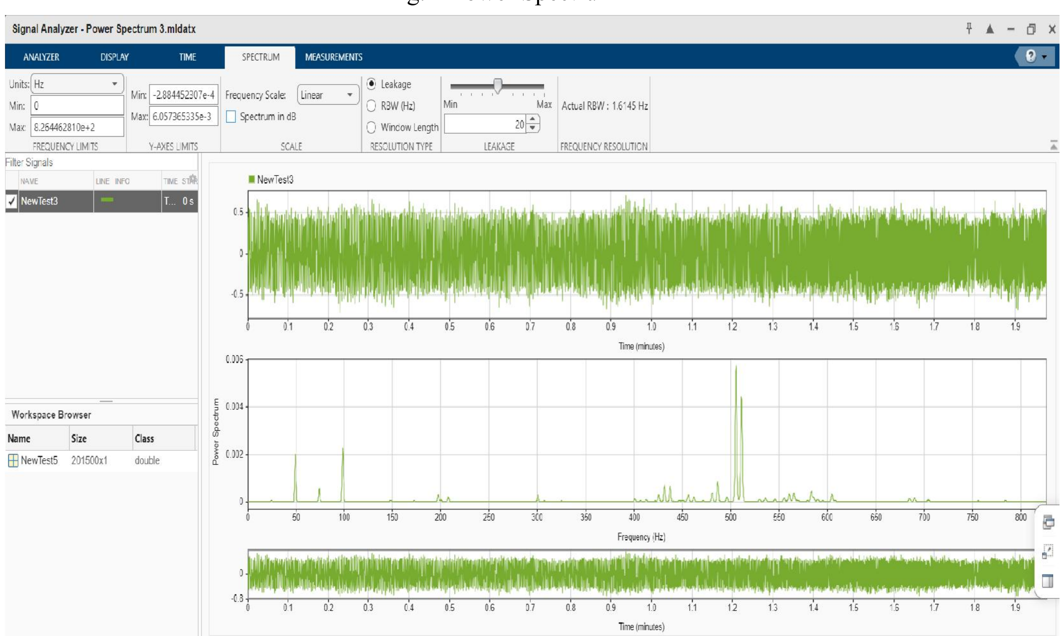

Fig. 5 Power Spectrum 3

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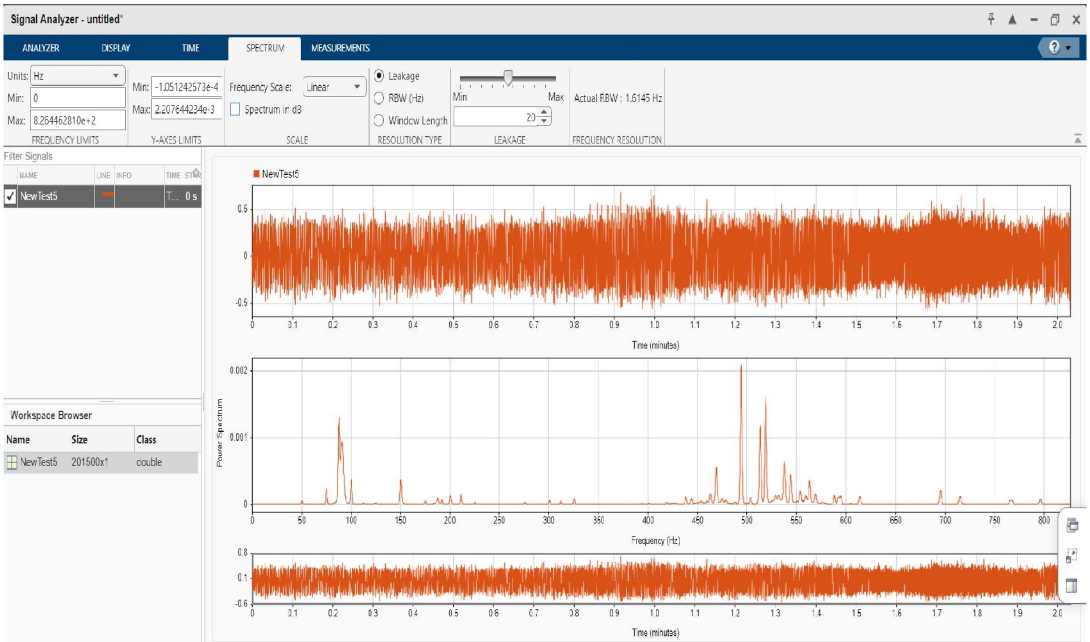

Fig. 6 Power Spectrum 4

Methods to read the Power Spectrum Graph:

- Unbalance: If the system shows peaks at its 1X Hz, then system is unbalanced.
- Misalignment: If the system shows peaks at 1X & 2X, the system is misaligned.

Bearing defect:

- BPFO (Ball Pass Frequency Outer): $\frac{n}{2} f\left(1 - \frac{BD}{PD} \cos\beta\right)$
- BPFI (Ball Pass Frequency Inner): $\frac{n}{2} f\left(1 + \frac{BD}{PD} \cos\beta\right)$
- BDF (Ball Defect Frequency): $\frac{PD}{BD} f\left(1 - (\frac{BD}{PD} \cos\beta)^2\right)$

Bearing in use:

- Ball Bearing SKF 6314 C3
- BD = 24mm
- PD = 110mm
- $\beta = 0$

***Calculations*:**

Also, f = 24 Hz

BPFO = $\frac{8}{24} 24\ (1 - \frac{24}{110} \cos 0°)$
= 75.05 Hz

BPFI = $\frac{8}{2} 24 \left(1 + \frac{24}{110} \cos 0°\right)$
= 116.94 Hz

$$\text{BDF} = \frac{110}{24}\, 24\left(1 - \left(\frac{24}{110}\ \cos 0°\right)^2\right)$$
$$= 104.76 \text{ Hz}$$

The fifth harmonic of the BALL DEFECT FAILURE (BDF) matches the highest peak in the power spectrum.

VII. CASE STUDY OF BEARING SET

The dataset utilized in this project was sourced from the IEEE on case study of bearings (reference [1]). The link to the dataset is cited in the references section.

For the dataset, the SVC algorithm is best suitable. The actual RUL for the bearing is 4840 s and the predicted RUL is 4767 s. The predicted RUL is very close to actual RUL, with an error of only 73 units. The error is about 1.5%. This indicates that the machine learning program is performing well and can accurately predict remaining useful life.

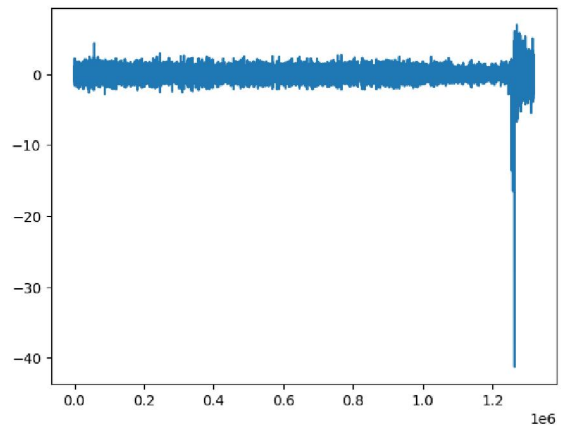

Fig. 7. Acceleration data

This graph does not show the whole lifecycle of the bearing. Instead of that, the reading is taken some few times before the actual degradation was started. In this case, the reading was started at the 9 hrs 10 min 39 sec after the bearing test setup was started until the failure of the bearing. The x-axis denotes the number of readings and y-axis denotes the acceleration due to gravity in ‘g’.

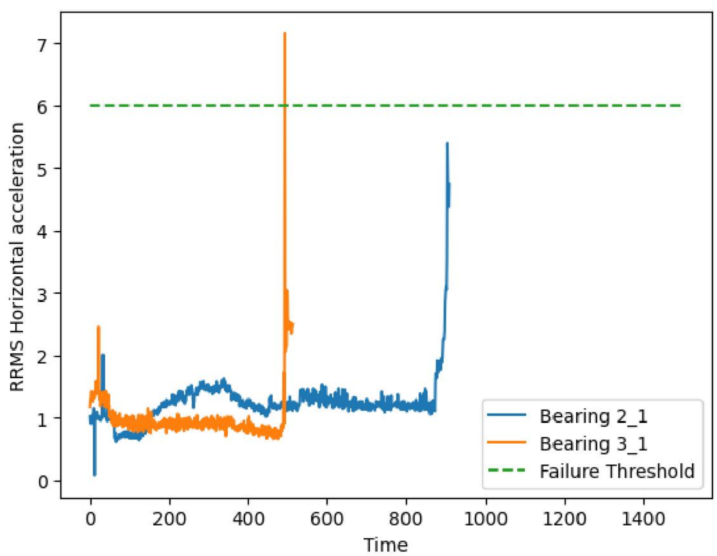

Fig. 8. RRMS Values with threshold range

By using the formula, converting the RMS values into the RRMS for clear identification of the nature of the graph made by the bearing during their lifecycle. One RMS value is generated for one file and after every 10 sec one file was generated.

Theoretically the failure threshold is 6 g. The graph shows the RRMS values for both bearings with the failure threshold value. It depends on the type of loading and bearing type and the type application.

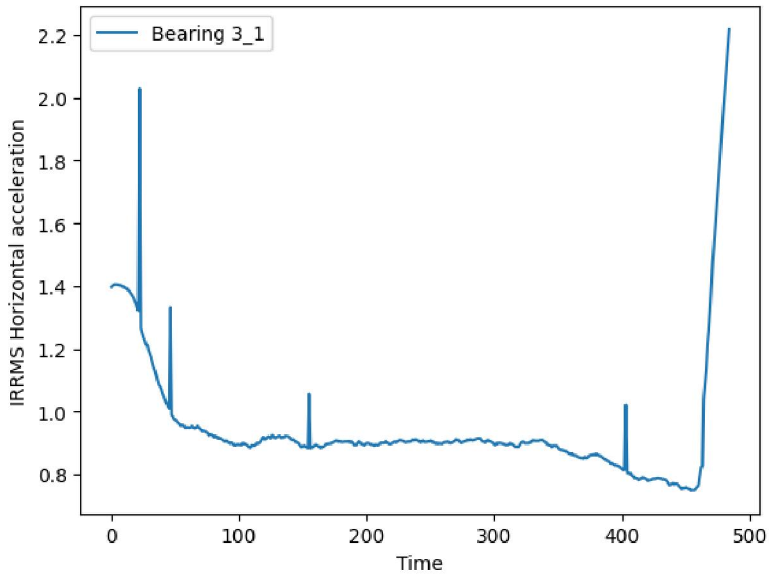

Fig. 9.IRRMS Values

For smoother graph, the RRMS values are then transform to the IRRMS values. It thereby removes the error by smoothing the curve. It gives more clarification over the nature of the data.

The x-axis denotes the time value which is directly represented in the form of no. of files generated. The y-axis denotes IRRMS values for the horizontal acceleration in ‘g’.

Actual RUL	4840 s (After the reading has started)
Predicted RUL	4766.9976 s

TABLE III: RUL Result of Case study

Calculations for RUL of bearing of the asset:

For the collected dataset, there is no variation in amplitude. The bearing is in healthy condition. In the program it is defined as, if the RRMS value is below 1.1 then it is considered to be in healthy state and return the 0 value in the list. The graph is coming out to be in straight line. There is no variation in the graph. Because of this the predicted RUL for the fetched dataset of the motor is“nan” i.e. infinite.

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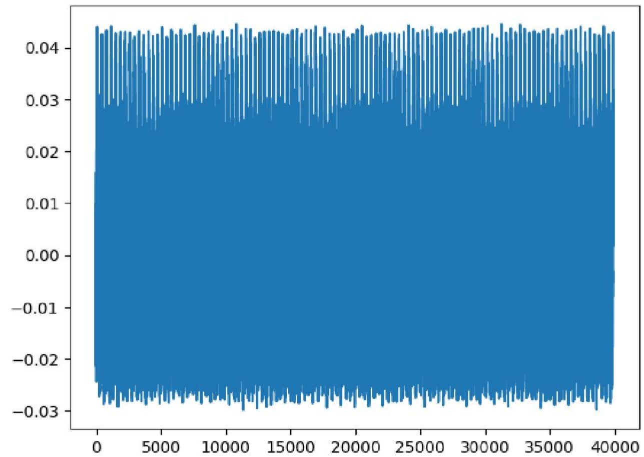

Fig. 10. Acceleration data

The graph shows the acceleration dataset for the experimental setup. The x-axis denotes the no. of samples and y-axis denotes the acceleration in m/s^2. This reading is taken by varying the load on motor provided by the DC generator. The load on motor was varied from 0 to partial load.

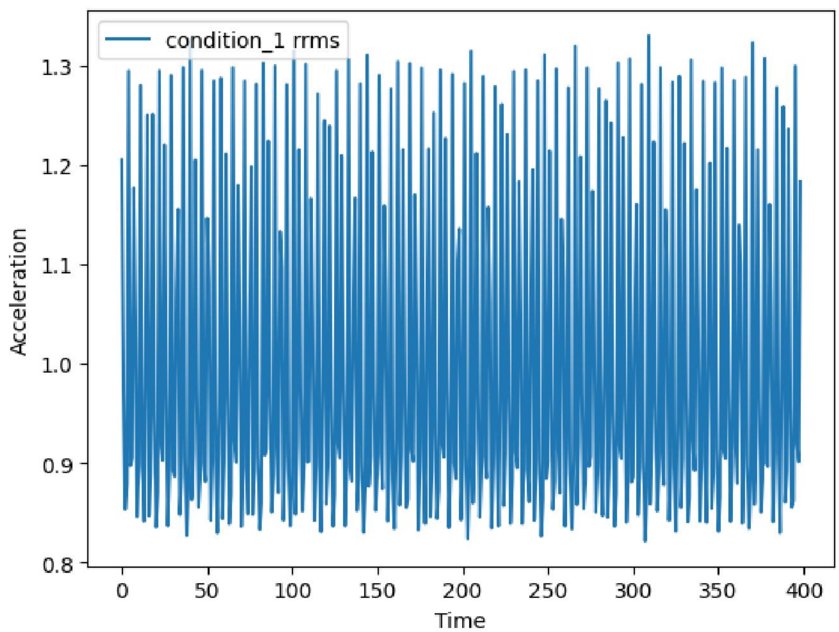

Fig. 11. RRMS Value

The RRMS values are calculated from the RMS values. In this graph the x-axis denotes the time in sec and y-axis is acceleration in m/s^2.

For generating RMS values, instead of generating files for every 10 sec, the single file is generated. By defining sampling frequency, in this case it is 100 Hz, for every 100 reading there are one RMS value is generated.

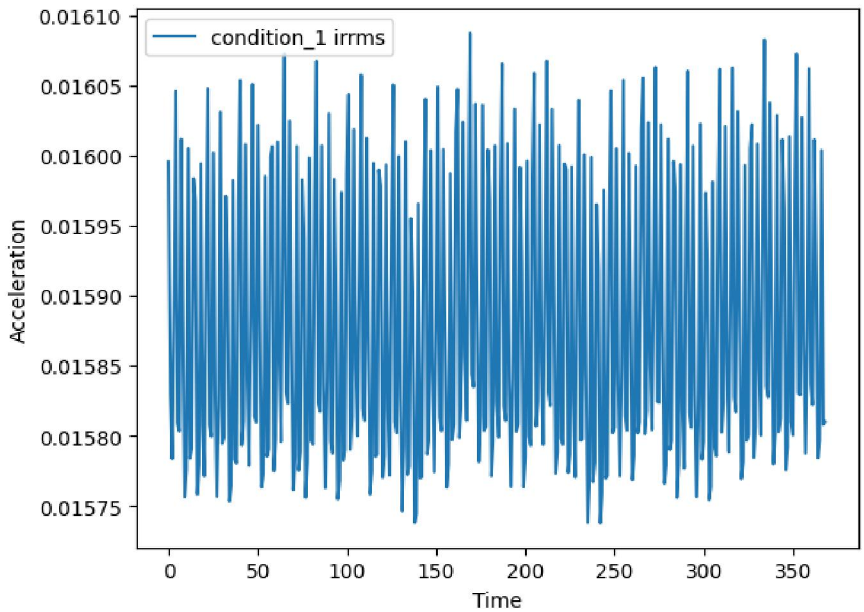

Fig. 12.IRRMS Values

The graph shows the IRRMS values for the experimental setup. IRRMS values are generated by formula using the RRMS values. The x-axis denotes the time and y-axis denotes the acceleration in m/s^2.

This graph clarifies the nature of the data and gives information about the bearing diagnostics.

Predicted RUL: Infinite

VIII. FUTURE SCOPE

To guarantee the accuracy and generalization of classification, the classification method employing on bearing degradation stage needs further research, such as XGboost, decision tree, extreme learning machines.

By using or gathering large amount of historic data can provide more accurate RUL prediction as machine learning models require large amount of historic data of asset.

IX. CONCLUSION

In summary, our project represents a significant advancement in the field of predictive maintenance for electric motors, particularly in addressing the prevalent issue of early bearing failure. Through meticulous planning and execution, we successfully implemented a methodology that combines data acquisition, preprocessing, condition monitoring, and machine learning techniques to assess and predict the health of motor bearings. By strategically placing sensors on the motor casing and systematically varying the load conditions, we obtained a comprehensive dataset capturing the dynamic behaviour of the motor under different operating conditions. Leveraging MATLAB, we conducted thorough analysis, quantifying vibration levels and generating condition monitoring graphs to assess the state of the bearings. Furthermore, our approach incorporated advanced machine learning algorithms implemented in Python to estimate the remaining useful life (RUL) of the bearings. The high accuracy achieved in RUL estimation, with negligible error in available datasets, underscores the effectiveness of our predictive maintenance strategy. 62 Importantly, our project highlights the practical application of predictive analytics in optimizing equipment reliability and operational efficiency in industrial settings. By proactively identifying potential failures and scheduling maintenance activities accordingly, businesses can minimize downtime, reduce maintenance costs, and enhance overall productivity.

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