CONDITION MONITORING OF SPUR GEAR USING VIBRATION SIGNAL AND MACHINE LEARNING TECHNIQUE

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Keywords

productivity slowdowns; reduced efficiency; increased maintenance time; unexpected maintenance; predictive maintenance techniques; maintenance costs; production efficiency; continuous operation; unexpected downtime; gearbox assemblies; condition monitoring techniques; prevent malfunctions; unforeseen downtimes; early fault detection; machine malfunctions; accidents; maintenance downtime; traditional gearbox maintenance; physical inspections; disassembly testing; slow scan approach; performance hindrance; fault visibility; gear problems prediction; artificial intelligence; AI; monitoring to prediction; vibration signal analysis; non-invasive technology; subtle changes; 100-hour intervals; gearbox internal state; interpret vibration signals

Introduction

In today's manufacturing industries, slow down's the productivity, efficiency and increase in maintenance time are mainly due to unpredicted maintenance encounter in machineries. The predictive maintenance techniques are used to reduce the maintenance cost and increase the production. As machineries in modern industries are expected to run continuously, which cause's an unexpected down time. Since most of the machineries contain gear box assembly, it is imperative to develop suitable condition monitoring technique to prevent malfunctioning and unexpected down time during operation. Early detection of fault is very important to avoid malfunction of machine that would leads to accidents and loss of time in maintenance of machine. Predicting a fault in gearbox is an important process in condition monitoring of gear box.

Traditional gearbox maintenance usually revolves around tedious physical inspections and tedious disassembly testing methods. This "slow scan" approach not only hinders performance, but also does not provide immediate visibility of faults. [8] What if we could predict gear problems before they stopped working? This study paves the way for changes in gearbox maintenance. We use the power of artificial intelligence (AI) to move from monitoring to prediction. Instead of laborious gearing, we use vibration signal analysis, a non-invasive technology that instantly captures the "whisper" of the gearbox.[3] These signals are collected every 100 hours of time interval, revealing the inner world of the transmission.[2] To understand these vibration signal's, we will unleash the power of machine learning, train the intelligence model to identify these statistical features and predict the epidemic with probabilities.

Objectives

The main Objective of this research work is to monitor the condition of the gear based on machine learning approach

- To acquire the vibration signals from the gear box under different conditions (100 hours interval of time period)
- To analyze the acquired vibration signals by the statistical features.
- To monitor the Condition of the gearbox using machine learning technique.

Methodology

The general flow of current research work is as below

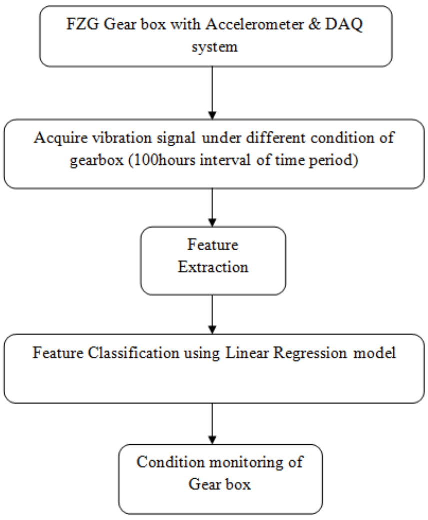

Figure 3.1 Methodology of condition monitoring system using machine learning technique

Integrating an accelerometer with a data acquisition (DAQ) system into a gearbox creates a powerful tool for condition monitoring and preventative maintenance. The accelerometer, mounted on the gearbox housing, captures vibrations generated by the gears and bearings. The DAQ system then amplifies, filters, and digitizes these vibrations, converting them into a data stream for analysis.

To acquire the vibration data from gear box we need to set all the tools and systems and configure them according, some of them mentioned below.

1. Accelerometer Placement: Secure accelerometers to gearbox housing, often near bearings or gear mesh points, for optimal vibration signal capture.
2. DAQ System Configuration: Set DAQ system to acquire vibration signals at 100-hour intervals. And adjust sampling rate and frequency range to match gearbox characteristics and expected fault frequencies.
3. Data Collection: Trigger data acquisition automatically at set intervals or manually initiate it. Collect vibration data for a sufficient duration to capture relevant gear mesh and bearing frequencies.

4. Data Storage and Management: Store acquired vibration signals for later analysis and comparison with historical data. Organize data by timestamp and gearbox condition for efficient retrieval and trend analysis.

5. Data Analysis: Employ vibration analysis techniques (e.g., time-domain, frequency-domain, time-frequency domain) to extract meaningful features and detect changes in signal patterns. Compare current vibration data with previous readings and baseline data for early fault identification.

After acquiring the vibration data we will proceed to words Data pre-processing, Visualization, Feature extraction, classification of model, and finally prediction of the condition of gear box

Now the gearbox monitoring is not relying on scheduled inspections and manual data readings, leaves machines vulnerable to unforeseen breakdowns. But continuous monitoring flips the script, transforming passive observation into proactive defense. By harnessing real-time sensors and intelligent data analysis, this approach offers a safety net for crucial machines.

A network of vibration sensors, temperature probes, and oil analysis probes continuously capturing the gearbox's vital signs. The data from these sensors streams into a central system, where advanced algorithms crunch the numbers in real-time. Deviations from normal operating parameters like increased vibration, elevated temperature, or changes in oil composition trigger instant alerts, notifying maintenance personnel of potential issues before they snowball into catastrophic failures.

Results:

Data Analysis Using Python

Time V/s Acceleration Time Domain chart of 700, 800, 900, 1000 hours running condition, with 0 seconds to 1 second time.

Plotting the Time vs Acceleration Time Domain chart for different running conditions allows visual comparison of acceleration patterns over time, spanning from 0 seconds to 1 second. This visualization aids in understanding how acceleration changes throughout the gearbox's operational lifespan, offering insights into its performance dynamics and potential variations or trends across different time intervals.

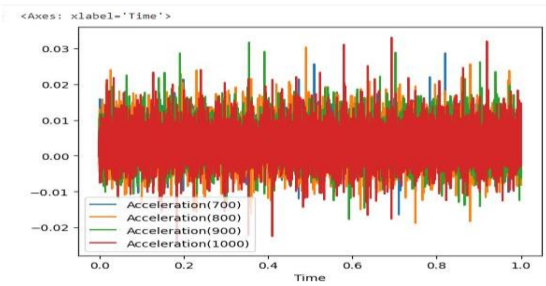

Fig: 4.1 Time V/s Acceleration chart

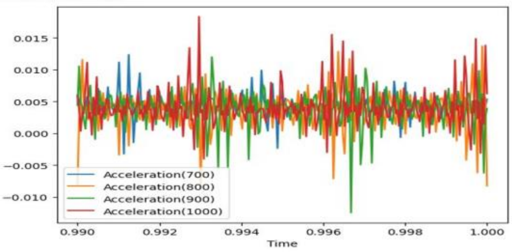

Fig: 4.2 Time V/s Acceleration chart with time 0.990 to 1 second

Some other graph which shows the all acceleration data by cutting time into slice,

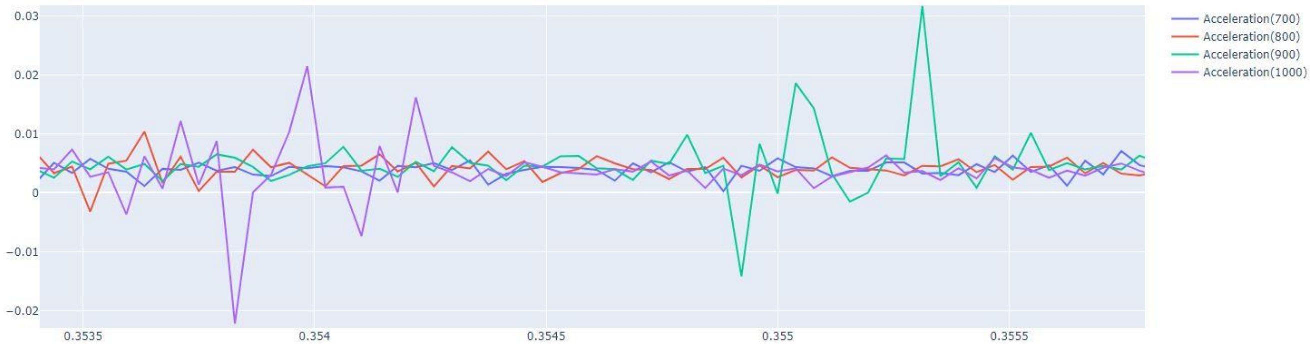

Fig: 4.3 Time V/s Acceleration chart. With time 0.3535 to 0.3555 second

Acceleration Analysis Using Power Spectral Density and Python

Vibration in the real world is often "random" with many different frequency components. Power spectral densities (PSD or, as they are often called, acceleration spectral densities or ASD for vibration) are used to quantify and compare different vibration environments.

Power spectral density (PSD) Chart with Bin Width value 1

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The Power Spectral Density (PSD) chart with a bin width value of 1 displays the distribution of power intensity across different frequency bins. A bin width of 1 indicates that each frequency bin represents a range of one unit. This visualization helps in analyzing the frequency distribution of the signal's power, aiding in identifying dominant frequencies and spectral characteristics

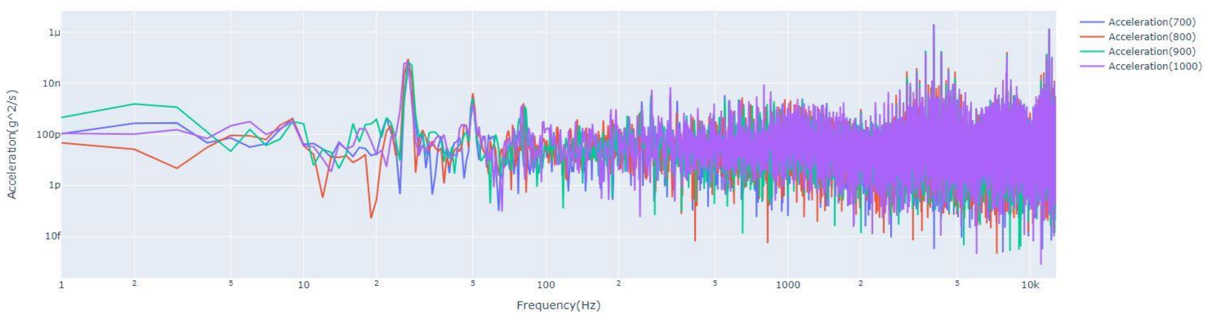

Fig 4.4: Frequency V/s Acceleration time domain chart.

Acceleration gRMS V/s Frequency chart for variation detection

Acceleration gRMS (root mean square) is a measure used in vibration testing and analysis to quantify the overall level of acceleration experienced by a system or component over time

The Acceleration gRMS vs. Frequency chart is crucial for variation detection as it displays the root mean square (RMS) acceleration values across different frequency bands. This visualization helps identify frequency regions where significant variations occur, highlighting potential areas of concern or anomalies in the system's vibration behavior. Analyzing this chart aids in pinpointing frequency-specific issues and guiding targeted troubleshooting or maintenance efforts

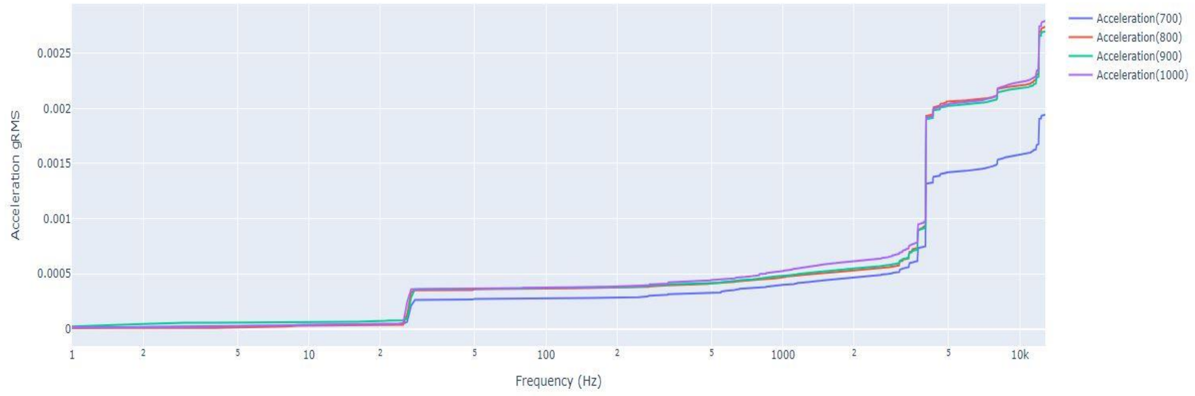

Fig: 4.6 Frequency V/s Acceleration gRMS

ANALYZING VIBRATION SIGNALS BY THE STATISTICAL FEATURES AND LINEAR REGRESSION MODEL (MACHINE LEARNING)

By using supervised machine learning technique i.e. linear regression model which based on one or more inputs, predict a value from a continuous scale. And Predicting the change in acceleration over a time using statical features.

Max Acceleration of 700 hours running condition vs Max Acceleration of 900 hours running condition

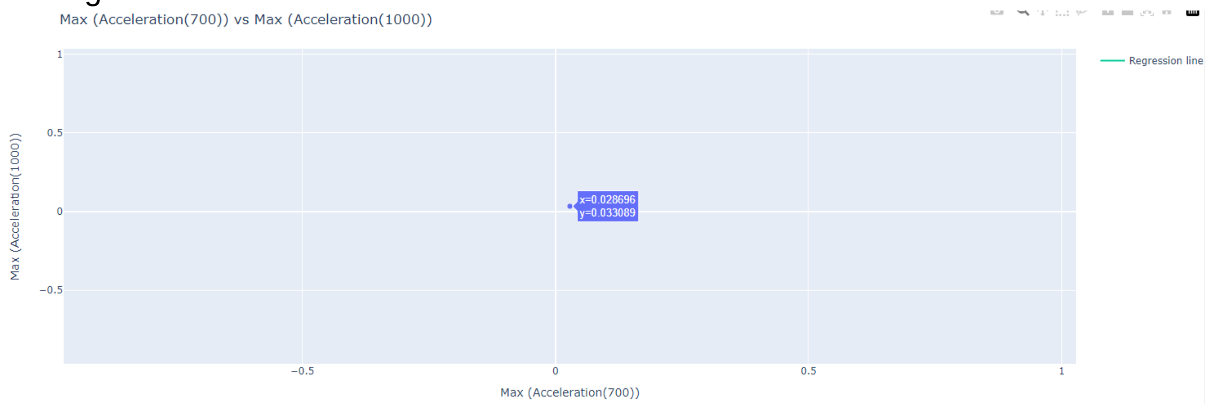

Fig: 4.7 showing change in Max acceleration 700 hours running condition vs 1000 hours running condition

The gearbox running data shows a consistent increase in maximum acceleration over time. At 700 hours of operation, the maximum acceleration was 0.028696. By 1000 hours, it had risen to 0.033089. This trend indicates that the gearbox is experiencing progressively higher levels of stress or wear. The increase in acceleration could be due to factors such as component degradation or increased load conditions. Continuous monitoring is essential to anticipate maintenance requirements and ensure reliable performance.

Mean Acceleration of 700 hours running condition vs Mean Acceleration of 1000 hours running condition

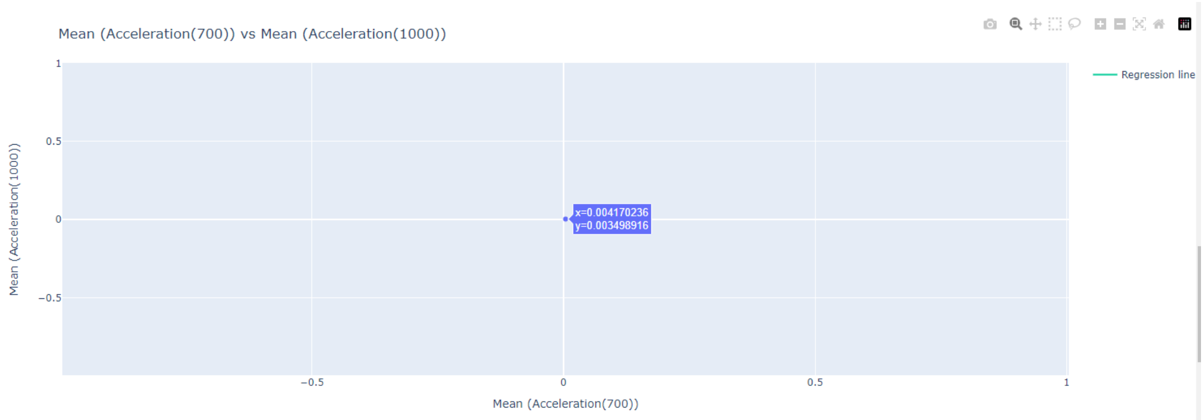

Fig: 4.8 showing change in Mean acceleration 700 hours running condition vs 1000 hours running condition

The gearbox running data shows a notable decrease in mean acceleration over a 300-hour interval. At 700 hours of operation, the mean acceleration was 0.004170236. By 1000 hours, it had decreased to 0.003498916. This significant reduction in mean acceleration suggests that the gearbox is operating more smoothly, possibly due to wear stabilizing or improved lubrication. This trend might indicate an adjustment period where the components are settling into a more efficient operating state. Continuous monitoring is essential to confirm this trend and to detect any future changes in performance.

Standard Deviation of Acceleration of 700 hours running condition vs Mean Acceleration of 1000 hours running condition

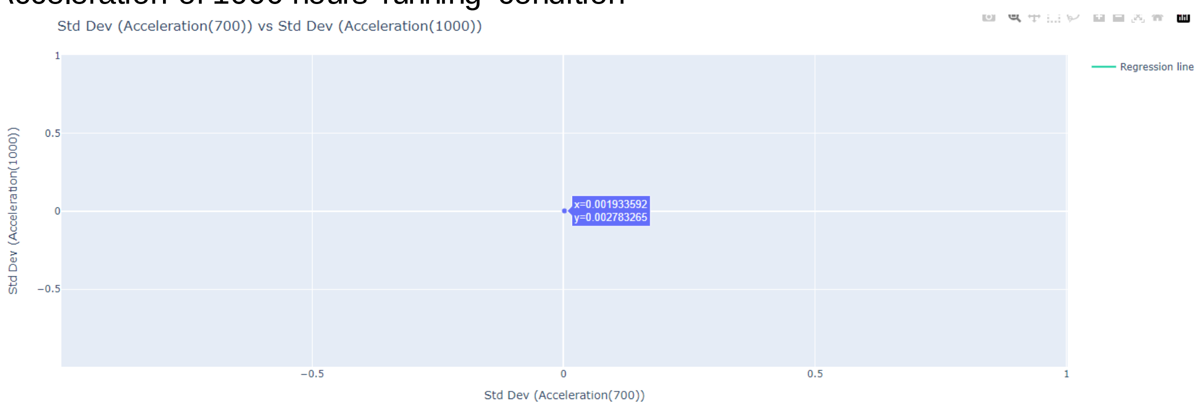

Fig: 4.9 showing change in Standard Deviation of acceleration 700 hours running condition vs 1000 hours running condition

The gearbox running data demonstrates a notable increase in the standard deviation of acceleration over a 300-hour period. At 700 hours of operation, the standard deviation of acceleration was 0.001933592, while at 1000 hours, it escalated to 0.002783265. This significant rise suggests a widening variability in acceleration values, indicating potential fluctuations in operating conditions or emerging mechanical issues within the gearbox. Monitoring this trend closely is crucial as it may signify evolving problems requiring maintenance to ensure continued optimal performance and reliability.

Maximum acceleration of all hours running condition

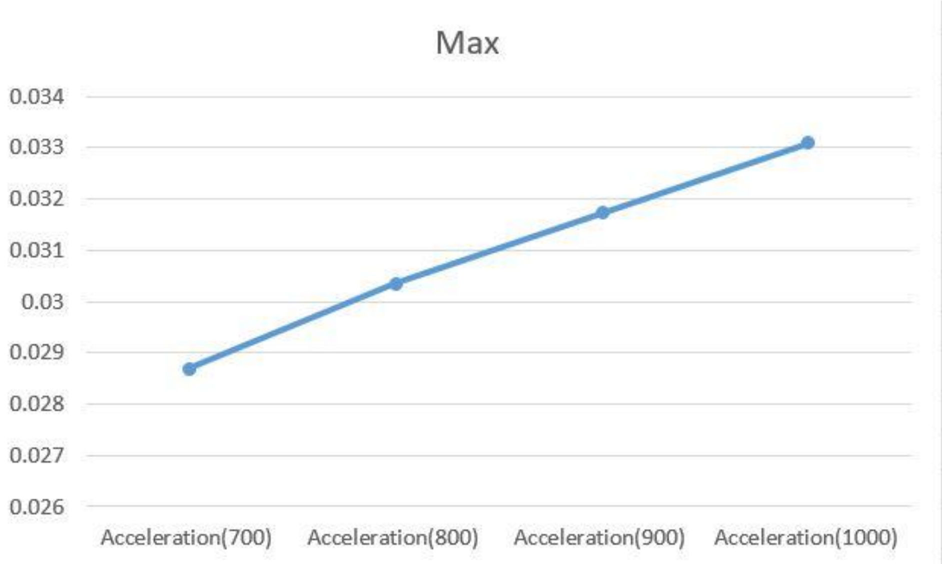

Fig 4.10 Change of maximum acceleration over a period of time or running condition

The graph shows an increase in maximum acceleration from 0.029 at 700 to 0.033 at 1000, indicating rising vibrations or forces with higher speeds. This trend suggests potential issues like wear and tear, insufficient lubrication, imbalance, misalignment, or varying loads. Regular inspections, proper lubrication, balancing, and alignment checks are essential to address these issues and maintain gearbox performance. Regular maintenance can help identify and rectify these problems before they lead to significant damage.

Minimum acceleration of all hours running condition

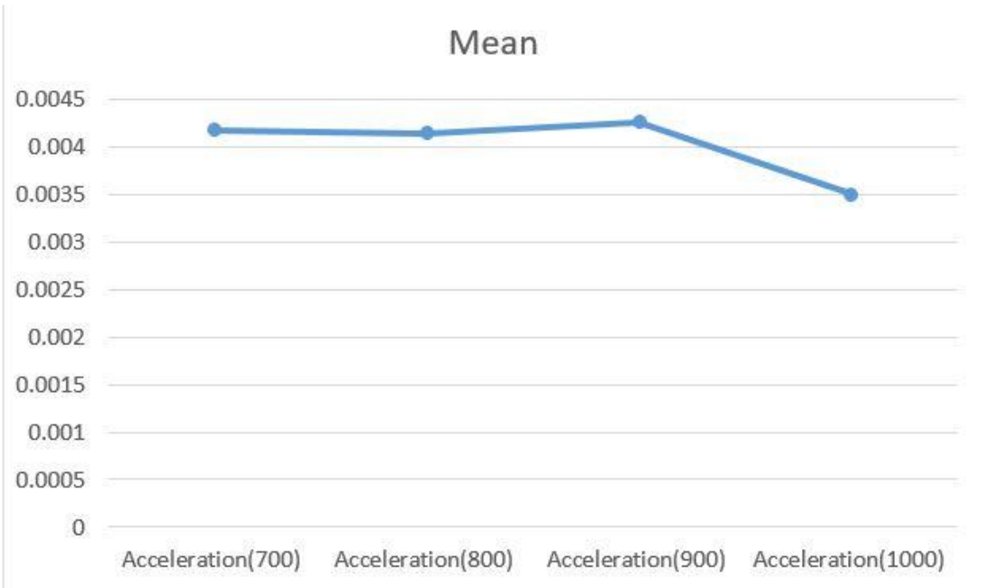

Fig 4.11 Change of minimum acceleration over a period of time or running condition

The graph shows a steady mean acceleration from 700 to 900, followed by a significant drop at 1000. This suggests possible operational adjustments, improved damping mechanisms, or mechanical adaptation at higher speeds reducing vibration. Regular monitoring and inspections are crucial to ensure these changes reflect stable operation and not underlying issues. Checking damping systems and load conditions to maintain optimal gearbox performance.

Standard deviation acceleration of all hours running condition

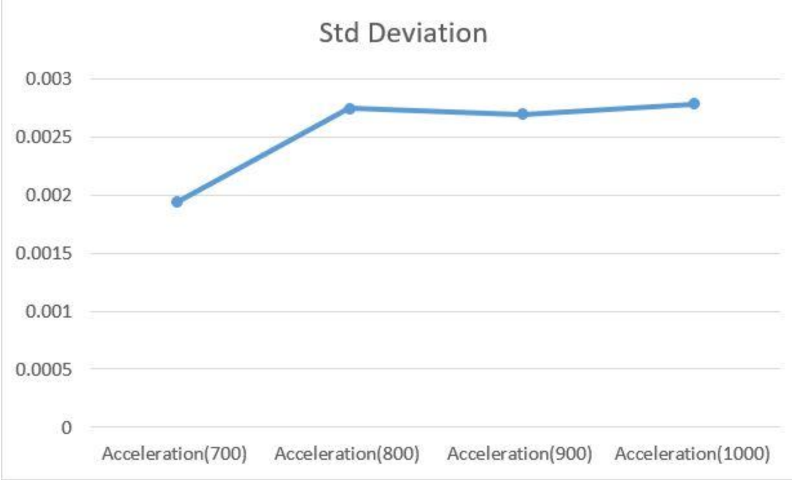

Fig 4.12 Change of Standard deviation acceleration over a period of time or running condition

The graph shows the standard deviation of acceleration for the gearbox at different speeds, increasing from 700 to 800 and then stabilizing from 800 to 1000. This indicates greater variability in acceleration at 800, likely due to transitional forces or imbalances at this speed. The stabilization at higher speeds suggests improved consistency. Regular monitoring and addressing any imbalances or transitional issues can help maintain this stability. Continued inspection ensures that variability remains low, indicating smooth operation.

Minimum acceleration of all hours running condition

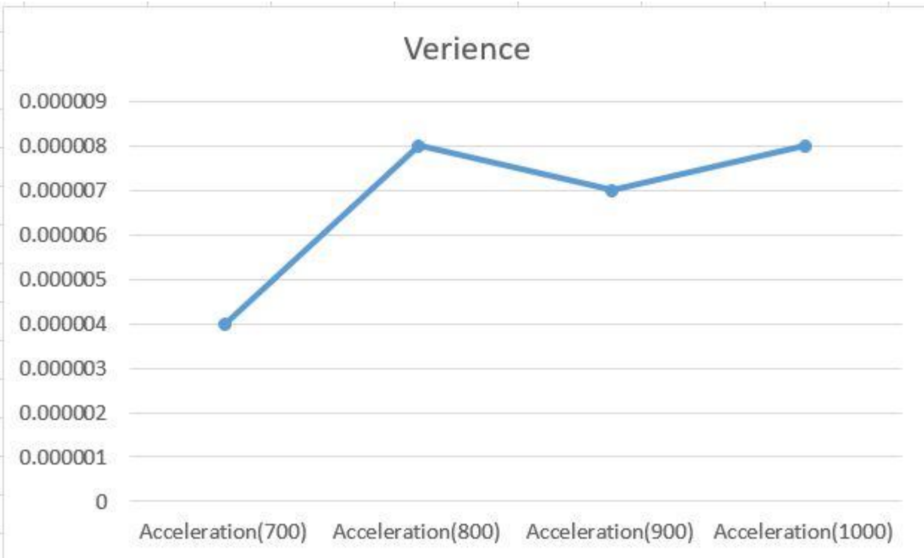

Fig 4.13 Change of Variance acceleration over a period of time or running condition

The chart shows the variance of gearbox acceleration at different running conditions: 700, 800, 900, and 1000 units. Initially, the variance increases sharply from approximately 0.000004 at 700 acceleration to about 0.000008 at 800 acceleration. This is followed by a slight decrease at 900 acceleration before rising again at 1000 acceleration. The fluctuations in variance indicate varying stability in the gearbox's performance under different acceleration conditions, which could be useful for identifying periods of potential instability or irregular operation. Monitoring these variances helps in predicting and preventing potential gearbox issues.

Conclusion

The notable increase in the all above results and in charts of acceleration in the gearbox from 700 hours to 1000 hours indicates a significant rise in variability. This trend suggests potential fluctuations in operating conditions or emerging small mechanical issues. It is crucial to monitor this closely and perform necessary maintenance to prevent further problems and ensure the gearbox's optimal performance and reliability.

Scope for Future Work

The future work for this advanced gearbox health monitoring system includes several key areas of development. Firstly, integrating additional sensors to monitor other parameters such as temperature, vibration, and noise could provide a more comprehensive analysis of gearbox health. Secondly, enhancing the machine learning algorithms to improve fault prediction accuracy and reduce false positives is essential. Developing adaptive algorithms that can learn from new data and adjust predictions accordingly will make the system more robust.

Another avenue is the integration with Internet of Things (IoT) platforms, allowing for remote monitoring and real-time data analysis. This would facilitate predictive maintenance across multiple gearboxes in different locations. Furthermore, creating a user-friendly interface for operators and maintenance personnel can improve usability and adoption.

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Collaboration with gearbox manufacturers to standardize data formats and diagnostic criteria could lead to industry-wide improvements. Additionally, investigating the environmental impacts on gearbox performance, such as extreme temperatures or corrosive conditions, can help tailor the system to various operational contexts. Finally, conducting extensive field tests and case studies will validate the system's effectiveness and guide future enhancements. This multifaceted approach ensures that the monitoring system evolves to meet the dynamic needs of modern industrial applications.

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