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Monitoring and Maintenance Tools for Turbine Bearing using Artificial Intelligence Technique

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ABSTRACT

Turbine reliability is crucial for ensuring uninterrupted power generation, and the health of bearings plays a vital role in this process. This research introduces a comprehensive framework for improving bearing monitoring and maintenance by integrating Internet of Things (IoT) technologies with machine learning. A network of strategically placed sensors collects real-time data on essential bearing parameters, such as temperature, vibration, and lubrication status. This data is transmitted through an IoT platform to a centralised system for continuous monitoring. Additionally, advanced machine learning algorithms are utilised to analyse the sensor data and predict potential bearing failures, which allows for proactive maintenance strategies. By using predictive analytics, this system aims to minimise downtime, reduce maintenance costs, and extend the operational lifespan of gas turbine bearings, ultimately enhancing overall system efficiency and reliability.

Keywords: Monitoring, Maintenance, Internet of Things, Turbine, Bearing, Artificial Intelligence Technique

1.0 INTRODUCTION

Turbine bearings are critical engine components, ensuring smooth operation, efficiency, and reliability. Their failure can result in significant downtime, increased maintenance costs, and even safety hazards. As such, advanced monitoring and maintenance tools have been developed to detect early signs of wear, predict remaining useful life, and enable proactive maintenance strategies. This response offers a comprehensive overview of these tools, drawing on recent research papers that highlight key technologies, methodologies, and future directions.

1.1 Monitoring Techniques for Turbine Bearings

i. Vibration-Based Monitoring

Vibration analysis is one of the most widely used techniques for monitoring the health of turbine bearings. Vibration signals contain valuable information about the mechanical condition of the bearings, including the presence of defects, wear, and imbalance. Advanced signal processing techniques, such as time-frequency domain analysis and wavelet transforms, are employed to extract diagnostic features from these signals[1] [2]. These techniques enable the detection of early fault indicators, such as changes in vibration amplitude, frequency, and modulation patterns.

ii. Temperature and Lubrication Monitoring

Temperature monitoring is also essential for assessing the health of turbine bearings. Elevated temperatures can indicate improper lubrication, misalignment, or excessive wear. Advanced sensors and thermal imaging techniques monitor temperature profiles and detect anomalies [3]. Additionally,

based on high-frequency vibration analysis, lubrication regime monitoring helps identify conditions such as oil starvation and asperity interactions, which can lead to bearing failure. [4]

iii. Cyclo-Non-Stationary Signal Analysis

Cyclo-non-stationary signal analysis has become a powerful tool for bearings operating under varying speed and load conditions. This approach generalises traditional cyclostationarity indicators to handle speed-varying conditions, providing insights into bearing health under dynamic operating regimes [3]. Techniques such as the Spectral Correlation Density (SCD) and Cyclic Modulation Spectrum (CMS) extract diagnostic features from these signals.

1.2 Diagnostic Techniques for Bearing Health Assessment

i. Fault Detection and Classification

Fault detection in turbine bearings involves identifying specific vibration and debris data patterns corresponding to known failure modes. Machine learning algorithms, such as artificial neural networks (ANN) and support vector machines (SVM), have been successfully applied to classify bearing faults, including surface damage, cage faults, and roller element defects [5] [6]. These algorithms leverage features extracted from vibration signals, such as root mean square (RMS) and kurtosis, to achieve high accuracy in fault detection.

ii. Prognostics and Remaining Useful Life (RUL) Estimation

Prognostics involve predicting the remaining useful life of bearings based on their current health and operating conditions. Data-driven approaches, such as Gaussian process regression (GPR) and deep learning models, have been developed to estimate RUL by analysing trends in vibration and debris data [7] [8]. These models integrate historical and real-time data to provide accurate predictions, enabling maintenance scheduling and reducing the risk of unexpected failures.

1.3 Internet of Things

The Internet of Things (IoT) plays a pivotal role by integrating sensors, data analytics, and machine learning to optimise operational efficiency and reduce downtime. This response explores the applications, benefits, challenges, and future directions of IoT in plant maintenance.

1.3.1 Key Technologies in IoT-Enabled Condition Monitoring

i. **IoT Sensors**: IoT sensors are deployed to monitor various parameters, including vibration, temperature, pressure, and operational speed. These sensors generate valuable datasets that can be analysed to predict equipment failures [9] [10].

ii. **Edge Computing**: Edge computing enables data processing at the source, reducing latency and improving real-time decision-making. This is particularly useful in industrial settings where timely interventions are crucial [10] [11].

iii. **Cloud Computing**: Cloud platforms store and analyse large volumes of data, enabling predictive maintenance and optimising maintenance schedules [11] [12].

iv. **Machine Learning:** Machine learning algorithms, such as Random Forests and Support Vector Machines, are employed to analyse sensor data and identify failure patterns [13] [14].

2.0 MATERIALS AND METHODS

2.1 Materials

i. **WTVB01-485 sensor:** The sensor collected the plant's real-time vibration, temperature, and pressure data. The sensor features a voltage stabilisation circuit, with a working voltage range of 5V to 36V. It supports a 485 interface. The serial port rate is adjustable from 4800 bps to 230400 bps; the default is 230400 bps in high-speed mode. The cut-off frequency is adjustable from 0 to 100 Hz, and the detection period is from 1 to 100 Hz.



Figure 1: WTVB01-485 Sensor

ii. Power Module:

The IoT power module is essential for providing stable and efficient power to IoT devices. It converts and regulates power from various sources (AC mains, batteries, solar) to meet device requirements, prioritising energy efficiency and low power consumption. Key features include voltage regulation, power source compatibility, compact design, and protection mechanisms like overvoltage and overcurrent protection.

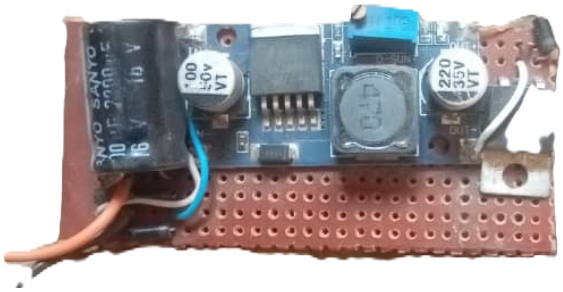


Figure 2: Power Module

iii. RS-485 Converter Module:

The RS-485 converter module converts RS-485 signals into a format compatible with standard microcontroller interfaces such as UART or USB. It converts the data signal from the USD interface.

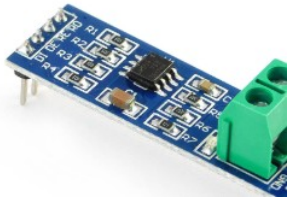


Figure 3: RS-485 Converter Module

iv. ESP32 Microcontroller:

ESP microcontroller integrates hardware and software to implement the Encapsulating Security Payload (ESP) protocol, a core part of IPsec, ensuring secure IP packet transmission.



Figure 4: ESP32 Microcontroller

2.2 Methods

i. Implementation Block

The IoT implementation consisted of a four-layer architectural mechanism. Bearing data are sent via the WTVB01-485 sensor. The RS-485 converts the sensor's signal to a USB interface. The microcontroller processes this data and transmits it to the remote Application Platform Interface (API) using the Wi-Fi module.

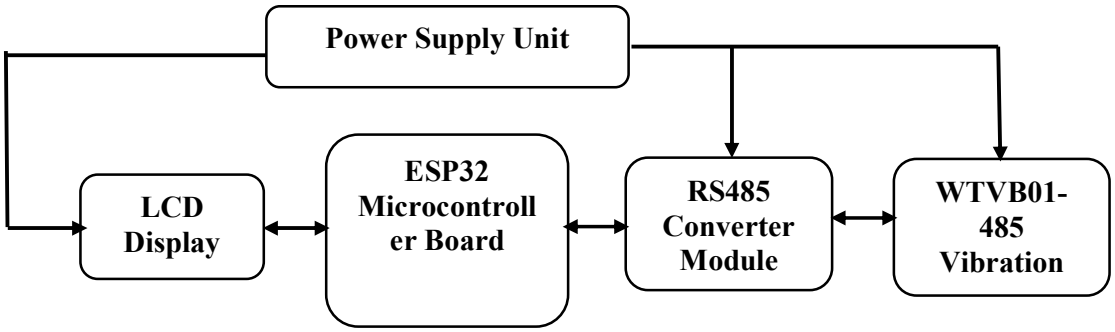


Figure 5: IoT System Block Diagram

ii. IoT Circuit

Figure 6 shows the circuit implementation of the IoT hardware system.

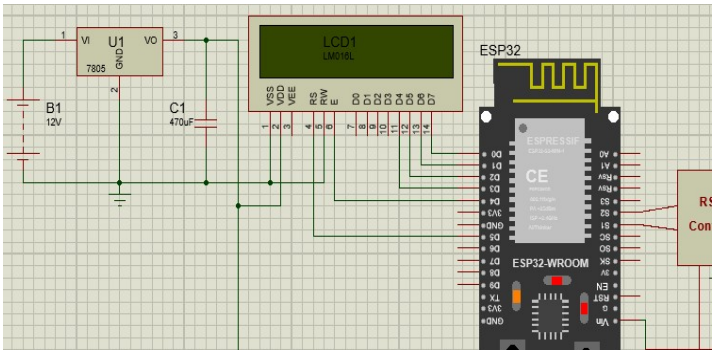


Figure 6: IoT Circuit Diagram

3.0 RESULTS AND DISCUSSION

3.1 Average Sensor Reading

Figure 7 below shows the real-time plot of sensor data transmitted through the IoT system. A densely clustered daily maintenance counts was observed and average sensor readings throughout 2024 and early 2025, with

values consistently ranging between approximately 20 and 50, indicating consistent system operation and notable sharp drop in February 2025.

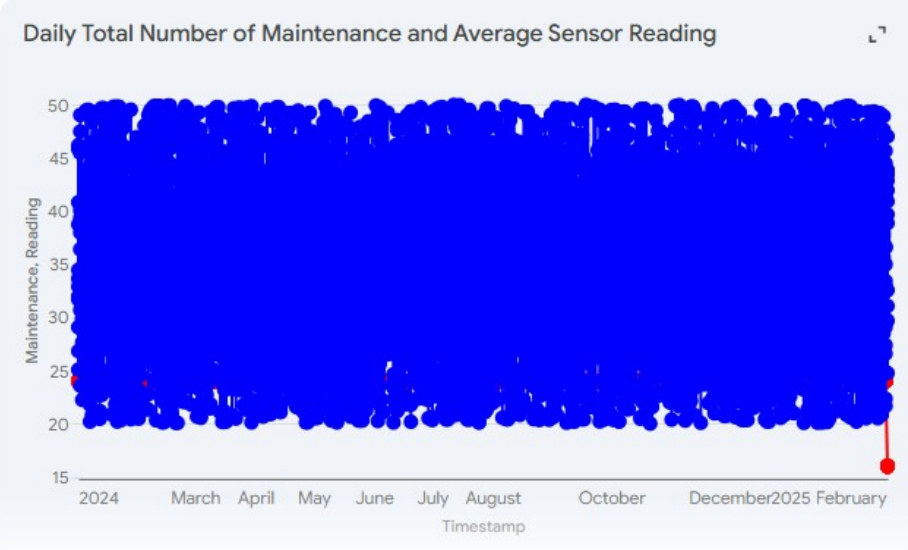


Figure 7: Daily Total Number of Maintenance and Average Sensor Reading

3.2 Bearing Vibration

Table 1 contains vibration data from a sensor monitoring a high-speed turbine bearing. The initial readings represent a stable, normal operational state. The subsequent readings show a developing anomaly, characterised by a marked increase in vibration amplitude, particularly in the radial (X and Y) axes. Generally, the findings showed consistently low amplitudes during normal operation (timestamps 0–10), followed by a sudden and significant increase in vibration levels on all three axes at timestamps 11–15, indicating the detection of an anomaly.

Table 1: Turbine Bearing Vibration Data

Timestamp	Vibration X	Vibration Y	Vibration Z	Operational State
0	0.01	-0.02	0.03	Normal
1	-0.01	0.01	0.02	Normal
2	0.02	-0.01	0.03	Normal
3	0.01	0.02	0.02	Normal
4	-0.02	-0.01	0.03	Normal
5	0.01	0.01	0.02	Normal
6	-0.01	0.02	0.03	Normal
7	0.02	-0.02	0.02	Normal
8	0.01	0.01	0.03	Normal
9	-0.01	-0.01	0.02	Normal
10	0.02	0.01	0.03	Normal
11	0.25	0.28	0.05	Anomaly Detected
12	-0.27	-0.26	0.04	Anomaly Detected
13	0.31	0.33	0.06	Anomaly Detected
14	-0.34	-0.32	0.05	Anomaly Detected
15	0.42	0.45	0.07	Anomaly Detected

Figure 8 illustrates three axes of vibration data (X, Y, Z) over time, with an anomaly period highlighted in orange. This provides a time-series visualisation of vibration data from a triaxial sensor mounted on a turbine bearing, captured over a 21-second interval. This visualisation model displays the data collected and analysed by the IoT system to monitor the health of critical industrial machinery. From 0 to around 10 seconds, vibrations on all axes remain relatively stable and low, indicating normal operational conditions. Starting just after 10 seconds, vibrations on the X and Y axes show a sudden increase in amplitude with highly fluctuating, oscillatory behavior, signaling significant abnormal vibrations. Meanwhile, the Z-axis vibration remains relatively steady with only minor changes. The shaded region marks the time frame when anomalies were detected, clearly corresponding to the increased and erratic vibration levels on the X and Y axes, suggesting mechanical irregularities or faults primarily affecting radial and tangential directions, while axial vibration remains less affected.

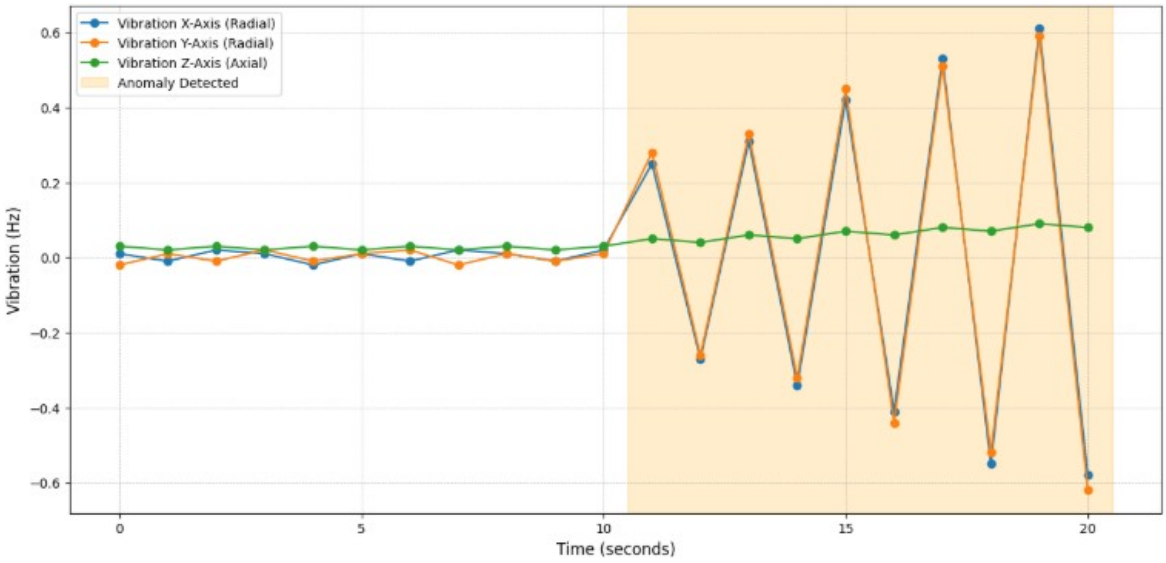


Figure 8: Tri-axial Vibration Readings of a Turbine Bearing

3.3 Bearing Temperature

Table 2 contains temperature data from a sensor on a turbine bearing. The rotor temperature data shows a stable operating temperature, around 550–556°C during normal operation (timestamps 0–10), followed by a sharp and continuous increase from 585°C at timestamp 11 to 810°C at timestamp 20, indicating the suggesting a potential cooling system malfunction or another critical anomaly likely caused by mechanical or operational faults that require immediate attention to prevent damaging failures.

Table 2: Turbine Temperature Data

Timestamp (seconds)	Rotor Temperature (°C)	Operational State
0	550	Normal
1	552	Normal
2	551	Normal
3	553	Normal
4	552	Normal
5	554	Normal
6	553	Normal
7	555	Normal
8	554	Normal
9	556	Normal
10	555	Normal
11	585	Anomaly Detected
12	610	Anomaly Detected
13	635	Anomaly Detected
14	660	Anomaly Detected
15	685	Anomaly Detected
16	710	Anomaly Detected
17	735	Anomaly Detected
18	760	Anomaly Detected
19	785	Anomaly Detected
20	810	Anomaly Detected

Figure 9 presents a time-series visualisation of temperature readings from a sensor monitoring a turbine bearing over a period. Figure 9 shows the rotor temperature steadily around 550°C during normal operation, followed by a sharp increase exceeding the critical threshold of 600°C after 10 seconds, with the anomaly clearly highlighted by the shaded region, indicating a rapidly escalating thermal fault.

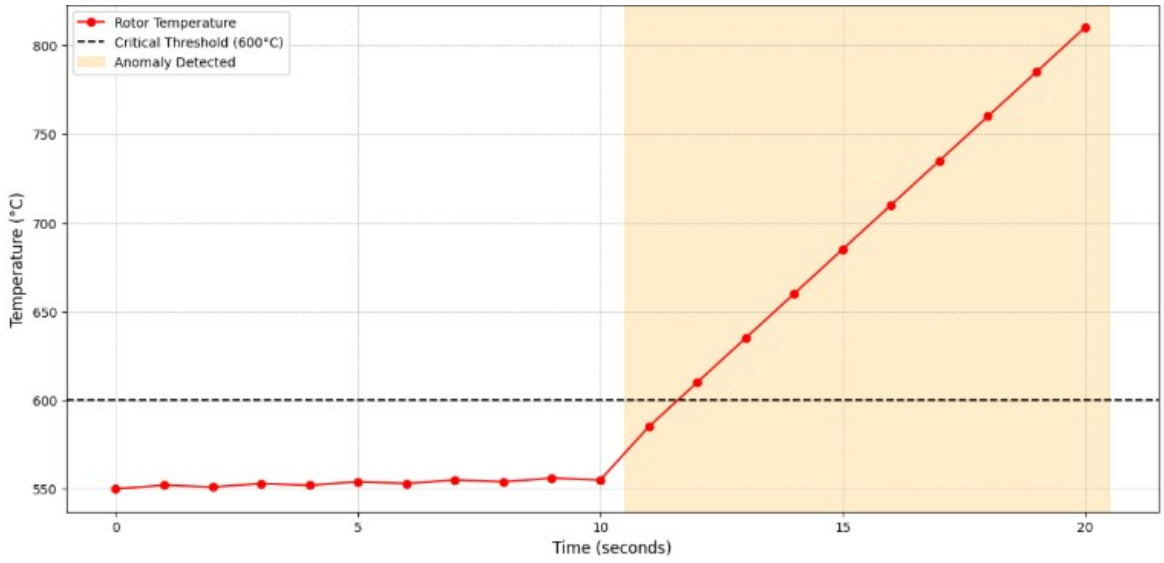


Figure 9: Temperature Readings of Turbine Bearing

4. CONCLUSION

This study demostrates that integrating IoT-based data collection with machine learning analytics effectively transforms turbine bearing maintenance from a reactive to a proactive strategy. In addition, the developed framework effectively enables early fault detection and prediction, thereby minimizing operational disruptions, extending asset lifespan, and improving overall system reliability. Specifically, the findings demonstrate stable vibration readings during normal operation (timestamps 0–10) before a significant increase in amplitude, particularly in the radial (X and Y) axes, signals an anomaly from timestamps 11 to 15. Also, temperature data confirms consistent rotor temperatures (550–556°C) during normal operation, followed by a sharp and continuous escalation from 585°C at timestamp 11 to 810°C at timestamp 20.

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