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Extending a Prognostic Bearing Test Simulator with Smart Data Acquisition and Monitoring Capabilities

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Abstract: Predictive maintenance is essential for modern industrial systems, enabling early fault detection and efficient asset management. This paper presents an enhanced prognostic bearing test simulator that upgrades a laboratory platform for controlled accelerated degradation experiments. The system integrates a LabJack T7 Pro data acquisition unit with a web-based application, enabling automated data logging, structured storage, and remote visualization. These features reduce manual effort, improve data consistency, and enhance usability for real-time monitoring and experiment control. The developed platform supports diverse operating conditions and generates high-quality datasets for testing predictive maintenance strategies. The paper outlines the system architecture, data framework, and experimental validation, demonstrating its relevance for advancing diagnostics in rotating machinery.

Keywords: bearing degradation; data acquisition; predictive maintenance; smart diagnostics; web-applications

1 INTRODUCTION

Maintenance strategies have evolved from corrective and preventive approaches to advanced predictive maintenance (PdM) systems. PdM utilizes real-time monitoring, smart sensors, and AI-based analytics to detect faults and optimize intervention timing, enhancing reliability and cost efficiency.

Predictive maintenance addresses these changes by utilizing continuous monitoring and data-driven diagnostics to predict and prevent potential failures before they occur [1, 2]. It employs real-time monitoring data, advanced sensors, and sophisticated analytics powered by artificial intelligence, thus optimizing the timing of maintenance interventions and significantly enhancing operational reliability and cost efficiency [1-3].

Bearings, as critical components in rotating machines, are prone to mechanical stress, wear, and thermal fatigue. Early fault signs often appear in vibration and temperature signals, making accurate, real-time monitoring essential for effective condition-based maintenance [4, 5].

Reliable experimental setups that simulate bearing degradation in controlled laboratory environments are becoming more and more important for developing, validating, and refining predictive maintenance methodologies [4]. The BTS-P3000 simulator enables realistic degradation experiments under controlled conditions, supporting systematic evaluation of prognostic techniques.

However, traditional setups often lack automation, robust data handling, and intuitive visualization. Manual acquisition and limited data management reduce repeatability and slow research progress [6]. To address these gaps, this paper presents an upgraded BTS-P3000 system that integrates high-resolution data acquisition with a modular web-based application.

The platform includes a LabJack T7 Pro device for real-time multi-sensor monitoring and a software stack based on FastAPI and React for experiment control and visualization. It supports reliable, scalable data processing and offers a foundation for testing prognostic algorithms in rotating machinery diagnostics.

The key contributions of this research include:

- Development of an automated and reliable Data Acquisition: Eliminating manual interventions, ensuring consistent and high-quality sensor data collection.
- Structuring efficient Data Storage: Employing optimized data formats, such as Apache Parquet [7], enabling effective retrieval and advanced analytics.
- Deploying Interactive Visualization: Providing intuitive dashboards and immediate monitoring of bearing conditions, significantly enhancing experimental diagnostics.

As a result, this research contributes meaningfully to predictive maintenance by improving the efficiency, repeatability, and diagnostic capabilities of laboratory experiments, aligning closely with modern trends in Industry 4.0 predictive maintenance research.

The paper is structured as follows: Chapter 2 provides a detailed overview of the system architecture. Chapter 3 describes the experimental setup and procedure. Chapter 4 presents and discusses experimental results, while Chapter 5 summarizes conclusions and suggests future research.

2 SYSTEM ARTHITECTURE

This chapter provides an overview of the detailed system design, including the overall architecture, selected technologies, and critical system components. The primary aim of the system design is to ensure effective real-time data acquisition, robust storage, scalable software architecture, and intuitive visualization capabilities. The implemented design ensures modularity, flexibility, scalability, and ease of maintenance, which tends to be the key characteristics for modern laboratory or industrial systems.

2.1 System Architecture Overview

The system follows a modular architecture composed of five integrated components: a user interface (frontend), a backend service, a relational database, a high-efficiency data repository, and industrial data acquisition hardware (LabJack

T7 Pro). The components communicate through RESTful APIs, enabling synchronized operation and flexible scalability.

Fig. 1 illustrates the high-level system design, where the user interface (React) enables experiment configuration and monitoring; the backend (FastAPI) manages data streams and business logic; the MySQL database stores experiment metadata and configurations; the Parquet-based repository logs high-frequency sensor data; and the LabJack T7 Pro ensures precise multi-channel acquisition. The backend is built on asynchronous FastAPI endpoints capable of handling concurrent API calls and continuous data ingestion. Sensor data includes vibration (AIN1), temperature (AIN2), RPM (AIN0), and axial/radial loads (AIN3, AIN4), acquired at sampling rates between 5000 and 8000 Hz. These are logged locally and transmitted to backend services in configurable intervals (~5 seconds) for structured storage.

While the current system focuses on real-time data capture and visualization, it is also designed to support future integration of prognostic algorithms (e.g., signal-based classifiers or ML models) for online degradation analysis.

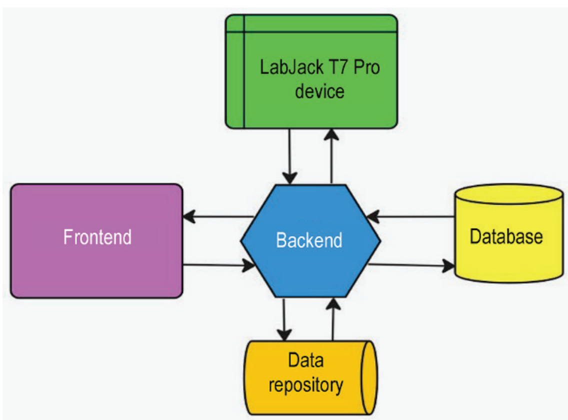

Figure 1 Modular architecture showing component interconnections, sensor data flow (AIN0–AIN4), acquisition frequency (5–8 kHz), and backend interfaces for real-time logging and experiment control

2.2 Functional Components of the Developed System

Each component within the modular architecture has clearly defined responsibilities, ensuring smooth and efficient system operations:

- **User Interface (Frontend - React):** Enables experiment configuration, live data visualization, and result analysis. Modular component design supports easy extension and future integration of diagnostic tools.
- **Backend (FastAPI):** Manages asynchronous data ingestion, experiment control, and communication with storage layers. Includes endpoints for configuration, data streaming, and metadata access.
- **Database (MySQL):** Stores structured experiment data, including sensor mappings, user-defined parameters, and system logs. Ensures transactional integrity and supports analytics queries.
- **Data Repository (Parquet-based storage):** Captures raw sensor data in compressed columnar format, optimized for high-speed access and batch analysis. Data is stored by experiment ID and sensor channel.
- **Data Acquisition Hardware Integration (LabJack T7 Pro):** Supports real-time, multi-channel data capture (analog/digital), Wi-Fi communication, and local SD logging. Sensors include accelerometers (vibration), thermocouples (temperature), and load cells.

2.3 Sequence of System Operations

The developed system follows a clearly defined operational workflow:

1) **Device Setup and Experiment Configuration:** Users configure device settings (sensor channels, calibration parameters, scan rate, etc.) via the React frontend. These settings are communicated to the backend via REST API endpoints, and the configuration parameters are stored securely in the MySQL database.
2) **Real-Time Data Collection:** Upon experiment initiation, the FastAPI backend initiates data collection via the LabJack T7 Pro device, continuously acquiring sensor data at predefined sampling rates and configurations. Collected raw data is temporarily stored locally on the hardware before transferring to the backend system.
3) **Data Transfer and Storage:** Real-time collected sensor data is systematically transferred from the LabJack T7 Pro device to the backend, where it is immediately stored in the Parquet-based repository, ensuring efficient long-term storage and rapid analytical accessibility.
4) **Data Visualization and Analysis:** Once data acquisition is completed, the React frontend retrieves experimental data through the backend APIs, presenting intuitive, interactive visualizations. Users can examine detailed graphical trends, analyze experiment parameters, export data (e.g., in CSV format), and conduct comprehensive data-driven diagnostics for maintenance decisions.

The sequential interaction between system components is illustrated in Fig. 2, which outlines the end-to-end workflow from device setup to final experiment result visualization.

Figure 2 Sequential workflow of system operations

2.4 Key System Features and Scalability

The developed system exhibits several features that contribute to its robustness and adaptability for diverse predictive maintenance scenarios:

- **Scalability:** The modularity of the architecture facilitates straightforward expansion, enabling the inclusion of additional sensors, data streams, or analytical capabilities without significant redesign.
- **Robustness:** Technologies such as FastAPI and React provide performance and reliability, especially under conditions requiring high concurrency and real-time responsiveness.
- **Flexibility:** Users can dynamically adapt system configurations (sensor channels, scan rates, and

experiment parameters), catering to various experimental and industrial needs.
- **Data Integrity and Security:** Consistent data integrity across transactions is maintained through MySQL's relational model and ACID properties, ensuring reliable and secure data storage.
- **Efficient Data Management:** Parquet storage optimizes sensor data compression and retrieval performance, crucial for handling vast datasets generated in long-term experiments.

3 EXPERIMENTAL SETUP

This chapter describes the experimental setup used to validate the effectiveness of the developed system for accelerated bearing degradation testing. The setup includes the description of the hardware components, their configuration, data acquisition procedures, as well as the integration with the developed software application. The experimental procedures were carefully designed to closely simulate real industrial conditions, thereby enabling thorough validation and accurate assessment of the system's performance.

3.1 Prognostic Bearing Test Simulator (BTS-P3000)

The core experimental apparatus used in this research was the Bearing Test Simulator BTS-P3000, as shown in Fig. 3. The BTS-P3000 is specifically designed for performing accelerated bearing degradation experiments by simulating realistic conditions of load, speed, and temperature, closely resembling those encountered in industrial environments. The main purpose of the simulator is to induce controlled bearing failures through accelerated degradation, allowing comprehensive study and validation of predictive maintenance strategies.

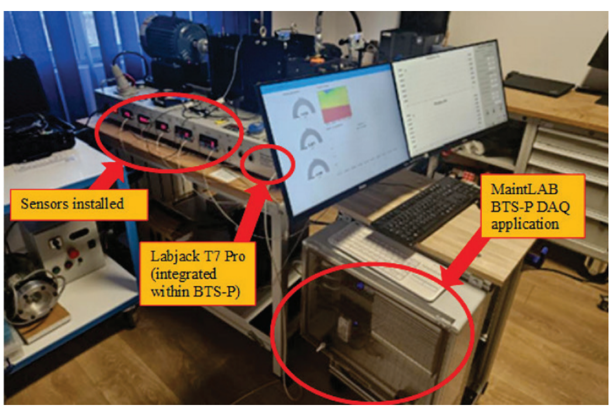

Figure 3 BTS-P3000 simulator after system upgrade

The BTS-P3000 provides the following key functionalities:
- Precise control over rotational speed (RPM), axial, and radial loading.
- Adjustable test parameters including temperature monitoring capabilities.
- Capability of running continuous or intermittent test cycles.
- Designed for durability and repeatability under extended testing conditions.

3.2 Data Acquisition Hardware

Data collection within the experimental framework was performed using the industrial-grade LabJack T7 Pro data acquisition device. The T7 Pro, depicted in Fig. 4.

Figure 4 LabJack T7 Pro

The main characteristics that influenced its selection for this research include:
- 14 Analog Inputs (up to 24-bit resolution via Sigma-Delta ADC).
- Digital I/O channels for auxiliary sensor integration.
- Integrated Wi-Fi connectivity for seamless communication and remote operation.
- Local data logging capability using microSD card, enabling secure and uninterrupted data storage.

Integration of the LabJack T7 Pro allowed continuous real-time data acquisition from multiple sensors, thus providing comprehensive monitoring of all relevant experimental parameters such as vibration, temperature, and loading forces.

3.3 Sensor Configuration and Measurement Parameters

The BTS-P3000 simulator was equipped with multiple sensors for real-time monitoring of critical parameters during degradation experiments.

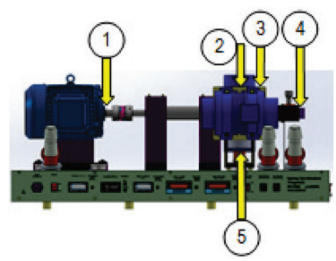

Figure 5 Schematic layout of sensor locations on the BTS-P3000 simulator for bearing fault analysis

The layout in Fig. 5 shows the physical positions of sensors: accelerometer sensor near the bearing housing (2), temperature sensor on the housing surface (3), speed sensor on the rotating shaft (1), and load cells at vertical (5) and axial (4) force application points, forming a comprehensive dataset for subsequent analysis.

3.4 Software Integration and Data Management

The developed hardware-software system integrates the DAQ hardware with a custom web-based application for device configuration, data collection, and visualization. Sensor channels were configured through the user interface, allowing adjustment of sample rates, calibration coefficients, and scaling parameters. During experiments, developed application enables LabJack T7 Pro monitoring while continuously recording data at predefined and front-end changeable rates and storing it locally.

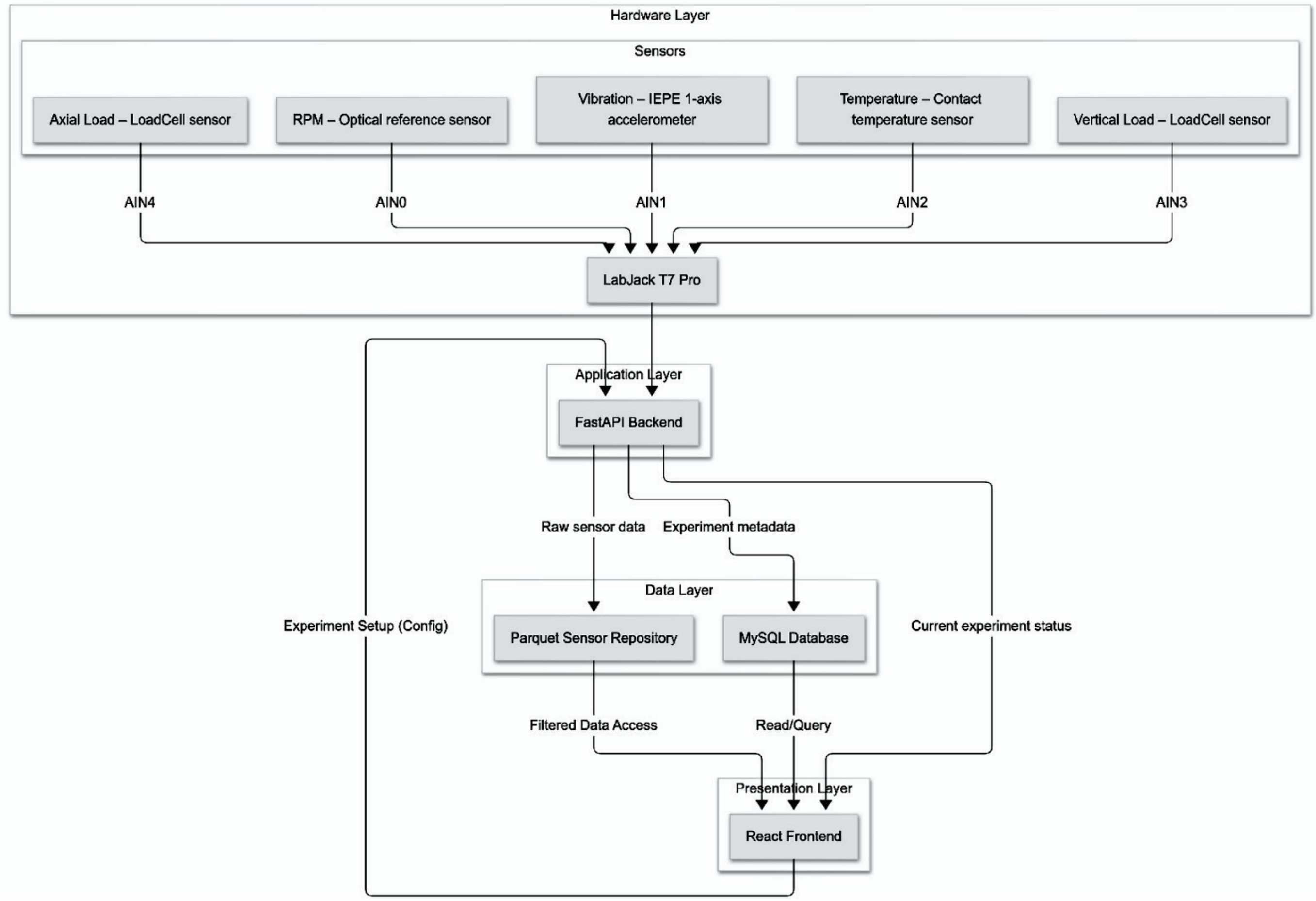

Figure 6 Layered software-hardware architecture of the developed bearing test simulator system

Fig. 6 illustrates the modular layered architecture of the extended BTS-P3000 system, structured into four functional layers: Presentation, Application, Data, and Hardware. The Presentation Layer includes the React-based frontend for experiment configuration and data visualization. The Application Layer features the FastAPI backend responsible for real-time data ingestion and control. The Data Layer comprises a relational MySQL database for experiment metadata and a Parquet-based repository for high-frequency sensor data. The Hardware Layer contains the LabJack T7 Pro acquisition device and five connected sensors: AIN0 – RPM (optical sensor), AIN1 – vibration (IEPE accelerometer), AIN2 – housing temperature (contact sensor), AIN3 – vertical load (load cell), and AIN4 – axial load (load cell). Bidirectional communication between layers enables full-cycle experiment execution, data logging, and on-demand access for visualization or export.

3.5 Experimental Procedure and Conditions

To comprehensively evaluate the system's capability, several experimental runs were conducted, each under different operational settings:

- **Variation of Scan Rates:** Experiments were performed at different scan rates to analyse the system's ability to accurately collect high-frequency data without data loss or distortion. Scan rates were carefully adjusted following manufacturer recommendations, typically ranging from 5000 to 8000 scans per second, ensuring optimal performance and avoiding system overload.
- **Controlled Operating Conditions:** Each experiment involved varying levels of axial and radial loads and speed settings. These controlled variations allowed assessment of the system's robustness and accuracy in handling diverse and dynamic operating scenarios.
- **Real-Time Monitoring:** Throughout each experiment, real-time data visualization was utilized to actively monitor sensor signals. The developed web-based application facilitated instant decision-making and troubleshooting, allowing immediate adjustments in test parameters if anomalies were detected.

3.6 Validation and Repeatability of Experimental Results

Experimental validation involved repeating the tests multiple times under identical conditions to ensure repeatability and consistency of collected data. This approach verified the system's stability and reliability. Data repeatability was confirmed by consistently obtaining similar sensor signals across multiple experimental runs under the same testing conditions, demonstrating the robustness and precision of the measurement system.

4 RESULTS AND DISCUSSION

Following the successful deployment of the MaintLAB BTS-P DAQ web application in a laboratory environment, a series of experiments were conducted to validate the system's functionality and the quality of collected data. The aim was to ensure that the application effectively manages device data acquisition, storage, and visualization under varying experimental conditions. This chapter presents the collected results, organized by experiment ID, and offers an objective analysis of the system's performance and signal consistency.

4.1 Overview of Measured Experiments

Six experiments were conducted to assess the system under different scan rate configurations. These experiments varied primarily by scan rate and active sensor conditions, allowing for comparative observation. Detailed analysis is focused on experiments ID 1 and ID 5, which were conducted at different scan rate configurations and provide representative examples of system behaviour under low and high data acquisition conditions.

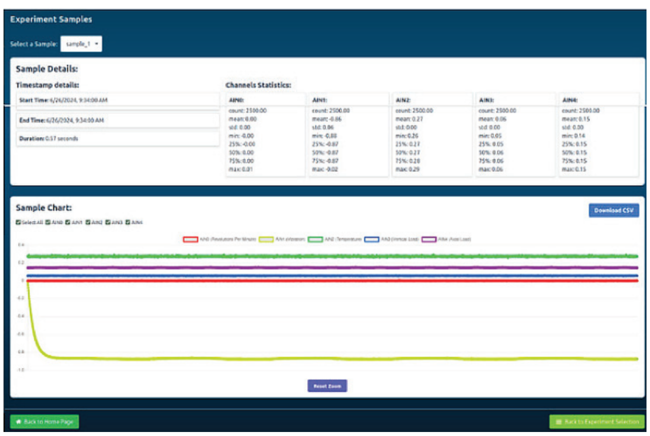

Figure 7 Detailed result view for Experiment ID 1

4.2 Experiment ID 1 – Lower Scan Rate Conditions

Experiment ID 1 was performed at a configured scan rate of 5000 scans per second. However, in accordance with LabJack T7 Pro documentation, the scan rate was automatically halved at the hardware level to avoid data overflow and ensure system stability. This is standard and not a result of any software limitation.

Fig. 7 shows the experimental detail screen within the application for Experiment ID 1. A consistent transient drop in vibration values (AIN1) was observed at the beginning of each measurement cycle, followed by signal stabilization. This pattern was confirmed by reviewing the exported CSV file, which contains raw measurement data for further analysis.

4.3 Experiment ID 5 – Higher Scan Rate Conditions

Experiment ID 5 was conducted using a scan rate setting of 8000 scans per second, again halved by the hardware to ensure optimal performance. Unlike the previous test, this experiment was carried out with the bearing test simulator fully active, exposing the system to increased signal dynamics.

4.4 Key Observations

An analysis of the experimental results identified specific signal deviations in two sensor channels: AIN1 (Vibration) and AIN4 (Axial Load). These channels displayed consistent anomalies across experiments, while other parameters such as AIN0 (RPM), AIN2 (Temperature), and AIN3 (Radial Load) remained within expected ranges and were correctly managed via configurable offsets and scaling in the device setup form.

Tab. 1 provides a summary of average values recorded for the most notable parameters based on visual inspection and CSV exports.

Table 1 Summary of key signal deviations for AIN1 and AIN4

Parameter	Expected Value	Observed Behavior	Remarks
AIN1 – Vibration	~Stable after init.	Transient drop at start	Possibly due to signal dynamics or sensor delay
AIN4 – Axial Load	~0.1 (no load)	~0.15 (persistent offset)	Likely calibration or sensitivity-related issue

These findings highlight the system's ability to consistently capture sensor data while also emphasizing the importance of calibration and signal stabilization during data collection.

4.5 Discussion and Recommendations

While the developed MaintLAB BTS-P DAQ system demonstrated reliable performance in data acquisition and visualization, several improvement areas were identified:

- **Vibration Signal Transients (AIN1):** The recurring drop at measurement start may be linked to sensor warm-up, mechanical dynamics, or signal latency. Future experiments should consider a brief buffer window before official data collection begins.
- **Axial Load Offset (AIN4):** A consistent elevation in expected zero-load values suggests the need for more precise calibration protocols. Revisiting sensor sensitivity and performing automated pre-experiment calibration routines may improve accuracy.
- **Software Stability:** Despite sensor-level discrepancies, the web application operated reliably across all experiments. System anomalies were hardware-related and not reflective of any backend or frontend software failure.
- **Future Integration:** Expanding the platform to incorporate additional sensor types (e.g., ultrasonic), real-time data streams, and advanced user interface

customization will further enhance the application's capabilities for industrial-scale predictive maintenance.

When comparing the developed system to existing experimental platforms, it is important to highlight key conceptual differences. The Case Western Reserve University bearing data center platform [13] is widely used for classification-focused research, offering standardized fault datasets suitable for machine learning benchmarking. In contrast, the primary goal of our system is to support prognostic modeling through controlled, long-term degradation experiments with adjustable operating conditions.

Furthermore, compared to PRONOSTIA [14], which is another reference platform for accelerated degradation studies, the BTS-P3000 simulator offers significantly higher mechanical flexibility. While PRONOSTIA employs a compact and constrained physical testbed, our platform allows broader variation in axial and radial loading, speed profiles, and sensor configuration, thereby enabling richer datasets for remaining useful life (RUL) estimation and model training.

5 CONCLUSION AND FUTURE WORK

This paper presented the development and validation of an extended prognostic bearing test simulator that integrates industrial-grade data acquisition hardware with a modular, web-based software application for monitoring and analysis that advances the capabilities of laboratory-based predictive maintenance research. By combining high-resolution data acquisition, structured analytics, and user-centric design

Future work will focus on three strategic directions. First, the integration of additional sensing modalities, such as ultrasonic sensors, would enrich the diagnostic context and improve fault detection coverage. Second, enhancing real-time visualization and enabling live anomaly detection can further support proactive decision-making. Third, automated sensor calibration routines, including dynamic offset and scaling adjustments, are essential to ensure measurement accuracy and repeatability, especially in long-term degradation studies.

In conclusion, the developed system advances the capabilities of laboratory-based predictive maintenance research. By combining high-resolution data acquisition, structured analytics, and user-centric design, it provides a foundation for scalable and reliable experimentation, as well as a promising platform for future extensions into real-world industrial applications.

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