Performance Evaluation of an IoT-Enabled Multi-Parameter Machine Health Monitoring System for Predictive Maintenance

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***Abstract*—Mechanical and electrical forces of industrial equipments are constantly on the brink hence an early fault notification is required so that the equipments do not fail suddenly and the cost of maintaining the equipments is also low. In this paper, a multi-parameter machine health monitoring system on top of the IoT and ESP32 will be developed and inferred. The proposed system is architected on Vibration, temperature, acoustic noise, rotational speed (RPM) and current sensing. Sensor-data are then recorded at the edge layer, and transmitted through a Wi-Fi connection to a Flask based server. Failure classification will be by the threshold and will be logged into a SQLite database where it can be analyzed on a historical basis by the backend. The trends and status of the system are provided in three categories as OK, WARN, and FAULT in real-time using a web-based dashboard. It is operating on low priced hardware, modular design and programmable thresholds to suit an extensive variety of industrial machinery. There is experimental validation that a high level of reliability of communication, the stability of the data recording and classification of conditions correctly existed in the controlled test conditions. The proposed solution provides the economical and scalable solution to the small and medium-scale industries with regards to predictive maintenance.**

Keywords — IoT, Predictive Maintenance, Machine Health Monitoring, ESP32, Vibration Analysis, Condition Monitoring.

I. INTRODUCTION

Mechanical and electrical stress in the industrial equipment (motors, pumps, and rotating assemblies) are constant. With time, the imbalance, overheating, excessive loading, and wear cause the performance reduction and unexpected breakdown. Conventional maintenance methods, such as reactive maintenance and time-based preventive methods do not offer real time information on the state of machine. The Internet of things (IoT) technologies allow monitoring the critical operational parameters on a continuous basis by having embedded sensing and wireless communication. The proposed work suggests the multi-parameter machine health monitoring system on IoT and ESP32 based on the application of vibration, temperature, noise, RPM, and current measurements. The goal is to offer a predictive maintenance solution that is scalable and cost-effective, enables visualization of the dashboard in real time, and can also be configured to different fault limits.

II. LITERATURE REVIEW

In recent years, with the development of the IoT and Industry 4.0 technologies, machine health monitoring and predictive maintenance has been actively studied. Different solutions have been suggested in order to improve the accuracy of fault detection and minimize industrial downtime.

Lee et al. [1] introduced a Cyber-Physical Systems (CPS) architecture of the Industry 4.0-based manufacturing setting. They focused on integrating physical systems and cloud-based analytics to allow intelligent predictive maintenance. Even though the architecture proved to be better in terms of monitoring, it increased the complexity and cost of the implementation due to reliance on centralized cloud infrastructure.

Lee et al. [2] in a separate study talked about predictive manufacturing systems in the big data environment. The authors emphasized the significance of constant sensor readings and massive analytics to predict faults. Although this method is more accurate in predicting, it consumes a lot of computing power, and it cannot be used in small and medium-sized industries since it needs a lot of cloud storage space.

Rai and Gupta [3] concentrated their works on vibration-based sensor of fault in rotating machines. Their study showed that the vibration amplitude analysis is an efficient tool to identify the imbalance and fault in the bearings. But the system proposed only monitored one mechanical parameter, which restricted the coverage of diagnostic.

Kumar et al. [4] designed a wireless motor monitoring system, which was based on GSM and it was able to measure the temperature and current values. The system was capable of triggering fault remotely but created a delay on communication and an extra cost of operation because of the reliance on cellular networks. Moreover, no RPM and acoustic noise parameters were factored in.

Santos et al. [5] introduced cloud-based monitoring system of IoT based on MQTT protocol and embedded computing devices. Their design enabled real time monitoring and scalability of deployment. But the need of continuous internet connection and increased cost of hardware limits its flexibility in localized industrial system.

The techniques of mechanical signature analysis presented by Braun [6] focus on frequency-domain vibration analysis on Fast Fourier Transform (FFT). These are very detailed in terms of fault signature as they require a greater computing power which might not be feasible when using the system with low-cost microcontrollers.

Embedded systems ESP32 is a microcontroller with built-in Wi-Fi capability, available in many forms documented in the technical manual, published by Espressif Systems [7] and is capable of offering the processing power needed to run an embedded IoT application. It is also appropriate in edge-level data acquisition systems because it is cheap and has a dual-core architecture.

The acceleration sensor ADXL345 [8] allows measuring the dynamic acceleration accurately in three directions, so it is applicable to vibration monitoring of rotating equipment. On the same note, ACS712 current sensor [9] also offers isolation based current measurement which can be used in monitoring electrical loads.

Collotta and Pau [10] examined the use of IoT-based real-time monitoring platform with cloud services and smart decision systems. Even though their system increased automation, they needed a centralized infrastructure and a sophisticated analytics system.

A comparative study of fault diagnosis methods in industrial systems carried out by Wu et al. [11] demonstrated that multi-parameter monitoring is a more reliable method than single-parameter methods. The proposed system closes these gaps proposing the multi-parameter monitoring (vibration, temperature, noise, RPM and current) in low-cost ESP32-based edge architecture. It provides a scalable and cost-effective predictive maintenance system, unlike cloud-dependent systems, which relies on a lightweight local Flask-based backend and can be configured with fault classification based on the threshold.

III. METHODOLOGY OF PROPOSED SYSTEM

A. Hardware Requirements

This system is suggested to combine various sensors with an ESP32 microcontroller in order to monitor the key mechanical and electrical monitoring parameters of a machine. The hardware used in the system is as follows:

- ESP32 Development Board
- DS18B20 Temperature Sensor
- Maximus, a microphone that measures the level of acoustic noise.
- Hall Effect Sensor (Rotational Speed Measurement) is a sensor that detects the speed at which the rotor turns.
- ACS712 Current Sensor
- Power Supply Unit

The ESP32 is the main chip used as both a communication and a processing unit. It is connected to all the sensors via I2C, ADC, and digital input pins. Sampling Sensor data are sampled periodically and transformed into useful engineering quantities, and then transmitted.

B. Block Diagram of Proposed System

The block diagram of the proposed machine health monitoring system is presented below.

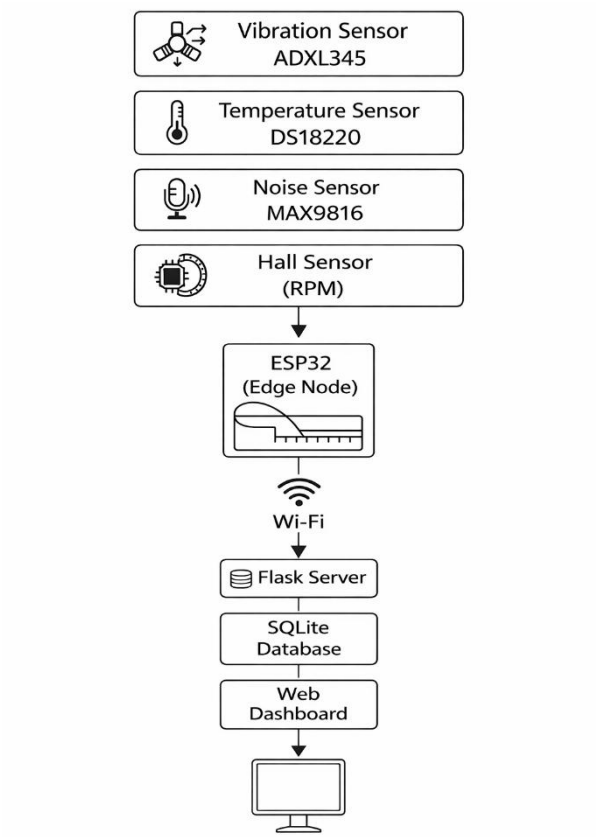

Fig. 1. Block Diagram of Proposed System

There are three key functional layers that make up the system:

• Edge Layer – Sensor acquisition and local process.
• Communication Layer – Wi-Fi based HTTP transmissions.
• Server Layer – Data storage and analysis.
• Application Layer – Dashboard visualization.

The physical parameters are read by the sensors and transmitted as raw signals to the ESP32.

The ESP32 interprets such values and sends formatted JSON packets to the backend server via Wi-Fi.

C. System Operation Flow Diagram

The flow chart of how the system works is demonstrated below.

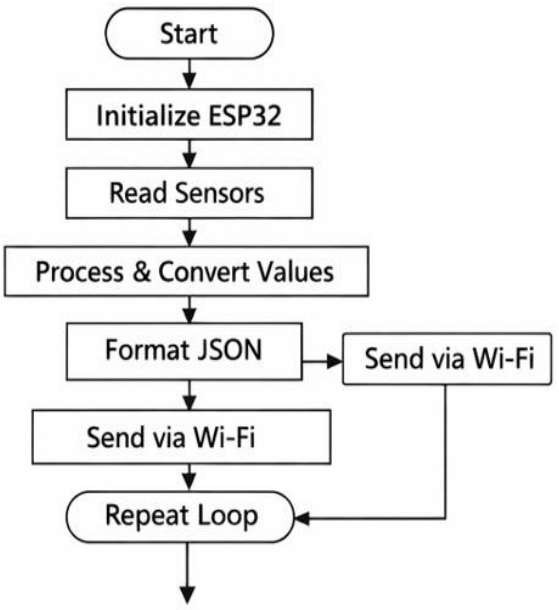

Fig. 2. Machine Monitoring Process Flow Diagram

The working process can be summarized as the following:

• System Initialization
• Sensor Calibration and preparation.
• Periodic Data Acquisition
• Processing and Conversion of parameters.
• JSON Formatting
• Wi-Fi Transmission to Server
• Threshold Evaluation
• Dashboard Update
• Repeat Cycle

The cycle is repeated with a time interval of five seconds so that real time monitoring can be done.

D. Sensor Data Processing and Mathematical Modeling

Each sensor output is converted to engineering units.
Vibration Measurement

The ADXL345 offers the acceleration on three axes. Magnitude of vibration is determined by excluding the effect of gravity:

$$V = \sqrt{(x^2 + y^2 + z^2)} - 1g$$

This is so to make sure that only the dynamic vibration because of machine movement is measured.

Noise Measurement

RMS computation is done over several samples of the ADC to measure acoustic noise:

$RMS = \sqrt{(1/N \Sigma xi^2)}$

This gives a constant depiction of sound intensity.

RPM Calculation

Hall effect sensor picks up magnetic pulses of the rotating shaft. RPM is calculated using:

RPM = (Pulse Count / time interval) × 60

Current Measurement

The sensor (ACS712) gives out a voltage depending on the current. Current is derived as:

I = (Vout − Voffset) / Sensitivity

These equations make sure that there is proper conversion of the parameters prior to transmission.

E. Fault Classification Threshold-Based

Parameters examined by the backend server are compared to configurable warning values.

The logic of classification can be defined as:

When Warning Threshold is set to OK
Parameters = 5
5.5; 5.0, 5.5; 5.5, 5.0; 5.0, 5.3; 5.3, 5.0; 5.3, 5.3; 5.3, 5.5.

In case Parameter = or exceeds 1.5 × Warning Threshold → FAULT.

It is able to flexibly adapt to new machine specifications without needing to make changes to embedded firmware.

F. Application and Dashboard Interface

The processed data are stored in SQLite database. The dashboard is made with a web-based interface that retrieves historical and real-time values using REST APIs.

Fig. 3. Dashboard of Real-Time Machine Health

The dashboard displays:

- Numerical data of all five parameters.
- Graphical trends – time-series.
- Status indicator (OK / WARN / FAULT)
- Fields of threshold configuration input.

This interface allows monitoring the condition continuously and detecting faults fast.

IV. EXPERIMENTAL SETUP

The system was validated using a laboratory motor setup. Sensors were mounted on the motor casing and shaft.

During normal operation, all parameters remained within safe thresholds, and system status displayed "OK." Artificial imbalance introduced on the shaft increased vibration amplitude, triggering "WARN" and subsequently "FAULT" classification as thresholds were exceeded.

When electrical load was increased, current readings crossed predefined limits, correctly indicating overload conditions. Temperature rise was observed under prolonged operation, validating thermal sensing capability.

Wireless transmission occurred at five-second intervals without packet loss under stable network conditions. Dashboard graphs updated automatically and accurately reflected real-time trends.

The integration of mechanical and electrical parameters improved diagnostic confidence compared to single-parameter systems reported in literature.

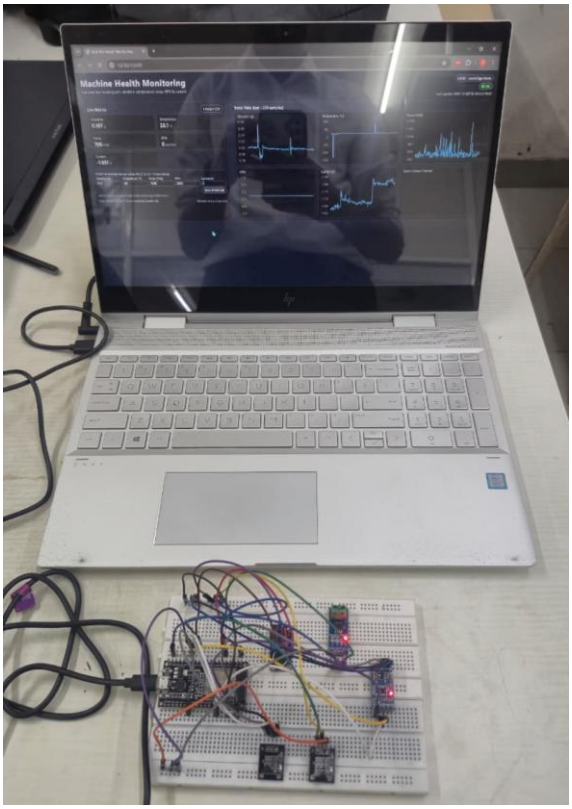

Fig. 4. Experimental Hardware Setup

V. CONCLUSION

This study presented a multi-parameter IoT-based machine health monitoring system using ESP32. The integration of vibration, temperature, noise, RPM, and current sensing provides comprehensive condition assessment.

The system demonstrated reliable wireless communication, real-time visualization, and accurate threshold-based fault detection.

The low-cost architecture and configurable dashboard make the solution suitable for predictive maintenance in small and medium industrial environments.

Future improvements may include frequency-domain vibration analysis, machine learning-based anomaly detection, and cloud-based scalability.

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