

IOT and Algorithmic Intelligent Motor Health Monitoring as Well as Maintenance Prediction

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Abstract

Manufacturing, transportation, and energy systems rely largely on industrial electric motors, and their untimely failure can result in expensive downtime, safety hazards, and decreased operational efficiency. The majority of traditional motor maintenance procedures rely on reactive methods or routine inspections, which frequently miss early-stage problems and lead to needless maintenance or unexpected breakdowns. This project offers an Intelligent Motor Health Monitoring and Predictive Maintenance System that combines Internet of Things (IoT) technology with machine learning (ML) for early defect prediction and real-time condition monitoring in order to get around these restrictions. Using embedded sensors mounted on the motor, the suggested system continuously gathers operating information like temperature, vibration, current, voltage, and rotational speed. An Internet of Things communication infrastructure is used to deliver this sensor information to These sensor readings are transmitted through an IoT communication framework to a cloud-based or edge-processing platform, where the data is stored, processed, and analyzed. Feature extraction techniques are applied to transform raw sensor data into meaningful indicators that reflect the motor's health condition. Machine learning algorithms are then trained on historical and real-time datasets to identify abnormal patterns, classify fault types, and predict potential failures before they occur, boosting reliability, cutting expenses, and improving the performance of the entire system.

Keywords: Motor health monitoring, predictive maintenance, internet of things (IoT), machine learning, condition monitoring, fault diagnosis, industrial automation, smart maintenance

INTRODUCTION

Electric motors are indispensable components in industrial and commercial applications, accounting for a major share of global electrical energy consumption. They are extensively utilized in industrial applications such as manufacturing setups, conveyor systems, pumps, compressors, and automated production processes. Due to their continuous operation under varying load and environmental conditions, motors are highly susceptible to faults such as bearing wear, insulation degradation, rotor imbalance, and overheating. Failure to detect these faults at an early stage can result in severe equipment damage, extended downtime, and financial losses [1], [2].

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Conventional motor maintenance strategies are primarily based on reactive or preventive approaches. Reactive maintenance addresses failures only after they occur, often leading to unexpected system shutdowns and high repair costs. Preventive maintenance follows fixed time intervals for servicing, regardless of the actual condition of

the motor. Although preventive maintenance reduces the risk of catastrophic failures, it may cause unnecessary servicing and inefficient resource utilization. These traditional methods lack adaptability and are insufficient for modern industrial systems that demand high reliability and continuous operation [3], [4].

With the rapid growth of smart manufacturing and Industry 4.0, there is an increasing demand for intelligent monitoring systems capable of providing real-time insights into equipment health. The Internet of Things (IoT) has evolved into a powerful technology that facilitates smooth interaction among physical devices, sensors, and data processing systems. IoT-based monitoring systems allow continuous acquisition of motor parameters such as temperature, vibration, current, voltage, and speed, which are crucial indicators of motor health [5], [6]. These parameters can be transmitted wirelessly to cloud or edge platforms for further analysis and visualization.

However, the massive volume of data generated by IoT sensors presents significant challenges in terms of analysis and fault interpretation. Traditional threshold-based or rule-based monitoring techniques are often unable to detect complex fault patterns or predict future failures accurately. To address these challenges, Machine Learning (ML) techniques are increasingly being adopted in condition monitoring systems. ML algorithms can automatically learn patterns from historical and real-time data, enabling accurate fault classification, anomaly detection, and performance degradation analysis [7].

Machine learning models such as decision trees, support vector machines, artificial neural networks, and ensemble methods have demonstrated strong capabilities in identifying motor faults under varying operating conditions. By analyzing multidimensional sensor data, these models can predict incipient faults and estimate the remaining useful life of motors with improved precision compared to conventional methods [8], [9]. This predictive capability plays a crucial role in transitioning from time-based maintenance to condition-based and predictive maintenance strategies.

The integration of IoT and machine learning enables the development of predictive maintenance systems, where maintenance actions are performed proactively based on predicted failure trends rather than scheduled intervals. Predictive maintenance significantly reduces unplanned downtime, lowers maintenance costs, and enhances equipment lifespan. Furthermore, it improves operational safety by providing early warnings and actionable insights to maintenance personnel [10].

This project presents an Intelligent Motor Health Monitoring and Predictive Maintenance System using IoT and Machine Learning, designed to continuously monitor motor operating conditions, analyze sensor data using machine learning algorithms, and predict potential faults in advance. The proposed system aims to improve motor reliability, optimize maintenance processes, and support smart industrial environments by leveraging data-driven decision-making and automation [11].

PROBLEM STATEMENT

Electric motors are critical assets in industrial, commercial, and infrastructure-based systems, where continuous and reliable operation is essential for maintaining productivity and safety. Despite their importance, motor failures remain a major challenge due to factors such as mechanical wear, electrical faults, thermal stress, and unfavorable operating conditions. Many industries still rely on conventional maintenance approaches that are either reactive addressing faults only after breakdowns occur or preventive, where maintenance is performed at fixed time intervals without considering the actual health condition of the motor [12]. These approaches often result in unplanned downtime, excessive maintenance costs, inefficient resource utilization, and reduced equipment lifespan [13].

Existing motor monitoring systems are limited in their ability to provide real-time insights and early fault detection. Manual inspections and basic threshold-based monitoring techniques fail to capture complex fault patterns and gradual degradation processes that develop over time. Additionally, the

increasing scale and complexity of modern industrial environments make continuous human supervision impractical and unreliable [14]. As a result, early-stage motor faults frequently go unnoticed until they evolve into severe failures, leading to production losses and safety risks.

Although sensor technologies and data acquisition systems are widely available, there is a lack of intelligent frameworks that effectively analyze the large volume of data generated by these sensors. Traditional analytical methods struggle to process high-dimensional and dynamic datasets and are unable to accurately predict future motor behavior. Without predictive capabilities, maintenance decisions remain reactive rather than proactive, limiting operational efficiency and reliability [15].

Therefore, there is a critical need for an intelligent motor health monitoring system that can continuously collect operational data, analyze it in real time, and predict potential failures before they occur. The problem addressed in this project is the absence of a scalable, automated, and data-driven solution that integrates Internet of Things (IoT) technology with machine learning techniques to enable accurate motor health assessment and predictive maintenance. Such a system should provide early fault detection, reduce unplanned downtime, optimize maintenance schedules, and enhance the overall reliability and safety of motor-driven industrial systems [16].

Objective

- To observe motor parameters like vibration, temperature, current, and speed as they occur.
- To identify irregularities and categorize motor defects through machine learning algorithms.
- With the aim of minimizing maintenance costs and downtime.
- For the provision of early warnings and alerts for predictive maintenance.

LITERATURE SURVEY

IoT-Based Predictive Maintenance for Electrical Machines and Industrial Automation Authors: Naveen Kumar V., Venkatesh A., Hemanth Kumar M. L. 2024 International Research Journal of Modernization in Engineering Technology and Science (IRJMETS)

Summary

This paper focuses on the application of Internet of Things (IoT) technology for predictive maintenance of electrical machines used in industrial automation. The authors emphasize the transition from traditional reactive and preventive maintenance to data-driven predictive maintenance. Sensors are deployed to continuously monitor parameters such as temperature, vibration, and electrical current, and the collected data is analyzed using machine learning techniques to identify early fault patterns. The study demonstrates how IoT-based monitoring improves system reliability, reduces unplanned downtime, and optimizes maintenance costs while enhancing overall industrial productivity.

Intelligent Predictive Maintenance System Using IoT and Machine Learning Authors: S. Rao, P. Kulkarni Year: 2022 IEEE International Conference on Smart Systems and Inventive Technology

Summary

This work presents an intelligent predictive maintenance framework that integrates IoT-based data acquisition with machine learning algorithms for industrial equipment monitoring. The system uses sensor data related to vibration and thermal behavior to detect anomalies in motor operation. By employing classification and prediction models, the system is capable of identifying potential failures before they occur. The authors report improved fault detection accuracy and reduced maintenance intervention compared to conventional techniques.

Machine Learning-Based Condition Monitoring of Induction Motors A. Kumar, R. Singh 2022 Journal of Electrical Engineering and Technology

Summary:

The authors investigate the effectiveness of machine learning techniques for condition monitoring of induction motors. Sensor data related to stator current, vibration, and temperature is analyzed using

supervised learning algorithms. The research emphasizes the ability of machine learning models to identify mechanical and electrical faults in their early stages. The findings corroborate that astute analysis boosts the precision of diagnoses and underpins predictive maintenance tactics.

IoT-Enabled Smart Monitoring System for Industrial Motors M. Patel, D. Shah 2022: International Journal of Engineering Research and Technology

Summary:

This paper proposes a smart monitoring system using IoT for continuous supervision of industrial motors. The system employs cloud-based data storage and visualization to track real-time motor health parameters. Threshold-based alerts combined with analytical techniques allow early fault detection. The authors conclude that IoT-based monitoring reduces manual inspection efforts and improves operational reliability in industrial environments.

Predictive Maintenance of Rotating Machines Using Data Analytics J. Lee, K. Park 2021 Elsevier Journal of Mechanical Systems and Signal Processing

Summary:

This research explores data analytics methods for predictive maintenance of rotating machinery. The study focuses on vibration signal processing and statistical feature extraction to identify fault trends. To estimate the remaining useful life of machines, advanced analytics and machine learning models are employed. The results demonstrate improved prediction accuracy and reduced maintenance costs compared to traditional maintenance approaches.

PROPOSED SYSTEM

The suggested system is a smart framework for monitoring motor health and predicting maintenance that combines IoT (Internet of Things) technology with machine learning methods. The system is intended to monitor motor operating conditions continuously, analyze data in real time, and foresee potential faults before they result in system failure.

System Overview

The proposed system provides a smart and automated solution for monitoring the health of industrial motors. It replaces conventional maintenance practices with a data-driven approach by continuously collecting operational parameters through IoT sensors. The acquired data is transmitted to a centralized platform where machine learning algorithms analyze motor behavior, detect anomalies, and predict faults. The system enables early warnings and supports proactive maintenance decisions, thereby improving motor reliability and operational efficiency.

Data Acquisition Using IoT Sensors

The system employs multiple IoT-enabled sensors installed on the motor to monitor critical parameters such as temperature, vibration, current, voltage, and rotational speed. These parameters are strong indicators of motor health and help identify electrical, mechanical, and thermal abnormalities. Sensors continuously capture real-time data during motor operation, ensuring accurate and up-to-date monitoring without human intervention.

Data Transmission and Communication Layer

The collected sensor data is transmitted to a cloud or edge processing platform using reliable communication protocols such as Wi-Fi, MQTT, or cellular networks. This communication layer ensures secure and low-latency data transfer from the motor to the processing unit. By leveraging IoT connectivity, the system enables remote monitoring and allows maintenance teams to access motor health information from any location.

Data Storage and Preprocessing

Once the sensor data reaches the cloud platform, it is stored in a structured database for further analysis. To enhance data quality, methods for preprocessing data like eliminating noise, normalizing,

and managing missing values are employed. With this step, it is made sure that the data is consistent and appropriate for machine learning analysis. Historical data is also retained to support long-term trend analysis and model training.

Feature Extraction and Data Analysis

Relevant features are extracted from the preprocessed data to represent the motor's operational behavior accurately. Statistical features, time-domain features, and frequency-domain features are derived from sensor signals, particularly vibration and current data. These features provide meaningful insights into motor condition and enhance the performance of machine learning models by highlighting fault-related patterns.

Machine Learning-Based Fault Detection and Prediction

Machine learning algorithms are trained using historical and real-time data to detect anomalies and classify motor faults. Supervised and unsupervised learning models are employed to recognize abnormal operating conditions and predict potential failures. The trained models can identify early signs of motor degradation, estimate fault severity, and forecast future failures, enabling predictive maintenance rather than reactive repair.

Alert Generation and Visualization

When the machine learning models detect abnormal behavior or predict an impending fault, the system generates automatic alerts and notifications. These alerts are sent to maintenance personnel through dashboards, mobile applications, or email notifications. A user-friendly visualization interface displays real-time motor parameters, health status, fault history, and predictive insights, assisting operators in quick decision-making.

Maintenance Decision Support and System Benefits

The proposed system provides actionable insights that help maintenance teams plan timely interventions based on actual motor condition. By enabling predictive maintenance, the system reduces unplanned downtime, minimizes maintenance costs, and extends motor lifespan. Additionally, it enhances workplace safety and supports smart industrial operations by enabling automated, reliable, and data-driven maintenance strategies aligned with Industry 4.0 principles.

SYSTEM DESIGN

The illustrated system in Figure 1 is a microcontroller-based monitoring and control unit centered around the ESP32 development board. The system integrates multiple sensors, input/output devices, and communication interfaces to collect physical parameters such as acceleration, temperature, voltage, and current, and then processes and displays the data while also enabling control of an induction motor through a relay. The ESP32 acts as the core processing unit that coordinates sensing, computation, decision-making, user display, and communication with an external laptop.

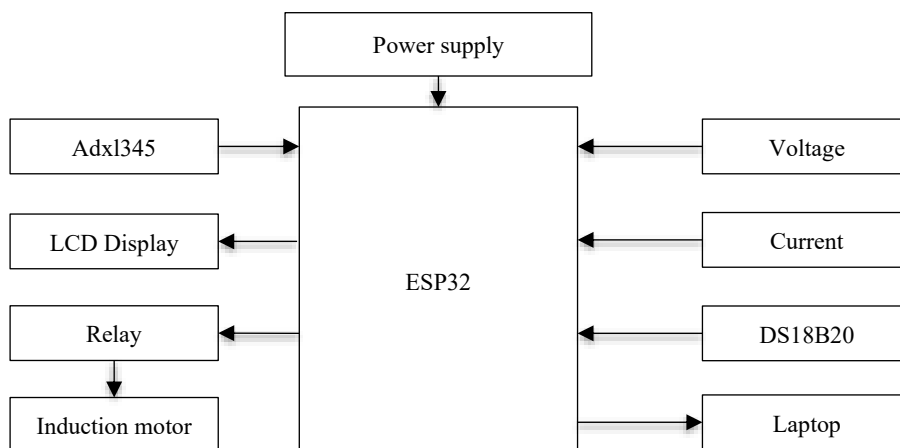


Figure 1. System architecture.

This architecture is suitable for applications such as industrial equipment monitoring, motor health analysis, predictive maintenance, IoT-based control systems, and embedded automation solutions, where real-time data acquisition, remote monitoring, and reliable actuation are essential.

Power Supply Unit

The power supply unit as shown in Figure 2 delivers regulated and stable electrical energy to all components of the system. It converts the available AC or higher DC input voltage into low-voltage DC outputs such as 5V and 3.3V, which are suitable for the ESP32 microcontroller and connected sensors. Proper voltage regulation ensures that the system operates reliably without voltage drops, electrical noise, or component damage. Protection elements such as capacitors, regulators, and filtering circuits improve power quality and prevent malfunction due to fluctuations or surges.

ESP32 Microcontroller (Central Processing Unit)

The ESP32 as shown in Figure 3 serves as the central processing and control unit of the entire system. It collects data from all connected sensors, processes the information using programmed algorithms, and makes decisions based on predefined logic conditions. The ESP32 also manages communication between system components, controls output devices such as the relay and LCD display, and sends data to an external laptop for monitoring or storage. Its built-in Wi-Fi and Bluetooth capabilities further allow wireless connectivity, making the system suitable for IoT-based applications and remote access.

ADXL345 Accelerometer Module

The ADXL345 accelerometer as shown in Figure 4 measures acceleration and vibration in three axes, enabling the system to monitor mechanical motion and structural behavior of the induction motor or connected machinery. It helps detect abnormal vibration patterns caused by imbalance, misalignment, or mechanical wear, which are early indicators of system faults. The sensor transmits digital acceleration data to the ESP32 through communication protocols such as I²C or SPI, allowing accurate and real-time motion analysis.



Figure 2. Power supply unit.



Figure 3. ESP32 Microcontroller.

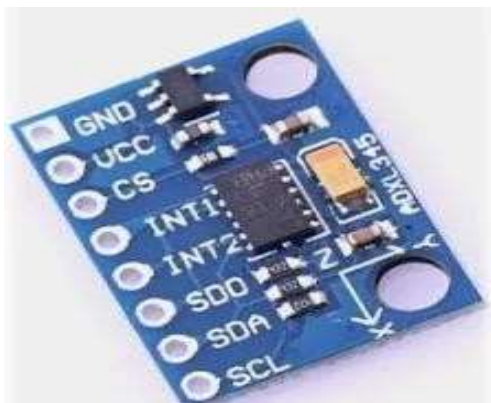


Figure 4. ADXL345 Accelerometer module

Voltage Sensor

The voltage sensor as shown in Figure 5 measures the electrical voltage supplied to the motor or system circuitry. Since the ESP32 operates at low voltage levels, the sensor uses voltage division or signal conditioning circuits to reduce high voltages to safe ranges for analog-to-digital conversion. Continuous voltage monitoring helps identify conditions such as under-voltage, over-voltage, or supply instability, which can negatively impact motor performance and system safety. The ESP32 processes this data to ensure reliable operation and initiate protective measures when necessary.

The current sensor measures the amount of current passing through the motor or linked electrical load. It is fundamental for establishing system load conditions, energy use, and efficiency. Unusual levels of current can suggest that the motor is experiencing mechanical issues, electrical faults, or overloads. By continuously analyzing current data, the ESP32 can generate alerts, log operational trends, and activate protection mechanisms such as disconnecting the motor through the relay.

DS18B20 Temperature Sensor

The DS18B20 temperature sensor as shown in Figure 6 measures temperature digitally and communicates with the ESP32 using a single-wire protocol, making it simple and reliable to integrate. It monitors ambient or motor surface temperature to detect overheating conditions that could damage components or reduce system lifespan. Accurate temperature data enables thermal protection strategies such as alarm generation, cooling system activation, or automatic shutdown of the motor when unsafe temperature levels are reached.

LCD Display Module

The LCD display as shown in Figure 7 provides a visual interface between the system and the user by presenting real-time values of voltage, current, temperature, and vibration data. It also displays system status messages such as motor ON/OFF state, fault alerts, and warning indications. This local display eliminates the need for external monitoring equipment and allows operators or technicians to quickly assess system performance and respond to abnormal conditions.

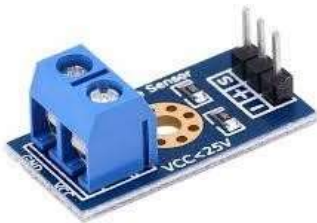


Figure 5. Voltage sensor



Figure 6. DS18B20 Temperature sensor.



Figure 7. LCD Display module.



Figure 8. Induction motor.



Figure 9. ESP32-Based motor monitoring system1.

Relay Module

The relay module as shown in Figure 9 functions as an electrically controlled switch, enabling the low-power output signals from the ESP32 to safely control the high-power induction motor. It ensures the safety of the user and device by electrically isolating the control circuitry from the high-voltage motor circuit. The relay enables automatic or manual switching of the motor based on sensor readings, threshold conditions, or external commands, making it an essential component for system actuation and protection.

Laptop / External Computer Interface

The laptop acts as an external interface for real-time monitoring, data visualization, configuration, and long-term storage of system parameters. The ESP32 communicates with the laptop through USB, Wi-Fi, or Bluetooth, allowing sensor data to be logged and analyzed using software tools or dashboards. This connection enables remote diagnostics, performance evaluation, and firmware updates, making the system more flexible, scalable, and suitable for advanced automation and IoT-based applications.

RESULT

Induction Motor

The induction motor is the primary mechanical load controlled and monitored by the system. It turns electrical energy into mechanical motion, and its efficiency and sturdiness make it popular for household and industrial use. The system as shown in Figure 8 continuously monitors the motor's electrical and mechanical parameters, such as voltage, current, vibration, and temperature, to ensure smooth operation and detect faults at an early stage, thereby improving reliability and reducing maintenance costs.

The proposed Intelligent Motor Health Monitoring and Predictive Maintenance System was evaluated using real-time operational data collected from industrial motor setups under various working conditions. The system continuously monitored key parameters such as temperature, vibration, current, voltage, and rotational speed using IoT sensors. The experimental results show that the sensor network successfully captured accurate and consistent data throughout motor operation. Variations in load conditions were clearly reflected in the sensor readings, demonstrating the system's ability to track real-time changes in motor behavior and provide continuous visibility into motor health.

The process of transmitting data from the sensors to the cloud platform was determined to be dependable and consistent. With minimal latency in data transfer, sensor data enabled near real-time analysis and response. The cloud-based storage system efficiently handled large volumes of data without loss or corruption. This confirms the suitability of the proposed IoT architecture for continuous monitoring in industrial environments where uninterrupted data flow is critical for effective predictive maintenance.

During data preprocessing, noise and inconsistencies present in raw sensor data were successfully removed using filtering and normalization techniques. This preprocessing stage significantly improved

data quality and ensured uniformity across different sensor measurements. The cleaned dataset enabled accurate feature extraction, where meaningful indicators such as vibration amplitude patterns, temperature trends, current fluctuations, and speed variations were derived. These features provided a clear distinction between normal motor operation and abnormal behavior, forming a strong foundation for machine learning analysis.

CONCLUSION

This project effectively showcases the design and execution of an Intelligent Motor Health Monitoring and Predictive Maintenance System leveraging Internet of Things (IoT) and machine learning technologies. By continuously monitoring critical motor parameters such as temperature, vibration, current, voltage, and speed, the system provides real-time insight into motor operating conditions. The integration of IoT sensors enables reliable data acquisition and remote monitoring, while cloud-based processing ensures scalable data storage and efficient analysis. The results confirm that the proposed system can accurately capture variations in motor behavior and maintain continuous visibility into motor health. The application of machine learning techniques significantly enhances the system's ability to detect anomalies and predict potential faults at an early stage. Unlike traditional maintenance approaches that rely on fixed schedules or reactive responses, the proposed system adopts a data-driven predictive maintenance strategy. The trained machine learning models effectively identify abnormal patterns and classify fault conditions, allowing maintenance teams to take timely corrective actions. This ability to predict helps avert abrupt motor breakdowns, decrease the amount of downtime that is not scheduled, and enhance reliability in operations.

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