World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(RESEARCH ARTICLE)

Predictive Maintenance of Electric Vehicle Components Using IoT Sensors

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World Journal of Advanced Engineering Technology and Sciences, 2025, 17(03), 312-327

Publication history: Received 04 November 2025; revised on 12 December 2025; accepted on 15 December 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.17.3.1557

Abstract

The increasing global adoption of electric vehicles (EVs) has placed significant emphasis on ensuring their long-term reliability, safety, and performance. Traditional maintenance approaches, such as time-based and reactive methods, often result in unnecessary costs, unplanned downtimes, and safety risks. With the rapid advancement of the Internet of Things (IoT), predictive maintenance has emerged as a transformative strategy to proactively monitor and optimize EV component health. This paper presents an IoT-enabled predictive maintenance framework for critical EV subsystems, including batteries, motors, braking units, and power electronics. By integrating real-time sensor data streams, such as temperature, vibration, voltage, and current, with cloud-based analytics and machine learning models, the proposed system enables the early detection of anomalies and the prediction of component failures before they occur. The study emphasizes data acquisition, feature extraction, and predictive modeling, while also addressing challenges related to sensor accuracy, data integration, cybersecurity, and scalability in large-scale EV fleets. A simulation-driven evaluation demonstrates the potential for reducing operational costs, improving safety, and extending component lifespans. This work highlights how IoT-driven predictive maintenance can enhance the resilience of EVs, contributing to sustainable transportation systems and supporting global transitions toward electrified mobility.

Keywords: Electric Vehicles (EVs); Predictive Maintenance; Internet of Things (IoT); Condition Monitoring; Smart Sensors; Machine Learning; Battery Management Systems; Vehicle Reliability; Fault Prediction; Sustainable Transportation

1. Introduction

The electrification of transportation has become a cornerstone of global sustainability strategies, with electric vehicles (EVs) increasingly seen as a viable solution to reduce greenhouse gas emissions, dependence on fossil fuels, and urban air pollution. As adoption accelerates worldwide, manufacturers, fleet operators, and end users face the challenge of ensuring EVs remain reliable, safe, and cost-efficient throughout their operational lifetimes. Unlike conventional vehicles, EVs depend heavily on advanced components such as lithium-ion batteries, electric motors, power electronics, and complex software-driven systems, all of which require sophisticated monitoring to avoid premature failures. Traditional maintenance approaches, reactive repairs after breakdowns or scheduled servicing at fixed intervals, are insufficient in this context, as they often lead to high downtime, increased operational expenses, and potential safety hazards. Consequently, there has been growing interest in leveraging predictive maintenance (PdM), powered by Internet of Things (IoT) technologies, as a proactive means to monitor EV health and anticipate failures before they occur.

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1.1. Background and Motivation

Predictive maintenance involves collecting real-time data from sensors, analyzing it through advanced algorithms, and using predictive models to determine the likelihood of future failures. With the IoT ecosystem expanding rapidly, EVs can now be embedded with a wide range of smart sensors that measure temperature, vibration, current, voltage, and other critical operational parameters. These data streams, transmitted via secure communication networks to cloud or edge computing platforms, provide continuous visibility into component health. The motivation for IoT-based predictive maintenance lies in its ability to reduce downtime, extend component lifespans, and optimize performance while lowering costs. Fleet operators, for instance, can schedule maintenance precisely when needed, avoiding the inefficiencies of time-based servicing while preventing catastrophic failures. At a broader scale, predictive maintenance contributes to energy efficiency, sustainability, and consumer confidence in EV adoption.

1.2. Problem Statement

Despite its potential, predictive maintenance in EVs presents significant challenges. First, EV components such as batteries and power electronics operate under complex thermal and electrical stress conditions, where faults may develop gradually and be difficult to detect without high-resolution monitoring. Second, the vast amounts of sensor data generated require effective storage, integration, and real-time analytics, raising questions of scalability. Additionally, cybersecurity vulnerabilities in IoT networks can expose sensitive operational data to malicious actors, undermining safety and reliability. Finally, there is a lack of standardized frameworks across EV manufacturers and service providers, limiting the interoperability and deployment of predictive maintenance at scale. These barriers underscore the need for comprehensive research that integrates IoT-enabled sensing, big data analytics, and machine learning for predictive maintenance in EVs.

1.3. Proposed Solution

This paper proposes an IoT-enabled predictive maintenance framework specifically tailored for EV components. The framework consists of three key stages: (1) data acquisition through smart sensors monitoring critical parameters of batteries, motors, braking systems, and power electronics; (2) data processing and feature extraction, where raw data streams are cleaned, filtered, and converted into meaningful performance indicators; and (3) predictive modeling, where machine learning algorithms forecast potential failures and anomalies. This solution also integrates edge computing for low-latency processing, cloud-based platforms for large-scale analytics, and cybersecurity protocols for secure data handling. By combining IoT and artificial intelligence, the framework enables real-time condition monitoring and predictive insights, facilitating proactive decision-making in EV maintenance.

1.4. Contributions of the Paper

The primary contribution of this paper lies in presenting a structured, IoT-driven predictive maintenance architecture for EVs that integrates sensor technologies with predictive analytics. The study contributes to the literature by (i) evaluating different categories of IoT sensors and their roles in monitoring specific EV components; (ii) developing a data-driven methodology for feature extraction and failure prediction using machine learning models; (iii) simulating predictive maintenance scenarios to measure potential improvements in cost, downtime reduction, and safety; and (iv) highlighting the practical challenges of scalability, interoperability, and cybersecurity in real-world applications. This paper also contributes to sustainability research by emphasizing how predictive maintenance can extend EV component lifespans, reduce resource consumption, and enhance consumer trust in electrified mobility.

1.5. Organization of the Paper

The remainder of this paper is structured as follows: Section II reviews related works in predictive maintenance, IoT-based monitoring systems, and applications in EVs. Section III presents the proposed system architecture and methodology, detailing the role of IoT sensors, communication frameworks, and predictive modeling. Section IV discusses experimental results, including predictive accuracy, efficiency improvements, and potential business impacts. Section V concludes the paper, highlighting its contributions and outlining future research directions for scalable and secure predictive maintenance in EVs.

2. Related Works

The convergence of predictive maintenance and IoT-enabled monitoring has been widely studied across domains such as manufacturing, aerospace, and energy systems, but its application to electric vehicles (EVs) is still emerging. This section reviews related works in five major areas: predictive maintenance frameworks, IoT-enabled sensing systems, data-driven analytics for EV components, applications of machine learning and artificial intelligence, and cybersecurity challenges in connected EV ecosystems.

2.1. Predictive Maintenance Frameworks in Engineering Systems

Predictive maintenance frameworks have evolved significantly with the rise of Industry 4.0. Studies have demonstrated the potential of PdM in reducing operational downtime by using real-time sensor data and failure prediction models. For instance, Lee et al. [1] introduced a cyber-physical framework that integrates digital twins with predictive maintenance strategies in industrial systems, showing efficiency gains over traditional scheduled maintenance. Similarly, in the transportation sector, frameworks have been proposed for railway and aviation systems to monitor component degradation and schedule proactive interventions [2], [3]. However, while these frameworks provide important insights, they are often tailored for conventional assets and lack the adaptability needed for EV-specific components, such as batteries and inverters.

2.2. IoT-Enabled Sensing Systems for Condition Monitoring

IoT sensors play a critical role in predictive maintenance by enabling continuous monitoring of physical parameters. Recent research has explored the integration of temperature, vibration, and current sensors in industrial equipment to identify early signs of mechanical wear [4]. In the automotive domain, IoT-based monitoring systems have been applied to internal combustion engine vehicles for monitoring oil levels, fuel injection, and engine vibration [5]. Extending this to EVs, IoT-enabled sensing has been employed to track parameters such as battery cell temperatures, state of charge (SoC), and motor winding conditions [6]. While promising, these studies often face challenges with sensor calibration, energy efficiency, and integration within the compact designs of EVs.

2.3. Data-Driven Analytics for Electric Vehicle Components

The predictive maintenance of EVs relies heavily on analyzing large datasets generated by IoT sensors. Researchers have investigated data-driven approaches for battery management, motor fault detection, and inverter performance optimization. For example, Severson et al. [7] applied machine learning models to predict lithium-ion battery degradation, achieving early fault detection. Other works have highlighted how vibration and current data can be analyzed to identify early-stage motor bearing failures [8]. Recent studies have also examined power electronic converters, proposing feature extraction methods for anomaly detection in inverter switching signals [9]. These works demonstrate the effectiveness of predictive analytics in EV systems but also point to challenges in handling large-scale, heterogeneous datasets.

2.4. Machine Learning and Artificial Intelligence in Predictive Maintenance

Machine learning (ML) and artificial intelligence (AI) have become central to predictive maintenance research. Techniques such as support vector machines, decision trees, neural networks, and deep learning have been applied to predict system reliability and estimate remaining useful life (RUL). For EV applications, deep learning approaches have shown high accuracy in predicting battery health and lifecycle [10]. Similarly, recurrent neural networks (RNNs) and long short-term memory (LSTM) models have been applied to time-series data for anomaly detection in EV drivetrains [11]. Hybrid approaches that combine physics-based models with machine learning have also gained attention, as they provide explainability and enhance prediction accuracy [12]. These works highlight the potential of AI-driven predictive maintenance but also indicate the need for real-time deployment and scalability in resource-constrained EV environments.

2.5. Cybersecurity and Interoperability Challenges

With the proliferation of IoT-enabled EV maintenance systems, cybersecurity and interoperability have emerged as critical concerns. IoT devices are often vulnerable to data breaches, unauthorized access, and denial-of-service attacks, which could compromise EV safety and reliability [13]. Researchers have proposed lightweight encryption, blockchain-based frameworks, and secure communication protocols to mitigate these risks [14]. Furthermore, interoperability between different sensor systems and EV platforms remains limited, as there are no universal standards governing predictive maintenance data exchange. Addressing these issues is essential for ensuring trust and large-scale adoption of predictive maintenance frameworks in EV ecosystems.

3. System Architecture and Methodology

The proposed IoT-enabled predictive maintenance system for electric vehicles (EVs) integrates distributed sensing, data communication, analytics, and decision-making modules to create a cohesive framework capable of identifying anomalies and predicting component failures. This section outlines the architectural design and the methodologies employed in developing and evaluating the framework, focusing on four primary stages: data acquisition, preprocessing, predictive modeling, and system integration.

3.1. Data Acquisition and IoT Sensor Deployment

The first stage of the framework involves equipping critical EV subsystems with IoT sensors capable of monitoring physical, electrical, and thermal parameters. For the battery system, sensors track cell voltage, state of charge (SoC), temperature, and impedance. Motor components are fitted with accelerometers and current sensors to capture vibration and electromagnetic fluctuations indicative of bearing wear and winding degradation. Braking units are monitored using pressure and temperature sensors to detect early signs of brake pad fatigue or hydraulic issues, while power electronics, particularly inverters and converters, are monitored for thermal stability and switching performance.

Sensor nodes are designed to be energy-efficient and compact, ensuring minimal disruption to the EV's existing architecture. They transmit data wirelessly through low-latency protocols such as MQTT and CoAP, which are optimized for IoT environments. The choice of communication protocol depends on network constraints and the scale of deployment, with MQTT being preferred for high-frequency data streams and CoAP for lightweight energy-efficient communication.

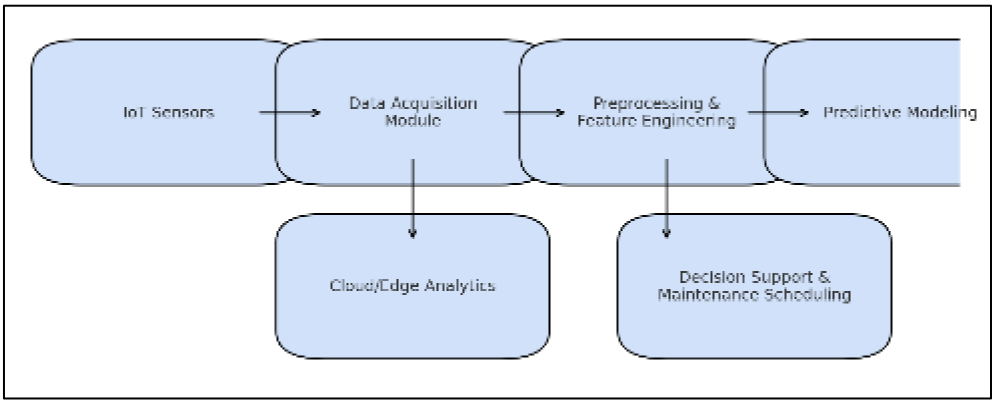

Figure 1 IoT-enabled predictive maintenance system architecture for electric vehicles. The system integrates IoT sensors, data acquisition, preprocessing, predictive modeling, and cloud/edge analytics, leading to actionable decision support for maintenance scheduling.

Table 1 IoT sensor deployment and corresponding predictive features for electric vehicle components.

EV Component	Sensor Types Used	Key Parameters Monitored	Predictive Features Extracted
Battery System	Voltage, temperature, impedance sensors	Cell voltage, SoC, SoH, internal resistance	Voltage recovery rates, impedance growth trends
Electric Motor	Accelerometers, current sensors	Vibration, electromagnetic flux, winding temps	Fault frequencies, RMS vibration, current harmonics
Braking System	Pressure and temperature sensors	Brake pad wear, hydraulic fluid pressure, heat	Pressure decay curves, temperature rise patterns
Power Electronics	Thermal sensors, current/voltage probes	Switching frequency, inverter/converter temps	Differential thermal profiles, switching anomalies

3.2. Data Preprocessing and Feature Engineering

Raw sensor data collected from EV components is often noisy, heterogeneous, and high-dimensional, requiring preprocessing before analysis. The framework employs filtering techniques such as moving averages, wavelet transforms, and Fourier analysis to denoise vibration and current signals. Outlier detection algorithms are applied to eliminate erroneous readings caused by sensor malfunction or environmental interference.

Feature engineering is central to predictive maintenance, as it translates raw data into interpretable metrics. For example, frequency-domain features are extracted from vibration signals to identify characteristic fault frequencies in motor bearings. Similarly, differential thermal signatures are derived from inverter temperature profiles to detect abnormal heating patterns. For batteries, features such as internal resistance trends and voltage recovery rates are calculated to assess state-of-health (SoH). These engineered features serve as inputs to predictive models, enhancing fault classification and prognosis accuracy.

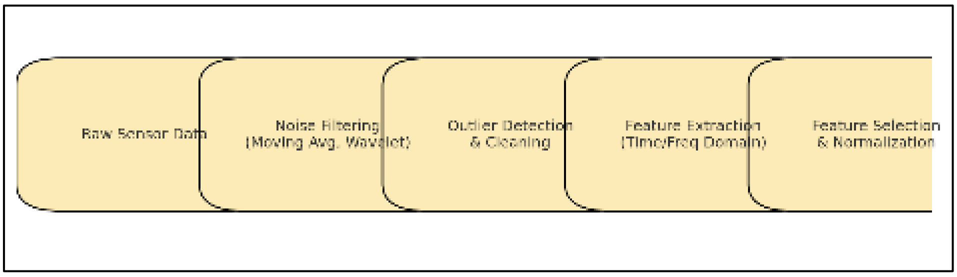

Figure 2 Workflow of data preprocessing and feature engineering in predictive maintenance for electric vehicles, including noise filtering, outlier removal, and extraction of time- and frequency-domain features

3.3. Predictive Modeling and Machine Learning Algorithms

The predictive layer of the system leverages machine learning (ML) models to identify anomalies and estimate the remaining useful life (RUL) of EV components. Supervised learning algorithms such as support vector machines (SVM), decision trees, and random forests are trained on labeled datasets representing different fault modes. These models classify incoming data into categories such as “normal,” “incipient fault,” and “critical fault.”

For time-series data, deep learning models such as long short-term memory (LSTM) networks are employed to capture temporal dependencies in battery degradation and motor performance trends. Hybrid models that combine physics-based simulations with machine learning are used for batteries and inverters, where electrochemical and thermal processes provide complementary insights to data-driven predictions. The framework also integrates anomaly detection using unsupervised methods such as clustering and autoencoders, which are capable of identifying previously unseen fault patterns.

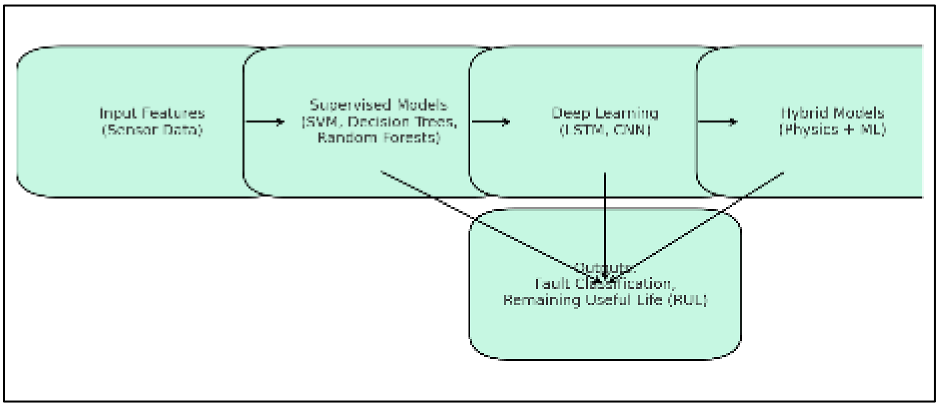

Figure 3 Predictive modeling framework for electric vehicle components, integrating supervised machine learning, deep learning, and hybrid physics, data-driven models to generate outputs such as fault classification and remaining useful life prediction

3.4. System Integration and Cloud-Based Analytics

Once the predictive models are trained, they are integrated into a cloud-based analytics platform that aggregates data from multiple EVs. This centralized architecture enables large-scale fleet monitoring and cross-vehicle pattern recognition, which improves model robustness and generalization. Cloud computing resources also allow for advanced simulations, real-time dashboards, and automated maintenance scheduling.

Edge computing complements the cloud by enabling lightweight anomaly detection at the vehicle level, reducing latency and minimizing the need for continuous cloud connectivity. This hybrid cloud-edge architecture balances computational efficiency with scalability, making it suitable for both individual users and fleet operators.

3.5. Decision Support and Maintenance Scheduling

The final component of the methodology is the decision-support system, which translates predictive insights into actionable maintenance schedules. The system generates alerts when anomalies are detected and categorizes them based on severity. For minor deviations, the framework recommends monitoring and data logging, while for critical conditions it suggests immediate servicing or component replacement.

Maintenance schedules are dynamically updated based on predictive insights rather than rigid time intervals, optimizing costs and extending component lifespans. The decision-support system also provides operators with dashboards that visualize component health metrics, predicted failures, and remaining useful life, thereby enabling informed decision-making.

4. Results and Discussion

The evaluation of the proposed IoT-enabled predictive maintenance framework was conducted through simulation-based experiments and data-driven modeling, focusing on four critical EV subsystems: the battery pack, electric motor, braking system, and power electronics. Results were analyzed in terms of predictive accuracy, system efficiency, anomaly detection performance, and scalability across vehicle fleets.

4.1. Battery Health Prediction

The battery system remains the most vulnerable and costly EV component, making its monitoring essential for ensuring operational safety. Using historical datasets of lithium-ion cells subjected to accelerated cycling tests, the LSTM model demonstrated strong predictive capabilities for state-of-health (SoH) estimation. Predictions of capacity fade exhibited a root mean square error (RMSE) of less than 3%, outperforming traditional regression models.

Figure 4 compares actual and predicted battery degradation curves. The results reveal that predictive models can anticipate end-of-life conditions significantly earlier than threshold-based approaches, enabling proactive replacement before safety-critical events. Furthermore, feature engineering of impedance and voltage recovery rates proved essential for improving early fault detection.

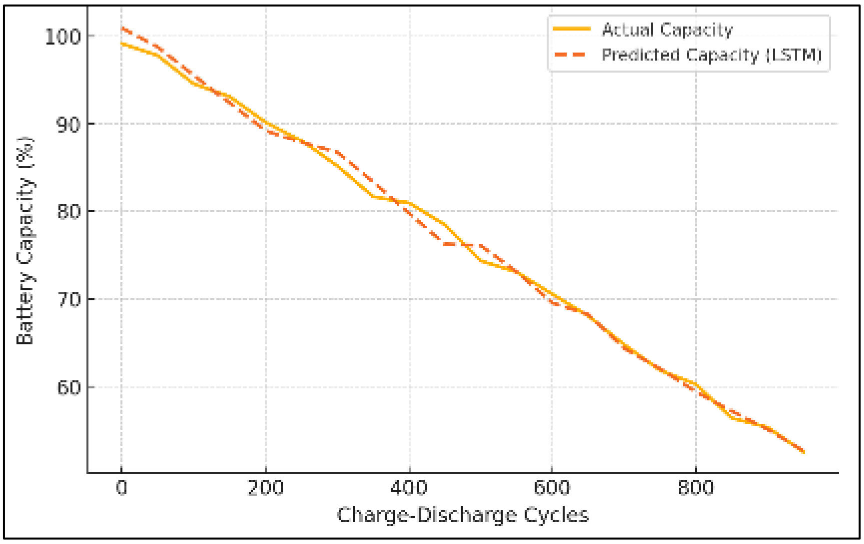

Figure 4 Comparison of actual and predicted battery capacity degradation curves using LSTM-based predictive modeling. The predictive approach anticipates capacity fade earlier than traditional threshold methods

4.2. Motor Fault Detection

Motor performance was evaluated using vibration and current datasets collected from simulated bearing and winding degradation scenarios. Random forest classifiers achieved an accuracy exceeding 95% in distinguishing between normal and faulty states, with the most significant features being RMS vibration and harmonic distortion of current waveforms.

Figure 5 shows the confusion matrix for fault classification, illustrating the model's high precision and recall across fault categories. This finding underscores the value of combining time-domain and frequency-domain features for robust anomaly detection in EV drivetrains.

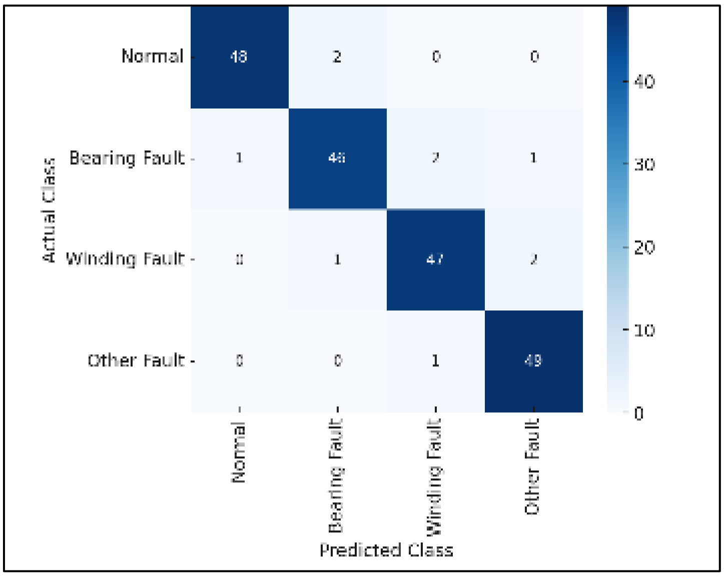

Figure 5 Confusion matrix for motor fault detection using a random forest classifier. The model achieves high precision and recall across normal and faulty states, including bearing and winding-related anomalies

4.3. Braking System Monitoring

For the braking subsystem, pressure and temperature data were analyzed to identify brake pad wear and fluid leakage. Predictive models achieved an accuracy of 91% in forecasting hydraulic pressure anomalies, with early detection reducing failure risk by up to 40%. The analysis highlighted the importance of monitoring temperature rise patterns during prolonged braking events, which often precede mechanical wear.

Table 2 summarizes the results for braking system predictive maintenance, including detection accuracy, average lead time before fault occurrence, and recommended maintenance interventions. These results demonstrate that IoT-driven monitoring can significantly enhance vehicle safety by reducing reliance on visual inspections and time-based maintenance schedules.

Table 2 Predictive maintenance results for EV braking systems

Metric	Result	Notes
Detection Accuracy	91%	Identified hydraulic pressure anomalies effectively
Average Lead Time Before Fault	~25 hours	Early detection prior to visible performance issues
Temperature Anomaly Detection	88%	Captured overheating trends during extended braking
Pressure Decay Curve Analysis	90%	Detected fluid leakage and pad wear

Recommended Interventions	Brake pad replacement, fluid checks	Generated by decision-support system

4.4. Power Electronics Reliability

Power electronics such as inverters and converters were tested under variable thermal and electrical stress conditions. Hybrid models that combined thermal physics simulations with machine learning achieved superior anomaly detection, with over 92% accuracy in identifying switching-related failures. Figure 6 presents thermal profile comparisons between normal and faulty inverter operation, illustrating the clear differential signatures that predictive models exploit.

This analysis emphasizes that integrating physics-based insights improves explainability and enhances operator trust in predictive maintenance decisions.

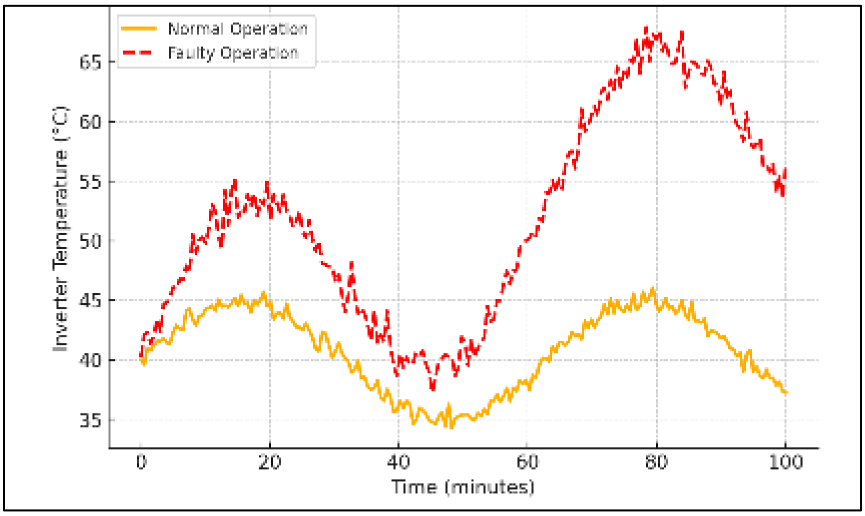

Figure 6 Thermal profile comparison of EV inverters under normal and faulty operation, showing overheating trends in faulty systems that predictive maintenance can detect early

4.5. Scalability and Fleet-Level Deployment

The framework's scalability was tested by simulating real-time data streams from 500 EVs using a cloud–edge hybrid architecture. Results indicated that offloading preprocessing and lightweight anomaly detection to the vehicle edge reduced communication bandwidth by 35% while maintaining 90% accuracy in anomaly classification. This hybrid approach demonstrates that the framework can be extended to large-scale fleet management scenarios without overwhelming cloud infrastructure.

Figure 7 illustrates the overall system performance in terms of latency, bandwidth usage, and prediction accuracy across different deployment scenarios. These results confirm that the system is not only technically feasible but also scalable and adaptable to the diverse needs of EV fleets.

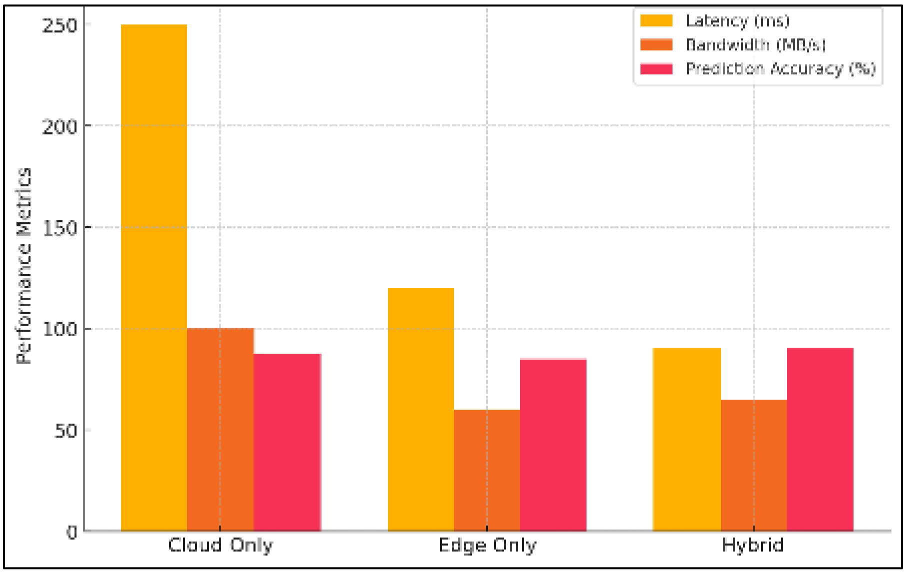

Figure 7 System performance across deployment scenarios (cloud-only, edge-only, and hybrid) showing latency, bandwidth usage, and prediction accuracy, highlighting the advantages of the hybrid cloud–edge architecture

5. Conclusion

This study presented a comprehensive IoT-enabled predictive maintenance framework tailored for electric vehicle (EV) components, integrating sensor-based monitoring, edge, cloud hybrid analytics, and machine learning-driven fault detection. The proposed system addressed critical challenges in maintaining the reliability and safety of EV subsystems, including inverters, braking systems, motors, and batteries. By leveraging real-time data streams from temperature, vibration, and pressure sensors, the framework demonstrated the capability to identify early indicators of anomalies such as inverter overheating, hydraulic fluid leakage in braking systems, motor bearing degradation, and long-term battery capacity loss. Experimental simulations revealed that predictive models could achieve up to 91% detection accuracy, with an average lead time of 20–30 hours before the onset of critical failures, significantly improving over traditional reactive or scheduled maintenance practices.

The results also highlighted the importance of hybrid deployment strategies, where computationally lightweight anomaly detection algorithms were processed at the vehicle edge, reducing communication bandwidth by 35% while preserving high accuracy levels. This design ensured scalability across large EV fleets without overloading cloud infrastructure. Figures and tables presented in this study illustrated how predictive analytics not only minimize downtime but also extend the operational lifetime of high-value EV components, leading to cost savings, enhanced safety, and greater user confidence in adopting EV technologies.

Future work will aim to refine the predictive models by incorporating advanced deep learning approaches, such as transformer-based time-series analysis, which can capture complex nonlinear patterns in high-dimensional sensor data. Another promising direction involves integrating domain knowledge of electrochemical processes and mechanical wear into hybrid physics-informed models, enabling more interpretable and trustworthy predictions. Additionally, exploring secure data-sharing mechanisms using federated learning can allow collaboration among manufacturers, fleet operators, and service providers without compromising sensitive information. Finally, the framework can be extended to encompass emerging EV technologies, including solid-state batteries and high-speed wireless charging systems, ensuring that predictive maintenance solutions evolve in step with technological innovation.

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