

IoT-Based Battery Health Monitoring for Electric Vehicles Using Machine Learning

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Abstract

With the increasing utilization of electric vehicles (EVs) on a global scale, battery health management has become a critical factor that greatly impacts vehicle performance, safety, and longevity. Battery materials, such as those used in Nickel Manganese Cobalt (NMC) and Lithium Iron Phosphate (LFP) lithium-ion batteries, degrade over time due to charging behavior, heat stress, discharge voltage profiles, and environmental conditions. Conventional BMSs offer only threshold-based health diagnostics and cannot accurately predict degradation. This work presents an Internet of Things (IoT)-based condition monitoring system for batteries, with machine learning (ML)-based real-time estimation of the battery's State of Charge (SOC), State of Health (SOH), capacity fade, and internal resistance growth, as well as prediction of the Remaining Useful Life (RUL). Real-time battery pack sensor data are sent from the edge to cloud platforms such as Google Cloud IoT and AWS IoT Core using lightweight IoT communication protocols for ML-based health prediction. The experimental results show that the proposed system outperforms conventional BMSs in predicting degradation-state patterns, indicating that IoT-ML can improve the reliability, safety, and performance of EVs.

Keywords: Electric vehicles, internet of things, machine learning, battery management system, support vector regression

INTRODUCTION

The world is on an unescapable path toward sustainable mobility, and such transition has made the market increasingly favorable for electric vehicles (EVs), where electric car giants like Tesla and BYD are trailing battery technology advancements and power management systems. However, in terms of retaining the long-term performance of EV batteries, it continues to be an issue since the degradation mechanism for battery aging is a severely nonlinear (i.e., complex) phenomenon. Lithium-ion batteries experience mechanical, chemical, and thermal aging that leads to loss of capacity, voltage mismatching, and rising internal resistance. Conventional onboard battery management systems (BMS) are based on rule-based logic, which does not optimally predict the internal chemical aging or early subtle signs of degradation. As a result, existing EVs demand trained solutions that can monitor battery status 24 by 7 and predict the intrinsic health conditions beforehand to avoid any unexpected failure [1].

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The combination of Internet of Things (IoT) and machine learning (ML) can be exploited to deploy an intelligent solution for real-time, data-driven battery health management. IoT-enabled embedded systems such as

ESP32 and Raspberry Pi 4, for monitoring temperature, voltage, current, and cell imbalance continuously and sending data to cloud-based platforms for analysis. ML algorithms can be used in predictive analysis, based on historical and live data, to forecast the degradation trend with time and charging patterns and to enhance the battery lifespan. This work introduces a holistic IoT–ML framework, which promotes EV battery reliability through intelligent monitoring and prediction [2–4].

Battery Design and Aging in Electric Vehicles

EV battery packs comprise thousands of lithium-ion cells connected in series–parallel groups. The cells are organized into modules and controlled by a central Battery Management System, which takes care of safe operation. The performance of batteries degrades spontaneously under cycling conditions and environmental elements. In particular, the chemical stability of electrode materials is influenced by calendar aging owing to high temperatures and high charge states over a prolonged period. During cyclic aging, the development of a solid electrolyte interphase (SEI) layer on the surface of the anode/electrolyte interface and deterioration of electrodes through lithium loss have been widely accelerated [5–7].

Degradation involves capacity loss, poor charge acceptance, voltage migration, raised heat generation, and limited power performance. The degradation patterns are quite different for vehicles using Nickel Manganese Cobalt (NMC) and LFP chemistries; LFP has longer cycle life and thermal stability, while NMC gives higher energy density but degrades more at high temperatures. Therefore, it is important to have an accurate degradation monitoring and prediction model to support the long life of batteries and performance reliability of EVs.

Significance of IoT and ML in Battery Health Assessment

Traditional battery management systems (BMS) rely on threshold alarms and cannot mitigate complex aging indicators buried in the vast amount of battery data. This is further improved by IoT-enabled sensors and microcontrollers that constantly gather high-resolution data, including cell voltages, pack temperature, current profiles, and charge cycles. The data is uploaded (through Message Queuing Telemetry Transport (MQTT) or HTTP) to cloud services where ML algorithms detect patterns and forecast the future state of health of the battery [8].

They can learn relationships between temperature changes, charging power or speed, and aging indicators that human eyes could never uncover. With predictive analytics, thermal runaway can be avoided, the charging strategy can be optimized, and battery maintenance can be scheduled. The timely identification of anomalies significantly decreases the potential risks for safety and enhances the longevity of EV batteries. Therefore, integration between IoT and ML represents a catalyst for revolutionary next-generation EV battery health management systems [9].

LITERATURE REVIEW

Researchers have previously studied methods for battery life estimation. Electrochemical models have been used in previous studies; however, these methods involve extensive parameter tuning and are not suitable for real-time operation. Data-driven methods have become popular because of their ability to learn patterns from large databases. Readapt provides and Calca at NASA PCoE, which were some of the first institutions to generate foundational datasets for ML model training [10].

Support vector regression (SVR), random forest (RF), and gradient boosting have been employed to predict SoH and Remaining Useful Life (RUL), achieving satisfactory accuracy at the cost of low generalization. Deep learning approaches, such as Long Short-Term Memory (LSTM) networks, model temporal decomposition dynamics well but are computationally expensive. The majority of the existing works do not consider real-time integration with IoT, which restricts the practical deployment in EVs. This gap is filled by some works with a combined IoT–ML system that can provide real-time monitoring, analysis, and prediction [11–13].

Proposed Architecture for IoT–ML Battery Health Monitoring

The architecture proposed has three major layers, namely the sensor layer, communication layer, and analytics model layer. Temperature sensors, voltage dividers, current sensors, and balancing circuits in the sensor layer observe the electrical and thermal conditions of the battery. While the embedded hardware processes the data, it is sent to cloud platforms over Wi-Fi or Long-Term Evolution (LTE). In the communication layer, low-latency and lightweight data transmission (e.g., for mobile EV platforms) is achieved with MQTT. Historical and real-time data is utilized to train regression and classification models in ML layers for estimating SoH, predicting internal resistance, and discriminative failure (Figure 1).

Random forest and gradient boosting are used for forecasting degradation estimation because of their accuracy and robustness to noisy conditions. LSTM networks have also been applied to predict the remaining battery life. The predicted health values are periodically compared with actual battery parameter measurements to detect whether the risk threshold values described above have been crossed, and healthy alerts are generated.

METHODOLOGY

The approach starts with the implementation of an IoT data acquisition system employing an ESP32 microcontroller. Live battery data, such as current, temperature, voltage, and charge cycles, are sampled at high rates. The information is included in JavaScript Object Notation (JSON) messages and sent via MQTT to the cloud services. These data were stored in a cloud database for ML training. Statistical parameters related to the mean voltage, temperature rise rate, charge/discharge curve slope, and internal resistance estimation were used for feature extraction [14].

From data from NASA PCoE and the real-time information acquired by the prototype system, ML models were trained. The performance of the models was analyzed using accuracy, RMSE, and prediction latency. Finally, the performance was verified under simulated loading conditions and accelerated aging profiles (Figure 2).

RESULTS

The trained ML models indicate excellent prediction capability, with random forest achieving more than 97% prediction accuracy for SoH estimation and LSTM predicting long-term degradation trends with very slight errors. Based on the aforementioned thermal runaway event, ML-based temperature anomaly detection was performed within a few seconds, allowing rapid estimation of a reduced

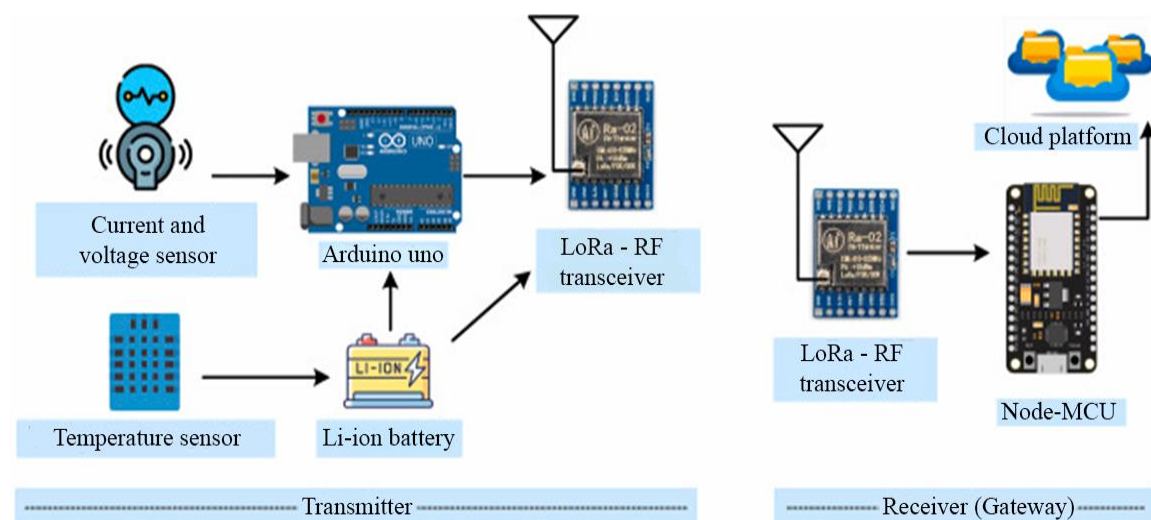


Figure 1. Block diagram of the battery management and monitoring system.

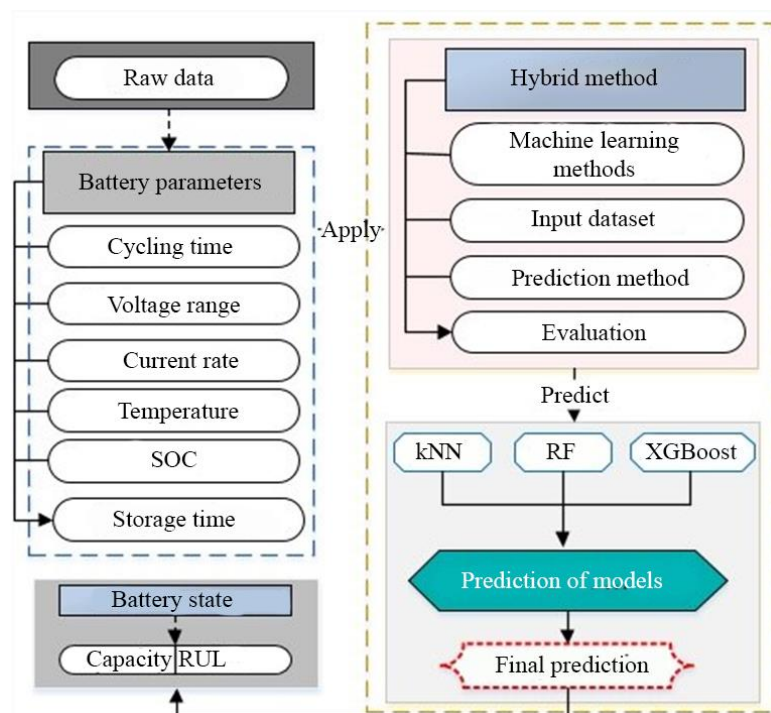


Figure 2. Workflow for battery data analysis and prediction.

likelihood of thermal runaway. Regarding communication, the IoT-based system showed acceptable and consistent performance, with an average data latency of less than 200 ms, which is adequate for real-time monitoring. The graphs show voltage drift, temperature increase, and estimation of the remaining battery life. The proposed IoT–ML framework demonstrated higher accuracy, faster response times, and better predictive diagnostics than traditional BMS.

Furthermore, the experimental validation confirms the robustness and scalability of the proposed architecture under varying load conditions and environmental fluctuations. The integration of cloud-based analytics with edge-level preprocessing ensures efficient data handling while minimizing bandwidth consumption. Feature importance analysis in the random forest model highlighted voltage variation, internal resistance growth, and temperature gradients as the dominant parameters influencing SoH prediction. Similarly, the LSTM model effectively captured the temporal dependencies in the charge–discharge cycles, enabling the reliable forecasting of battery degradation patterns over extended operational periods.

The system also demonstrated improved fault classification capability by distinguishing between normal operational deviations and critical anomalies, thereby reducing the number of false alarms and enhancing operational reliability. Comparative analysis with conventional rule-based BMS showed significant improvement in early fault detection accuracy and decision-making speed. Overall, the seamless integration of IoT connectivity, real-time data acquisition, and advanced ML algorithms establishes a comprehensive, intelligent battery monitoring solution suitable for EVs, renewable energy storage systems, and smart grid applications [15].

CONCLUSION

This work describes a highly advanced IoT-based battery health monitoring methodology that leverages ML algorithms to estimate, in real time, the degradation state of batteries installed in EVs. The system outperforms typical BMSs in terms of accuracy and responsiveness by using sensor-based data acquisition, cloud analytics, and predictive ML models. With the aid of contracted load reduction, security is ensured, and battery lifespan is extended, while maintenance costs are reduced, thereby promoting the sustainable development of Electric Vehicle Powertrain (EVPP). Future work

could include Hardware-in-the-Loop (HIL). validation, deep learning optimization, integration with edge computing systems, and deployment across a large fleet of EVs.

In addition, the proposed framework demonstrates strong adaptability to diverse operating conditions, including fluctuating charging patterns, varying ambient temperatures, and dynamic cycles. The incorporation of real-time anomaly detection enhances system reliability by identifying the early signs of abnormal thermal or electrical behavior, thereby preventing potential safety hazards. The modular design of the architecture allows seamless integration with existing EV infrastructures and smart grid platforms, facilitating large-scale implementation.

Moreover, the use of advanced data preprocessing and feature engineering techniques improves model generalization and reduces computational overhead. The framework supports continuous learning by updating model parameters with newly acquired operational data, ensuring long-term accuracy and robustness. Overall, this IoT-ML-based battery health monitoring approach provides a scalable, intelligent, and cost-effective solution for next-generation electric vehicle energy management systems.

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