International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

# Battery Health Prediction and Self-Healing Using Xgboost and PWM

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**Abstract**

As electric vehicles and renewable energy drive the demand for lithium-ion batteries, predicting their lifespan and maintaining performance have become critical success factors. Our intelligent Battery Management System (BMS) tackles these challenges head-on, using machine learning to monitor and predict battery health with precision. Built around an ATMEGA328P microcontroller and sensors, the system tracks voltage, current, and temperature in real-time, sending data to the cloud via the ESP8266 Wi-Fi module. By applying advanced algorithm like XGBoost, we accurately determine the State of Health (SoH) and predict battery lifespan. The system's innovative self-healing mechanism extends battery life by minimizing wear through Pulse Width Modulation (PWM). Users can access system insights effortlessly through an LCD display and online dashboard. By combining hardware and AI expertise, we've created a reliable, efficient, and sustainable battery management solution that supports the adoption of electric vehicles and renewable energy.

**Keywords** - Battery Management System (BMS),Lithium-ion Battery, State of Charge(SOC), State of Health(SOH), Artificial Intelligence (AI), Gradient Boosting Model (XGBoost), Electrical Vehicle (EVS), Battery Performance Prediction, Energy storage system, Data-Driven Methods, Machine Learning Approaches, Battery Degradation Modeling, RealTime Monitoring, Safety and Reliability in Automotive Applications, Battery Lifespan Optimization, Predictive Maintenance in Electric Vehicles.

## 1. Introduction

As electric vehicles (EVs) continue to reshape the landscape of sustainable transportation, ensuring the longevity and reliability of their lithium-ion batteries has become a critical challenge. Battery packs, composed of multiple interconnected cells, are highly susceptible to degradation, which can compromise the overall performance and safety of EV systems. This project proposes an intelligent Battery Management System (BMS) that combines machine learning and embedded systems to address these challenges.

Leveraging the capabilities of the XGBoost algorithm, the system is designed to predict the State of Health (SOH) of lithium-ion batteries with high accuracy. In parallel, Pulse Width Modulation (PWM) techniques are employed to implement self-healing mechanisms that mitigate the effects of wear and improve battery lifespan. By integrating real- time data collection through sensors and wireless communication modules, the proposed system offers a proactive solution to monitor, manage, and enhance battery health in electric vehicles. This approach not only increases operational efficiency but also supports the broader goals of environmental sustainability and energy optimization.

Smith et al. [1] emphasized the importance of lithium-ion batteries in electric vehicles (EVs) and renewable energy setups due to their compact size, high energy density, and efficiency. However, Lee and Kumar [2] noted that maintaining consistent performance and tracking battery aging in real-time remains a complex challenge, as even a small fault can affect the whole battery system's functionality and safety.

Ahmed et al. [3] proposed a smart Battery Management System (BMS) that integrates AI with real-time sensor data to evaluate the battery's State of Health (SoH), using parameters like voltage, current, temperature, and charge cycles. Chen and Guestrin [4] developed XGBoost, a high- performance machine learning algorithm that has since become central to battery health prediction due to its ability to process large and complex datasets. Zhao et al. [5] further validated its effectiveness in fault detection and prediction accuracy.

To enhance the system, Wang et al. [6] applied the XGBoost model to historical battery data and ongoing sensor inputs to spot early signs of degradation, enabling preventive maintenance and extending battery life. Park and Tanaka [7] introduced a self-healing approach using Pulse Width Modulation (PWM), which manages current flow during charging and discharging to reduce stress on cells. This concept was strengthened by Huang et al. [8], who demonstrated that PWM could restore performance in partially degraded cells.

On the hardware side, Gomez and Patel [9] incorporated the ADS1115 analog-to-digital converter for accurate signal capture, while Singh and Rao [10] implemented the NodeMCU ESP8266 to facilitate wireless communication between sensors and the cloud. Lopez et al. [11] highlighted that this setup allows real-time monitoring, alert systems, and continuous battery performance tracking.

Lastly, Cheng et al. [12] advocated for the repurposing of used EV batteries in solar energy systems, promoting sustainability. Nelson and Ibrahim [13], along with Mehta and Zhou [14], supported this approach as it aligns with eco- conscious energy trends and circular economy principles.

In conclusion, the intelligent BMS developed in this project enhances battery lifespan, improves safety, and contributes to green energy goals by combining AI-driven analytics with active self-healing capabilities.

## 2. Problem Statement

Electric vehicles (EVs) are increasingly essential for sustainable transportation, with lithium-ion batteries at their core. However, maintaining the long-term efficiency and safety of these batteries remains a significant challenge. Traditional Battery Management Systems (BMS) often struggle with real-time analysis, relying on set parameters that may miss early signs of cell degradation. Consequently, a single failing cell can initiate a chain reaction, affecting neighboring cells and resulting in accelerated wear, decreased performance, or even safety risks.

To address these challenges, there is a need for a more adaptive and intelligent battery monitoring system. This project presents a smart, AI-driven BMS that incorporates machine learning algorithms—specifically XGBoost along with Pulse Width Modulation (PWM) techniques. By analyzing real-time sensor data and providing more accurate predictions of the State of Health (SoH), the system enhances fault detection and introduces self-healing capabilities. This proactive strategy aims to extend battery life, lower maintenance requirements, and improve the reliability and sustainability of contemporary EV systems.

## 3. Existing System

Conventional Battery Management Systems (BMS) primarily rely on basic monitoring parameters such as voltage, current, and temperature to manage battery health. These systems typically lack advanced analytics and predictive capabilities, making them unable to effectively detect potential faults or optimize charging and discharging protocols. Consequently, they often fail to implement self- healing measures, leading to premature battery degradation and diminished performance. Manual intervention is frequently required to address issues, which increases downtime and maintenance needs. Additionally, these traditional systems pose safety risks due to undetected faults, which can result in critical failures or hazardous situations during operation.

## 4. METHODOLOGY

The proposed system dramatically enhances battery health prediction and introduces advanced self-healing capabilities within a Battery Management System (BMS) for electric vehicles. The core architecture seamlessly integrates a microcontroller (ATmega328P) with current and voltage sensors to precisely monitor battery parameters, such as voltage, current, and charge-discharge cycles. Real-time readings are transmitted to a cloud server using the ESP8266 NodeMCU module, enabling remote access and continuous data logging.

The XGBoost machine learning algorithm, trained on historical battery datasets, accurately estimates the State of Health (SoH) by analyzing features such as cycle count, voltage fluctuations, and discharge rates. The system employs Pulse Width Modulation (PWM) to regulate charging and discharging behavior, minimizing battery stress. When degradation is detected, the BMS takes corrective action by adjusting charge inputs or isolating weak cells, effectively introducing advanced self-healing.
The entire setup is clearly visualized through a user-friendly interface with ThinkSpeak integration, providing real-time battery status tracking and predictive alerts. This innovative approach ensures the system predicts health conditions and takes proactive steps to extend battery life and maintain operational safety.

## 5. PROPOSED SYSTEM

The proposed system is an innovative Battery Management System (BMS) aimed at monitoring, managing, and extending the lifespan of lithium-ion batteries through a blend of sensors, microcontroller processing, and AI- powered cloud analytics.

It begins with a power supply that activates the central components, particularly the controller, which is the heart of the system. The controller gathers data, makes decisions, and oversees operations. It connects to vital sensors: a current sensor, a voltage sensor, and a temperature sensor, which provide real-time insights into the battery's electrical and thermal states.

To accurately interpret the sensor data, the system utilizes an ADS1115 analog-to-digital converter, ensuring the controller receives precise digital information. A potentiometer (POT) is also included for manual adjustments during testing or setup.

Data collected by the sensors is displayed locally on an LCD screen, allowing technicians or users to quickly evaluate battery conditions. Concurrently, the system sends this data to a cloud platform via IoT connectivity. In the cloud, a machine learning model, like XGBoost, analyzes the information to assess battery health and forecast potential issues or degradation.

The processed results are accessible through a user-friendly application, enabling remote monitoring and notifications. If any irregularities are detected, the controller can automatically use Pulse Width Modulation (PWM) techniques to manage charging and discharging cycles. This adaptive control not only protects the battery but also promotes self-healing by reducing wear on compromised cells.

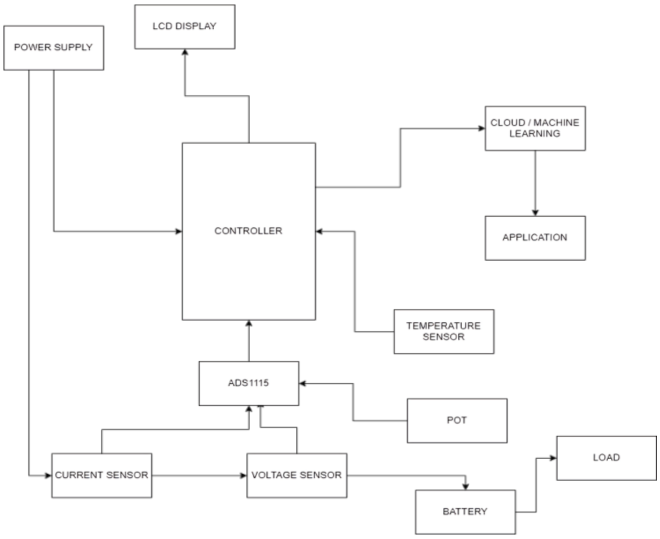

Fig 1: System Design

(Fig. 1) illustrates the block diagram of a proposed intelligent Battery Management System (BMS) that integrates real-time monitoring, data processing, and cloud- based machine learning for advanced battery health prediction and management. At the core of the architecture lies a controller responsible for coordinating various hardware components. Key operational parameters such as voltage, current, and temperature are captured using respective sensors. These analog signals are digitized via the ADS1115 Analog-to-Digital Converter and processed by the controller. A potentiometer (POT) is included for manual calibration. The system displays real-time information on an LCD while simultaneously transmitting data to a cloud platform for analysis. Machine learning algorithms, such as XGBoost, are utilized in the cloud to assess the battery's State of Health (SoH) and detect early signs of degradation. Based on this analysis, the controller adjusts battery behavior using Pulse Width Modulation (PWM) techniques to optimize performance and enhance battery lifespan. A load is managed accordingly to ensure operational stability, making this system suitable for electric vehicles and renewable energy storage applications.

## 6. Result and Discussion

The AI-powered Battery Management System (BMS) was successfully implemented and tested using a combination of hardware setup, Python scripting. We evaluated the system's performance across several areas, including real-time data monitoring, State of Health (SoH) prediction accuracy , and user interface effectiveness.

In the software aspect, the XGBoost algorithm was trained using the Thonny IDE with a carefully selected dataset, as shown in (Fig. 2) The training utilized battery charge- discharge characteristics, voltage fluctuations, and usage cycles as input features. Results, illustrated in (Fig. 2.1), demonstrate that the model accurately predicts SoH, distinguishing between healthy and degraded battery cells. This capability allows for timely corrective actions before battery failure occurs.The (Fig. 2.1) depicts a Python script designed to interact with a Machine Learning model for predicting battery parameters using real-time data. The script starts by importing key libraries, including pickle for loading the trained model, requests for making API calls, and json for data handling. It loads the model file from a .pkl file using pickle.load, which contains a pre-trained XGBoost model.

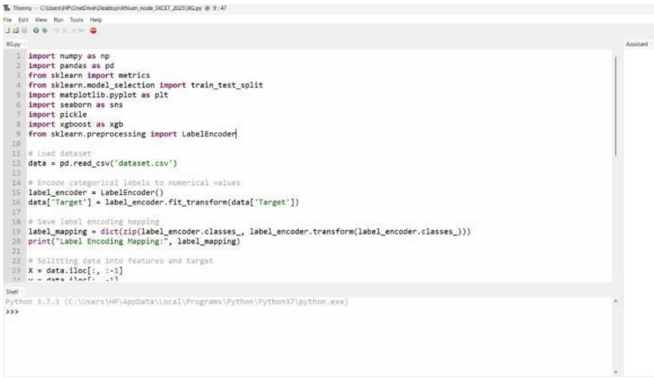


Fig 2: XGBOOST DATASET TRAINING [THONNY IDE]

The script defines a set of essential features for battery health prediction, which includes parameters like voltage, current, charge current, discharge current, and temperature. It also contains an inference section that utilizes these inputs to generate predictive results, showing that the script functions as a component of a larger AI-driven system for monitoring battery health using machine learning algorithms. This setup enables real-time analysis of battery behavior, allowing for early detection of faults or performance decline. By leveraging historical and real-time data, the system improves the accuracy of state-of-health estimations. Ultimately, it supports proactive maintenance and enhances the overall reliability of lithium-ion battery systems.


Fig 2.1: XGBOOST PREDICION RESULT [THONNY IDE]

The monitoring interface, developed with HTML and integrated with ThinkSpeak (as seen in Fig. 3), enables users to visualize real-time battery data on a web dashboard. This cloud-based monitoring enhances accessibility and supports proactive maintenance by sending alerts when anomalies are detected.

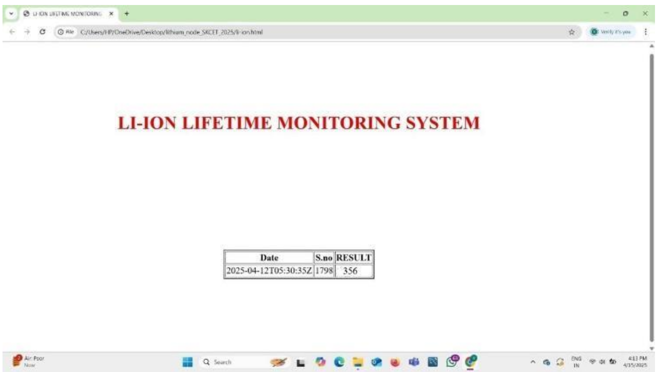


Fig 3: HTML PAGE FOR MONITORING SYSTEM

simulation (Fig. 4) was employed to validate the predictive and self-healing logic in a controlled environment. The simulation assessed the system's response to various degradation patterns and confirmed the effectiveness of PWM-based control in stabilizing voltage and reducing thermal stress during charge/discharge cycles.

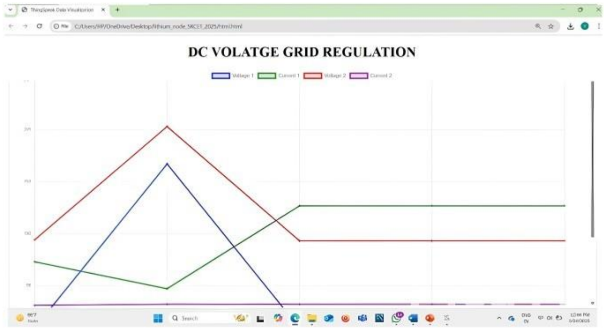


Fig 4: THINKSPEAK DATA VISUALIZATION

In summary, the experimental results affirm the effectiveness of combining XGBoost-based predictive modeling with real-time IoT monitoring and PWM-based control. The system not only enhances battery safety and lifespan but also lays the groundwork for a self-healing mechanism, which is currently uncommon in traditional BMS platforms.

*a)* Recuperation Testing

Recuperation testing in this project focused on checking whether the system could help restore battery health by adjusting how it charges and discharges. Using predictions from the XGBoost machine learning model, the system detects early warning signs of battery wear. When issues are spotted, it responds by modifying the charge cycles through Pulse Width Modulation (PWM). This test confirmed that the system can take smart corrective actions that help maintain battery performance and extend its lifespan.

*b)* Testing Plan

The testing process was carefully structured, starting with individual checks of each hardware and software part. First, sensor accuracy for voltage, current, and temperature was verified, along with the ability of the NodeMCU to send data to the cloud. Then, the machine learning model was tested using real battery datasets to ensure reliable predictions. Finally, combined testing through ThinkSpeak cloud monitoring verified that the system correctly predicted State of Health (SoH), activated PWM controls as needed, and displayed the data accurately online.

*c)* Integration Testing

Integration testing made sure that all parts of the system— sensors, the ADC module, the microcontroller, and the cloud software—worked smoothly together. The test confirmed that sensor readings were correctly collected, processed, and sent to the cloud. It also verified that the machine learning model could respond in real-time, and that its health predictions were used to manage the battery charging/discharging through PWM. This ensured reliable communication between all components without data loss or delays.

*d)* Framework testing

Framework testing looked at the complete system architecture, combining embedded electronics, machine learning, and IoT features. This phase checked whether the whole framework—data collection from sensors, prediction by the XGBoost model, control using PWM, and visualization on ThinkSpeak—worked efficiently as one unit. The testing confirmed the system's reliability, real- time processing ability, and consistency in handling data, making it a solid digital twin solution for monitoring battery health.

*e)* Specialized Specification
Several advanced features were included to meet the project's goals. The XGBoost algorithm was chosen for its accurate battery health predictions. The ADS1115 module provided high-resolution analog-to-digital conversion, and the NodeMCU ESP8266 offered reliable wireless communication. The system also supported automated self- healing responses, graphical data display via ThinkSpeak. These specific technologies worked together to support a smart, predictive battery management approach ideal for electric vehicles.

## 7. HARDWARE SYSTEM

The hardware setup shown in (Fig. 5) represents the practical implementation of the proposed smart Battery Management System (BMS). The system is built on a wooden base to hold and organize the electronic components securely. Central to the circuit is a microcontroller that acts as the main control unit, coordinating all sensor data and communication.

Several sensors are clearly integrated, including a voltage sensor, current sensor, and a temperature sensor, responsible for collecting real-time battery metrics. These are connected via jumper wires to an ADS1115 analog-to-digital converter, enabling the system to process analog signals with high accuracy. A motor and load are included to simulate real- world energy consumption scenarios.
Power is supplied using multiple lithium-ion batteries, as seen on the left side, along with a charging module for energy management. The presence of a Bluetooth or Wi-Fi module suggests IoT connectivity, enabling wireless transmission of data to a cloud or user interface.

Indicator LEDs on the board confirm system activity, while the neatly arranged wiring indicates modularity and scalability for future upgrades. Overall, the hardware system successfully demonstrates the real-time monitoring, control, and predictive capabilities essential for intelligent battery health management.

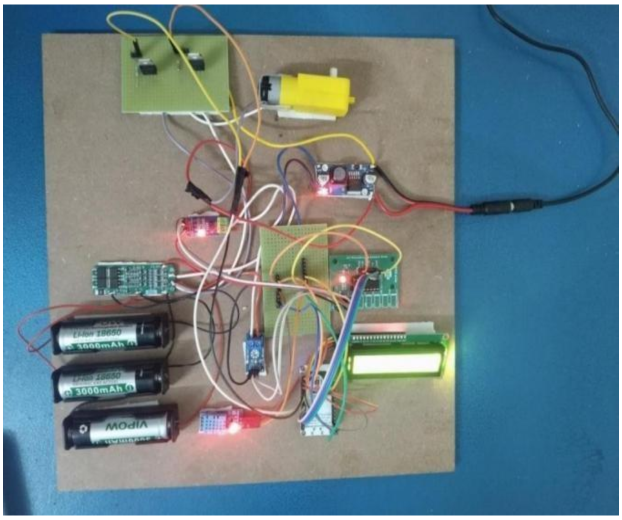

Fig 5: HARDWARE SYSTEM

## 8. Conclusion

This project showcases a revolutionary Battery Management System (BMS) that combines cutting-edge sensor technologies, intelligent control strategies, and machine learning to transform battery performance and longevity. The system leverages a set of high-precision sensors and the ADS1115 analog-to-digital converter to provide real-time, high-accuracy monitoring of essential battery parameters.

At the heart of the system lies the XGBoost machine learning algorithm, trained on historical battery data to accurately estimate the State of Health (SoH) and detect degradation trends early. This predictive approach enables the system to prevent sudden battery failures and ensure safer, more efficient operation.

The system seamlessly integrates cloud connectivity, enabling remote data transfer and analysis for continuous, off-site health diagnostics. This feature makes it an ideal solution for modern Internet of Things (IoT) ecosystems. The user interface, accessible locally and remotely, provides real-time insights into the battery's status, enhancing overall usability.

The system's Pulse Width Modulation (PWM) control method dynamically manages charging and discharging cycles based on battery conditions, reducing operational stress on weakened cells and forming the basis of a self- healing capability that enhances battery durability. Furthermore, the system enables battery repurposing for secondary applications, promoting sustainability and reducing environmental impact. Retired electric vehicle batteries can be reused in energy storage setups like solar backups. This innovative BMS contributes to safer, smarter, and greener energy solutions, paving the way for the future of electric mobility and renewable energy systems.

## 9. Future Scope

Our smart Battery Management System (BMS) will improve battery health prediction accuracy by integrating deep learning models. Future versions will support new battery chemistries like solid-state and lithium-sulfur batteries, making the system adaptable to emerging technologies.

Real-time thermal modeling and automatic cell balancing will optimize performance and safety. Vehicle telematics will enable centralized monitoring for EV fleets, while a user-friendly mobile or web interface will improve accessibility.

We will implement cybersecurity measures to protect cloud data. By expanding the system for use in smart grids and renewable energy storage, we will promote sustainability and enable second-life battery applications.

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