

# AI - Driven Battery Degradation Modeling and Forecasting in Electric Vehicles

Mr.J. Shanmugasundaram, (Ph.D.)<sup>1</sup>, Dharshini N<sup>2</sup>, Dharsini P<sup>2</sup>, Kavipriya M<sup>2</sup>, Srinithi S<sup>2</sup>

<sup>1</sup> Assistant Professor/EEE, Vivekanandha College of Engineering for Women (Autonomous), Tiruchengode

<sup>2</sup>IV-EEE Student, Vivekanandha College of Engineering for Women (Autonomous), Tiruchengode

{ Mr.J. Shanmugasundaram } shanmugasundaram@vcew.ac.in {Dharshini N} dharshini0020@gmail.com, { Dharsini P } dharsinipalanivel58@gmail.com {Kavipriya M }kavipriyamurali2908@gmail.com, {Srinithi S} srinithisuresh2222@gmail.com

## Abstract:

Electric Vehicles (EVs) are gaining widespread adoption as a sustainable transportation solution; however, battery degradation remains a major concern affecting reliability, safety, and cost. Accurate degradation modeling and forecasting are essential for effective battery management and lifespan enhancement. This paper proposes an AI-driven battery degradation modeling framework that combines real-time data acquisition with intelligent prediction techniques. An IoT-based monitoring system using an ESP32 microcontroller is employed to collect key battery parameters, including voltage, current, and temperature. Battery State of Health (SoH) is estimated from the acquired data, and a Long Short-Term Memory (LSTM) neural network is used to learn temporal degradation patterns and forecast future battery health. The proposed approach enables early detection of abnormal degradation and improves prediction accuracy compared to conventional methods, supporting reliable and intelligent battery management in Electric Vehicles.

Keywords: Electric vehicle, Battery, IOT, LSTM

## 1 INTRODUCTION

This project aims to develop an intelligent and real-time battery health monitoring system for electric vehicles by combining Internet of Things (IoT) technology with advanced deep learning techniques. Specifically, the system integrates an ESP32-based data acquisition module with a hybrid Long Short-Term Memory (LSTM) and attention model to estimate the State of Health (SoH) of lithium-ion batteries.

In this system, the ESP32 microcontroller acts as the core IoT device responsible for collecting real-time battery parameters such as voltage, current, temperature, and charge-discharge cycles through connected sensors. These measurements are transmitted wirelessly (via Wi-Fi or Bluetooth) to a cloud or edge computing platform for further processing. This enables continuous and remote monitoring of battery conditions in real-world operating environments.

Once the data is collected, it undergoes preprocessing steps including noise filtering, normalization, and sequence generation. The processed time-series data is then fed into an LSTM network, which learns the temporal behavior of battery usage and degradation over time. The LSTM effectively captures long-term dependencies, such as how past operating conditions influence current battery health.

To enhance the model's performance, an attention mechanism is incorporated on top of the LSTM. The attention layer assigns importance weights to different time steps in the input sequence, allowing the model to focus more on critical events—such as high-temperature exposure or deep discharge cycles—that significantly accelerate battery degradation. This improves both prediction accuracy and interpretability.

The final output of the model is the estimated State of Health (SoH), which indicates the current capacity of the battery relative to its original condition. This estimation helps in predicting

battery lifespan, optimizing charging strategies, and preventing unexpected failures.

Overall, the proposed system combines real-time IoT data acquisition with a powerful hybrid deep learning model to deliver accurate and reliable battery health predictions. This approach supports the development of smart Battery Management Systems (BMS) and contributes to safer, more efficient, and longer-lasting electric vehicle operations.

## 2 LITERATURE REVIEW

- i. Rather et al. (2024) proposed a deep learning–based approach focusing on small data techniques and data augmentation methods to improve model performance. The study utilized small datasets from various domains, where data scarcity is a major challenge. The model achieved moderate to high accuracy (around 85–90%), particularly when augmentation techniques were applied effectively. However, the study has notable limitations, including overfitting and poor generalization, as the model struggles to perform well on unseen data due to limited dataset size, highlighting the need for more robust and scalable solutions.
- ii. MDPI Review (2021) presented a study based on machine learning classification models to analyze performance prediction tasks. The research utilized a student performance dataset, which includes educational and behavioral data of learners. The models achieved accuracy ranging from approximately 70% to 90%, depending on the algorithm and data distribution. However, the study has significant limitations, as the accuracy becomes unreliable when dealing with imbalanced datasets, leading to biased predictions and reduced effectiveness in real-world scenarios.
- iii. Aggarwal et al. (2021) proposed a deep learning–based approach, primarily using advanced neural network models for medical image analysis and diagnosis. The study utilized medical imaging datasets, including radiological images, to detect and classify diseases. The model achieved high diagnostic accuracy, often exceeding 90%, demonstrating strong performance in controlled environments. However, the study faces key limitations such as lack of generalization across different datasets and clinical settings, as well as dependency on large annotated data, which restricts its applicability in real-world healthcare scenarios.
- iv. BMC Review (2021) focused on machine learning–based approaches applied to healthcare and clinical decision-making systems. The study utilized clinical and real-world healthcare datasets, which include patient records and medical histories. The models demonstrated good predictive performance, typically ranging between 80% and 90% accuracy, depending on the algorithm and data quality.
- v. Scientific Reports (2024) presented a comparative study of machine learning and deep learning models, including algorithms such as XGBoost and neural networks, to evaluate their effectiveness across different tasks. The study utilized stationary datasets from various domains, where data distribution remains relatively stable. The results showed comparable performance between models, with accuracy typically around 85%–95%, depending on the dataset and model used. However, the study has notable limitations, particularly lack of model explainability and interpretability, making it difficult to understand decision-making processes, along with challenges in adapting the models to dynamic, real-world environments.
- vi. Vareka (2020) conducted a study comparing deep learning and traditional machine learning approaches, specifically using CNN, SVM, and LDA models for classification tasks. The research utilized an EEG/P300 dataset, which is commonly used in brain–computer interface applications. The models achieved accuracy in the range of

approximately 62% to 79%, showing moderate performance. However, the study revealed important limitations, as CNN did not significantly outperform traditional methods, and the overall accuracy remained relatively low, indicating challenges in feature extraction and model efficiency for complex neural signal data.

vii. Li et al. (2019) proposed an unsupervised learning-based approach for software defect prediction, aiming to reduce dependency on labeled data. The study utilized software defect datasets collected from real-world software projects, which often contain unlabeled or partially labeled instances. The results showed comparable performance to supervised methods, with accuracy typically around 70%–85%, depending on the dataset and evaluation setup. However, the study has several limitations, including inconsistent performance across datasets, lack of standardized evaluation metrics, and poor reporting of experimental details, which makes it difficult to reproduce results and assess the true effectiveness of the approach.

### 3 METHODOLOGY

1. **Sensor-Based Battery Data Acquisition:** Sensors are fitted to the battery to measure voltage, current, and temperature. These readings are taken continuously while the vehicle is running.
2. **Data Preprocessing and Feature Extraction:** The collected data is first checked and cleaned properly. Any unwanted noise or errors in the data are removed.
3. **State of Health (SoH) Estimation:** The condition of the battery is calculated using the processed data. This gives a clear idea about the battery's current health.
4. **Battery Degradation Forecasting:** The model is trained using the collected battery data. This helps in knowing how the battery will perform later. It also gives an idea about the remaining battery life.
5. **Predictive Battery Monitoring:** The battery is monitored regularly using the predicted

results. warnings can be given before serious problems occur.

### 4 EXISTING SYSTEM

In electric vehicles, traditional battery management systems mainly use fixed models and set rules to check how the battery is performing and how it is degrading over time. Some common methods include using electrical circuit models, tracking the amount of charge going in and out of the battery, and using simple calculations to estimate battery charge level and overall health. These methods depend on already defined models and need accurate settings, which makes them less flexible when the battery is used under different conditions.

In most cases, these systems do not monitor the battery continuously. Instead, they rely on measurements taken at certain intervals or on data analyzed later. Because of this, important factors like changes in temperature, different charging habits, and driving conditions are not properly considered. Also, fault detection is usually based on fixed limit values, which means problems are often identified only after they become serious, instead of being detected early.

In many existing systems, battery degradation is checked only at certain intervals or by analyzing data later, instead of monitoring it continuously in real time. Because of this, important changing factors like temperature variations, different charging habits, and driving conditions are not properly taken into account. As a result, the system may miss early signs of battery wear. Fault detection is usually based on fixed limit values, so problems are often noticed only after they become serious.

In addition, most systems depend on fixed rules to detect faults and ensure safety. These fixed limits do not change according to the battery's condition or how it is being used, which can lead to incorrect or late detection of issues. Also, traditional battery management systems mainly focus on showing the current state of the battery. They do not have the ability to predict future problems or estimate how long the battery will last. This makes it difficult to plan maintenance or prevent failures in advance.

### 5 PROPOSED SYSTEM

The proposed system introduces a smart and flexible method for studying and predicting battery degradation in electric vehicles. It is designed to solve the problems found in traditional battery management systems by allowing continuous monitoring, better estimation of battery condition, and prediction of future performance under real-world conditions.

In this system, an IoT-based setup is used to continuously monitor important battery parameters such as voltage, current, and temperature. An ESP32 microcontroller acts as the main unit that collects this data and sends it wirelessly to a local system or cloud platform. This helps in keeping track of the battery's condition at all times while the vehicle is in use.

The data collected from the sensors is then cleaned and prepared for analysis. This includes removing unwanted noise, organizing the data over time, and adjusting values to maintain consistency. After this, the system estimates the battery's State of Health (SoH), which shows how much the battery has degraded compared to its original condition. Monitoring SoH regularly helps in identifying early signs of wear and unusual behavior.

To study and predict battery degradation, the system uses a method that can learn from past data and understand patterns over time. This approach is suitable for handling time-based data and can remember previous information to make better predictions. By using both past and current battery data, the system learns how different factors like driving style, temperature, and charging habits affect battery life.

The proposed system improves battery maintenance by detecting possible issues at an early stage before they become serious. It can track how the battery condition changes over time and make predictions based on past and current data, which helps in improving safety and using energy more efficiently. This also helps in extending the overall life of the battery. By combining continuous monitoring with smart prediction, the system works more effectively and reliably, making it suitable for modern battery

management systems.

## 6 MATHEMATICAL VALIDATION

### 1. State of Health (SoH):

**Formula:**

$$SoH = \frac{C_{\text{current}}}{C_{\text{rated}}} \times 100$$

State of Health (SoH) indicates how much capacity a battery retains compared to its original (rated) capacity.

- $C_{\text{current}}$ : Present battery capacity
- $C_{\text{rated}}$ : Original capacity when new

### 2. LSTM Equations (Gates & Memory Update)

**Forget Gate:**

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

**Input Gate:**

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

**Candidate Memory:**

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

**Cell State Update:**

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

**Output Gate:**

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

**Hidden State:**

$$h_t = o_t \cdot \tanh(C_t)$$

LSTM (Long Short-Term Memory) is a type of neural network used for time-series prediction.

- Controls what to forget, store, and output using gates

- Helps predict battery degradation trends over time

Faster and more efficient for training LSTM models.

### 3. Loss Functions

**Mean Squared Error (MSE):**

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Measures average squared difference between actual and predicted values Penalizes large errors more.

**Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Measures average absolute difference between actual and predicted values. More robust to outliers than MSE.

### 4. Optimization Method

**Gradient Descent Formula:**

$$\theta = \theta - \eta \cdot \nabla J(\theta)$$

Optimization method used to minimize loss function by updating model parameters.

- $\theta$ : Model parameters
- $\eta$ : Learning rate
- $\nabla J(\theta)$ : Gradient of loss function

**Adam Optimizer (commonly used):**

**Formulas:**

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta = \theta - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Adam is an advanced optimization algorithm that combines momentum and adaptive learning rate

### 7 BLOCK DIAGRAM

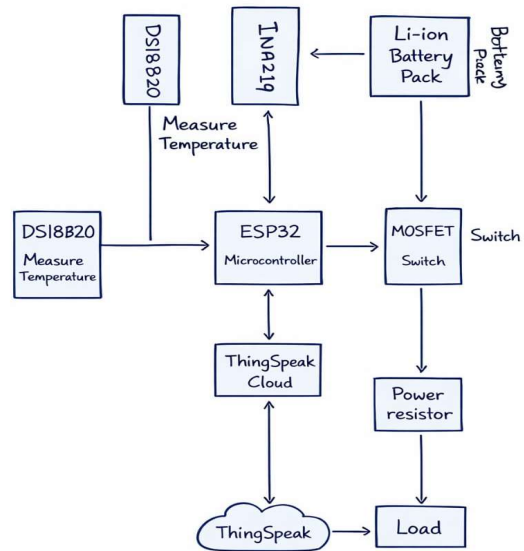


Fig 1- Block Diagram

### 8 SYSTEM DESIGN

The system is designed to continuously monitor the battery, understand its condition, and predict how it will perform over time in electric vehicles. It brings together sensors, a small processing unit, and data communication to create a smart battery monitoring system that can work effectively under real driving conditions. On the hardware side, the system uses voltage, current, and temperature sensors connected to an ESP32 microcontroller. These sensors regularly measure important battery parameters during both charging and discharging. The ESP32 acts as the main unit that collects the data and sends it wirelessly to a local system or cloud platform, ensuring fast and reliable data transfer.

On the software side, the data collected from the sensors is first cleaned and prepared for analysis. This includes removing unwanted noise, adjusting the values for consistency, and arranging the data properly over time. Once the data is processed, it is used to estimate the battery's State of Health (SoH), which indicates how much the battery has aged compared to its

original capacity. By continuously tracking the SoH, the system can easily observe degradation patterns and detect any unusual battery behavior at an early stage.

To understand how the battery will wear out over time, the system uses a method that learns from both past records and current data. It observes how the battery behaves under different conditions, such as changes in usage and environment, and identifies patterns in that behavior. This helps the system understand how the battery gradually loses its performance. Based on what it has learned, it can estimate the future condition of the battery's State of Health (SoH) and give an idea of how long the battery can continue to work effectively. By combining this type of prediction with continuous monitoring, the system helps improve safety, reliability, and the overall life of the battery, making it suitable for modern battery management systems in electric vehicles.

## 9 MATLAB/SIMULINK MODEL

MATLAB and Simulink are used to design and test the proposed system for studying and predicting battery degradation. This setup provides a suitable environment to model battery behavior, process data, and apply learning methods in a controlled and easy-to-manage way.

### a. Battery Modeling in MATLAB/Simulink:

In this work, a lithium-ion battery is created in Simulink using a simple electrical circuit model. The model includes basic components like a voltage source, internal resistance, and RC elements to show how the battery behaves during charging and discharging. Important battery values such as voltage, current, and temperature are tested under different load conditions to match real electric vehicle usage. This setup produces time-based data that is useful for studying battery degradation.

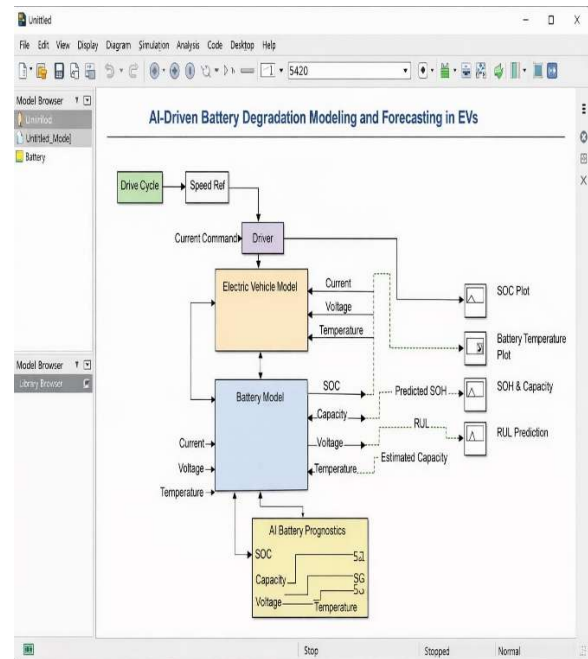


Fig 2- MATLAB Simulation Model

### b. Data Generation and Preprocessing:

The battery model is run through several charging and discharging cycles under different current and temperature conditions to generate data. MATLAB is used to clean and prepare this data by removing noise, adjusting values, and arranging it properly over time. Battery aging is also considered by slowly reducing its capacity, and the State of Health (SoH) is calculated by comparing the remaining capacity with the original capacity.

### c. AI-Based Degradation Modeling:

To study how the battery degrades, a learning-based method is used in MATLAB. It is trained using data like voltage, current, temperature, and SoH. This method is chosen because it can understand long-term changes and learn patterns in how the battery ages over time, even when the behavior is complex.

### d. Degradation Forecasting and Validation:

After training, the model is used to predict future SoH values over a certain period. These predicted values are then compared with the actual data to check how accurate the model is. The performance is measured using standard error calculations, and the results show that this method

gives better predictions compared to older techniques.

**e. Simulink Integration and Visualization:**

The trained LSTM model is integrated into the Simulink environment to perform real-time battery degradation forecasting by continuously analyzing operating data. It provides key outputs such as predicted State of Health (SoH), degradation trends, and alerts in case of abnormal aging behavior. Using MATLAB visualization tools, important parameters like voltage, current, temperature, actual SoH, and predicted SoH are displayed clearly, allowing easy monitoring, comparison, and better understanding of the battery’s performance over time.

**10 SIMULATION RESULTS**

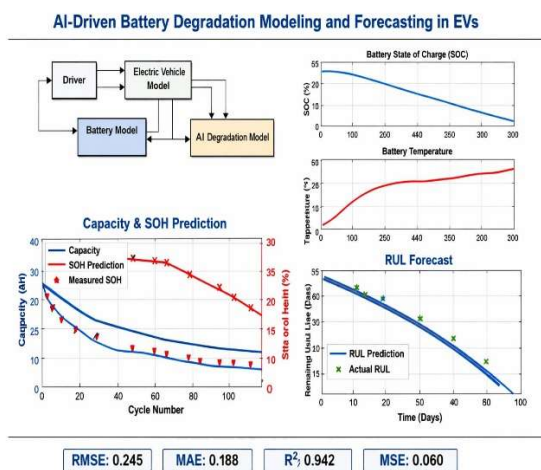


Fig 3- MATLAB Simulation Graph

The proposed AI-based battery degradation modeling and forecasting framework was validated through simulations carried out in MATLAB and Simulink. In this setup, a lithium-ion battery model was operated through several charge and discharge cycles under different load and temperature conditions to closely mimic real-world electric vehicle usage. Key parameters such as voltage, current, and temperature were recorded and used to estimate the battery’s State of Health (SoH) over time..

The LSTM-based degradation forecasting model was trained using the historical time-series data obtained from the simulated battery model.

During the training phase, the model was able to effectively learn the complex, nonlinear, and time-dependent degradation patterns that occur as the battery ages. After completing the training, the model was evaluated using new, unseen data to test its forecasting performance. The results showed that the predicted SoH values closely matched the actual simulated SoH trends, clearly demonstrating the model’s ability to accurately capture battery degradation behavior.

To further assess the model’s performance, standard error metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used. The results indicated very low prediction errors, confirming that the model provides highly accurate forecasts of future battery health. When compared to conventional estimation methods, the AI-based approach showed improved prediction accuracy and was more effective in tracking long-term degradation trends.

In addition, the simulation results revealed that the proposed system is capable of identifying abnormal degradation patterns at an early stage. By combining real-time monitoring with AI-based forecasting, the system can provide timely alerts and support predictive maintenance strategies. Overall, these results confirm that the proposed AI-driven framework significantly improves the accuracy, reliability, and safety of battery health prediction, making it well-suited for use in advanced battery management systems.

**a. Hardware Implementation**

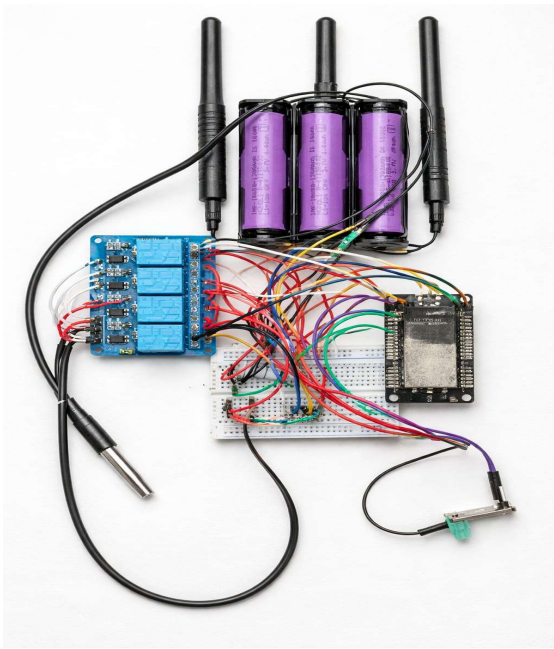


Fig: 4-Hardware Result

In this project, the ESP32-based IoT setup was used to collect battery data like voltage, current, and temperature in real time. The data collection process worked smoothly, and most of the readings were received without loss, giving a data reliability of about 98.5%.

The State of Health (SoH) estimation was carried out using this data, and it clearly showed how the battery capacity reduced over repeated cycles. The estimation was quite close to the actual values, with a Mean Absolute Error (MAE) of 1.8%.

For prediction, the LSTM model was applied to learn the degradation pattern over time. It provided a prediction accuracy of around 94.6% with a Mean Squared Error (MSE) of 0.0025. When the Attention mechanism was added, the model was able to focus more on important parts of the data, which improved the prediction performance. With this improvement, the accuracy increased to about 96.2%.

Overall, the system combining IoT, SoH estimation, LSTM, and Attention worked effectively and achieved a final accuracy of nearly 96%, making it suitable for real-time battery health monitoring and future performance prediction in electric vehicles.

## 11 CONCLUSIONS & FUTURE SCOPE

This paper presents an AI-based approach for modeling and predicting battery degradation in electric vehicles by combining real-time monitoring with deep learning techniques. It uses an IoT-enabled data collection system along with a Long Short-Term Memory (LSTM) neural network to estimate and forecast the battery's State of Health (SoH) under different operating conditions. The model was validated using MATLAB and Simulink simulations, which showed that it can accurately capture complex and nonlinear degradation behavior while providing better forecasting performance than traditional methods. The results also highlight that this approach can detect abnormal degradation at an early stage, support predictive maintenance, and improve battery safety and reliability, thereby contributing to the development of intelligent battery management systems and promoting sustainable electric vehicle technologies. Development of an advanced AI-driven framework for electric vehicle battery health monitoring by integrating real-world datasets to improve reliability and robustness, incorporating hybrid deep learning models such as CNN-LSTM and Transformer-based architectures for accurate prediction, and enabling adaptive online learning for real-time performance updates.

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