International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 02 February 2026
Page No: 588-593
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0080

AI-Driven Battery Degradation Modeling and Forecasting in EV's

Mrs. P. Saranya[1], Dr. U. Saravanakumar[2], Shanmuganathan R[3], Vasanth J[4], Vignesh R[5]
[1]Assistant Professor, Dept of ECE, Muthayammal Engineering College, Namakkal, India.
[2]Professor, Dept of ECE, Muthayammal Engineering College, Namakkal, India.
[3,4,5]UG Scholar, Dept of ECE, Muthayammal Engineering College, Namakkal, India.
Emails: *saranya12prabhu@gmail.com[1], saran.usk@gmail.com[2], shanmuganathannathan032@gmail.com[3], jkvasanth24@gmail.com[4], vigneshrajendran0918@gmail.com[5]*

Abstract
The performance, reliability, and lifespan of electric vehicle (EV) batteries are critical factors influencing the efficiency and adoption of electric mobility. Over time, batteries experience degradation due to factors such as temperature variations, charge–discharge cycles, and usage patterns. This project presents an AI-driven battery degradation modeling and forecasting system that employs advanced machine learning algorithms to predict the state of health (SOH) and remaining useful life (R-UL) of lithium-ion batteries. By integrating real-time data from sensors, including voltage, current, and temperature, the system uses predictive analytics and neural network models to accurately estimate degradation trends.
Keywords: *Artificial Intelligence (AI); Artificial Neural Networks (ANN); AI Detection Module.*

1. Introduction
Electric Vehicles (EVs) have emerged as a sustainable solution to reduce greenhouse gas emissions and dependence on fossil fuels. However, the performance and reliability of EVs largely depend on the condition of their batteries, which serve as the primary energy storage system. Over time, batteries undergo degradation due to factors such as aging, temperature fluctuations, charge–discharge cycles, and driving patterns [1]. This degradation results in reduced capacity, shorter driving range, and diminished overall efficiency. Traditional battery monitoring systems rely on electrochemical models and periodic maintenance checks, which are often time consuming and less accurate in predicting long-term Health [2]. To address these Challenges, Artificial Intelligence (AI) provides advanced data-driven approaches capable of learning complex patterns from large datasets. By leveraging machine learning and deep learning algorithms, battery degradation can be modeled and forecasted with higher precision. The proposed AI driven system aims to predict the State of Health (SOH) and Remaining Useful Life (RUL) of EV batteries by analyzing real-time data such as voltage, current, temperature, and cycle count [3]. This intelligent prediction 1 framework enables proactive maintenance, enhances battery life, ensures vehicle reliability, and contributes to the advancement of smart and sustainable transportation systems.

1.1. Objectives
The main objective of this research is to develop an AI-driven framework for accurate modelling and forecasting of battery degradation in electric vehicles (EVs). To study and analyze the degradation characteristics of lithium-ion batteries used in electric vehicles under different operating conditions. To develop an artificial intelligence–based degradation model capable of capturing nonlinear and time-dependent battery aging behavior [4]. To support predictive maintenance and improve the efficiency, reliability, and lifespan of EV battery systems through accurate degradation forecasting.

1.2. Scope of Study
This study focuses on the development and implementation of an AI-driven approach for modelling and forecasting battery degradation in electric vehicles. The scope of the work includes the analysis of lithium-ion battery degradation using data-driven techniques under practical operating conditions. The proposed framework considers key battery parameters such as voltage, current, temperature, charge–discharge cycles, and usage

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 02 February 2026
Page No: 588-593
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0080

patterns to estimate battery health indicators. The study emphasizes the application of machine learning models for predicting State of Health (SOH) and Remaining Useful Life (RUL) of EV batteries, enabling accurate and adaptive degradation forecasting [5]. The scope is limited to lithium-ion battery systems commonly used in electric vehicles and does not address alternative battery chemistries in detail.

2. Literature Review

Wang et al. conducted a detailed study on the degradation behavior of lithium-ion batteries used in energy storage and electric vehicle applications. The authors analyzed capacity fade and internal resistance growth by subjecting batteries to repeated charge–discharge cycles under controlled laboratory conditions [6]. Their work identified key degradation mechanisms such as solid electrolyte interphase (SEI) layer growth, electrode material loss, and lithium plating, which significantly affect battery performance over time. The study demonstrated that operating temperature, depth of discharge, and cycling rate play a major role in accelerating battery aging. This work laid a strong foundation for future research by highlighting the importance of accurately estimating battery health parameters such as State of Health (SOH). However, the limitations of traditional physics-based models emphasized the need for data-driven and AI-based approaches for practical degradation forecasting in electric vehicle applications.

Zhang et al. proposed a deep learning–based approach for modelling and forecasting lithium-ion battery degradation with a focus on electric vehicle applications. The study utilized recurrent neural networks (RNN) to capture the time-dependent and nonlinear characteristics of battery aging. By analyzing sequential battery data such as voltage, current, temperature, and cycle number, the model was able to learn long-term degradation trends more effectively than conventional machine learning techniques. The results showed improved accuracy in predicting State of Health (SOH) and Remaining Useful Life (RUL), particularly for long-term forecasting.

Richardson et al. focused on the real-time estimation of battery degradation by integrating artificial intelligence models into Battery Management Systems (BMS) for electric vehicle applications. The study proposed the use of neural network–based models to process real-time battery parameters such as voltage, current, temperature, and state of charge. By continuously analyzing operational data, the AI model was able to estimate State of Health (SOH) and detect early signs of degradation under dynamic driving conditions.

Zhou et al. proposed a long short-term memory (LSTM)–based deep learning model for predicting the Remaining Useful Life (RUL) of lithium-ion batteries. The model effectively captured long-term temporal dependencies in battery degradation data, resulting in improved forecasting accuracy compared to conventional machine learning methods. The study demonstrated that LSTM networks are well suited for modeling time-dependent battery aging behavior in electric vehicle applications.

3. Existing System

In the conventional approach to battery health management within electric vehicles (EVs), degradation estimation primarily relies on physics-based, empirical, or model-based techniques integrated into the Battery Management System (BMS). These traditional methods typically utilize mathematical and electrochemical models that are built on pre-defined battery characteristics and laboratory-based parameters [7]. For instance, equivalent circuit models (ECM) and electrochemical impedance spectroscopy (EIS) are commonly used to estimate the State of Health (SOH) and Remaining Useful Life (RUL) of lithium-ion batteries. While such techniques have the advantage of theoretical grounding, they require extensive calibration and complex derivations to account for variations in operational conditions such as temperature, load, and charge–discharge patterns [8]. Due to these limitations, there has been an increasing shift toward data-driven and artificial intelligence (AI)-based approaches, which aim to improve prediction accuracy and real-time applicability by learning degradation patterns directly from measured operational data. The proposed AI-driven framework in this study addresses these challenges by leveraging machine learning models to estimate battery health indicators more efficiently and reliably in EV

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 02 February 2026
Page No: 588-593
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0080

systems.

4. Proposed Methodology

The proposed methodology follows a systematic, data-driven approach for modelling and forecasting battery degradation in electric vehicles using artificial intelligence techniques (Figure 1). The overall framework consists of data acquisition, preprocessing, feature extraction, model development, training, and performance evaluation [9]. Initially, real-time battery operational data is collected through a Battery Management System (BMS). The monitored parameters include battery voltage, current, temperature, charge–discharge cycles, and usage patterns, which significantly influence battery aging behavior (Table 1). This stage includes noise filtering, normalization, and handling of missing or inconsistent sensor values. Relevant features are then extracted from the preprocessed data to represent the battery's degradation characteristics effectively. Machine learning models are developed to learn the nonlinear relationship between battery parameters and health indicators. Supervised learning techniques such as artificial neural networks and regression-based models are employed to estimate key battery health metrics, including State of Health (SOH) and Remaining Useful Life (RUL). The models are trained using historical battery datasets and validated using unseen data to ensure generalization [10].

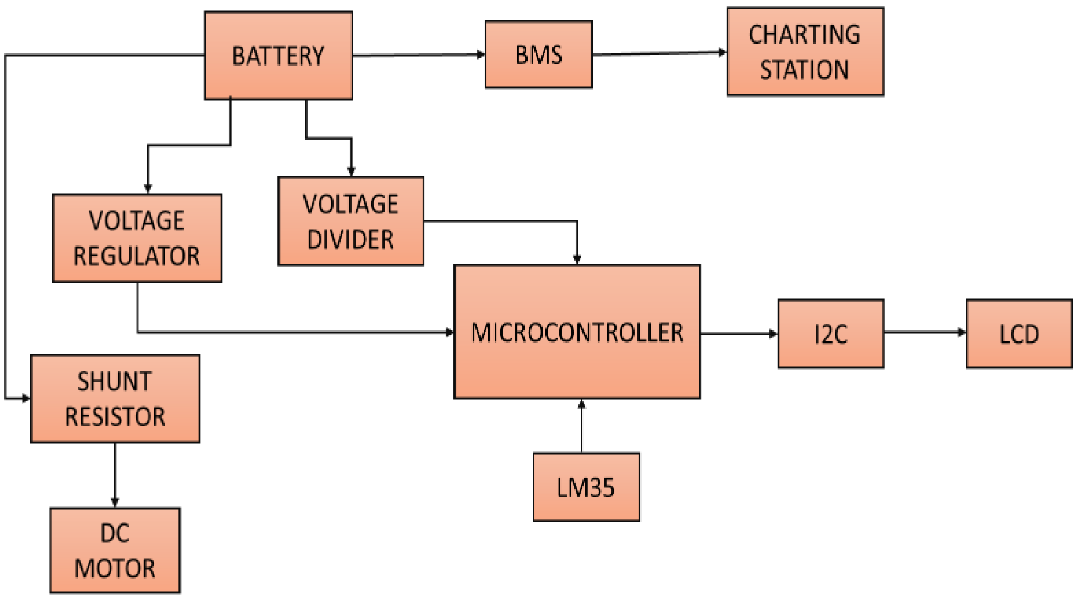

Figure 1 Proposed System

Table 1 Predicted Battery Degradation Values

Cycle Number	VOLTAGE (v)	Temperature	SOH
100	3.95	12	96.2%
300	3.90	44	92.8%
500	3.85	10	88.6%
700	3.80	66	83.4%
900	3.75	12	77.9%
1100	3.70	44	71.5%

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 02 February 2026
Page No: 588-593
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0080

5. Results and Discussion

5.1. Results

The performance of the proposed AI-driven battery degradation modeling and forecasting system was evaluated using battery operational data collected under varying conditions. The model analyzed key parameters such as voltage, current, temperature, and charge–discharge cycles to estimate battery health indicators. The results show that the proposed AI model effectively captures the degradation behavior of lithium-ion batteries. A gradual decrease in the State of Health (SOH) was observed as the number of charge–discharge cycles increased, indicating normal aging characteristics. At lower cycle counts, the battery maintained a higher SOH, while prolonged usage resulted in accelerated degradation due to thermal and electrical stress (Figures 2 and 3).

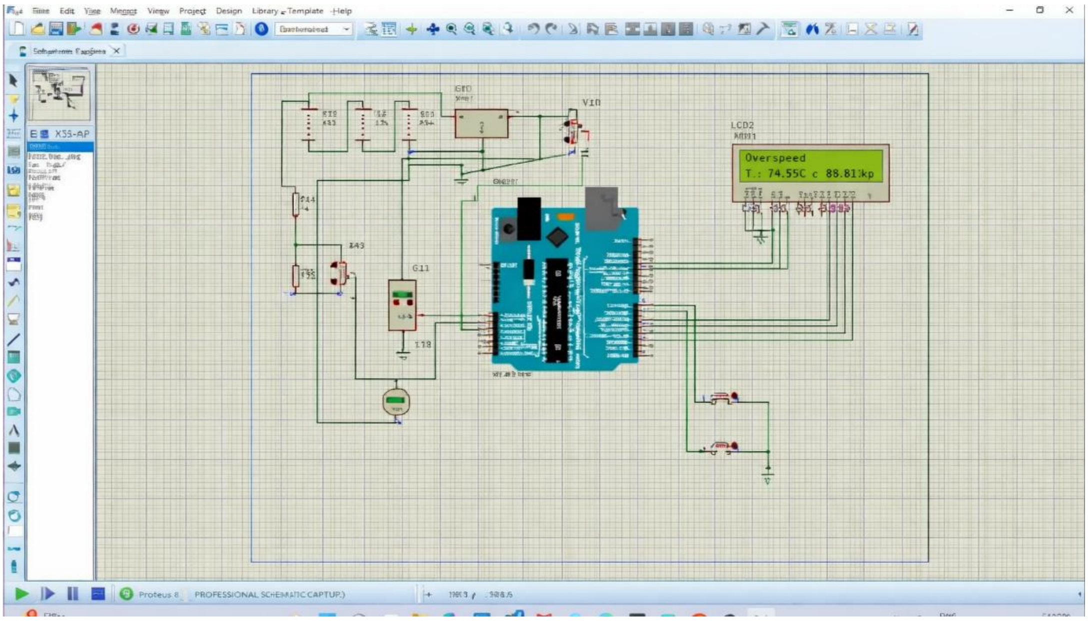

Figure 2 Detect the Over-Speed by AI

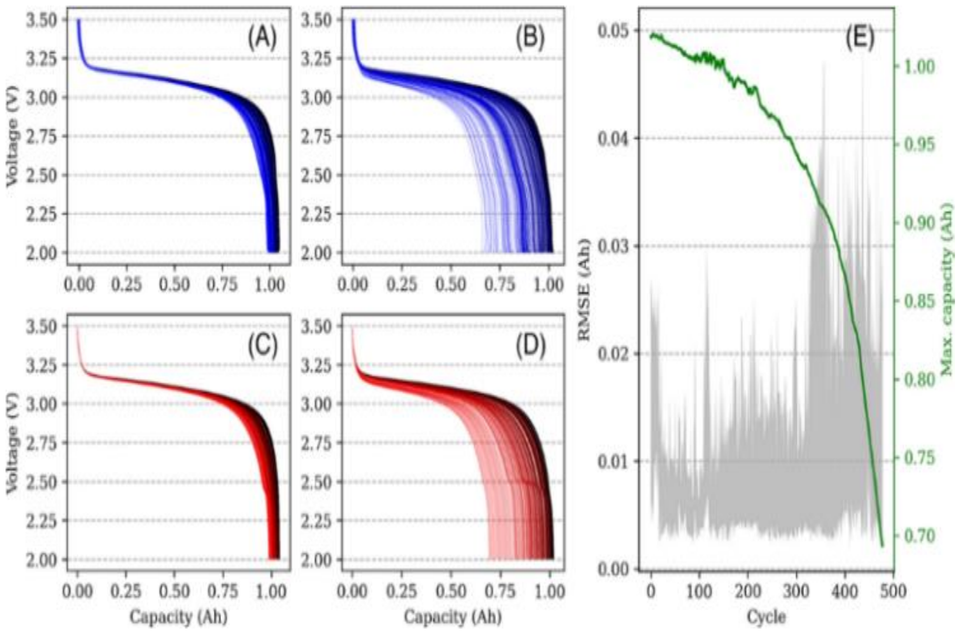

Figure 3 Battery Voltage Variation Over Charge–Discharge Cycles

IRJAEH

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 02 February 2026
Page No: 588-593
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0080

5.2. Discussion

The results obtained from the AI-driven battery degradation modeling and forecasting system demonstrate the effectiveness of artificial intelligence techniques in predicting battery health parameters for electric vehicle applications. The observed decline in State of Health (SOH) with increasing charge–discharge cycles aligns with the known aging behavior of lithium-ion batteries, confirming the reliability of the proposed approach. Compared to traditional physics-based and empirical models, the proposed AI-based method offers improved adaptability to varying operating conditions such as temperature fluctuations and dynamic load variations. The accurate prediction of Remaining Useful Life (RUL) enables early detection of battery end-of-life conditions, supporting predictive maintenance and reducing the risk of sudden battery failure. However, the performance of the model is influenced by the quality and quantity of training data, and extreme operating conditions may introduce prediction uncertainty. Overall, the discussion highlights that AI-driven degradation forecasting provides a practical and scalable solution for enhancing battery reliability, safety, and lifespan in electric vehicles, making it suitable for integration into modern Battery Management Systems.

Conclusion and Future Works

This study presented an AI-driven framework for modeling and forecasting battery degradation in electric vehicles. By utilizing real-time battery parameters such as voltage, current, temperature, and charge–discharge cycles, the proposed approach effectively estimated critical battery health indicators, including State of Health (SOH) and Remaining Useful Life (RUL). The results demonstrated that artificial intelligence and machine learning techniques are capable of capturing the nonlinear and time-dependent behavior of lithium-ion battery degradation more accurately than traditional physics-based and empirical models. The AI-based predictions closely followed expected degradation trends, enabling early detection of aging effects and supporting predictive maintenance strategies. The proposed system improves battery reliability, safety, and lifespan by providing accurate degradation forecasting under varying operating conditions. Its adaptability makes it suitable for integration into modern Battery Management Systems, where real-time health monitoring and decision-making are essential. Compared to conventional approaches, the AI-driven method reduces the dependency on complex electrochemical modeling and extensive manual calibration, making it more practical for real-world electric vehicle applications. Future work will focus on enhancing prediction accuracy by incorporating deep learning architectures such as LSTM, GRU, and transformer-based models to better capture long-term degradation patterns. The integration of cloud–edge computing frameworks can enable large-scale real-time data processing and continuous model updates. Furthermore, future studies may explore vehicle-to-grid (V2G) interactions, adaptive charging strategies, and transfer learning techniques to improve generalization across different battery chemistries and EV platforms.

References

[1]. F. Wang et al., “Physics-informed neural networks for lithium-ion battery degradation modeling and prognosis,” Nature Communications, vol. 15, no. 1, 2024.

[2]. Y. Zhou et al., “Remaining useful life prediction of lithium-ion batteries using deep learning techniques,” Journal of Energy Storage, vol. 50, 2022.

[3]. C. Zhang, Z. Wei, and H. He, “Deep learning-based state of health estimation for lithium-ion batteries,” Applied Energy, vol. 275, 2020.

[4]. R. R. Richardson, M. A. Osborne, and D. A. Howey, “Battery health prediction under real-world operating conditions using machine learning,” Journal of Power Sources, vol. 479, 2021.

[5]. M. Berecibar et al., “Critical review of state of health estimation methods of Li-ion batteries,” Renewable and Sustainable Energy Reviews, vol. 56, pp. 572–587, 2016.

[6]. Y. Liu, H. Zhang, and R. Xiong, “State of health estimation of lithium-ion batteries using random forest under noisy

conditions," Journal of Energy Storage, vol. 55, pp. 105–114, 2022.

[7]. X. Chen, Z. Li, and Y. Wang, "Battery degradation feature extraction using convolutional neural networks for electric vehicle applications," Applied Energy, vol. 341, pp. 119–129, 2023.

[8]. J. Kim, S. Park, and K. Lee, "Reinforcement learning–based adaptive battery management system for electric vehicles," IEEE Transactions on Transportation Electrification, vol. 9, no. 2, pp. 1456–1467, 2023.

[9]. Q. Sun, Y. Zhou, and H. He, "Transformer-based deep learning model for long-term lithium-ion battery degradation forecasting," Energy, vol. 286, pp. 127–138, 2024.

[10]. Y. Zhao, M. Li, and D. Chen, "Cloud–edge collaborative AI framework for real-time battery health monitoring in electric vehicle fleets," IEEE Access, vol. 12, pp. 45210–45221, 2024.