ISSN 2277-2685
IJESR/Jan-Mar. 2026/ Vol-16/Issue-1/627-633
Battula Ramana Trivedi *et. al.,* / International Journal of Engineering & Science Research

Full Length Article

Explainable Data Driven Digital-Twins For Predicting Battery Status In Electric Vehicles Using Machine Learning

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Accepted 29-0-2026

Abstract

Electric Vehicles (EVs) are emerging as a cornerstone of sustainable transportation, where battery systems play a critical role in determining performance, safety, and operational lifespan. Conventional Battery Management Systems (BMS) primarily focus on real-time monitoring of parameters such as voltage, current, and temperature, offering limited predictive capability and minimal interpretability. This study proposes an explainable, data-driven digital twin framework for predicting EV battery behavior using machine learning techniques. The framework constructs a virtual representation of the battery system that dynamically simulates performance based on input variables including speed, State of Charge (SOC), State of Health (SOH), temperature, terrain, and auxiliary loads. Machine learning models are employed to estimate key performance metrics such as driving range, energy consumption, and battery degradation trends. To enhance transparency, Explainable Artificial Intelligence (XAI) techniques are integrated, enabling interpretation of model predictions and identification of influential parameters. The system is implemented using a FastAPI-based backend for simulation and prediction, coupled with a Next.js interactive dashboard for visualization. The proposed approach facilitates predictive analytics, scenario simulation, and informed decision-making, thereby extending traditional BMS capabilities toward a more intelligent and user-centric EV battery management solution.

Keywords*—Electric Vehicles, Digital Twin, Battery Management System, Machine Learning, Explainable AI, Battery Prediction, Smart Mobility.*

Introduction

The rapid growth of electric vehicles has significantly influenced the evolution of modern transportation by offering a cleaner and more sustainable alternative to conventional internal combustion engine systems. Increasing environmental concerns, depletion of fossil fuels, and global efforts to reduce carbon emissions have accelerated the adoption of EV technology. Despite these advancements, the reliability and efficiency of EVs are strongly dependent on the performance of their battery systems, which remain a major technical and economic challenge.

The battery pack is the most critical component of an electric vehicle, directly impacting driving range, charging efficiency, durability, and overall user experience. Any inconsistency in battery performance can lead to reduced efficiency, increased operational costs, and range anxiety among users. Therefore, accurate monitoring and prediction of battery behavior are essential for improving reliability and user confidence in EV systems.Traditional Battery Management Systems (BMS) are designed to ensure operational safety by continuously monitoring parameters such as voltage, current, temperature, and charge levels. These systems implement protective mechanisms to prevent conditions such as overcharging, deep discharge, and thermal instability. Although modern BMS can estimate parameters like State of Charge and State of Health, their functionality is largely reactive, focusing on real-time status rather than predictive analysis. Additionally, these systems operate with limited transparency, offering minimal insights into the underlying causes of performance variations.Battery behavior in EVs is influenced by multiple dynamic factors, including driving patterns, environmental conditions, terrain variations, and battery aging. These nonlinear relationships are difficult to capture using traditional rule-based or purely physics-driven models. As a result, there is a growing need for intelligent, data-driven approaches capable of learning complex patterns and predicting future battery performance under varying conditions.Digital Twin technology provides an effective solution by creating a virtual representation of the physical battery system. This virtual model continuously reflects real or simulated behavior, enabling predictive analysis and performance optimization without requiring physical testing. When combined with machine learning techniques, digital twins become adaptive systems capable of learning from data and generalizing across diverse operational scenarios.Machine learning models offer the advantage of capturing intricate relationships between input variables and battery performance indicators. These models can predict critical outcomes such as energy consumption, driving range, and battery degradation trends with improved accuracy. However, a significant limitation of machine learning approaches is their lack of interpretability, as many models function as black boxes, providing outputs without clear explanations.

Literature Survey

Recent advancements in EV battery management have increasingly focused on the integration of digital twin technology and machine learning approaches. Digital twins have been widely adopted for simulating battery behavior and enabling predictive maintenance, offering significant improvements in efficiency and lifecycle management. Machine learning models, including neural networks and regression-based techniques, have demonstrated strong capabilities in predicting battery parameters such as SOC, SOH, and remaining useful life.

In addition, the application of artificial intelligence in battery systems has enhanced safety and performance by enabling intelligent monitoring and decision-making. Recent research has also emphasized the importance of explainability in AI-driven systems. Techniques such as SHAP and LIME have been utilized to provide insights into model predictions, improving transparency and trust.Hybrid approaches combining physics-based modeling with data-driven techniques have further improved prediction accuracy by leveraging both theoretical knowledge and empirical data. However, most existing systems focus on isolated aspects such as prediction or simulation, with limited integration of visualization and user interaction. This highlights the need for a comprehensive framework that combines prediction, explainability, and interactive simulation within a unified platform.

DIGITAL TWIN–BASED EV BATTERY SYSTEM

Electric vehicles are playing a transformative role in modern transportation due to their potential to reduce environmental impact and improve energy efficiency. The battery system serves as the core component of an EV, directly influencing its driving range, operational reliability, and overall performance. Consequently, accurate analysis and prediction of battery behavior are essential for enhancing efficiency and strengthening user confidence.Conventional battery management systems are primarily designed to monitor real-time parameters such as voltage, current, and temperature to ensure safe operation. Although these systems are effective in maintaining battery safety, they provide limited capabilities for predicting future performance or analyzing battery behavior under varying operating conditions. This limitation restricts their usefulness in advanced decision-making and performance optimization.To address these challenges, the proposed system introduces a digital twin-based framework integrated with machine learning techniques. The system creates a virtual representation of the EV battery that dynamically simulates its behavior based on user-defined inputs. This approach enables predictive analysis, performance evaluation, and scenario-based simulation without requiring physical testing, thereby enhancing understanding and optimization of battery performance.

System Architecture and Block Diagram

The proposed system is designed using a client–server architecture that separates the user interface from computational processing. This modular design improves scalability, flexibility, and system maintainability. The architecture consists of a frontend interface, a backend processing layer, and integrated prediction and simulation modules.The frontend, developed using Next.js, provides an interactive dashboard where users can input parameters such as vehicle speed, State of Charge (SOC), temperature, and battery health. These inputs are transmitted to the backend through API requests. The backend, implemented using FastAPI, handles data processing, machine learning predictions, and digital twin simulation.Within the backend, the input data undergoes validation and preprocessing before being passed to the prediction module. The machine learning model estimates key battery performance parameters such as driving range and temperature behavior. These predicted outputs are then processed by the digital twin simulation module, which models the battery’s response under the specified operating conditions.The results generated by the backend are returned to the frontend, where they are visualized using charts, graphs, and performance indicators. This architecture ensures efficient data flow and enables real-time interaction between the user and the system.The system comprises several functional components, each contributing to the overall workflow. The user input module collects operational parameters from the dashboard. The data preprocessing module validates and formats the inputs to ensure consistency. The machine learning module generates predictions based on learned relationships between inputs and outputs. The digital twin module simulates battery behavior using these predictions. The backend processing layer coordinates all computations, while the visualization layer presents results in an intuitive format.

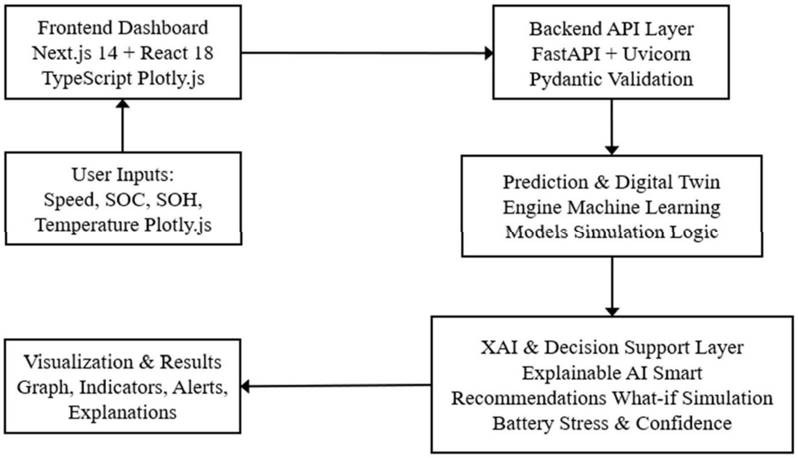


Fig 1; Block Diagram of the Proposed EV Battery Digital Twin System

Machine Learning Prediction Model

The machine learning prediction model forms the core of the proposed system by enabling data-driven estimation of battery performance parameters. The model accepts input features such as vehicle speed, State of Charge, State of Health, ambient temperature, and load conditions. Based on these inputs, it predicts outputs including driving range, temperature variation, and battery health trends.Unlike traditional rule-based methods, the model learns relationships directly from data. A lightweight regression-based approach is employed to ensure efficient computation and real-time responsiveness. The model is trained using simulated and research-based datasets that capture typical EV battery behavior across different operating conditions.During training, the model identifies patterns and dependencies among variables. For instance, higher vehicle speed typically increases energy consumption, leading to reduced driving range, while temperature variations influence battery efficiency and degradation. By learning such relationships, the model can generate realistic predictions for unseen input conditions.The prediction process involves feeding preprocessed input data into the trained model, which computes outputs based on learned patterns. The model is integrated into the backend and operates in real time, enabling instant feedback when users modify input parameters. This capability ensures a smooth and interactive experience while maintaining computational efficiency.

SYSTEM ANALYSIS AND DESIGN OF EV BATTERY DIGITAL TWIN

Existing System

The conventional approach to battery monitoring in electric vehicles is based on the Battery Management System (BMS), which ensures safe and reliable operation of the battery pack. The BMS continuously monitors key parameters such as voltage, current, temperature, and State of Charge, while implementing protective mechanisms including overcharge prevention, deep discharge protection, thermal regulation, and cell balancing.Advanced BMS implementations are capable of estimating parameters such as State of Charge and, in some cases, State of Health using model-based techniques like equivalent circuit models and filtering methods. However, these systems are predominantly designed for real-time monitoring and safety assurance rather than predictive analysis. They do not effectively account for dynamic factors such as driving behavior, terrain conditions, environmental temperature, or auxiliary loads, which significantly influence battery performance.Another key limitation of traditional BMS is the lack of interpretability. Although the system provides numerical outputs and warning signals, it does not explain the underlying reasons for performance variations. For instance, a reduction in driving range is not accompanied by insights into whether the cause is increased speed, environmental factors, or battery degradation. Furthermore, existing systems do not support scenario-based analysis or decision-making assistance, limiting their usability in optimizing battery performance.

Proposed System

The proposed system introduces an explainable, data-driven digital twin framework that enhances battery performance prediction and analysis. Unlike traditional systems that rely solely on real-time monitoring, this approach creates a virtual representation of the battery system capable of simulating behavior under varying operating conditions. The digital twin is driven by machine learning models that learn complex relationships between input parameters and battery performance indicators.Users interact with the system through a web-based dashboard developed using Next.js, where they can input parameters such as vehicle speed, State of Charge, State of Health, temperature, and auxiliary load. These inputs are transmitted to a backend system implemented using FastAPI, where preprocessing, prediction, and simulation processes are carried out.The machine learning component generates predictions for key performance metrics such as driving range, thermal behavior, and battery health trends. In addition, Explainable AI techniques are integrated to provide insights into how each input parameter contributes to the prediction outcome, thereby improving transparency and user trust. The system also supports what-if analysis, enabling users to simulate alternative scenarios and evaluate the impact of different operating conditions without physical experimentation.

Estimated Driving Range

Estimated driving range is a critical performance metric that represents the distance an electric vehicle can travel under specific operating conditions. In the proposed system, this parameter is predicted using a machine learning model that considers multiple inputs, including vehicle speed, State of Charge, battery capacity, and environmental conditions.

The model captures the relationship between energy consumption and operating parameters, allowing it to generate realistic range estimates. For example, higher vehicle speeds typically result in increased aerodynamic resistance and energy consumption, leading to a reduction in range. The predicted range is presented through numerical values and graphical visualizations, enabling users to easily interpret the results and understand the impact of different driving conditions.

Battery 3D View

The battery 3D visualization module provides an interactive representation of the internal structure of the battery pack. It models the battery as a collection of individual cells arranged in a three-dimensional layout, with each cell dynamically reflecting its operational status.

Cells are categorized based on their condition, such as normal, stressed, or critical, using parameters like temperature and load. The color-coded visualization enhances clarity and allows users to quickly identify abnormal conditions. This feature strengthens the digital twin concept by providing an intuitive and detailed view of internal battery behavior, improving overall system understanding.

Implementation Details

The implementation of the proposed EV battery digital twin system is carried out using a combination of modern web technologies and machine learning frameworks to ensure efficiency, scalability, and real-time interaction. The backend of the system is developed using FastAPI, which provides a lightweight and high-performance framework for handling API requests, managing data processing, and executing prediction logic. Machine learning models are implemented in Python using libraries such as NumPy, Pandas, and Scikit-learn, which support efficient numerical computation, data manipulation, and model development.The frontend is developed using Next.js, enabling the creation of a responsive and dynamic user interface that allows seamless interaction between the user and the system. For visualization purposes, Plotly is integrated into the frontend to generate interactive graphs and charts, helping users explore prediction results in an intuitive manner. Additionally, the Battery 3D View is implemented as part of the frontend dashboard using interactive graphical components. In this module, individual battery cells are represented as visual elements arranged in a structured layout, and their states are dynamically updated based on system outputs such as temperature and stress levels. The interactive design allows users to inspect individual cells and understand internal battery conditions more effectively.

Working Methodology

The working methodology of the proposed EV battery digital twin system follows a structured and sequential process that transforms user inputs into meaningful predictions and visual insights. The process begins with user interaction through a web-based dashboard, where parameters such as vehicle speed, State of Charge (SOC), State of Health (SOH), ambient temperature, and load conditions are provided. These inputs represent the operational state of the electric vehicle and form the basis for all subsequent computations.Once the inputs are submitted, they are transmitted to the backend server through API requests. In the backend, the data undergoes preprocessing, where it is validated and formatted to ensure accuracy and consistency. This step ensures that input values fall within acceptable ranges and eliminates inconsistencies that could negatively impact prediction performance. The processed data is then passed to the machine learning prediction module, which analyzes the relationship between input parameters and battery performance using trained models. Based on this analysis, the system generates predictions for key outputs such as driving range, temperature variation, and State of Health trends.Following prediction, the outputs are processed by the digital twin simulation module, which acts as a virtual representation of the EV battery. This module simulates battery behavior under the given operating conditions and ensures that predicted values follow realistic performance characteristics. The system further enhances understanding by generating a three-dimensional visualization of the battery pack, where individual cells are represented using color-coded indicators based on their condition.

Results

The system operation begins when the user provides input parameters such as vehicle speed, State of Charge, State of Health, battery capacity, and ambient temperature through the web-based dashboard. These inputs are transmitted to the backend, where they are processed using machine learning models to generate predictions. The predicted values are further refined through the digital twin simulation module, which replicates battery behavior under the specified conditions. The system computes outputs such as estimated driving range, temperature trends, and SOH projections, which are then displayed on the dashboard in real time.The dashboard offers multiple visualization components, including range indicators, comparative graphs, temperature trend charts, and SOH analysis plots. These visual elements enable users to clearly understand the influence of different input parameters on battery performance. The results demonstrate consistent and realistic behavior, reflecting known EV battery characteristics. For instance, the predicted driving range decreases as vehicle speed increases, indicating higher energy consumption. Similarly, the temperature prediction shows a gradual increase during operation, aligning with expected thermal behavior. The SOH trend remains relatively stable under normal conditions, with gradual degradation over time, which reflects typical lithium-ion battery performance.The estimated driving range is presented both numerically and graphically, showing a clear relationship between speed and energy consumption. Comparative scenario analysis further highlights that lower speeds result in improved range, while higher speeds significantly reduce it. The battery temperature prediction module generates a time-based trend, indicating a gradual increase in temperature under load while remaining within safe limits. The SOH prediction provides a long-term view of battery health, illustrating gradual degradation over time.The range breakdown table offers a detailed representation of energy usage across different conditions, enabling users to understand how individual parameters contribute to the overall performance. The explainable AI panel identifies the contribution of each input parameter, enhancing interpretability. The recommendation system suggests possible actions for improving performance, while stress analysis categorizes operating conditions into different levels. Prediction confidence values provide an indication of reliability, helping users assess the trustworthiness of the outputs. The battery cell visualization presents a detailed and intuitive view of internal battery conditions.

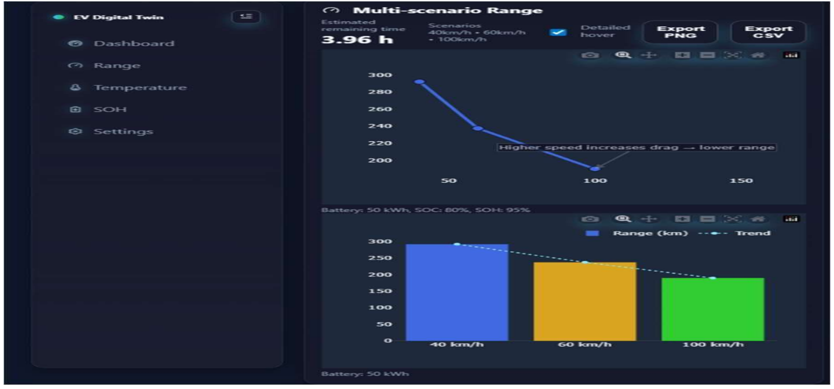
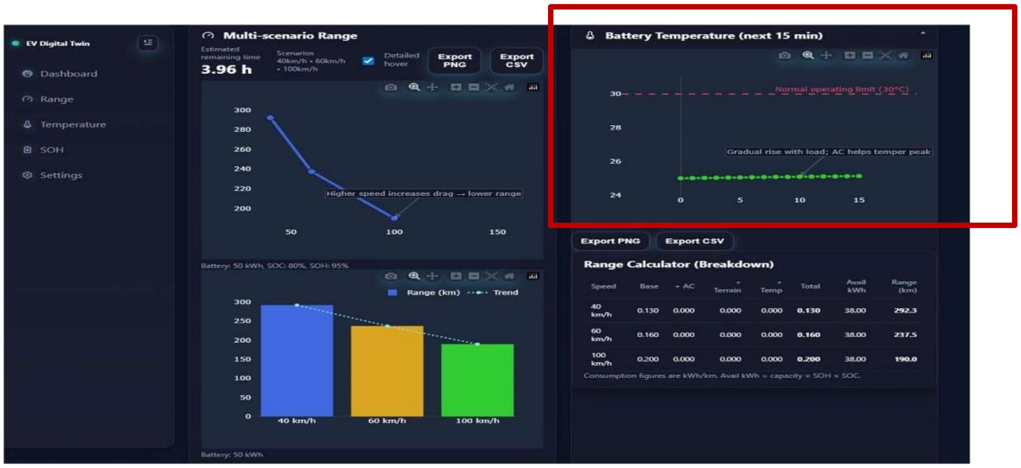


Fig 2 : Multi Range Scenario Graphs



Range Calculator (Breakdown)

Speed	Base	+ AC	+ Terrain	+ Temp	Total	Avail kWh	Range (km)
40 km/h	0.130	0.000	0.000	0.000	**0.130**	38.00	**292.3**
60 km/h	0.160	0.000	0.000	0.000	**0.160**	38.00	**237.5**
100 km/h	0.200	0.000	0.000	0.000	**0.200**	38.00	**190.0**

Consumption figures are kWh/km. Avail kWh = capacity × SOH × SOC.

Fig 3; Battery temperature (next 15min)

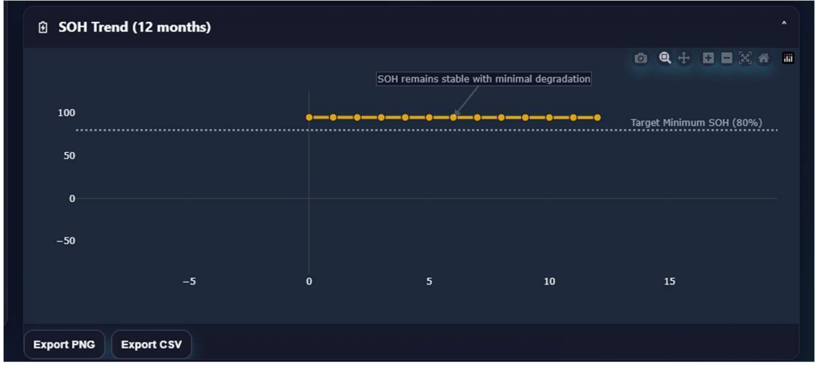


Fig 4 State of Health View for (12 months)

Battery conditions are optimal for efficient operation.

Fig 5; Battery Stress and Prediction Confidence

Click a cell to view details.

Fig 6;Battery Cell 3D View

Conclusion

This project presented the design and implementation of an explainable, data-driven digital twin framework for EV battery status prediction using machine learning. The Phase-I system successfully demonstrates how battery performance parameters such as driving range, temperature variation, and State of Health can be predicted using a software-based approach without relying on real-time vehicle data.The integration of digital twin technology with machine learning enables the system to simulate battery behavior under different operating conditions, providing predictive insights that extend beyond traditional monitoring systems. The interactive dashboard developed using modern web technologies allows users to visualize results effectively, improving understanding of battery performance and enabling informed decision-making.The system is further enhanced with advanced features such as explainable AI, smart recommendations, scenario analysis, battery stress indicators, prediction confidence estimation, and 3D battery visualization. These features improve transparency, usability, and analytical capabilities, making the system more comprehensive and user-friendly.

Future Scope

The proposed system can be significantly enhanced by incorporating real-time telemetry data from electric vehicles, which would improve prediction accuracy and enable practical deployment. The integration of advanced machine learning techniques such as deep learning and time-series analysis can further enhance the system's ability to model complex battery behavior.Future development may include cloud-based deployment for large-scale data processing and remote monitoring of multiple vehicles. Integration with IoT devices can enable continuous data collection and real-time updates of the digital twin model, making the system more dynamic and adaptive.The decision-support capabilities can be improved by incorporating automated optimization algorithms and intelligent recommendation systems that adapt to user behavior. Advanced explainable AI techniques can be introduced to provide deeper insights into model predictions and improve user trust.

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