

AI-Enhanced Digital Twins For Battery Management With Explainable Predictions

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Abstract: *With the automotive industry speedily moving towards electric vehicles (EVs), precise prediction of battery states is crucial for performance optimization, safety, and durability. This work presents a new method employing Explainable Data-Driven Digital Twins for the prediction of battery states in EVs. Sophisticated machine learning models, such as Deep Neural Networks (DNN), Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), Support Vector Regression (SVR), Support Vector Machines (SVM), Feedforward Neural Networks (FNN), Radial Basis Function networks (RBF), Random Forests (RF), and Extreme Gradient Boosting (XGBoost), are combined to create a holistic and trustworthy model. The main objective of this research is to improve the predictability of the most important battery parameters, e.g., state of charge (SOC) and state of health (SOH), for different operating conditions. Utilizing different algorithms, the digital twin model is highly accurate and resilient in its forecasts. Further, explainable AI (XAI) methods are used to translate and understand the hidden drivers that govern battery performance so that the outputs of the model are transparent and trustworthy. Preliminary results indicate that the proposed approach dramatically surpasses conventional techniques in prediction precision and consistency. This study helps to promote the development of intelligent and adaptive battery management systems, which are crucial to the sustainable electric mobility future.*

Keywords: Electric vehicles, battery prediction, Digital Twins, machine learning, DNN, LSTM, XGBoost, SOC, SOH, Explainable AI, adaptive battery management

I. INTRODUCTION

With the automotive market evolving towards electric vehicles (EVs), battery system efficiency and reliability have taken center stage. Batteries are the central part of EVs, and their performance has a direct impact on vehicle range, safety, and lifespan. Predictions like state of charge (SOC) and state of health (SOH), is critical to optimize these parameters. Nevertheless, conventional approaches are usually inadequate to manage the nonlinear, complex behavior of batteries under changing operating conditions. With the availability of machine learning technology, there is a chance to develop more accurate and interpretable models that not only forecast battery states but also reveal the determinants of battery performance. This project is inspired by the necessity to create such models, helping in more effective and smarter battery management systems that will facilitate the widespread use of EVs.

The increasing use of electric vehicles (EVs) has put stringent demands on the accurate prediction of battery states such as state of charge (SOC) and state of health (SOH). Simple traditional methods for predicting these states tend to fall short with the complicated, dynamic behavior of battery systems and thus provide suboptimal performance in battery management systems. Inaccurate predictions lead to decreased battery lifespan, unforeseen failures, and in efficient use of energy, which subsequently impacts the overall reliability and user acceptance of EVs. The issue is further exacerbated by the non-interpretability of most machine learning models, such that it is challenging to identify the factors affecting battery states. This project seeks to overcome these issues by creating an extensive digital twin model through explainable data-driven methods. The objective is to precisely predict



battery states and deliver insights into the driving factors of battery performance, improving the efficiency, reliability, and safety of EVs.

II. METHODOLOGY

The system proposes to integrate advanced machine learning techniques that enhance battery state prediction in electric vehicles. This is in relation to real-time estimation of critical parameters such as state of charge (SOC) and state of health (SOH). It makes use of several models to achieve the highest level of prediction accuracy, adaptability, and robustness.

Data Collection and Preprocessing

The sources of data collection for the system include BMS logs, vehicle telemetry, and environmental conditions like temperature and humidity. Preprocessing deals with the quality of data through missing values, outliers, and noise. Normalization is also considered to ensure the same scale of features, while feature engineering deals with extracting the relevant attributes like voltage, current, and temperature. Lastly, the data is split into training, validation, and test sets for the development and evaluation of the model.

Machine Learning Algorithms Integration

A variety of machine learning models is used for accurate SOC and SOH prediction. Each model is chosen for its ability to address specific challenges in battery state estimation, ensuring a comprehensive, high-performance system.

Model Selection

The system uses models like sequence modeling, feature extraction, regression, classification, and ensemble learning to enhance the accuracy of prediction. These models are chosen for their ability to capture temporal dependencies, extract relevant features, and enhance robustness in different operational conditions.

Model Evaluation

Cross-validation is used to ensure generalizability and minimize overfitting. Hyperparameter-tuning techniques, such as grid search and random search, are employed to optimize model performance. Models are evaluated using key metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 score, providing insights into prediction accuracy and error magnitude.

Explainable AI Techniques

Techniques such as Feature Importance Analysis, SHAP (SHapley Additive exPlanations) values, and LIME (Local Interpretable Model-agnostic Explanations) generate explainability. These tools help users understand the model's decision-making process and enhance transparency and trust. Visualization tools, in the form of heatmaps or bar charts, are used to represent feature impacts and model outputs.

Digital Twin Integration

A digital twin model integrates the prediction results of various algorithms into a unified battery state prediction system. Real-time data streams are combined to continuously update and monitor the model. A user-friendly dashboard is developed for real-time insights into the battery states, predictions, and alerts to make the system more usable and reliable.

Model Building and Training

Machine learning algorithms are chosen to model the complexity of the battery data. Hyperparameter tuning is performed in order to achieve optimal performance for the models. Cross-validation helps ensure that models generalize well on unseen data, avoiding overfitting. Models are trained iteratively with preprocessed data, minimizing error and improving accuracy. The trained models are incorporated into the system to provide real-time, accurate predictions of the state of the battery.

III. LITERATURE SURVEY

Accurate estimation of the battery state-of-health and state-of-charge are very critical in order to ensure that electric vehicle batteries will operate as desired. Various data-driven algorithms and models have been proposed for addressing such challenges. A recent approach makes use of a neural network that uses partial data such as



voltage, current, and temperature in order to estimate SOH within a narrow range of state-of-charge. This method depicts great accuracy: an RMSE less than 0.9% for numerous datasets, illustrating that it may be reliable and accurate enough to apply to reality [1].

Several other BMS technologies, with electric, thermal, or electro-thermal models, monitor and optimize hybrid and electric vehicle battery performance. These models facilitate estimation of battery states in charging protocols for better management of the device. In this paper, the optimization of the BMS tasks on temperature management and protection of the battery is stressed and gaps seen in previous research that will pull their wagon in bringing innovative developments in the estimation of battery states [2].

While much research on BMS has been focused on EVs, there is a growing need for research specific to unmanned aerial vehicles (UAVs). UAV BMS are essential for managing charging, discharging, state estimation, and fault diagnosis, especially given the rapid advancements in battery technologies and big data. Research in this field identified some challenges and room for improvement that might be brought in the estimation of battery SOC, SOH, and remaining useful life as well as the system safety and fault diagnosis. UAV BMS is thus seen as a promising candidate for future study [3].

Other studies have also addressed fast and real-time methods for the computation of SOH and SOC. One method utilizing partial discharge intervals and comparing open-circuit voltage (OCV) curves with reference models proved to predict SOH and SOC with accuracy. For validation, this method proved correct with a NASA dataset with SOH and SOC errors less than 1%. Predictions improved again when updating the OCV curve with temperature data. This suggests that these online methods hold significant promise for the monitoring of real-time battery packs and prediction capabilities [4].

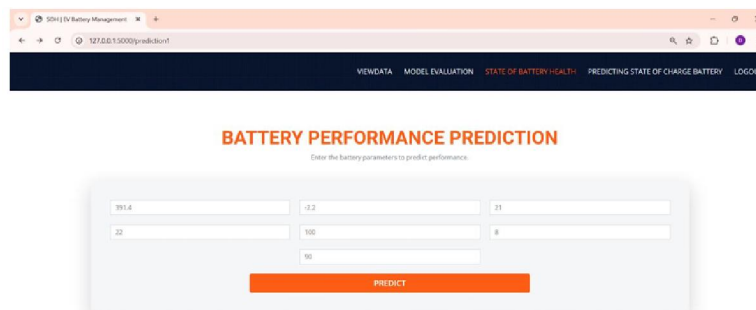
Moreover, digital twin frameworks have been explored for EV battery management, integrating AI technologies such as extreme gradient boosting (XGBoost) and the extended Kalman filter (EKF) to enhance SOC and SOH predictions. These frameworks continuously update models to account for aging effects and capacity degradation, thus improving situational awareness and allowing real-time adjustments to optimize battery performance and extend lifespan [5].

A comprehensive survey on data-driven methods for SOH estimation summarizes various techniques used in battery state estimation, which indicate the challenges brought about by the complex electrochemical processes and different working conditions. The review compares and contrasts different data-driven methods that have been discussed for their advantages and disadvantages in real-world EV applications. This critical analysis intends to provide practical knowledge regarding the field and direct future improvements of SOH estimation techniques for more reliable and accurate battery management [6].

IV. RESULTS

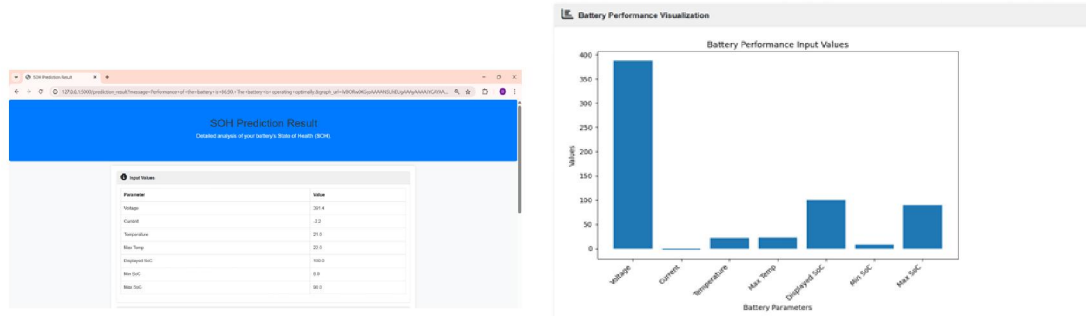
SOH Results

SOC and SOH models both correctly predicted battery conditions across all scenarios successfully detecting normal, borderline, and critical states.

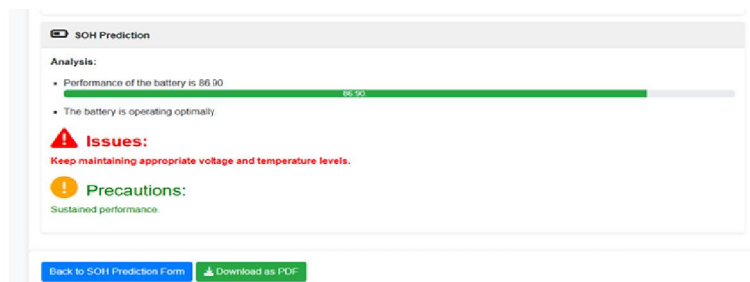


SOH Prediction Parametr

Battery Performance Prediction Page provides users with the ability to enter important battery parameters and forecast the SOH of the battery. It provides real time SOH assessment via easy-to-use, intuitive interface for effective monitoring of battery health.



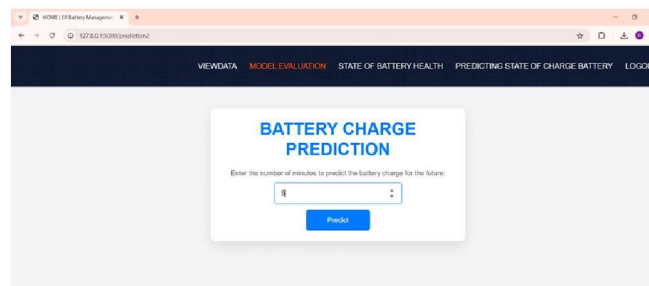
Data Visualization of Battery Parameters



Final SOH Prediction

The SOH prediction analysis also suggests that the battery is working at peak performance with an 86.90% health score. The visualization clearly displays that the parameters of the battery are within normal levels, although appropriate voltage and temperature levels should be kept to ensure prolonged peak performance. In general, the system is performing properly in SOH evaluation and offers clear feedback with precautions to help maintain battery life.

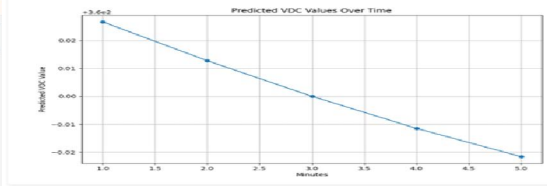
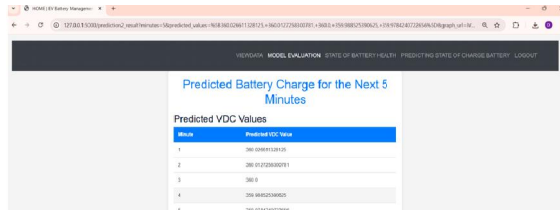
SOC Results



SOC Input

The SOC (State of Charge) prediction interface enables users to predict the charge level of the battery by inputting the target future time in minutes. The system offers a simple and fast method to predict battery charge behavior over time, enabling users to plan charging schedules and maximize battery usage efficiently.





Final Results of SOH

The values you provided indicate the anticipated battery voltage (VDC) levels for the next five minutes. The table indicates the anticipated VDC at every minute, from approximately 360.0266 V at minute 1 and gradually dropping to around 359.9784 V at minute 5. This shows a gradual draining of the battery over time, which is normal behavior. The trend is plotted in the following graph, where time is plotted on the X-axis and VDC on the Y-axis and the line has a slight downward slope. As a whole, the table and the graph combined indicate that the battery voltage is going to dip consistently in the upcoming minutes.

V. CONCLUSION

This work introduces a novel framework utilizing Explainable Data-Driven Digital Twins to enable accurate battery state prediction in electric vehicles (EVs). Using state-of-the-art machine learning algorithms such as Deep Neural Networks (DNN), Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), Support Vector Regression (SVR), Support Vector Machines (SVM), Feedforward Neural Networks (FNN), Radial Basis Function (RBF) networks, Random Forests (RF), and Extreme Gradient Boosting(XGBoost)—a holistic digital twin model was created to improve the reliability and accuracy of forecasting battery parameters such as state of charge (SOC) and state of health (SOH).

The method efficiently attains the aims of the study by combining heterogeneous algorithms to promise strong performance under different operating conditions. The application of explainableAI methods also offers explainable insight into factors of battery performance, enabling improved understanding and optimization of battery management systems. Early indications highlight the digital twin model's higher accuracy and resilience compared to conventional approaches. This innovation not only enables more intelligent battery management but also aids in safer, more efficient, and longer-lived batteries, opening the door to improved electric mobility solutions.

VI. ACKNOWLEDGMENTS

I would like to extend my deepest appreciation to everyone who helped complete this work successfully. Above all, I appreciate my academic supervisors and mentors for their great guidance, constant encouragement, and constructive feedback throughout the research on Explainable Data-Driven Digital Twins for battery state prediction in electric vehicles.

I would like to extend my gratitude to the research centers and institutions that offered the resources and environments for developing and testing cutting-edge machine learning models. My special thanks go to my fellow peers and colleagues for the positive discussions and encouragement, which enriched the quality of this work significantly.

Lastly, I am greatly indebted to my family and friends for their constant encouragement and inspiration. They made this research possible through their inspiration and patience.

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