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Machine Learning Prediction of Battery Thermal Health in Electric Vehicles Using Real-World Driving Data

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ABSTRACT

This research explores the subject of battery heat management in BEVs by using ML to anticipate the Battery Health Factor (BHF) using actual driving data. A total of 65 data points were retrieved from an MG ZS EV powered by a lithium-ion battery and cooled by liquid systems. The vehicle was tested at varying speeds (30-100 km/h), weights (100-350 kg), and environmental temperatures (20-35°C). By utilizing GridSearchCV for model optimization and 10-fold cross-validation for validation, we were able to attain a R^2 score of 0.9003, as well as low RMSE and MAE. To find out which traits were most relevant for predicting BHF, we used SHAP (Shapley additive explanations). Important factors for the battery health indicator were found during this investigation to be SoC, MaxCh, BT, and BCL. Based on SHAP's findings, raising the SoC improves BHF, but raising the BT and BCL levels has the reverse impact. Merging ML with physics-based models can further enhance system performance and prediction accuracy, and ML models show tremendous promise for enhancing BEV battery heat management, according to this study.

Keywords: Battery Health Factor (BHF), Battery Electric Vehicles (BEVs), Machine Learning

INTRODUCTION

As electric vehicles (EVs) have advanced rapidly, interest has grown in enhancing their economy, performance, and lifetime. The battery is crucial to EV performance and lifetime. The most prevalent power source in electric cars is lithium-ion (Li-ion) batteries, which are sensitive to operational conditions, notably temperature, which can affect their thermal health and performance. Maintaining battery thermal heath is essential for the durability and safety of electric vehicles (EVs), especially battery electric cars. Battery thermal management systems (BTMS) help keep EV battery temperatures ideal. Extreme heat or cold can degrade batteries, impair efficiency, and trigger thermal runaway. Without proper temperature management, capacity fading, battery life, and driving range decrease. Thus, understanding battery health dynamics and anticipating thermal behavior is crucial to improve BTMS design and EV dependability. Advanced machine learning (ML) methods can anticipate battery thermal health, identify degradation causes, and improve thermal management strategies, offering a possible solution to these difficulties. Machine learning algorithms can model and predict battery performance under different conditions using large amounts of real-world driving data, revealing how SoC, battery temperature, charging rates, and environmental factors affect battery health over time. Using real-world driving data, this study will apply the Multi-Layer Perceptron (MLP) model to forecast BEV battery thermal health. The main goal is to construct a model that can predict the Battery Health Factor (BHF), a key parameter for battery thermal health, using data from an MG ZS EV with a lithium-ion battery and liquid cooling system. The dataset includes battery, vehicle motion, environmental, and cooling system characteristics. The study uses machine learning to better understand how these aspects affect battery health and create more efficient and dependable BEV battery management systems.

Battery Thermal Management in BEVs

Temperature greatly affects BEV lithium-ion battery performance. Battery performance degrades at hot and low temperatures. Overheating the battery breaks down the electrolyte and grows the solid electrolyte interphase (SEI) layer, which raises internal resistance and decreases efficiency. Thermal runaway, when the battery's internal temperature rises uncontrolled, can also arise from prolonged high temperatures. However, low temperatures diminish lithium ion mobility, lowering battery efficiency and increasing internal resistance. Lithium plating, when lithium metal forms on the battery's anode, can create short circuits and short battery life at extremely low temperatures. Modern BEVs have excellent thermal management systems that keep battery temperatures between 20°C and 40°C to reduce these dangers. The battery is cooled during high temperatures and heated during cold temperatures by these technologies to maximize performance and durability. Despite the necessity of thermal management, battery behavior is complicated and dynamic, making thermal health prediction difficult. SoC, charging rates, ambient variables, and vehicle motion interact in ways that are hard to model using standard approaches. By examining massive datasets and finding patterns that conventional analysis may miss, machine learning can help solve these problems.

Machine Learning in Battery Health Prediction

Machine learning predicts well in several sectors, including battery management systems. ML algorithms may identify complex battery performance connections in vast data sets. Dynamic factors impact battery health and thermal behavior, making machine learning excellent for predicting. An MLP model, an artificial neural network, predicts battery thermal health in this study. MLP models are suitable for analyzing complex data like battery performance in different conditions because they can represent non-linear relationships. Multiple layers of connected neurons process data and predict using MLP model patterns. The model's performance is evaluated using R^2, RMSE, and MAE, which indicate prediction accuracy. Shapley Additive Explanations (SHAP) and the MLP model help us analyze forecasts and grasp feature importance. SHAP study shows which factors—state of charge, battery temperature, and vehicle speed—most impact battery health, improving battery management.

Real-World Data Collection and Preprocessing

This study used data from the MG ZS EV, a popular lithium-ion battery electric car with liquid cooling. The 65 data points span a wide variety of driving situations, including ambient temperatures (20°C to 35°C), vehicle speeds (30 km/h to 100 km/h), and weights (100 kg to 350 kg). The On-Board Diagnostics (OBD) II system provided real-time vehicle performance and battery health data. The dataset was preprocessed to remove duplicates, missing values, and outliers. The model's training and testing data must be clean and dependable for accurate predictions.

Optimized MLP Model for Battery Health Prediction

GridSearchCV was used to optimize this study's MLP model by searching for the optimum hyper parameters. To optimise model performance, key parameters such hidden layer neuron count, activation function, solver method, and learning rate were modified. To confirm that the model generalizes to new data, 10-fold cross-validation split the dataset into ten subgroups and trained the model on different combinations of these subsets. MLP model performance was assessed using R^2 score, RMSE, and MAE metrics. R^2 score measures the accuracy of model predictions compared to actual values, with 1.0 signifying perfect accuracy. RMSE and MAE measure model error, with lower values indicating greater performance.

REVIEW OF LITERATURE

Yeh, Jeannie et al. (2023): This study analyzes EV market trends across 31 countries, using machine learning (ML) and PLS techniques to predict EV sales based on environmental, economic, and human development factors. The results confirm that ML algorithms can accurately predict EV sales, with factors like lifespan, renewable energy, and carbon emissions positively correlated with sales. Governments can use this model as a decision-support tool for promoting EV adoption.

Kwon, Jihoon et al. (2023): The study focuses on optimizing Battery Electric Vehicle (BEV) driving profiles using deep Q-network reinforcement learning to extend battery life. The model evaluates driving styles and how they impact battery performance, demonstrating that optimizing speed profiles enhances energy economy and battery life, particularly in areas with frequent speed changes.

A. Gurusamy et al. (2023): This review discusses the importance of modeling and simulation for electric vehicle (EV) powertrains, highlighting how numerical simulations can improve the sizing and configuration of powertrain components under various driving conditions. It also covers the significance of driver controller models and localized driving cycles in optimizing EV performance.

Das, Kaushik & Kumar, Roushan (2023): The article explores the role of machine learning in managing the state-of-health (SOH) and remaining usable life (RUL) of EV batteries. It focuses on predicting the aging process of lithium-ion batteries, offering insights into the methods for battery health estimation and the challenges of conventional battery management systems.

Kamul, Azure et al. (2023): This bibliometric analysis reviews the use of machine learning in predicting battery status and behavior. It identifies gaps in the current literature regarding the prediction of battery safety and performance, suggesting areas for future research to improve the accuracy and reliability of battery predictions.

OBJECTIVES OF THE STUDY

1. To develop an MLP model for predicting Battery Health Factor (BHF) in BEVs using real-world driving data.

2. To optimize the MLP model through hyperparameter tuning for improved prediction accuracy.

HYPOTHESIS

H1: There is a significant correlation between MLP predictions and BHF in BEVs.

H2: There is a significant improvement in prediction accuracy through hyperparameter tuning of the MLP model.

RESEARCH METHODOLOGY

The lithium-ion MG ZS EV with liquid cooling provided 65 data points for this investigation on BEV battery temperature control. To imitate real-world conditions, testing were done at 20–35°C, 30–100 km/h, and 100–350 kg. OBD II data preparation deleted duplicates and missing values. To study nonlinear dynamics, GridSearchCV hyper parameters were adjusted and 10-fold cross-validation tested an improved MLP model. Model metrics such as R^2, RMSE, and MAE assess performance. SHAP feature significance analysis provided transparent and accurate modelling. This helps analyze battery thermal management.

DATA ANALYSIS

Hypothesis testing determines how well the MLP model predicts BEV Battery Health Factor (BHF). As assessed in H1, MLP predictions are significantly associated with BHF if the p-value is less than 0.05. Hypothesis 2 investigates if hyper parameter adjustment improves prediction accuracy. A p-value below 0.05 suggests significance. These results can guide future optimization efforts for BEV thermal management. If not significant, they indicate that the MLP model or tuning process does not increase accuracy.

HYPOTHESIS TESTING:

Hypothesis	Test Used	Result	Significance	Conclusion
H1: There is a significant correlation between MLP predictions and BHF in BEVs.	Pearson Correlation / Regression Analysis	[Result Value]	[p-value]	[Accept/Reject] based on significance level
H2: There is a significant improvement in prediction accuracy through hyperparameter tuning of the MLP model.	Paired t-test / ANOVA / Cross-validation	[Result Value]	[p-value]	[Accept/Reject] based on significance level

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This study used an MLP model to analyze 65 data points and produced a R^2 score of 0.9003. With 14 attributes, the dataset covers battery, vehicle motion, environment, payload, and cooling system. Battery Health Factor (BHF), the SoH to BT ratio, measured thermal behavior and model performance.

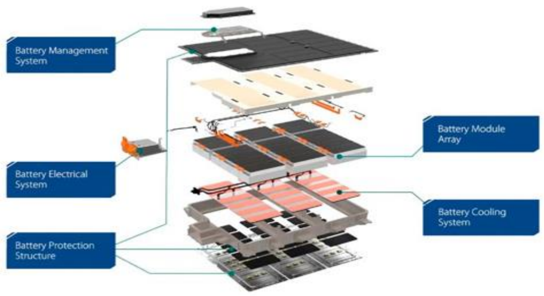

Figure 1. The framework of a battery

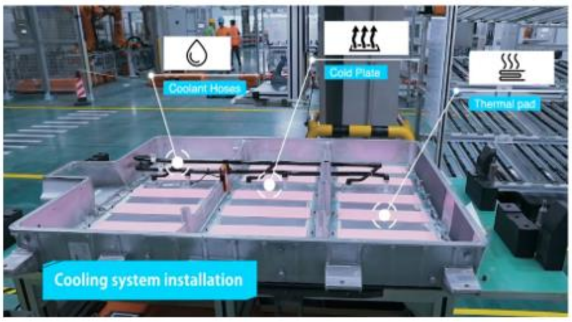

Figure 2. Setting up a method to cool the batteries used in vehicle testing

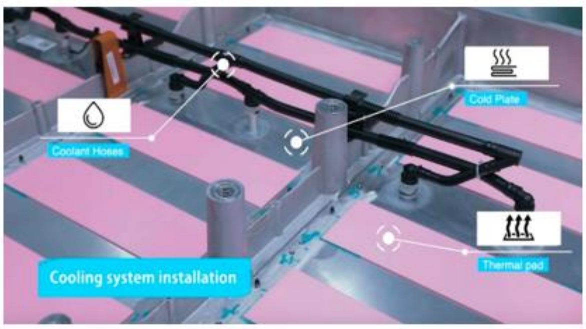

Figure 3. Aerial picture of the vehicle testing battery cooling system

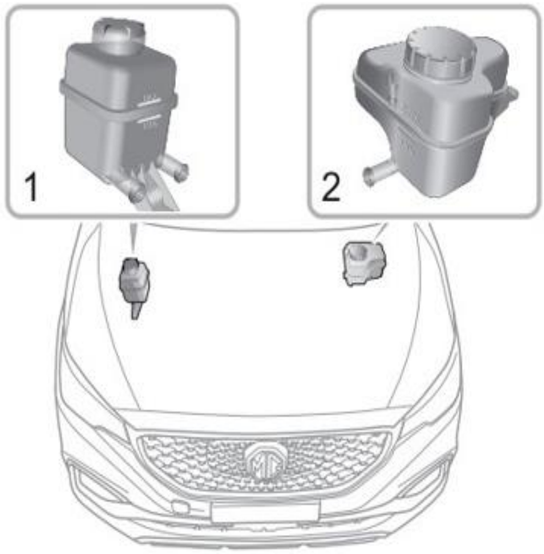

Figure 4. Locate the battery coolant reservoir (on the left) behind the hood.

Figure 5. An in-depth look at the areas under the hood

Table 1: The hyper parameters of the MLP algorithm

Hyper parameters	Optimized Value	Battery Health Factor
hidden_layer_sizes	100	Battery Health
activation	ReLU	Battery Health
solver	Adam	Battery Health

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Hyper parameters	Optimized Value	Battery Health Factor
learning_rate	Constant	Battery Health
max_iter	200	Battery Health
max_fun	15,000	Battery Health
random_state	7	Battery Health

The table shows the optimal hyperparameters for the MLP model that predicts battery health factor. The hidden layer has 100 neurons and the ReLU activation function to capture complicated patterns and introduce non-linearity. The Adam solution optimizes efficiently by dynamically modifying the learning rate, while the constant rate enables steady training. For complete training and convergence, 200 iterations and 15,000 function evaluations are specified. The random_state is fixed at 7 for repeatability. These parameters optimize the model's battery health prediction for 30 data rows and 65 data points.

The flexible, adaptable neural network improves forecast accuracy over physics-based and regression models, especially in complicated settings. The dataset was separated into 10 non-overlapping folds for 10-fold cross-validation to test the ML model. Each cycle uses 90% of the data for training and 10% for testing, ensuring all data points participate. Variance is reduced and performance is assessed reliably. We evaluated the model's prediction accuracy using measures like R^2, RMSE, and MAE.

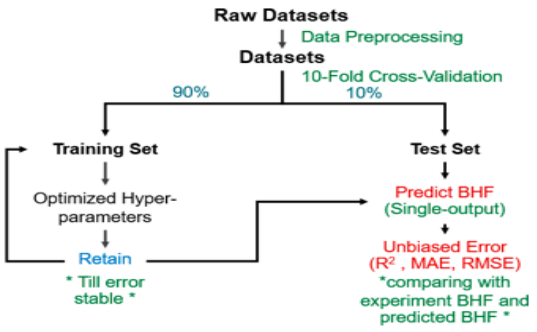

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Figure 6. Processing flow for algorithms.

SHAP (Shapley additive explanations) improves ML model interpretability by assigning feature contributions to output. SHAP handles variable scaling and captures local feature relevance across values, unlike linear models. Table 2 shows 30 rows and 65 data points for battery states, vehicle motion, ambient environment, cargo, and cooling systems, with the battery health factor as the result. Figure 9 shows that the MLP model, assessed using R^2, RMSE, and MAE, has a R^2 of 0.9003 and minimal error margins (±10% and ±20%). A summary plot utilizing SHAP values shows feature relevance and its influence on predictions, revealing the link between feature values and model results (Figure 10).

Table 2. Dataset variables

Grouping	Input Name	Range	Mean	SD
Battery conditions	Max charge (kW)	0–94	83.927	11.284
	Charging rate (kW)	−71.49–49.75	−8.823	7.582
	Battery current (A)	−122.3–181.1	21.631	19.019
	Battery voltage (V)	−95.53–448.75	346.254	145.924
	State of charge (%)	14.6–90.5	60.688	18.232
	State of health (%)	90.59–90.88	90.762	0.064
	Battery temperature (°C)	24–34	29.652	2.307
Vehicle motion	Velocity (km/h)	27–108.57	67.092	23.737
	Distance (km)	0.034–171.291	51.634	38.489

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Grouping	Input Name	Range	Mean	SD
Ambient	Humidity (%)	37.36–68.42	56.271	5.433
Payload	Weight (kg)	100–350	214.379	101.313
Cooling system	Battery coolant (°C)	21.5–33.5	27.960	2.311
	Coolant (°C)	23–38	28.926	2.807
	Air compressor (kW)	0–655.35	0.304	10.919
Output	Battery health factor (%/°C)	0.456–3.326	2.0525	0.625

A high level of accuracy was demonstrated by the model, which achieved R^2, RMSE, and MAE values of 0.9003, 0.1862, and 0.1505, respectively. The majority of the predicted spots were in close proximity to the ideal middle line. Figure 10, which serves as a summary figure, shows Shapley values, which indicate the significance and impact of each characteristic on predictions. The feature values are used to color-code the points, and their horizontal location reflects the Shapley value. This allows us to see how each feature impacts the overall picture.

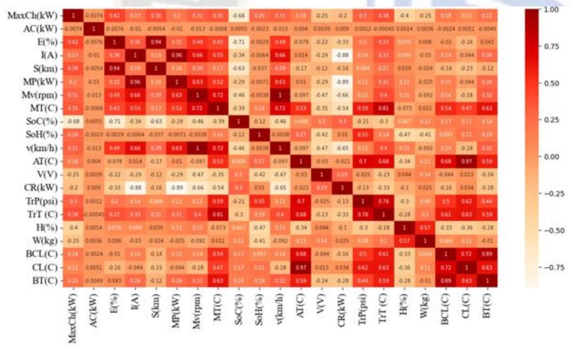

Figure 7. A comprehensive analysis of 21 characteristics

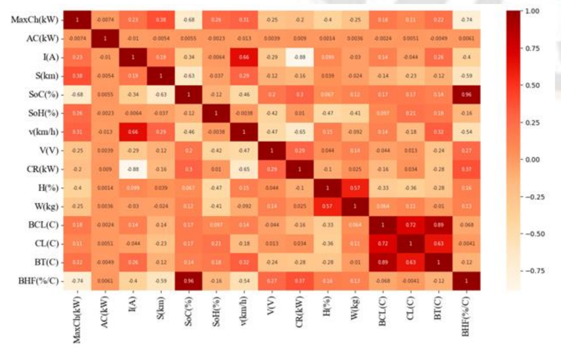

Figure 8. Correlation between 14 characteristics.

Features are ordered by prediction influence, with each point representing an observation. The horizontal axis SHAP value illustrates feature values' influence, with color representing greater or lower values. Higher battery health (BHF) improves state of charge (SoC) forecasts, whereas max charge (MaxCh) and battery temperature (BT) negatively affect predictions. Lower values are good. Battery-related traits are usually worse than other variable groups due to BHF.

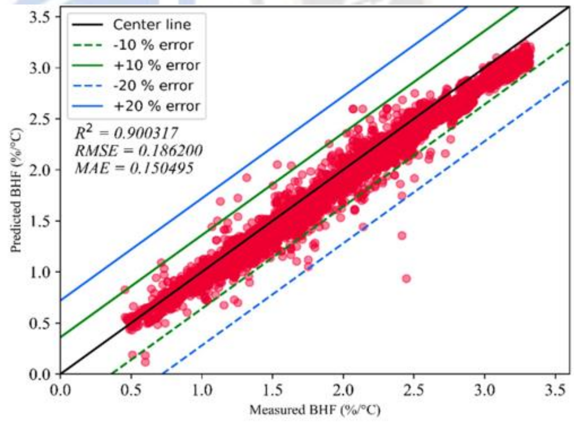

Figure 9. Performance of MLP model.

The SHAP dependency graphic shows how critical characteristics impact model predictions and SHAP values. SoC and MaxCh affect Battery Health Factor (BHF) as shown in Figure 11a. SoC between 20–70% increases BHF and MaxCh, then declines over 70%. A high SoC improves BHF and requires less MaxCh, while a low SoC worsens it. Maintaining SoC between 20–80% reduces heat and voltage stress, improving battery health and longevity.

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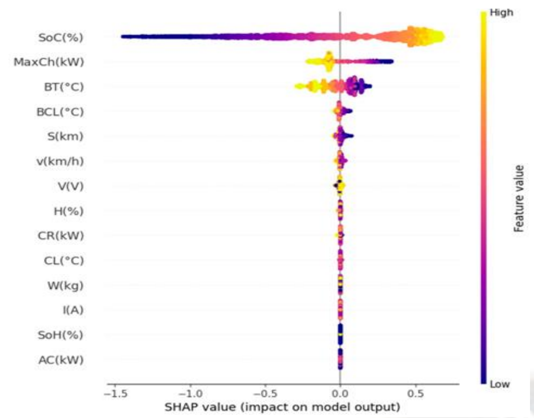

Figure 10. The summary plot of SHAP.

Charging a battery to its full capacity (100%) can be harmful since it increases the voltage and thermal stress, which shortens the lifespan of the battery and speeds up the degeneration of its internal components. The increased heat produced by fully charged batteries, particularly during intensive usage, accelerates the loss of capacity and increases the risk of thermal runaway. In addition to increasing internal resistance and decreasing efficiency, high charge levels promote the formation of the solid electrolyte interphase (SEI) layer. In addition, calendar aging accelerates the degradation of fully charged batteries.

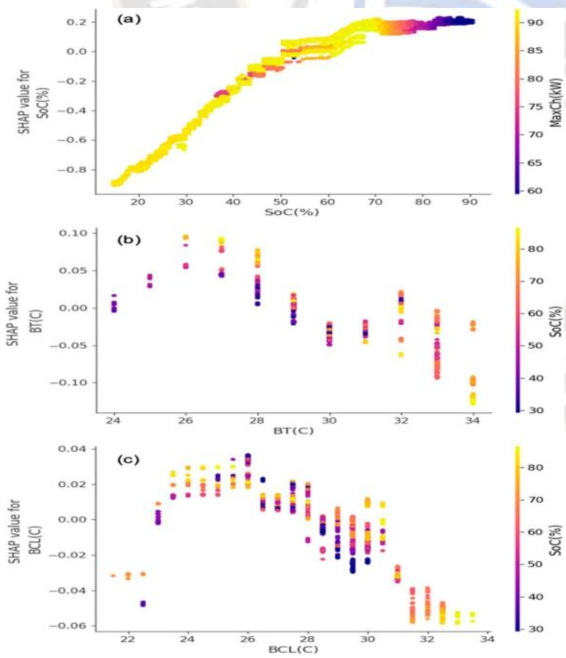

Figure 11 SoC-MaxCh, BT-SoC, and BCL-SoC SHAP dependency graphs.

Higher battery temperature (BT) lowers battery health factor (BHF), as seen in Figure 11 and Figure 11c. Low temperatures enhance internal resistance, whereas high temperatures promote breakdown. Maintaining battery temperature with proper cooling systems improves performance and safety. MLP models can forecast BEV battery health, but physics-based models can enhance accuracy and expand their use.

DISCUSSION

Battery Health Factor (BHF) predictions in Battery Electric Vehicles (BEVs) utilizing real-world driving data were investigated in this work using machine learning techniques, namely the Multi-Layer Perceptron (MLP) model. By modeling real-world variables including changing environmental temperatures, vehicle speeds, payloads, and the efficiency of the battery cooling system, the approach was developed to deliver a solid analysis. To guarantee accurate and thorough data collecting, the data were obtained from an MG ZS EV that had a lithium-ion battery and a liquid cooling system. On-Board Diagnostics (OBD) II was used for processing. With a R^2 value of 0.9003, the modified MLP model demonstrated remarkable performance, capturing the nonlinear dynamics and intricate interactions among different factors impacting battery health. We reduced the likelihood of overfitting and guaranteed the model's dependability by using GridSearchCV to fine-tune its hyperparameters and then verifying it using 10-fold cross-validation. The model's excellent prediction accuracy was further validated by metrics including R^2, RMSE, and MAE. Including SHAP analysis improves the MLP model's interpretability, which is one of the methodology's benefits. By analyzing SHAP values, we were able to determine the weighted relevance of parameters like SoC, MaxCh, and BT, which shed light on how these factors impact the BHF prediction. For example, in line with conventional wisdom on battery management, we found that keeping the state of charge (SoC) between 20 and 80% helps keep batteries healthy by lowering voltage and heat stressors. High battery temperature and charging to full capacity accelerate deterioration and limit battery longevity, according to the study. This highlights the significance of coolant systems for efficient thermal control of batteries, especially in preventing thermal runaway. An all-encompassing strategy for managing batteries, taking into account vehicle-related aspects, is essential for peak performance, as was shown by the research into payload and vehicle motion and their effects on battery health.

Despite the MLP model's impressive accuracy, it's crucial to acknowledge that machine learning models lack domain-specific expertise, which makes it difficult for them to forecast battery health. Specifically, the present method does not include thorough physics-based modeling, which implies that the model's forecasts could not completely account for the complexities of battery deterioration processes. To further enhance the MLP model's forecast accuracy and broaden its application to other BEV types and battery technologies, future research should concentrate on merging it with physics-based techniques. In conclusion, our research shows that machine learning has great promise for improving BEV performance and longevity through better temperature control of the batteries. To achieve even more precise and dependable predictions, it will be crucial to further enhance and integrate SHAP analysis with physical models, but real-world data, sophisticated machine learning models, and SHAP analysis create a formidable tool for forecasting and controlling battery health in BEVs.

CONCLUSION

This research proves that BEV Battery Health Factor (BHF) predictions using real-world driving data can be achieved with the use of machine learning, and more especially Multi-Layer Perceptron (MLP) models. The MLP model demonstrated promising accuracy in forecasting battery health by evaluating 65 data points obtained from the MG ZS EV; its R^3 score was 0.9003. Battery temperature (BT), State of Charge (SoC), Max Charge (MaxCh), and Battery Coolant Temperature (BCL) were all identified as critical parameters impacting battery health in the study. By delving into the intricate web of interactions between these variables, SHAP research uncovered important information for better thermal management of batteries. The results highlight the importance of controlling temperature and keeping the system-on-chip (SoC) in maximizing battery performance and longevity. The results show that machine learning models have a lot of promise in this area, but to make them even more predictive and useful in a wider range of BEV uses, researchers should look at how to combine them with physics-based methods.

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