38th International Electric Vehicle Symposium and Exhibition (EVS38) Göteborg, Sweden, June 15-18, 2025

Optimization of Battery Conditioning Systems for Electric Vehicles through Artificial Intelligence

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Executive Summary

The widespread deployment of charging infrastructure has driven an exponential increase in the demand for electric vehicles (EVs). However, the degradation of EV battery performance caused by variations in ambient temperature has disrupted vehicle operation, negatively impacting this growing demand. To address this issue, thermal management control technology has been developed to optimize battery performance through precise temperature regulation. Maintaining the battery temperature within a specific range during charging has been shown to enhance charging capacity and reduce charging time. In this study, an AI-based time-series forecasting model was developed to optimize battery temperature upon arrival at a charging station. The model predicts changes in battery temperature in advance, improving the accuracy of temperature control and enhancing the energy efficiency of thermal management. The developed AI model was deployed in a target vehicle to evaluate its effectiveness in predicting battery temperature variations.

Keywords: Electric Vehicles, Smart Charging, Energy storage systems, Energy management, Thermal management, Advanced control of EVs

1 Introduction

The rapid adoption of electric vehicles (EVs) has been significantly driven by the extensive expansion of charging infrastructure, resulting in an exponential increase in demand. However, this surge in popularity comes with several challenges, particularly the pronounced degradation of EV battery performance under extremely low-temperature conditions during winter. Such temperature fluctuations can disrupt vehicle operation, raise reliability concerns, and potentially impede the sustained growth of EV adoption[1]. To address these challenges, advanced thermal management control technologies have been developed to optimize battery performance through precise temperature regulation. By maintaining battery temperature within the optimal range of 20–30°C, these technologies enhance charging capacity, reduce charging time, and improve overall battery lifespan[2-4]. This battery thermal management system is referred to as battery conditioning, and Figure 1 illustrates the sequence of the battery conditioning function.

In this study, an AI-based time-series forecasting model was developed to further advance EV battery thermal management by optimizing battery temperature upon arrival at a charging station. By predicting changes in battery temperature in advance, the model enables more accurate temperature control, reduces thermal fluctuations, and improves energy efficiency. This approach not only enhances the effectiveness of EV thermal management systems but also contributes to sustainable energy utilization

and reduced operational costs. The prediction of battery temperature was divided into two cases: temperature rise and temperature fall. The model was developed by considering battery heat generation and cooling factors, which vary depending on driving conditions. In particular, as heat generation increases significantly during rapid changes in battery current or under high discharge or charging conditions, the model was trained separately for different driving scenarios[5]. This tailored approach improved the accuracy of battery temperature predictions.

To validate its practical applicability, the developed AI model was deployed in a target vehicle, where its effectiveness in predicting battery temperature variations was thoroughly evaluated. The results demonstrate the potential of AI-driven approaches to revolutionize EV thermal management, paving the way for more sustainable and efficient energy utilization in next-generation automotive systems.



Figure 1: Battery Conditioning Sequence Diagram

2 Battery temperature forecasting

The AI algorithm used for battery temperature prediction is Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN) specifically designed for time-series forecasting. LSTM is particularly well-suited for capturing long-term dependencies and sequential patterns in data, making it highly effective in predicting dynamic changes in battery temperature under varying driving and environmental conditions. Using LSTM, the algorithm was designed to predict battery temperature changes for the next timestamp. The predicted temperature values were iteratively fed back into the model as input, enabling the algorithm to continuously forecast temperature changes until the battery reached its optimal temperature. The battery system of the target vehicle is equipped with temperature sensors at two distinct locations: one is mounted at the top of the battery housing, and the other is positioned at the bottom of the battery, where coolant flows. Accordingly, the battery temperature prediction algorithm was designed to provide predictions for both sensors. Table 1 summarizes the input parameters used in the AI model for battery temperature prediction. In the case of battery cooling temperature, ambient temperature was included as an input feature due to its significant influence. Additionally, a larger model size was employed to enhance learning performance.

Table 1: AI model	parameters for batter	y temperature prediction

Parameter	Battery Cooling Temperature Model	Battery Heating Temperature Model	
Model input	Battery Max Temperature Battery Min Temperature Ambient Temperature	Battery Max Temperature Battery Min Temperature	
Model Output	Battery Max Temperature Battery Min Temperature	Battery Max Temperature Battery Min Temperature	
Window Size	10	10	
Number of Layer	2	1	
Hidden Layer	100	50	
Epoch	500	500	
Batch Size	32	32	
Learning Rate	0.001	0.001	

3 EV battery conditioning with AI

3.1 Impact of Battery Conditioning Temperature Prediction

The proposed algorithm utilizes real-time driving data acquired through CAN (Controller Area Network) signals to predict the completion time of battery conditioning. This method optimizes EV charging performance by ensuring it occurs at the optimal time, reducing charging time and extending battery lifespan. Accurate prediction of battery temperature and conditioning time is essential for optimizing thermal management strategies in electric vehicles (EVs). The effectiveness of the proposed AI-based prediction model can be further analyzed by evaluating how deviations in prediction—either overestimation or underestimation—impact system performance, including vehicle energy efficiency and charging effectiveness.

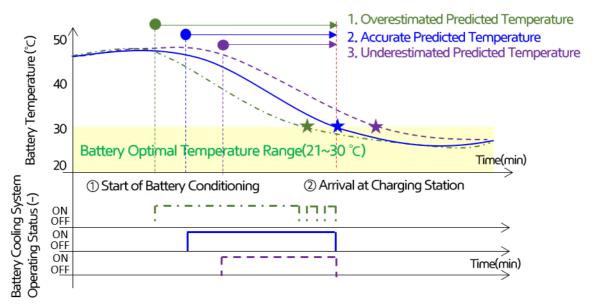


Figure 2: Impact Analysis Based on Battery Conditioning Temperature Prediction Results

Figure 2 illustrates the impact of overestimation or underestimation in the predicted battery cooling temperature, as demonstrated through graphical analysis. In some cases, the prediction model overestimated the required time or extent of battery cooling. As observed in Case 1, such over prediction led to prolonged operation of the thermal management system even after the battery temperature had reached the target range. This unnecessary control activity not only resulted in energy waste but also contributed to a measurable decline in the vehicle's overall energy efficiency. Conversely, underestimation of the required thermal conditioning time, as seen in Cases 3, can result in the battery failing to reach the optimal charging temperature range (typically 21–30°C). This condition negatively impacts the charging efficiency by extending the charging time or reducing the achievable charge rate. Additionally, repeated occurrences may have long-term effects on battery health. Hence, accurate temperature forecasting is vital to ensuring that the conditioning process completes before the vehicle reaches the charging station.

3.2 Experimental Results and Analysis

To evaluate the performance of the proposed AI-based battery conditioning model, comparative tests were conducted under four distinct driving scenarios reflecting both seasonal and driving condition variations. These scenarios include summer/urban, summer/highway, winter/urban, and winter/highway conditions. The performance of the AI model was benchmarked against a conventional rule-based model utilizing MAP data. The primary metrics used for evaluation were cooling/heating duration and prediction error rate, calculated as the percentage deviation from the actual conditioning time.

Each test case focused on achieving a target battery temperature range(21°C~30°C), either by cooling or heating. The baseline data included actual conditioning durations observed in real vehicle tests, while predictions from both the rule-based model and the AI model were compared against these values. The detailed test results are summarized in Table 2.

Table 2: Evaluation Results of AI-based Battery Conditioning Performance

Test Scenario				Test Results			
Test Case	Driving Conditions	Target Temperature	Actual Duration	Rule-based Prediction	Error Rate	AI Model Prediction	Error Rate
Case1	Summer /Urban	$36^{\circ}\text{C} \rightarrow 30^{\circ}\text{C}$ (Cooling)	32 min	43 min (+11 min)	34%	37 min (+5 min)	16%
Case2	Summer /Highway	$34^{\circ}\text{C} \rightarrow 30^{\circ}\text{C}$ (Cooling)	21 min	33 min (+12 min)	57%	25 min (+4 min)	19%
Case3	Winter /Urban	9°C → 21°C (Heating)	42 min	26 min (-16 min)	38%	49 min (+7 min)	16%
Case4	Winter /Highway	$3^{\circ}\text{C} \rightarrow 21^{\circ}\text{C}$ (Heating)	61 min	44 min (-17 min)	28%	63 min (+2 min)	3%

In cooling scenarios (Cases 1 and 2), the AI model consistently outperformed the rule-based model in terms of accuracy. While the rule-based model tended to overestimate the required cooling time, resulting in error rates of 34% and 57% respectively, the AI model provided significantly improved estimations with reduced error rates of 16% and 19%. These results indicate that the AI model can more reliably predict battery thermal behavior during high-temperature conditions, enhancing charging readiness while avoiding unnecessary thermal management overhead.

In heating scenarios (Cases 3 and 4), the rule-based model demonstrated considerable underestimation of the required heating duration, with deviations of -16 and -17 minutes, leading to error rates of 38% and 28%, respectively. This underestimation poses a risk of incomplete thermal conditioning before the charging session, potentially reducing charging efficiency and battery safety. In contrast, the AI model achieved much closer predictions, especially in Case 4 (winter/highway), where it produced an error rate of only 3%. This highlights the AI model's robustness in low-temperature environments, where accurate heating predictions are critical.

Precise estimation of battery conditioning time allows the thermal control system to operate efficiently and in alignment with the EV's arrival at the charging station. Accurate predictions ensure that the battery reaches its optimal temperature range just in time for charging, thereby minimizing idle thermal control activity and avoiding energy loss. This aspect is a core strength of the AI-based model, which demonstrated significantly improved timing accuracy compared to rule-based methods in multiple test scenarios

4 Conclusion

This study proposed an AI-based time-series prediction model to enhance the thermal management of electric vehicle (EV) batteries through accurate forecasting of battery conditioning time and temperature. By leveraging real-time driving data collected via CAN signals, the model was able to dynamically predict the thermal behavior of the battery under varying driving and environmental conditions. The use of LSTM networks enabled the model to effectively capture long-term dependencies in battery temperature changes, allowing for continuous and adaptive forecasting throughout different driving scenarios.

The experimental validation, conducted using a high-performance automotive controller in real vehicle environments, demonstrated the superiority of the AI-based approach over conventional rule-based methods. Specifically, in cooling scenarios, the AI model reduced the prediction error rate by more than half compared to the rule-based model, while in heating scenarios, it avoided the significant underestimations observed in traditional methods, achieving as low as a 3% error rate. These improvements resulted in more efficient activation of the battery thermal control system, reduction in unnecessary energy usage, and timely attainment of optimal battery temperatures prior to charging.

Furthermore, a detailed analysis of overestimation and underestimation impacts confirmed the

importance of accurate prediction. Overestimation led to prolonged operation of cooling systems, wasting energy and reducing vehicle energy efficiency. Conversely, underestimation hindered the battery's ability to reach optimal charging temperatures, leading to extended charging times and potential long-term degradation of battery health. The AI model successfully mitigated both risks by providing accurate and context-aware predictions.

In conclusion, the proposed AI-based battery conditioning model offers a practical and effective solution for enhancing EV thermal management. By ensuring timely and precise temperature control, the model contributes to reduced charging time, improved battery longevity, and enhanced vehicle efficiency. This research underscores the potential of intelligent thermal control systems as a critical enabler for sustainable, high-performance electric mobility and lays the groundwork for further development of predictive control strategies in next-generation automotive platforms.

Acknowledgments

This research was generously supported by Hyundai Motors Group.

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Presenter Biography



Youngho Jun, a senior research engineer at Hyundai KEFICO, holds a Master of Science degree in Mechanical Engineering from SungKyunKwan University in Korea. His scholarly pursuits encompass the domains of control engineering and application software development, with a particular emphasis on electrified vehicles. Presently, he is actively engaged in a research initiative focused on the development of on-device artificial intelligence tailored for electric vehicles.