

Battery Temperature Prediction in Electric Vehicles Using Bayesian Regularization

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Abstract— This study is focused on developing a new temperature prediction model to be used in battery thermal management systems. Electric vehicle (EV) application is considered as a case study however, the proposed model is applicable in other applications too. The final goal is to improve batteries' performance, durability, and safety. By specifically examining two types of batteries, which are Lithium Iron Phosphate (LFP) and Nickel Cobalt Aluminum (NCA), the proposed model utilizes Bayesian Regularization to precisely predict variations in the battery's surface temperature in an EV application. The present study experimentally evaluates the accuracy of the proposed model for prediction of the batteries' surface temperature under various conditions. According to the results, average errors of less than 0.1°C and 0.3°C are achieved when predicting the batteries' surface temperature in 30 and 90 seconds ahead. This study is expected to have an impact on the advancement of EVs' battery technologies by improving the battery's performance and safety.

Keywords—Electric Vehicle, Battery Thermal Management, Bayesian Regularization, LFP Battery, NCA Battery

I. INTRODUCTION

The initial popularity of EVs in the early 20th century due to their eco-friendly features was followed by a decline with the rise of internal combustion engines. The 1970s oil crisis reignited the interest in EVs, but progress was slow until the 1990s when environmental concerns and legislation against emissions spurred advancements in EV technology, especially in traction batteries [1]. EVs rely on batteries for energy, making them emission-free but also highlighting the need for efficient battery systems. These batteries, crucial for driving range and cost, convert chemical to electrical energy through redox reactions [2]. However, performance and safety limitations exist, addressed by Battery Management Systems (BMS) which monitor and control battery packs, focusing on voltage, current, and temperature to ensure safety and efficiency [3, 4]. Research in battery management has evolved to include machine learning (ML) approaches for predicting state of charge (SoC), state of health (SoH), and battery temperature [5-8]. BMS modelling has expanded to electrical and thermal models, incorporating electrochemical models, equivalent circuit models, and data-driven models, with notable works like the P2D model by Doyle et al. [9] and various studies estimating SoC [10, 11].

The present study is focused on developing a novel battery temperature prediction model to be implemented into the next-generation BMSs. Such temperature prediction models can help the BMS to perform predictive control actions if required. The existing BMSs work based on monitoring the current state of the battery rather than predicting what can happen in a short time horizon ahead. Although the Bayesian regularisation method is used in this study for performing the prediction task, the proposed concept is not limited to that method and other prediction models can be used for the same purpose too. Two case studies are considered here, NCA and LFP cells, to validate the proposed method. Again, that does not mean the proposed concept is not applicable to other types of batteries.

II. EXPERIMENTAL TESTS AND BATTERY DATA

A. Test Equipment

In this study, experimental tests are performed on two types of batteries: a 4800 mAh NCA cylindrical cell and an 800 mAh LFP pouch cell. This section provides a concise overview of the experimental setup and test procedures. The test rig includes a computer, a power supply, a climate chamber, and thermocouples connected to battery cells. The test devices and the cells are shown in Figures 1 and 2 respectively. Test control is administered using MATLAB/Simulink software, which regulates the charge and discharge signals through the power source/sink. The power supply oversees the voltage at the battery terminal and regulates the charge/discharge rates according to the target duty cycle. The computer logs all the measurement signals (mainly including the battery terminal voltage and the load current) from the power supply during the tests. On the other hand, the thermocouples measure the cell's surface temperature, which is also recorded by the computer. A sampling rate of 1 second is considered for the collected signals. Two thermocouples are installed on the cylindrical NCA cell - one in the middle and another near the positive terminal. For the LFP cell, thermocouples are placed at the center, bottom, and terminal sides. Given the minor sensor discrepancies in our 1D thermal model, we averaged the temperatures from all sensors to reduce computational load.



Fig. 1. Battery test equipment: (left) climate chamber, (right) power supply



Fig. 2. LFP pouch cell (left) and NCA cylindrical cells (right) used in experiments

B. Test Procedure

This study utilises the Worldwide Harmonised Light Vehicle Test Procedure (WLTP) as a standard automotive drive cycle to offer an accurate portrayal of EV usage. The objective is to construct a functional temperature forecasting model for industrial purposes. The tests, performed on individual cells, are calibrated to match the specific capabilities of each cell and are repeated in cycles until the battery is fully discharged. In order to more accurately replicate real-life circumstances, the experiments are conducted at ambient temperatures ranging from -10°C to 40°C , enabling the evaluation of the influence of temperature on battery's performance. These insights are highly helpful for enhancing the design and optimisation of the battery performance in EVs.

An example WLTP test is shown in Fig.3. In that test, the cell is fully charged before starting the WLTP discharge profile and the whole charge/discharge cycle is repeated several times in this case.

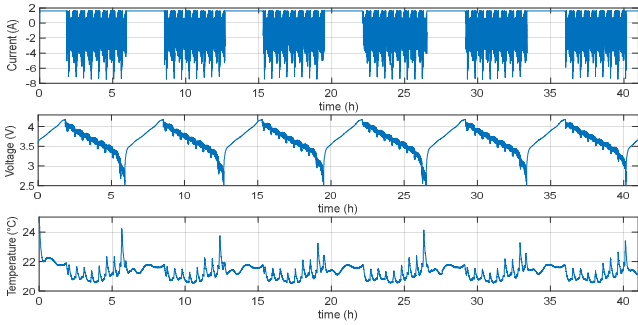


Fig. 3. Battery load current, terminal voltage and temperature signals recorded during a WLTP test

III. IMPORTANCE OF BATTERY THERMAL MANAGEMENT AND THERMAL RUNAWAY

Lithium-ion batteries are valued for their high energy and power densities but face issues such as thermal runaway, a dangerous situation induced by exothermic reactions within the battery leading to failure [12]. Thermal runaway can occur due to mechanical harm, electrical problems such as overcharging, or thermal circumstances including extreme heat [13]. Ensuring the prevention of thermal runaway is of utmost importance for battery safety, since it has the potential to result in fires and explosions [14].

The operating temperature significantly impacts the performance and lifespan of lithium-ion batteries. Both very low and high temperatures can have a negative impact on battery performance, either by increasing internal resistance or by hastening deterioration, respectively [15]. The recommended temperature range for optimal operation of these batteries is between 20°C and 40°C , with fluctuations ideally kept within a 5°C range [16-18]. Implementing an effective heat management system is critical for preserving battery safety [19].

Furthermore, the crucial aspect of battery temperature management in energy storage devices is becoming more significant due to the rising use of EVs. The statement emphasises the crucial influence of a battery's thermal characteristics on its safety, efficiency, and durability.

IV. METHODOLOGY

A. An Overview

The methodology of this study is focused on prediction of battery temperature proactively to mitigate the potential risks associated with battery thermal runaway. This paper investigates the utilisation of Bayesian regularisation technique for the prediction of battery temperature, specifically for EV application. The aim of this study is to evaluate the precision of the proposed Bayesian regularisation model in predicting upcoming temperature fluctuations. This enables a thorough examination of the algorithm's capabilities, particularly within the realm of battery temperature

regulation. As shown in Fig. 4, the temperature prediction unit incorporates real-time data inputs such as battery's current temperature, history of load current, and the ambient temperature. The objective is to forecast fluctuations in battery temperature within a time range of 1-3 minutes. This approach efficiently combines diverse data elements to generate precise temperature forecasts. These predictions enable the vehicle's battery management system to modify thermal management tactics proactively, boosting battery efficiency, safety, and lifespan by responding pre-emptively to temperature variations. In addition to this, in this study, we employ various artificial intelligence algorithms to predict the temperature of electric vehicle batteries 1-2 minutes in advance. To specify the battery location for which the temperature will be predicted, the target time is programmatically defined within the MATLAB code used for modeling. This approach facilitates real-time temperature predictions, crucial for optimizing battery performance and longevity. The predictive model integrates temporal and spatial data of the battery's operational parameters to forecast its thermal state, providing essential insights for efficient thermal management systems in electric vehicles.

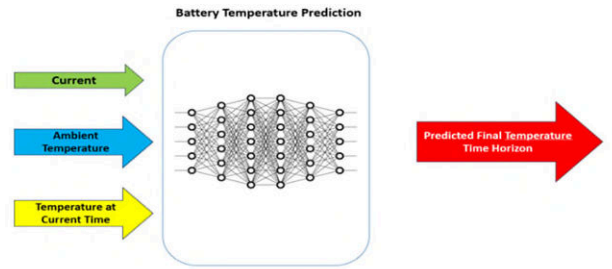


Fig. 4. Schematic of the proposed battery temperature prediction unit

B. Bayesian Regularization

As mentioned earlier, Bayesian Regularization (BR) technique is used in this study for a prediction task by using real-time time-series data. The BR method evaluates uncertainty in both model structure and observations by employing data-driven and variational Bayesian nodes [20]. When combined with Artificial neural Networks (ANN), BR employs ANN to automatically discover the optimal regularisation parameters. BRANN models employ prior probability distributions to regularise the parameters of the model [21]. Compared to typical back-propagation networks, BRANNs are robust and rarely require cross-validation. Bayesian regularisation renders nonlinear regression problems statistically well-defined, such as ridge regression [21].

The primary advantages of BRANNs are their endurance and elimination of validation, which outperform standard regression approaches such as back propagation. These networks deal with tasks such as selecting the appropriate model, ensuring its robustness, determining the validation set, estimating the required validation effort, and optimising network architecture. The objective Bayesian criterion for halting training [22] reduces overtraining through evidence-based strategies. BRANN mitigates overfitting by optimising and training on a reduced number of influential network parameters or weights, while deactivating unnecessary ones. The effective parameter count in a fully connected back-propagation neural network is typically much lower than the number of weights [23].

C. Model Training

Several tests were conducted on both LFP and NCA cells at various temperatures. As a result of that, enough data was obtained to be used for training and validation of the BR prediction model. Part of the data is used for training whereas the other part is kept separate for validation. Furthermore, during the optimization of the model, the number of hidden neurons and epochs were systematically varied. It was determined that the optimal configuration should consist of 30 hidden neurons and be trained by

1000 epochs. Therefore, tests were conducted based on these parameters. The training dataset includes the whole range of temperature from -10°C to 40°C however, the validation tests are performed at selected temperatures only. In terms of the data structure, three main inputs are used as illustrated in Fig. 4. Because the original data was in the format of timeseries, it was necessary to convert it to the matrix format (i.e. three inputs and one output). For that purpose, segmentation is applied to the timeseries of current and temperature. Each training data point contains three elements corresponding to the three inputs and one element related to the output. Consequently, each test dataset was converted to a $n \times 4$ matrix in which each row represents one data point and n is the length of that test. Because the sampling rate was 1 second, the length of the matrix equals to the time of that test in second. By combining all the individual training matrices, the big training matrix is shaped. In a similar way, a validation dataset is constructed.

The credibility of any model lies in its validation. The evaluation of each approach is conducted using conventional metrics such as maximum and average error. These metrics demonstrate the precision and robustness of the model in forecasting the battery temperature. Evaluation of the predictions is performed by comparing the model's output with experimental data. Such evaluation ascertains the precision, dependability, and suitability of the model.

V. RESULTS AND DISCUSSIONS

As mentioned earlier, the Bayesian Regularisation method is used here to develop a battery surface temperature prediction model enabling the BMS to know the temperature variations in a finite time horizon ahead. To achieve the best performance of the proposed model, various combinations of epochs (100, 400, 700, 1000) and hidden neurons (10, 20, 30, 40) are tested. According to the results, the most effective configuration, which yields the lowest prediction errors, is found to consist of 30 hidden neurons trained over 1000 epochs. Using the best model, Table 1 provides two performance measures, average error and maximum error, in various validation case studies. As mentioned earlier, the validation tests are conducted on both the NCA and the LFP cells. In addition, two lengths of 30 and 90 seconds are considered as the prediction horizon.

According to the results presented in Table 1, the average errors are obtained around 0.08°C and 0.04°C for the NCA and LFP cells when predicting the temperature 30 seconds ahead. The maximum error though reaches to 1.88°C and 1.01°C in those cases respectively. Figures 5 and 7 illustrate the NCA and LFP cells' surface temperatures predictions in 30 seconds ahead during a WLTP test. The results demonstrate that the proposed technique is quite successful in predicting the temperature within that short time window.

In order to challenge the proposed algorithm, the prediction horizon is increased to 90 seconds. As a general expectation, we expect to see higher errors when predicting a variable within a longer period. According to the results presented in Table 1, the average errors are obtained around 0.27°C and 0.11°C for the NCA and LFP cells when predicting the temperature 90 seconds ahead. The maximum error though reaches to 6.22°C and 3.25°C in those cases respectively. Figures 6 and 8 illustrate the NCA and LFP cells' surface temperatures predictions in 90 seconds ahead during a WLTP test. Although the results are not perfect, they are still usable.

The fluctuations observed in the temperature signal are caused by the dynamic load current of the WLTP test. In fact, there is a relationship between the charge/discharge rate and the amount of heat which is generated inside the cells. The generated heat will then cause a change in the cell's surface temperature. According to the overall results presented in Figures 5-8, the proposed prediction model is able to track the temperature variations with an acceptable accuracy.

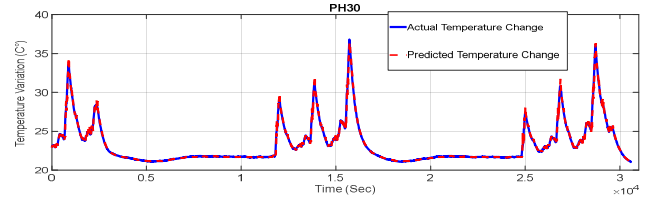


Fig. 5. NCA cell's surface temperature prediction in 30 seconds ahead using Bayesian Regularization method

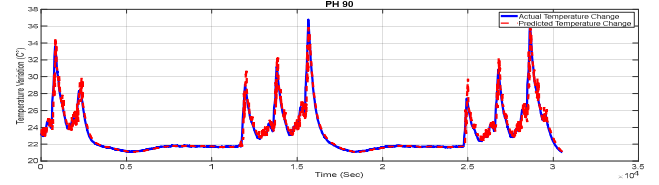


Fig. 6. NCA cell's surface temperature prediction in 90 seconds ahead using Bayesian Regularization method

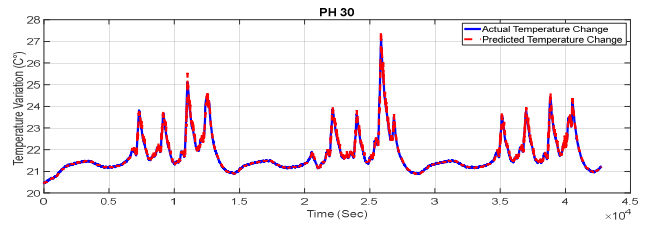


Fig. 7. LFP cell's surface temperature prediction in 30 seconds ahead using Bayesian Regularization method

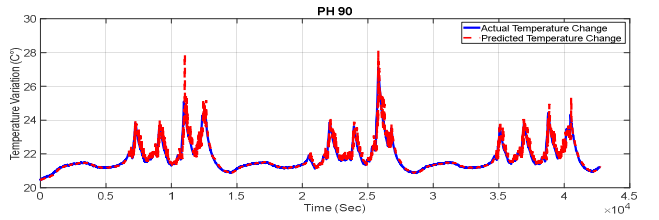


Fig. 8. LFP cell's surface temperature prediction in 90 seconds ahead using Bayesian Regularization method

Table 1: Error rates of test results of NCA and LFP cells

Cell Type	Prediction Horizon (s)	Average Error ($^{\circ}\text{C}$)	Maximum Error ($^{\circ}\text{C}$)
NCA	30	0.0754	1.8864
NCA	90	0.2673	6.2203
LFP	30	0.0371	1.0092
LFP	90	0.1144	3.2542

VI. CONCLUSIONS

A new method was proposed for online battery temperature predictions to be implemented in the next generation of battery management systems. Such temperature prediction models can help the BMS to perform predictive control actions if required. The existing BMSs work based on monitoring the current state of the battery rather than forecasting what can happen in a short time horizon ahead. The proposed method was validated for EV application according to the WLTP driving cycle. Two types of battery, NCA and LFP, were experimentally tested to collect the required data for validation of the proposed technique. Bayesian Regularisation method was used to construct the prediction model structure. The model was then trained using the experimental data. Part of the data was also kept aside for validation purpose. Although the Bayesian regularisation method was used in this study for performing the prediction task, the proposed concept is not limited

to that method and other prediction models can be used for the same purpose as well. Exploring other prediction techniques is left for the future works.

According to the results, average errors of less than 0.1°C and 0.3°C were achieved when predicting the batteries' surface temperature in 30 and 90 seconds ahead in both cases of NCA and LFP batteries. The same analysis is applicable to other types of batteries. Again, that is left for future works.

Implementation of such a temperature prediction unit in BMSs can improve the performance and safety of the whole battery system. The battery performance can improve by pushing the battery closer to its performance boundaries using such prediction models. On the other hand, battery safety is improved by having more time to take predictive safety actions ahead of time. This study contributes to

development of efficient thermal management techniques for a wide range of applications including EVs.

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