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Estimated State of Charge of Li-Ion Batteries Using GRU Deep Learning

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Abstract: State of Charge (SoC) estimation is one of the most important functions of a Battery Management System (BMS) because it directly affects the performance, lifespan, and operational safety of lithium-ion batteries, particularly in renewable energy applications with dynamic operating conditions. Conventional estimation methods are susceptible to cumulative integration errors and performance degradation under varying ambient temperatures. This study proposes a Gated Recurrent Unit (GRU)-based deep learning model for SoC estimation using five input features: voltage (V), current (I), temperature (T), moving average voltage (V_{avg}), and moving average current (I_{avg}). The additional moving-average features were introduced to enhance the temporal representation of battery behavior and improve estimation accuracy. Experimental data from the LG 18650 HG2 battery dataset were used under four operating temperatures (0°C, 10°C, 25°C, and 40°C). The proposed GRU model was evaluated using different training epochs, where optimal performance was achieved at 2,400 epochs, resulting in a validation RMSE of 1.42%. Furthermore, the proposed five-input configuration reduced the validation RMSE from 4.34% to 1.43% at 1,200 epochs, corresponding to an improvement of 67.05% compared with the conventional three-input configuration. These results demonstrate that incorporating moving-average features significantly improves the estimation accuracy and robustness of the GRU model under varying temperature conditions, providing an effective data-driven approach for lithium-ion battery SoC estimation.

Keywords: Deep Learning, Gated Recurrent Unit, Li-ion Battery, Renewable Energy, State of Charge.

Abstrak: *Estimasi State of Charge (SoC) merupakan salah satu fungsi paling penting dalam Battery Management System (BMS) karena berpengaruh langsung terhadap performa, masa pakai, dan keselamatan operasional baterai litium-ion, khususnya pada aplikasi energi terbarukan dengan kondisi operasi yang dinamis. Metode estimasi konvensional rentan terhadap akumulasi galat integrasi dan penurunan performa di bawah temperatur lingkungan yang bervariasi. Penelitian ini mengusulkan model deep learning berbasis Gated Recurrent Unit (GRU) untuk estimasi SoC menggunakan lima fitur masukan: tegangan (V), arus (I), temperatur (T), tegangan rata-rata (V_{avg}), dan arus rata-rata (I_{avg}). Fitur rata-rata berjalan tambahan tersebut diperkenalkan untuk meningkatkan representasi temporal dari perilaku baterai dan memperbaiki akurasi estimasi. Data eksperimental dari dataset baterai LG 18650 HG2 digunakan di bawah empat temperatur operasi (0°C, 10°C, 25°C, dan 40°C). Model GRU yang diusulkan dievaluasi menggunakan jumlah epoch pelatihan yang berbeda, di mana performa optimal dicapai pada 2.400 epoch, menghasilkan RMSE validasi sebesar 1,42%. Lebih lanjut, konfigurasi lima masukan yang diusulkan berhasil menurunkan RMSE validasi dari 4,34% menjadi 1,43% pada 1.200 epoch, yang selaras dengan peningkatan sebesar 67,05% dibandingkan dengan konfigurasi tiga masukan konvensional. Hasil ini menunjukkan bahwa integrasi fitur rata-rata berjalan secara signifikan meningkatkan akurasi estimasi dan ketahanan model GRU di bawah kondisi temperatur yang bervariasi, serta menyediakan pendekatan berbasis data (data-driven) yang efektif untuk estimasi SoC baterai litium-ion.*

Kata kunci: *Baterai Li-ion, Deep Learning, Energi Terbarukan, Gated Recurrent Unit, State of Charge.*

INTRODUCTION

Rapid population growth has increased reliance on non-renewable fossil fuels and, therefore, the need to switch to sustainable energy sources. Energy storage technology is an important component for the stability of renewable energy ecosystems [1]. Lithium-ion (Li-ion) batteries have been widely applied as an essential component for electric vehicle applications and energy storage systems due to their high energy density, good charging efficiency, and long cycle life [2], [3]. However, an intelligent Battery Management System (BMS) is required to properly manage variable power inputs from renewable energy sources and changes in battery behavior [2]. The BMS has the primary function of providing reliable State of Charge (SoC) estimation to avoid permanent damage due to overcharging or over-discharging, and to guarantee operational safety [3]–[5]. There are several ways to estimate an SoC. One of them is the Adaptive Extended Kalman Filter with Improved Thevenin Model, which has been shown to improve the estimation accuracy of Li-ion batteries under dynamic conditions [6].

Therefore, adaptive approaches such as machine learning and deep learning are being developed to model non-linear relationships without specific information about the internal physical parameters of the battery [7]–[9]. Recent studies have shown that the Recurrent Neural Network (RNN), especially the Gated Recurrent Unit (GRU), is highly effective in handling time-series data and temporal dependence on batteries [10]–[13]. The GRU architecture is simpler, having fewer parameters than the Long Short-Term Memory (LSTM) architecture, and is resistant to the phenomenon of vanishing gradients in dynamic data [14], [15]. Studies have shown that GRU can achieve high accuracy in a wide range of load conditions, when combined with optimization algorithms such as the Adaptive Kalman Filter, and can outperform conventional methods [10]. Further, the estimation accuracy can also be improved by considering other features such as the charging profile and battery health features under long-term operating conditions [16]–[18].

Although deep learning models have demonstrated promising performance for SoC estimation, several limitations remain. Most previous GRU-based studies have primarily focused on network architecture improvements or hyperparameter optimization while relying only on instantaneous battery measurements, such as voltage (V), current (I), and temperature (T), as input features [19]. Consequently, the contribution of feature engineering to improving SoC estimation accuracy has not been sufficiently investigated. In addition, many studies evaluate model performance only under limited operating conditions, making the robustness of the proposed models under different battery temperatures difficult to assess [20]. Furthermore, tests at high temperatures (40°C) are carried out to simulate the extreme operating conditions that can be encountered in practice [19].

To address these limitations, this study proposes a GRU-based SoC estimation model using an enhanced five-input feature set consisting of voltage (V), moving average voltage (V_{avg}), current (I), moving average current (I_{avg}), and temperature (T). The moving average features are introduced to provide short-term temporal trend information and reduce the influence of measurement fluctuations, enabling the model to capture battery dynamics more effectively. The proposed model is evaluated under four operating temperatures (0°C, 10°C, 25°C, and 40°C) and compared fairly with Deep Neural Network (DNN) models using identical datasets and training hyperparameters. Experimental results demonstrate that the proposed five-input configuration reduces the validation RMSE from 4.34% (using three input features) to 1.43%, corresponding to an improvement of approximately 67.05%. Therefore, the contribution of this work extends beyond hyperparameter tuning by experimentally demonstrating the effectiveness of feature engineering for improving GRU-based SoC estimation. Furthermore, this study investigates the trade-off between estimation accuracy, training time, and training epoch to identify an efficient, lightweight model suitable for future Battery Management System applications.

METHODS

The research method is carried out with the aim of describing the procedures used to solve the problem. In this study, several stages were conducted to estimate the State of Charge (SoC) in lithium-ion batteries using Gated Recurrent Unit (GRU) neural network modeling. The stages are illustrated in Figure 1.

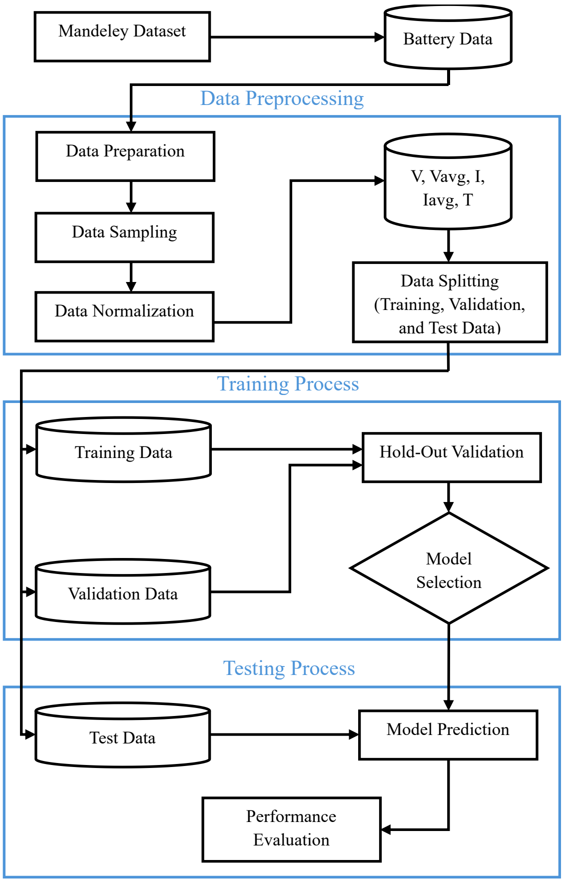

Figure 1. SoC estimation system architecture

Data Collection

The data collection stage in this study is an important foundation that determines the quality of training and evaluation of the Gated Recurrent Unit (GRU)-based State of Charge (SoC) estimation model. The data used are sourced from a well-documented experimental dataset containing laboratory test data on LG 18650 HG2 type lithium-ion batteries. This dataset was developed based on a series of battery discharge and charge cycles under real-world conditions. Each data record contains the measured battery voltage, current, temperature, and accumulated ampere-hour (Ah), from which the State of Charge (SoC) is calculated.

Initial Data Processing

After the dataset was collected, a preprocessing stage was performed to ensure data consistency and improve model performance. First, all battery measurements obtained under different driving cycles and operating temperatures were resampled to 1 Hz to establish a uniform sampling interval. The datasets corresponding to each operating temperature were then synchronized and concatenated into continuous time-series data. Subsequently, the State of Charge (SoC) was calculated by dividing the accumulated ampere-hour (Ah) by the nominal battery capacity while maintaining both the discharge starting point and the charging endpoint at 100% SoC. Data anomalies, including voltage, current, and Ah spikes, were removed to improve data quality. The predictor variables, consisting of voltage, current, and temperature, were then normalized using the Min-Max normalization method to scale each feature into the range of 0 to 1, as expressed by Equation 1.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x represents the original value, x_{min} and x_{max} denote the minimum and maximum values of the corresponding feature, respectively, and x_{norm} is the resulting normalized value.

After normalization, two additional input features, namely moving average voltage (V_{avg}) and moving average current (I_{avg}), were generated using a moving average window of 10 samples to capture short-term temporal trends and reduce measurement fluctuations. Finally, the processed dataset was partitioned into three independent subsets for model development: a training dataset consisting of driving cycles at an ambient temperature of 25°C, a validation dataset used to monitor the training process, and testing datasets consisting of four independent driving cycles at ambient temperatures of 0°C, 10°C, 25°C, and 40°C.

Model Training Process

All simulations were performed using MATLAB R2023a on a computer equipped with an Intel® Core™ i7-12700 processor (2.10 GHz), 16 GB DDR4 RAM, 1 TB SSD storage, and an NVIDIA GeForce GTX 1660 SUPER GPU (6 GB) running Windows 11 Home Single Language. The GPU was utilized to accelerate the training process.

At this stage, model training for the Gated Recurrent Unit (GRU) architecture was carried out using a hold-out validation strategy with independent training and validation datasets. The overall training workflow involved several key steps. First, the network structure was determined by defining the input layer, hidden layer, and output layer. Next, the Adaptive Moment Estimation (Adam) optimizer was selected due to its ability to adaptively compute learning rates for individual parameters and efficiently handle sparse gradient problems. The primary hyperparameters were then configured, including the initial learning rate, learn rate drop period, learn rate drop factor, and the total number of training epochs. Finally, a hold-out validation scheme was applied by partitioning the dataset prior to model execution to effectively monitor performance and prevent overfitting during training.

Model Testing Process

After the GRU modeling process was completed using the training data, the next stage was to test the model on experimental battery data to evaluate its performance in estimating State of Charge (SoC) values. The test aimed to measure the accuracy and robustness of the model when exposed to variations in environmental conditions, particularly significant temperature changes. The test data were sourced from the preprocessed LG 18650 HG2 dataset, consisting of four evaluation scenarios under different ambient temperatures: 0°C, 10°C, 25°C, and 40°C. Each scenario represents a battery discharge cycle during driving simulation and contains a time-series of five input variables (voltage, moving average voltage, current, moving average current, and temperature) alongside the target calibrated SoC.

System Evaluation

Following the model training and testing procedures, the prediction results were analyzed quantitatively and visually to evaluate the model's performance in estimating the SoC across various temperature conditions. The model's SoC predictions were compared directly with the actual target values obtained from the experimental data to assess generalization capabilities and consistency across thermal variations. To measure model performance, the Root Mean Square Error (RMSE) was utilized as the evaluation metric, where a value closer to 0 indicates higher estimation accuracy.

Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU) is a variant of the Recurrent Neural Network (RNN) designed to address the vanishing gradient problem in deep sequence models [20]. The GRU architecture features two primary gating mechanisms: the reset gate (r_t) and the update gate (z_t), which control the flow of information through the network. The update gate determines how much information from the previous time step is carried over, while the reset gate decides how much past information should be forgotten [16].

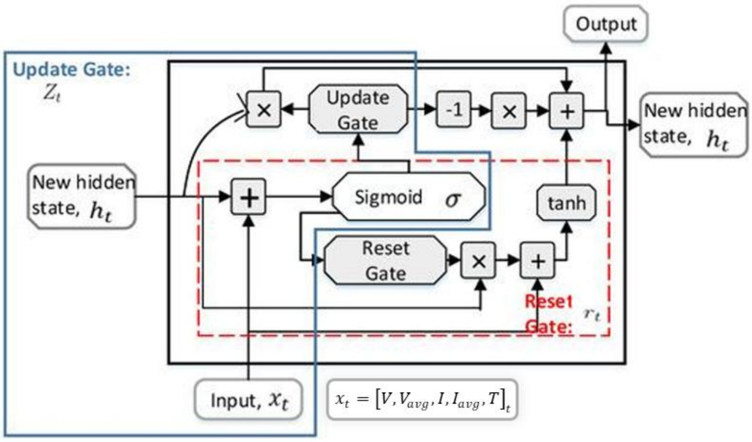

Figure 2. GRU model structure

The operational workflow of the GRU model shown in Figure 2 processes the five-input feature set, consisting of voltage (V), moving average voltage (V_{avg}), current (I), moving average current (I_{avg}), and temperature (T), combined with the previous hidden state (h_{t-1}) to calculate the target SoC output.

Reset Gate (r_t)

The reset gate (r_t) determines how much past information should be discarded when computing the candidate hidden state. By modulating memory retention, the reset gate enables the network to selectively preserve or forget details from previous time steps, capturing temporal dynamics effectively. The reset gate calculation is expressed in Equation 2.

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (2)$$

where r_t is the reset gate vector, W_r denotes the weight matrix for the reset gate, h_{t-1} represents the previous hidden state, x_t is the input vector at time step t containing the five features ($V, V_{avg}, I, I_{avg}, T$), and b_r represents the bias vector for the reset gate.

Update Gate (z_t)

The update gate (z_t) controls how much of the previous information is retained and how much new information is added to the current state. The update gate calculation is expressed in Equation 3.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (3)$$

where z_t represents the update gate vector, σ denotes the sigmoid activation function scaling values between 0 and 1, W_z is the weight matrix for the update gate, and b_z is the corresponding bias vector.

Candidate Hidden State ($\tilde{h}_t$)

The candidate hidden state ($\tilde{h}_t$) calculates a new candidate activation based on the current input (x_t) and the previous hidden state (h_{t-1}) modulated by the reset gate. The candidate hidden state is calculated as shown in Equation 4.

$$\tilde{h}_t = \tanh(W \cdot [r_t \odot h_{t-1}, x_t] + b) \quad (4)$$

where $\tilde{h}_t$ represents the candidate hidden state, tanh is the hyperbolic tangent activation function outputting values between -1 and 1, W denotes the weight matrix for the candidate hidden state, and b is the associated bias vector.

New Hidden State (h_t)

The final hidden state (h_t) at time step t is obtained by linearly interpolating between the previous hidden state (h_{t-1}) and the current candidate hidden state ($\tilde{h}_t$) using the update gate (z_t). The calculation is expressed in Equation 5.

$$h_t = (1 - z_t) \,.\, h_{t-1} + z_t \,.\, \tilde{h}_t \quad (5)$$

where $(1 - z_t)$ determines the proportion of the previous hidden state retained, while z_t dictates the proportion of the new candidate hidden state added to the update.

Output Layer

The hidden state (h_t) generated by the GRU layer contains temporal representations extracted from the voltage, moving average voltage, current, moving average current, and temperature sequences. The output layer maps this hidden representation into the predicted State of Charge (SoC) through a fully connected regression layer, as shown in Equation 6.

$$\hat{y}_t = W_{out} \,.\, h_t + b_{out} \quad (6)$$

where $\hat{y}_t$ denotes the predicted State of Charge, W_{out} represents the weight matrix of the output layer, b_{out} is the bias of the output layer, and h_t is the hidden state generated by the GRU layer at time step t.

GRU Training Configuration

The GRU model used in this study was configured using five input features consisting of voltage (V), moving average voltage (V_{avg}), current (I), moving average current (I_{avg}), and battery temperature (T). These input features were processed by a single GRU hidden layer containing 55 hidden units, followed by a fully connected layer and a regression output layer to estimate the battery State of Charge (SoC). The number of hidden units was adopted from the baseline neural network implementation provided with the LG HG2 battery dataset and maintained throughout the experiments to ensure a fair comparison between different deep learning models. The detailed GRU training configuration parameters are presented in Table 1.

Table 1. GRU training configuration

Parameter	Value
Input Features	5 (V, V_{avg}, I, I_{avg}, T)
GRU Hidden Layer	1
Hidden Units	55
Output Layer	Fully Connected + Regression
Optimizer	Adam
Initial Learning Rate	0.0001
Learning Rate Drop Period	400
Learning Rate Drop Factor	0.1
Mini-Batch Size	1
Validation Frequency	30
Validation Strategy	Hold-out Validation
Epochs Evaluated	1200, 2400, 5000

RESULTS AND DISCUSSION

This section presents the simulation results from three experiments conducted under four different temperature conditions (0°C, 10°C, 25°C, and 40°C). By varying key parameters, the Gated Recurrent Unit (GRU) neural network model aims to produce accurate State of Charge (SoC) estimation values with minimal error relative to the observational dataset. Five input features were used, consisting of voltage (V), current (I), moving average voltage (V_{avg}), moving average current (I_{avg}), and temperature (T). The experiments were conducted using the LG HG2 Li-ion battery dataset. A total of 669,956 samples were used for training, while 39,293 samples were used for validation. The proposed model was further evaluated using four independent testing datasets corresponding to temperatures of 0°C, 10°C, 25°C, and 40°C, as summarized in Table 2.

Table 2. Summary of dataset sizes used for all experiments

Dataset	Number of Samples	Data Type
Training	669,956	Float64
Validation	39,293	Float64
Dataset 0°C	47,517	Float64
Dataset 10°C	44,284	Float64
Dataset 25°C	42,530	Float64
Dataset 40°C	39,293	Float64

Comparison of 3-Input and 5-Input GRU Models

To evaluate the effect of input features on estimation performance, a comparison was conducted between the GRU model using three input features and the GRU model using five input features. The simulation results are presented in Figures 3 and 4. Both models were trained using identical hyperparameter settings, including 1,200 epochs, 1,200 iterations, an initial learning rate of 0.0001, a validation frequency of 30 iterations, and 55 hidden units, ensuring a fair performance comparison.

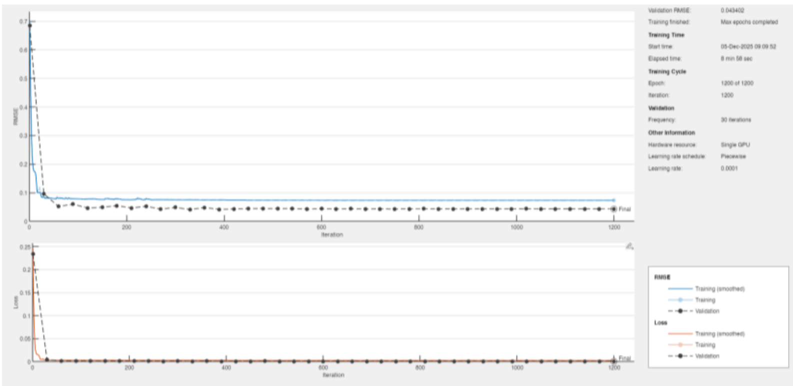

Figure 3. Training and validation results of the 3-input GRU model

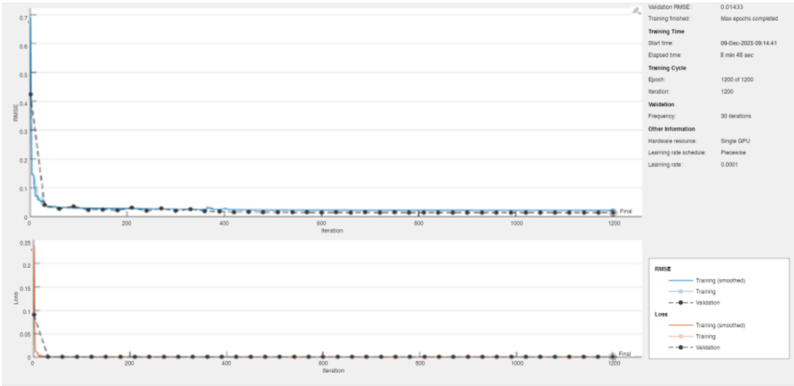

Figure 4. Training and validation results of the 5-input GRU model

Table 3. Comparison of training performance between GRU models with 3 and 5 input features

Parameter	3 Input Features	5 Input Features
Epoch	1200	1200
Iteration	1200	1200
Initial Learning Rate	0.0001	0.0001
Validation Frequency	30	30
Hidden Units	55	55
Training Time	8 min 58 sec	8 min 43 sec
Validation RMSE (%)	4.34	1.43
Improvement (%)		67.05

Based on the simulation results presented in Figures 3 and 4 and Table 3, the comparison between the three-input and five-input configurations confirms the effectiveness of the proposed feature engineering strategy. The model using only instantaneous measurements (voltage, current, and temperature) achieved a validation RMSE of 4.34%. After incorporating the moving average voltage (V_{avg}) and moving average current (I_{avg}), the validation RMSE decreased to 1.43%, representing an improvement of approximately 67.05%. These findings demonstrate that the contribution of this study is not limited to the GRU architecture itself, but also lies in the proposed feature engineering approach through the addition of V_{avg} and I_{avg}, which significantly improves SoC estimation accuracy.

GRU and DNN Model Test Comparison

To evaluate the performance of the proposed approach, the Gated Recurrent Unit (GRU) model was compared with a Deep Neural Network (DNN) model. The simulation results are presented in Figures 5 and 6. Both models were trained using identical hyperparameter settings, including 1,200 epochs, 1,200 iterations, an initial learning rate of 0.0001, a validation frequency of 30 iterations, two hidden layers, and 55 hidden units, ensuring a fair performance comparison.

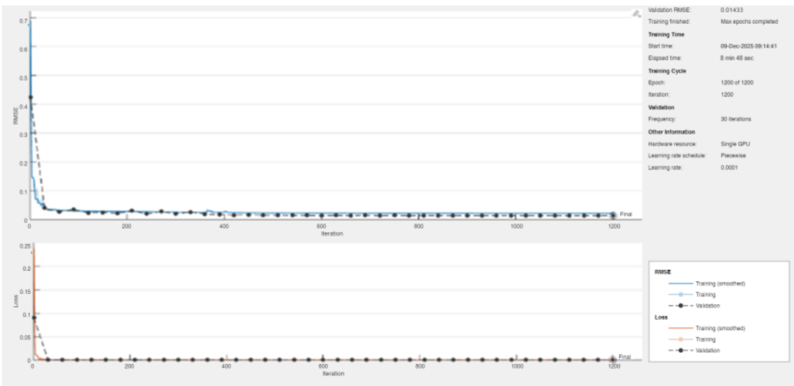

Figure 5. Training and validation results of the GRU model

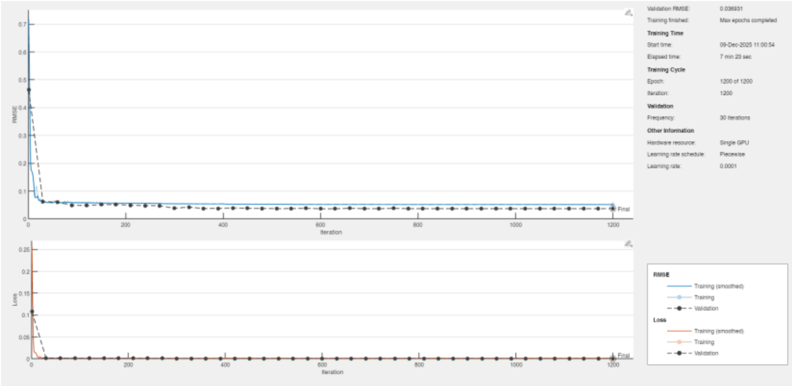

Figure 6. Training and validation results of the DNN model

Table 4. Comparison of training performance between GRU and DNN models with 5 input features

Parameter	GRU	DNN
Epoch	1200	1200
Iteration	1200	1200
Initial Learning Rate	0.0001	0.0001
Validation Frequency	30	30
Hidden Units	55	55
Training Time	8 min 43 sec	7 min 23 sec
Validation RMSE (%)	1.43	3.69

Based on the simulation results presented in Figures 5 and 6 and Table 4, the GRU model demonstrates superior performance compared with the DNN model by achieving a lower validation RMSE of 1.43%, whereas the DNN yields 3.69% under the same training configuration. The training and validation RMSE curves of the GRU model converge rapidly and remain closely aligned, indicating strong generalization capability and more accurate SoC estimation. This superior performance is attributed to the GRU's recurrent architecture, which utilizes update and reset gates to capture temporal dependencies during battery charging and discharging processes, whereas the DNN processes each input independently without modeling sequential relationships. Although the DNN requires a shorter training time (7 min 23 sec) than the GRU (8 min 43 sec) due to its simpler feedforward structure, the GRU provides substantially higher estimation accuracy, demonstrating a more favorable trade-off between computational complexity and prediction performance for Li-ion battery State of Charge estimation.

The following section presents the simulation results obtained from the proposed GRU model. To identify the optimal model configuration, a series of experiments was conducted by varying selected training hyperparameters. The model was evaluated using datasets collected at four ambient temperatures (0°C, 10°C, 25°C, and 40°C). For each temperature, the experiments investigated the effects of different hyperparameter settings, including the number of epochs, iterations, initial learning rate, validation frequency, and hidden units, on SoC estimation performance.

First Experiment of the GRU Model

The first experiment was conducted using parameters of 1,200 epochs, 1,200 iterations, an initial learning rate of 0.0001, a validation frequency of 30 iterations, two hidden layers, and 55 hidden units. The training and validation curves at 1,200 epochs are shown in Figure 7, while the State of Charge (SoC) estimation test graphs across the four operating temperatures are presented in Figures 8 to 11.

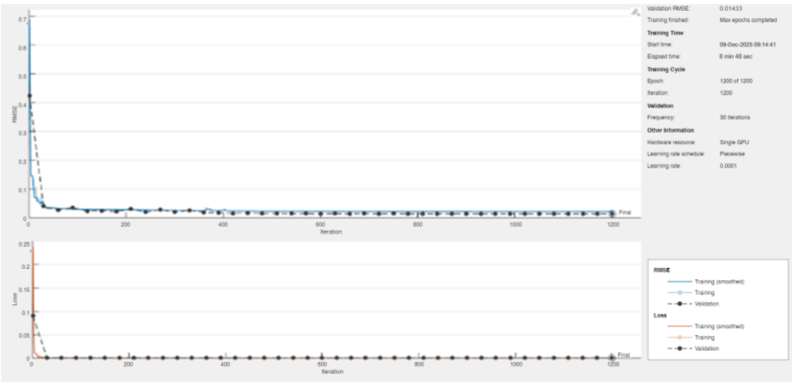

Figure 7. Training and validation results of the GRU model in the first experiment

Table 5. Training hyperparameters and performance of the first GRU experiment

Parameter	Value	Validation RMSE (%)
Epoch	1200	
Iteration	1200	
Initial Learning Rate	0.0001	1.43
Validation Frequency	30	
Hidden Units	55	
Training Time	8 min 48 sec	

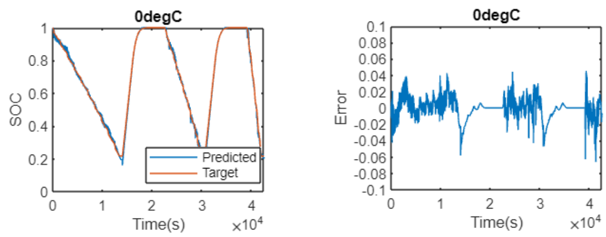

Figure 8. Predicted SoC and estimation error of the first experiment at 0°C

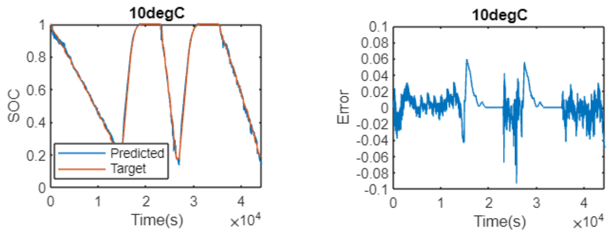

Figure 9. Predicted SoC and estimation error of the first experiment at 10°C

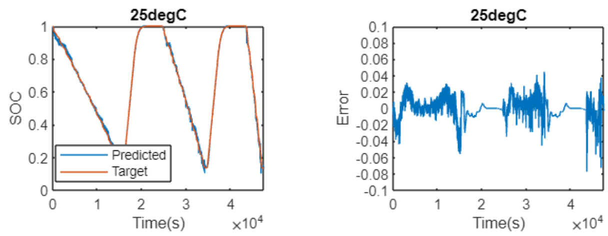

Figure 10. Predicted SoC and estimation error of the first experiment at 25°C

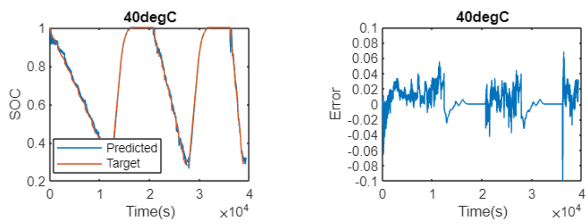

Figure 11. Predicted SoC and estimation error of the first experiment at 40°C

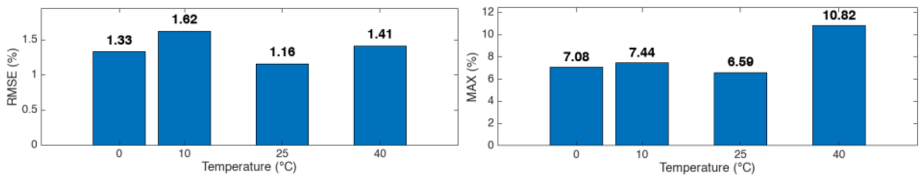

Figure 12. RMSE and MAX Error of the first experiment

Table 6. RMSE and MAX error of the first experiment

Temperature (°C)	RMSE (%)	MAX Error (%)
0	1.33	7.08
10	1.62	7.44
25	1.16	6.59
40	1.41	10.82

The results of the first experiment are summarized in Table 5. The corresponding training and validation performance curves are shown in Figure 7. Both the training and validation RMSE decreased rapidly during the initial training stage before gradually converging to stable values, indicating that the GRU model learned the nonlinear relationship between the input variables and the battery SoC efficiently. A similar convergence trend was observed for the loss function, while the close agreement between the training and validation curves suggests that the model achieved good generalization performance without evident overfitting. Using this hyperparameter configuration, the model achieved a validation RMSE of 1.43% with a training time of 8 min 48 sec, demonstrating accurate prediction performance with relatively low computational cost.

The SoC estimation results obtained under ambient temperatures of 0°C, 10°C, 25°C, and 40°C are summarized in Table 6. The proposed GRU model achieved RMSE values of 1.33%, 1.62%, 1.16%, and 1.41%, respectively, indicating consistent estimation accuracy across different operating temperatures. Based on the results in Figure 12, the lowest RMSE was obtained at 25°C, whereas the highest maximum error (10.82%) occurred at 40°C, suggesting that high-temperature conditions produced larger instantaneous prediction deviations despite maintaining a low overall estimation error. Overall, these results demonstrate that the selected hyperparameter configuration provides fast convergence, stable training behavior, and reliable SoC estimation performance under various ambient temperature conditions.

Second Experiment of the GRU Model

The second experiment was conducted using parameters of 2,400 epochs, 2,400 iterations, an initial learning rate of 0.0001, a validation frequency of 30 iterations, and 55 hidden units. The training and validation curves at 2,400 epochs are shown in Figure 13, while the State of Charge (SoC) estimation test graphs across the four operating temperatures are presented in Figures 14 to 17.

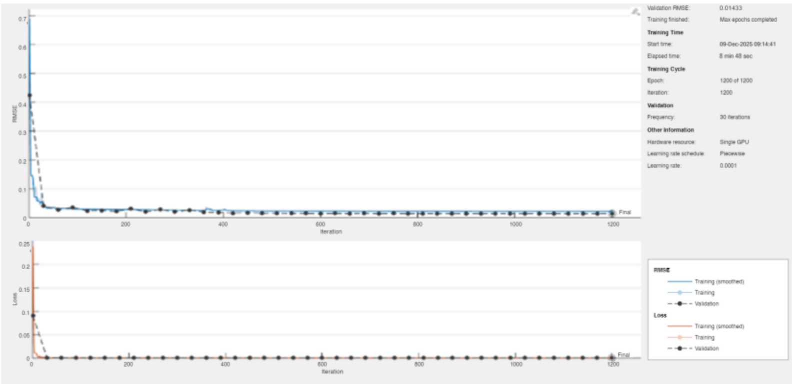

Figure 13. Training and validation results of the GRU model in the second experiment

Table 7. Training hyperparameters and performance of the second GRU experiment

Parameter	Value	Validation RMSE (%)
Epoch	2400	
Iteration	2400	
Initial Learning Rate	0.0001	1.42
Validation Frequency	30	
Hidden Units	55	
Training Time	18 min 30 sec	

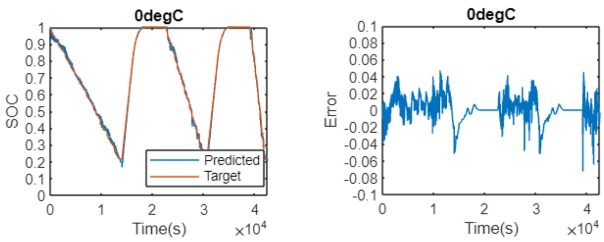

Figure 14. Predicted SoC and estimation error of the second experiment at 0°C

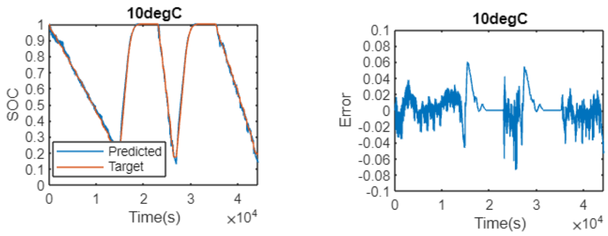

Figure 15. Predicted SoC and estimation error of the second experiment at 10°C

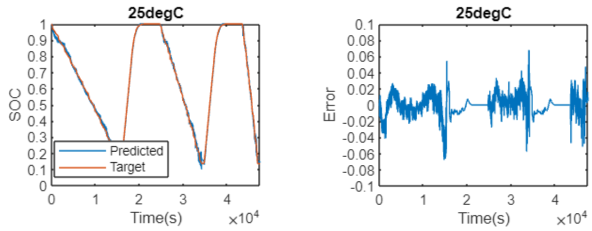

Figure 16. Predicted SoC and estimation error of the second experiment at 25°C

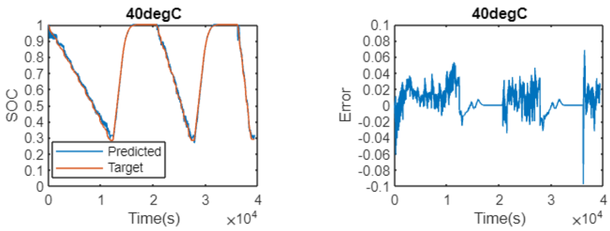

Figure 17. Predicted SoC and estimation error of the second experiment at 40°C

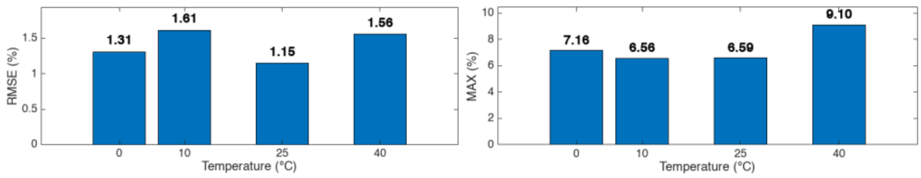

Figure 18. RMSE and MAX Error of the second experiment

Table 8. RMSE and MAX error of the second experiment

Temperature (°C)	RMSE (%)	MAX Error (%)
0	1.31	7.16
10	1.61	6.56
25	1.15	6.59
40	1.56	9.10

The results of the second experiment are summarized in Table 7. As shown in Figure 13, both the training and validation RMSE and loss decreased rapidly during the initial training stage before converging to stable values, indicating stable model convergence throughout the training process. The model achieved a validation RMSE of 1.42% with a training time of 18 min 30 sec, representing only a slight improvement over the first experiment while requiring approximately twice the training time. The SoC estimation results presented in Figure 18 and Table 8 show RMSE values of 1.31%, 1.61%, 1.15%, and 1.56% at ambient temperatures of 0°C, 10°C, 25°C, and 40°C, respectively, with the lowest RMSE obtained at 25°C. In addition, the maximum error at 40°C decreased from 10.82% in the first experiment to 9.10%, indicating improved robustness under high-temperature conditions. Overall, increasing the number of training epochs from 1,200 to 2,400 resulted in slightly better estimation accuracy and more stable convergence; however, the improvement was relatively small compared with the substantial increase in training time, suggesting that the trade-off between computational cost and prediction performance should be considered when selecting the optimal hyperparameter configuration.

Third Experiment of the GRU Model

The third experiment was conducted using parameters of 5,000 epochs, 5,000 iterations, an initial learning rate of 0.0001, a validation frequency of 30 iterations, and 55 hidden units. The training and validation curves at 5,000 epochs are shown in Figure 19, while the State of Charge (SoC) estimation test graphs across the four operating temperatures are presented in Figures 20 to 23.

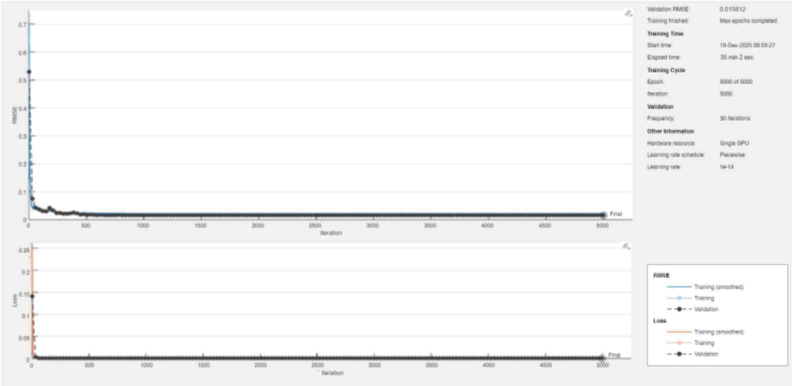

Figure 19. Training and validation results of the GRU model in the third experiment

Table 9. Training hyperparameters and performance of the third GRU experiment

Parameter	Value	Validation RMSE (%)
Epoch	5000	1.58
Iteration	5000	
Initial Learning Rate	0.0001	
Validation Frequency	30	
Hidden Units	55	
Training Time	35 min 2 sec	

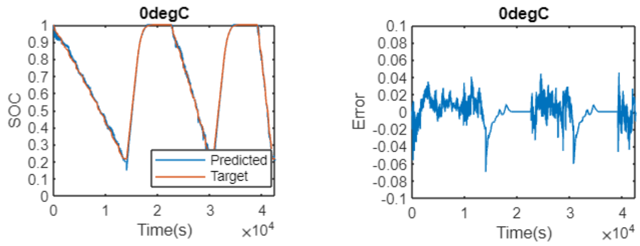

Figure 20. Predicted SoC and estimation error of the third experiment at 0°C

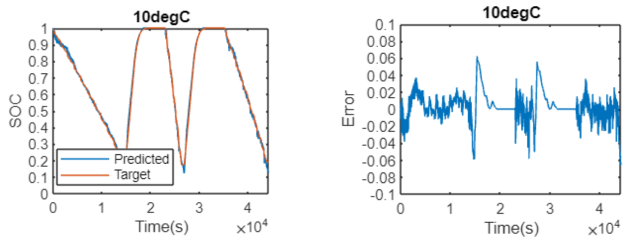

Figure 21. Predicted SoC and estimation error of the third experiment at 10°C

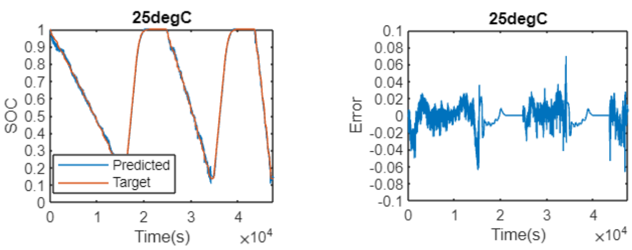

Figure 22. Predicted SoC and estimation error of the third experiment at 25°C

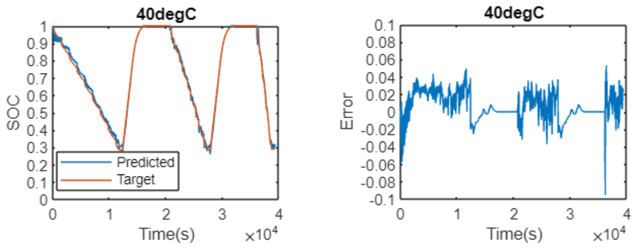

Figure 23. Predicted SoC and estimation error of the third experiment at 40°C

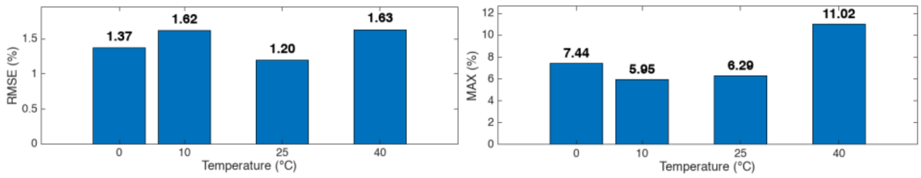

Figure 24. RMSE and MAX Error of the third experiment

Table 10. RMSE and MAX error of the third experiment

Temperature (°C)	RMSE (%)	MAX Error (%)
0	1.37	7.44
10	1.62	5.95
25	1.20	6.29
40	1.63	11.02

Table 11. Comparison of training performance of the second GRU experiment

Parameter	First Experiment	Second Experiment	Third Experience
Epoch	1200	2400	5000
Iteration	1200	2400	5000
Initial Learning Rate	0.0001	0.0001	0.0001
Validation Frequency	30	30	30
Hidden Units	55	55	55
Training Time	8 min 48 sec	18 min 30 sec	35 min 2 sec
Validation RMSE (%)	1.43	1.42	1.58

Table 12. Comparison of SoC prediction between the first, second, and third experiments of the GRU model

Experiment	Temperature (°C)	RMSE (%)	MAX Error (%)
First Experiment	0	1.33	7.08
	10	1.62	7.44
	25	1.16	6.59
	40	1.41	10.82
Second Experiment	0	1.31	7.16
	10	1.61	6.56
	25	1.15	6.59
	40	1.56	9.10
Third Experiment	0	1.37	7.44
	10	1.62	5.95
	25	1.20	6.29
	40	1.63	11.02

The results of the third experiment are summarized in Tables 9 and 10. The corresponding training and validation curves shown in Figure 19 indicate that both the RMSE and loss decreased rapidly during the initial training stage before converging to stable values. However, extending the training process from 2,400 to 5,000 epochs did not improve the validation performance. As shown in Figure 24, Table 11, and Table 12, the validation RMSE increased from 1.42% in the second experiment to 1.58%, while the training time nearly doubled from 18 min 30 sec to 35 min 2 sec.

In addition, the experiment results presented in Tables 10 and 12 show that the RMSE increased at 0°C, 25°C, and 40°C, while the maximum error at 40°C rose to 11.02%, the highest among all experiments. Although the training curves remained stable, the degradation in validation accuracy together with the increased testing error indicates that additional training beyond 2,400 epochs no longer improved the model's ability to generalize to unseen data. Instead, the model began to fit the training data more closely without achieving better prediction performance on the validation and testing datasets, which is a characteristic symptom of overfitting. Therefore, the 2,400-epoch configuration provides the best trade-off between estimation accuracy, convergence stability, computational cost, and generalization performance for the proposed GRU-based SoC estimation model.

CONCLUSIONS

This study demonstrates that the proposed Gated Recurrent Unit (GRU) model provides accurate and reliable State of Charge (SoC) estimation for lithium-ion batteries under varying ambient temperature conditions, highlighting its potential for future real-time implementation in Battery Management Systems (BMS). The effects of varying the number of training epochs and iterations (1,200, 2,400, and 5,000) were investigated while maintaining a consistent learning rate, validation frequency, and number of hidden units. The experimental results show that the training configuration significantly affects both the prediction accuracy and computational efficiency of the model. Among the evaluated configurations, 2,400 epochs and 2,400 iterations achieved the best overall performance, yielding the lowest validation RMSE of 1.42%, stable convergence, and strong generalization capability. Increasing the number of epochs to 5,000 did not improve estimation accuracy, but instead increased training time and exhibited indications of overfitting, demonstrating that excessive training does not necessarily enhance model performance. Furthermore, the GRU model consistently produced low testing errors across all evaluated temperatures (0°C, 10°C, 25°C, and 40°C) and outperformed the Deep Neural Network (DNN) model by achieving a substantially lower validation RMSE (1.43% compared with 3.69% at 1,200 epochs). Future research should consider expanding the dataset to encompass more diverse operating conditions, applying advanced hyperparameter optimization techniques, and comparing the proposed GRU model with other deep learning architectures, such as Long Short-Term Memory (LSTM) and Transformer networks, to further improve the accuracy and robustness of SoC estimation.

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