

Ensemble Projected Gated Recurrent Units for State of Charge Estimation: A Case Study on Lithium-Ion Batteries in Electric Vehicles [†]

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Abstract: State of Charge (SoC) estimation is important for improving performance and longevity of lithium-ion batteries in electric vehicles (EVs). Traditional methods such as voltage measurements and Coulomb counting lie in the inability to account for factors like battery aging and operational conditions variations, leading to potential errors in SoC estimation. Accordingly, this work overcomes these limitations by utilizing Ensemble Projected Gated Recurrent Units (E-PGRUs) for enhancing SoC estimation. Traditional methods often struggle with the non-linear dynamics and transient behaviors of battery systems, leading to suboptimal predictions. The proposed E-PGRU model leverages the adaptability of GRU, which efficiently handles time-series data, while employing an ensemble strategy to mitigate the risks of overfitting and improve generalization. In our methodology, we employed a publicly available dataset specifically dedicated to the particular topic of real-world EV operations involving driving cycles and capturing varying operating conditions. E-PGRU architecture consists of multiple GRU networks, with projected layer features, each trained on different subsets of the data, and their outputs are aggregated to produce a more reliable SoC estimate. This ensemble technique targets specific variability in prediction (i.e., standard deviation minimization), increasing prediction confidence and allowing the model to learn complex patterns in the battery's operational behavior. The experiments revealed a higher coefficient of determination, providing an explanation of the variance in dependent variables by independent variables in the SoC estimation model. The curve fit results also clearly demonstrate improvements in prediction performance compared to baseline models of recurrent neural networks in both the coefficient of determination (i.e., due to ensemble learning) and computational time (i.e., due to projection layers) indicating a strong alignment with SoC values. Furthermore, E-PGRU showed superior adaptability to different usage scenarios and conditions, suggesting the potential for its application in battery management systems.

Keywords: electric vehicles; gated recurrent unit; lithium-ion batteries; state of charge



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1. Introduction

SoC estimation is important in managing lithium-ion batteries for EVs, as accurate predictions affect battery performance, safety, and longevity. Traditional methods like voltage measurements and Coulomb counting face limitations in accounting for non-linear battery behavior, aging, and varying operational conditions, leading to inaccuracies [1,2]. These issues are exacerbated in real-world EV applications, where factors such as rapid load changes and temperature variations significantly impact SoC predictions. This has shifted research in this field toward machine learning, specifically deep learning [3]. However, while deep learning models like recurrent neural networks and their variants offer some

improvement, they often suffer from overfitting and high computational demands. To address these challenges, this research introduces an Ensemble Projected Gated Recurrent Unit (E-PGRU) model [4]. By combining ensemble learning with GRU networks that use projected layers, the model improves generalization, reduces computational complexity, and offers more accurate SoC predictions. The E-PGRU model successfully balances accuracy and efficiency, demonstrating superior performance compared to traditional methods and existing machine learning models. It mitigates overfitting, enhances generalization across varying operating conditions, reduces prediction variability, and increases confidence in SoC estimates. The incorporation of projected layers reduces computational complexity, making the model more efficient while maintaining high accuracy. The model's effectiveness is validated using a real-world EV driving cycle dataset, ensuring its practical relevance and adaptability to diverse conditions [5]. Overall, this work presents a practical, accurate, and computationally efficient solution for deployment in EV battery management systems.

This paper is organized as follows: Section 1 provides the introduction. Section 2 focuses on the materials, describing the datasets used. Section 3 covers the methods, explaining the GRU and PGRU models in detail. Finally, Section 4 presents the results and discussion.

2. Materials

This work adopts a lithium-ion battery dataset derived from tests conducted at the University of Wisconsin–Madison [5]. The dataset focuses on the performance evaluation of the Panasonic 18650PF cell. These tests were conducted in an 8-cubic feet thermal chamber using a 25 ampere, and 18-volt Digatron Firing Circuits Universal Battery Tester. The experiments involved multivariate conditions, including different ambient temperatures across multiple experimental scenarios, to assess the battery's characteristics. The dataset includes detailed records from several types of tests: pulse discharge tests, electrochemical impedance spectroscopy (EIS) tests, and drive cycles under varying temperature conditions. Among many tests conducted at different temperatures, including $-20\text{ }^{\circ}\text{C}$, $-10\text{ }^{\circ}\text{C}$, $0\text{ }^{\circ}\text{C}$, and $10\text{ }^{\circ}\text{C}$, this work utilized the test related to $0\text{ }^{\circ}\text{C}$ as an initial step in our experiments. This means that two subsets are used. The first subset provides detailed results from the five-pulse discharge Hybrid Pulse Power Characterization (HPPC) test performed at an ambient temperature of $0\text{ }^{\circ}\text{C}$. The Hybrid Pulse Power Characterization test involves applying a series of high-rate discharge pulses to the battery at varying currents (0.5, 1, 2, 4, and 6 times the capacity of the battery, also known as C) to evaluate its performance under different SoCs. This file captures critical data, including the voltage and current responses of the battery during these pulses. The second subset focuses on the discharges occurring between the pulses of the HPPC test. This file includes data on the battery's performance during the intervals between high-rate discharge pulses. The first subset is vital for assessing the battery's behavior under high-power conditions and at low temperatures, offering insights into its dynamic performance and efficiency. Meanwhile, the second subset helps analyze the battery's performance during periods of lower discharge rates and its ability to handle successive high-power demands. Together, these datasets are essential for understanding the battery's response to rapid discharge conditions and its recovery behavior, particularly at low temperatures. Table 1 summarizes the subsets used in our analysis, detailing their specific test conditions, key data components, and overall purpose.

Table 1. Summary of datasets used in the analysis of Panasonic 18650PF cell performance. The table outlines the file names, descriptions, test conditions, key data components, and the purpose of each dataset.

Data Label (This Work)	File Name	Description	Test Conditions	Key Data	Purpose
Data 1	05-20-17_10.44 0degC_5pulse_HPPC_Pan18650PF.mat	Contains results from the five-pulse discharge HPPC test.	Ambient temperature: 0 °C	High-rate discharge pulses at 0.5, 1, 2, 4, 6C; includes voltage and current responses at various states of charge (SOC). Discharge performance data during intervals between HPPC pulses; provides information on recovery and capacity.	Assess battery performance under high-power conditions and low temperatures.
Data 2	05-20-17_12.07 3619_dis5_10p.mat	Includes data on the discharges between the pulses of the HPPC test.	Ambient temperature: 0 °C		Evaluate how the battery recovers from high-power pulses and its efficiency during lower discharge rates.

3. Methods

In this work, PGRU is incorporated into ensemble learning to enhance model performance [4]. The PGRU extends the traditional GRU by introducing projected layers, which improve computational efficiency and accuracy. GRU is described by Equations (1)–(4), where α denotes the sigmoid function, and W and b represent weight matrices and biases, respectively. z_t , r_t , \tilde{h}_t , and h_t are update gate, reset gate, candidate activation, and hidden state, accordingly. The PGRU introduces projected layers to modify these equations. Specifically, the PGRU incorporates a projection step to reduce the dimensionality of the hidden state, improving both the efficiency and generalization of the model. This modification is achieved by adding a projection matrix P to the update and reset gate calculations as in (5)–(7). By projecting the hidden states into a lower-dimensional space before applying the activation functions, the PGRU enhances the model’s efficiency while maintaining high accuracy. This adaptation allows for faster training and better performance, particularly when integrated into ensemble learning frameworks.

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

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

$$\tilde{h}_t = \tanh(W_h [r_t h_{t-1}, x_t] + b_h) \tag{3}$$

$$h_t = (1 - z_t) h_{t-1} + z_t \tilde{h}_t \tag{4}$$

$$z_t = \sigma(P(W_z [h_{t-1}, x_t] + b_z)) \tag{5}$$

$$r_t = \sigma(P(W_r [h_{t-1}, x_t] + b_r)) \tag{6}$$

$$\tilde{h}_t = \tanh(P(W_h [r_t h_{t-1}, x_t] + b_h)) \tag{7}$$

4. Results

The results presented in Figure 1 highlight the predictive performance of the E-PGRU and PGRU models for SoC prediction, using the coefficient of determination. For Data

1, the coefficient of determination indicates that the E-PGRU model performs better than the PGRU model, with values of 0.9943 and 0.9940 for training and testing, respectively, compared to 0.9829 and 0.9817 for PGRU. This suggests that E-PGRU accounts for a greater proportion of the variability in SoC and demonstrates slightly better generalization to new data. In Data-2, both models exhibit high coefficients of determination, with E-PGRU achieving 0.9961 and 0.9941 for training and testing, respectively, while PGRU records 0.9958 and 0.9919. These results indicate that both models are robust, with E-PGRU consistently showing superior predictive accuracy. Overall, the data underscore the effectiveness of the E-PGRU model in capturing and predicting SoC, as evidenced by its higher coefficient of determination compared to the PGRU model.

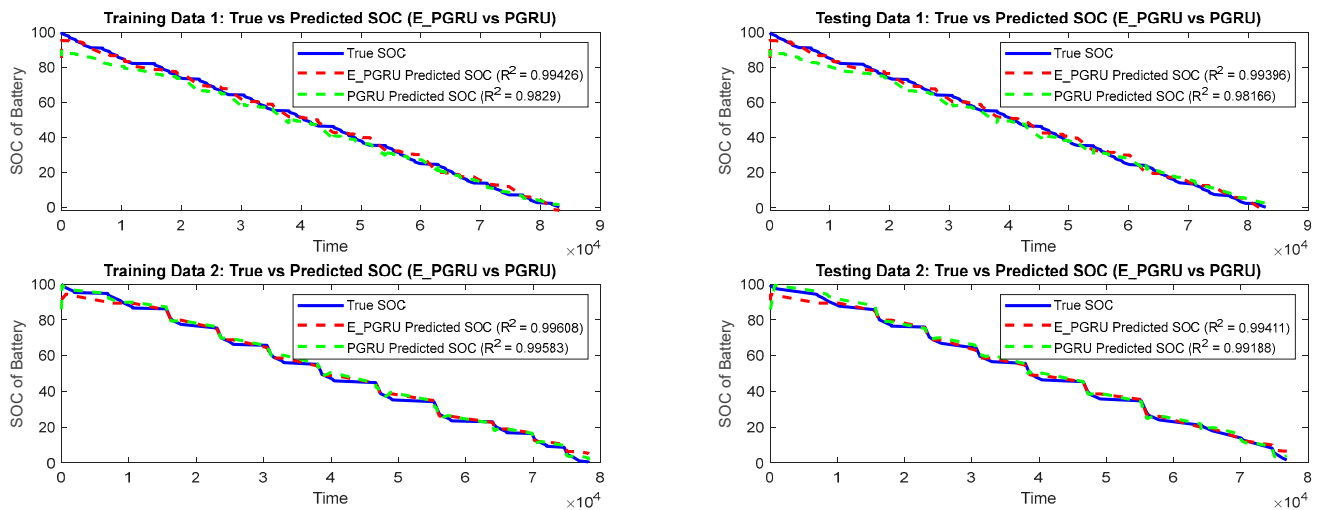


Figure 1. Curve fit and coefficient of determination results.

5. Conclusions

In this study, we compared the performance of two predictive models, E-PGRU and PGRU, for estimating the SoC of lithium-ion batteries using two different datasets. The results demonstrated that the E-PGRU model consistently outperformed the PGRU model, showing superior accuracy in predicting SoC. The E-PGRU model's enhanced performance across the datasets highlighted its potential for more effective battery management. Given its robust predictive accuracy, the E-PGRU model proved particularly well-suited for applications in EVs, where precise SoC estimation is crucial for optimizing battery performance and extending vehicle range. Consequently, we recommend adopting the E-PGRU model for EV battery management systems to improve reliability and efficiency in real-world applications.

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References

1. Hannan, M.A.; Lipu, M.S.H.; Hussain, A.; Mohamed, A. A Review of Lithium-Ion Battery State of Charge Estimation and Management System in Electric Vehicle Applications: Challenges and Recommendations. *Renew. Sustain. Energy Rev.* **2017**, *78*, 834–854. [[CrossRef](#)]
2. Pop, V.; Bergveld, H.J.; Notten, P.H.L.; Regtien, P.P.L. State-of-the-Art of Battery State-of-Charge Determination. *Meas. Sci. Technol.* **2005**, *16*, R93. [[CrossRef](#)]
3. Berghout, T.; Benbouzid, M.; Amirat, Y.; Yao, G. Lithium-Ion Battery State of Health Prediction With a Robust Collaborative Augmented Hidden Layer Feedforward Neural Network Approach. *IEEE Trans. Transp. Electrification*. **2023**, *9*, 4492–4502. [[CrossRef](#)]
4. Cheng, G.; Povey, D.; Huang, L.; Xu, J.; Khudanpur, S.; Yan, Y. Output-Gate Projected Gated Recurrent Unit for Speech Recognition. In Proceedings of the Interspeech 2018, Hyderabad, India, 2–6 September 2018; ISCA: Singapore, 2018; Volume 2018, pp. 1793–1797.
5. Kollmeyer, P. Panasonic 18650PF Li-Ion Battery Data. *Mendeley Data* **2018**, *1*, V1. [[CrossRef](#)]

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