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Battery State of Charge Estimation Utilizing Gated Recurrent Unit Recurrent Neural Network with Self-Attention Mechanism Under Low Power

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Abstract. Precisely estimating the battery State of Charge (SOC) can maximize the utilization of battery energy and reduce energy consumption. The tradition neural network-based battery SOC estimation methods have a common defect, that is, the input of the model is a continuous constant current or a periodic current that does not change drastically under normal power. These traditional methods are not accurate when the battery is in a low power condition. Aiming at the above problems, this paper proposed a battery SOC estimation method based on a gated recurrent unit recurrent neural network with self-attention mechanism (GRU-Attention) under low power. Firstly, to validate the new method, experiments were conducted using datasets from real battery tests. Then, preprocess the data by serializing the discharge data of the battery. Finally, these data are input into the GRU-Attention model for training. The experimental results indicate that under low power, the maximum error for DST dataset is 4.75%, while for UDDS dataset, it is only 3%, demonstrating its capability to accurately estimate battery SOC. In summary, the new approach provides a novel and effective pathway for battery management under low power conditions, holding significant theoretical and practical implications for the advancement of battery technology.

Keywords. SOC, GRU-Attention, BP, complex working conditions, low power

1. Introduction

Batteries provide power for electric vehicles. In order to ensure optimal performance of the battery and extend its lifespan, it is necessary to manage and control the battery. Battery SOC is crucial in battery management systems. Therefore, accurately and reliably estimating the battery SOC using measurable battery parameters has always been a hot research topic.

Although there are many SOC estimation methods, the mainstream methods include open-circuit voltage (OCV) method [1,2], coulomb counting method [3,4] and Kalman filtering method [5,6]. The OCV method infers the SOC by measuring the voltage of battery under open circuit conditions and combining it with a pre-established model relating voltage to SOC. This approach is straightforward but sensitive to environmental conditions. The coulomb counting method for estimating battery SOC is

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based on the principle of accumulating the charge flow during the charging and discharging processes. Although this method has a lower cost, it also tends to lead to error accumulation. The Kalman filtering method integrates the system's dynamic model and actual measurement values to optimally estimate the battery SOC. Although the Kalman filtering method performs well in terms of prediction accuracy, the model is complex and time-consuming.

The deep learning method can adapt to complex nonlinear relationships and adjust adaptively according to actual conditions. Therefore, it has great potential and prospects, and is expected to further drive the development and application of SOC estimation technology, providing more advanced and efficient solutions for battery management systems. Currently, numerous scholars both domestically and internationally have conducted research on this method. Wang et al. [7] proposed a NARX recurrent neural network (RNN) to build a battery model. At the same time, a moving window approach is used to address the potential issues of gradient vanishing and gradient exploding. Quan et al. [8] obtained estimated SOC values through the parallel fusion of Residual Shrinkage Network (RSN) and GRU, with experimental evidence demonstrating higher estimation accuracy compared to using GRU or RSN alone. Hannan et al. [9] designed a deep fully convolutional network (FCN) by optimizing the learning rate to predict the battery SOC. Feng et al. [10] used clockwork RNN to learn and estimate the SOC, and proved that it has better performance than Long Short-Term Memory (LSTM), GRU and Extended Kalman Filter (EKF). Wang et al. [11] implemented battery SOC prediction over its usage cycle using LSTM combined with deep RSN with channel-wise thresholds (DRSN-CW). Zhu et al. [12] improved the output structure of GRU by adopting a recursive updating method for inheriting the network's hidden state sequence, thereby achieving SOC estimation with only one network calculation on sampled data. Pan et al. [13] added the Adam optimization algorithm and dropout regularization method to the LSTM training process to make the model more robust to the initial SOC. Qiao [14] utilized Radial Basis Function neural network to develop a battery SOC prediction model. Huang et al. [15] proposed Sequence to Sequence network with LSTM module to enhance the precision of predicting battery SOC in different temperature environments.

Although the above studies have been able to effectively control the SOC estimation error, they used continuous constant current or periodic current that does not change drastically, and few people pay attention to the SOC estimation problem under low power. In the continuous constant current or periodic current that does not change drastically, the sample and test data have good consistency. But in the interval constant current, there may be some differences between sample and test data, thus making SOC estimation challenging. In addition, in a low power condition, the battery performance becomes unstable, which may introduce nonlinear characteristics, leading to increased estimation error. Therefore, some measures need to be taken to cope with this situation and more accurately capture the behavioral characteristics of the battery under complex working conditions and low power.

This paper proposes a method that utilizes GRU-Attention model to extract features from battery data under complex operating conditions, learns the estimation patterns of SOC, and ultimately achieves SOC estimation. Firstly, this method introduces time series so that the neural network can effectively capture temporal correlations in the data. Secondly, the introduction of the self-attention mechanism enables the model to dynamically assign weights based on the discharge data, thus improving its computational efficiency.

2. The Experimental Data

Dynamic Stress Test (DST) and Urban Dynamometer Driving Schedule (UDDS) tests were performed on the test samples with the equipment shown in Figure 1. The DST and UDDS datasets simulate the behavior of vehicles under various driving conditions, including time series of relevant parameters. These data provide abundant input features for battery SOC estimation methods, hence are widely utilized. In the DST condition, the variation of current and voltage tends to be more dynamic and irregular, as shown in (a) of Figure 2. The discharge scheme of DST consists of multiple cycles of high-current charging and discharging processes, with a prolonged resting period in between discharge cycles. The voltage change is very intense and the nonlinear characteristics are enhanced after the SOC is less than 20%. In the UDDS condition, the variation of current and voltage is relatively smoother, exhibiting a more regular and periodic pattern, as shown in (b) of Figure 2.

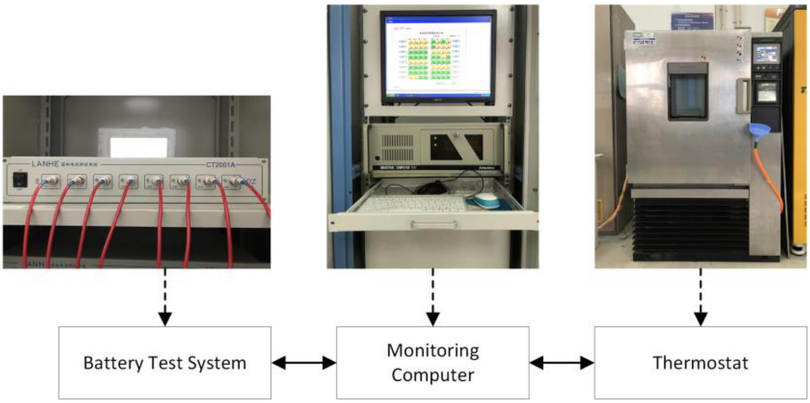
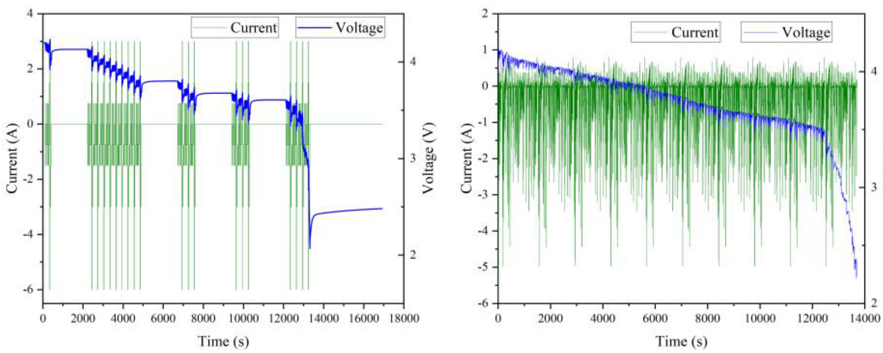


Figure 1. The experimental equipment.



(a). DST **(b).** UDDS

Figure 2. Current and voltage data in the DST and UDDS datasets.

3. The Improved Method

As shown in Figure 3, the technical route of this study is as follows: Firstly, the raw data undergoes serialization, ensuring each input sample for the neural network comprises discharge data spanning various time points. Secondly, the serialized data is fed into the GRU network for training. Finally, the self-attention mechanism is incorporated to accentuate crucial features to enhance task performance.

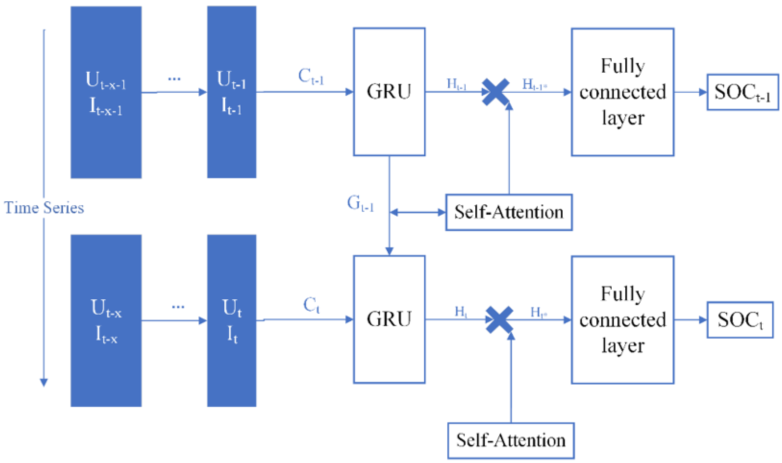


Figure 3. GRU-Attention structure.

3.1. Serialization of Discharge Data

The traditional BP neural network processes each input independently without considering the temporal dependencies between input data. In contrast, RNN capture the temporal dynamics in data by utilizing their internal state mechanism to handle sequences of data points with temporal dependencies. Therefore, the traditional BP neural network usually handles data from a single moment, while RNN mostly deal with sequential data containing multiple moments. As shown in Figure 4, $X_t = [U_t, I_t]$, which represents the serialized data, containing voltage and current data for n moments.

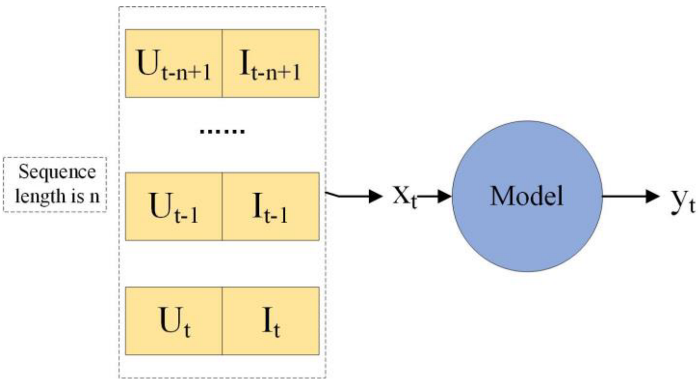


Figure 4. Data serialization.

3.2. GRU Network

RNN can maintain memory and capture temporal dependencies when processing sequential data. However, the traditional RNN faces gradient issues, inflexible memory unit updates, and complex structures, so this study adopts the variant form of traditional RNN, GRU network with filtering information function.

RNN consists of individual recurrent units, which receive input and produce output at each time step. Its execution process is as follows:

- Initialize the hidden state.
- Provide the current input along with the hidden state from the previous time step as input to RNN.
- Calculate the hidden state and output for the current time step.
- Save the current time step's hidden state as one of the inputs for the next time step.

When there are many input time steps, RNN tends to forget information from earlier time steps. This is because during the computation of RNN, when derivatives are calculated using the chain rule, if the values are very small, gradient will be very close to zero, leading to forgetting issues.

Compared to simple RNN, LSTM can effectively address the forgetting problem and handle longer sequences of time units. The design of LSTM includes an important information storage unit and three gate structures relative to RNN. Its execution process is as follows:

- The output from the previous time step and the current input are taken together as input, and through transformation, corresponding forget, input, and output gates are obtained.
- The forget gate acts on the memory information from the preceding time step.
- The input gate acts on the input information processed through the tanh activation function.
- The information processed by two gates is summed to obtain the current memory information.
- The output gate acts on the current memory information, resulting in the output of the current time step.
- The output at the current time step is also propagated backward to serve as the input for the next time step.

Compared to LSTM, GRU simplifies the structure of memory units, resulting in a reduction in parameter count. The core idea of the GRU is to introduce the reset gate r_t and the update gate z_t. These gates can effectively manage and utilize information within the input sequence. The function of the reset gate is to control how the input at the current time step interacts with the prior memory. It allows the model to redefine memory according to the present input. The update gate regulates how the model combines old memories with new inputs at each time step. Its output range is between 0 and 1, where 0 indicates complete disregard for past states, and 1 indicates full retention. The internal structure of each GRU cell is depicted in Figure 5.

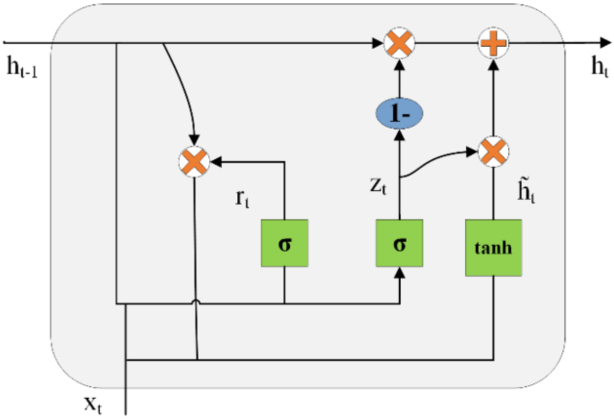


Figure 5. The internal structure of GRU cell.

3.3. The Self-attention Mechanism

The self-attention mechanism has an equal number of input and output elements, and it assigns different attention scores to each input. The process of self-attention mechanism is as follows: by inputting the sequence data into the GRU, an output with a dimension of (step size, time node, number of neurons) can be obtained, which is regarded as the feature of each time node. After 2 and 1 axis flip, the dimension is transformed into (step size, number of neurons, time node). After a fully connected layer, the weight of each time node is calculated. Then the dimension is restored through the flip layer. Its description becomes (step size, feature weight of time node, number of neurons). Finally, this result is multiplied element-wise with the input to obtain a feature combination with the weight of the original input.

The self-attention mechanism enhances the model's ability to perceive positional information within the input sequence, enabling the model to automatically focus on different positions of information according to task requirements, thus achieving global dependency modeling of the sequence.

4. Experiments

4.1. Overall Experiment Analysis

In this study, the maximum error and Mean Squared Error (MSE) are used as metrics to evaluate battery SOC estimation. The battery discharge data for both UDDS and DST conditions are separately input into the BP, GRU and GRU-Attention neural networks for training. Each set of data undergoes 100 rounds of training and prediction, and the result with the smallest error among them is selected for comparison. Table 1 shows the error results of SOC values. Figure 6 shows the curves of actual SOC values and SOC values predicted by different neural network under the DST condition. Figure 7 shows the curves of actual SOC values and SOC values predicted by different neural network under the UDDS condition.

For the DST dataset, the MSE and maximum error obtained from using the new method to predict SOC values are 0.62 and 6.99%, respectively. For the UDDS dataset, the maximum error and MSE obtained from using the new method to predict SOC values are 3.30% and 0.47, respectively. Regardless of the dataset, the error of the new method is the smallest. Additionally, as depicted in the Table 1, the GRU network exhibits a smaller error compared to the traditional BP network, because GRU has an advantage in handling long sequential data. The GRU with the added self-attention mechanism can better model sequences and has stronger generalization ability, thus resulting in smaller network errors compared to before the addition.

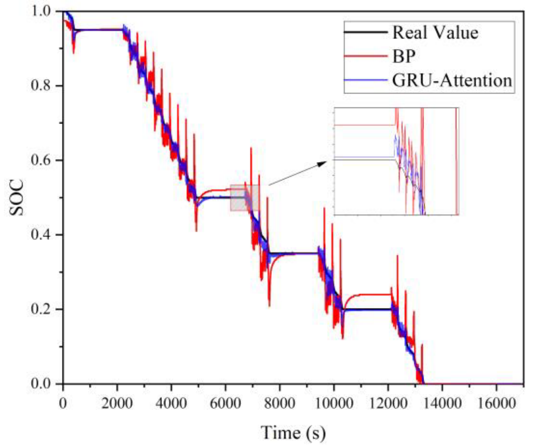


Figure 6. The actual SOC values and predicted SOC values by the two models. (DST)

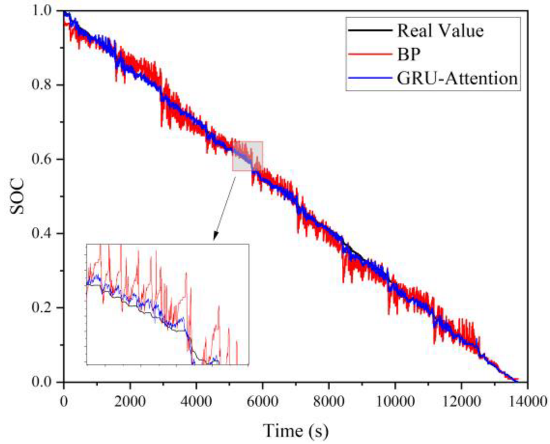


Figure 7. The actual SOC values and predicted SOC values by the two models. (UDDS)

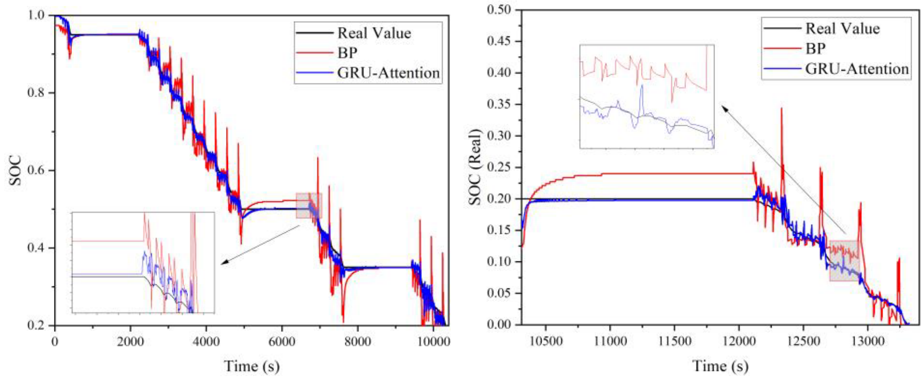
Table 1. The comparison of error results

	DST		UDDS	
	Maximum Error	**MSE**	**Maximum Error**	**MSE**
BP	16.38%	7.21	11%	4.27
GRU	8.47%	0.84	4.42%	0.59
GRU-Attention	6.99%	0.62	3.30%	0.47

4.2. Experiment Analysis under Low Power

Under low power, the characteristics of the battery may undergo changes, such as an increase in internal resistance or alterations in electrochemical reaction kinetics. These changes can lead to inaccurate SOC estimation. To test the performance of the proposed method under low power, the error results under different SOC values are compared. Figure 8 show the SOC value curves for normal and low power under DST condition, respectively. The specific error values are presented in Table 2. Figure 9 show the SOC value curves for normal and low power under UDDS condition, respectively. The specific error values are presented in Table 3.

Regardless of the dataset used, in both scenarios (SOC>20% and SOC<20%), the GRU-Attention model outperforms the BP model, as it has lower values for both metrics. The performance difference is more pronounced when SOC is less than 20%. From Table 2 and 3, it can be observed that regardless of which dataset is used, the traditional BP method exhibits significantly larger prediction errors under low power compared to its performance under normal power. This may be due to the presence of more noise and interference in the samples under low power, making it difficult for the BP to extract and capture patterns and features related to SOC in this state. However, the proposed method in this paper does not experience an increase in errors due to changes in battery SOC values. This indicates that the GRU-Attention can maintain stable performance even at low battery levels, effectively learning and adapting to complex battery behaviors without being significantly affected by increased noise or interference.

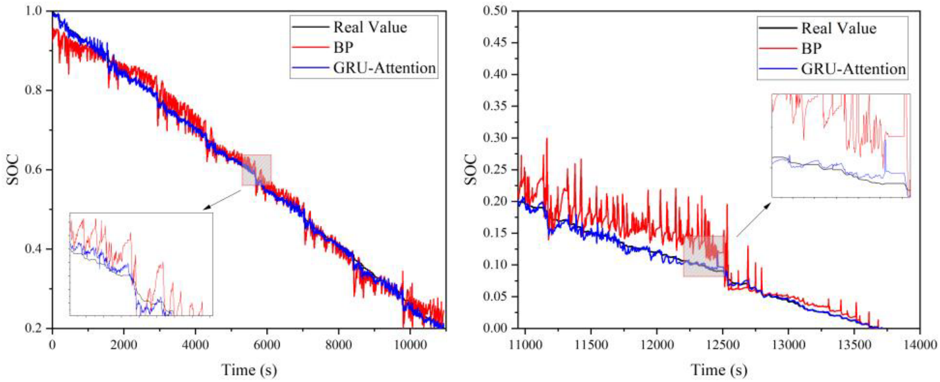


(a). normal power. **(b).** low power

Figure 8. The SOC value curves under normal and low power conditions in the DST dataset.

Table 2. The comparison of error results

DST	SOC>20% Maximum Error	SOC>20% MSE	SOC<20% Maximum Error	SOC<20% MSE
BP	15.72%	8.34	16.38%	11.91
GRU-Attention	6.99%	0.89	4.75%	0.43



(a). normal power **(b).** low power

Figure 9. The SOC value curves under normal and low power conditions in the UDDS dataset.

Table 3. The comparison of error results

UDDS	SOC>20%		SOC<20%	
	Maximum Error	MSE	Maximum Error	MSE
BP	11.49%	5.50	11.73%	7.87
GRU-Attention	3.30%	0.52	3.00%	0.27

5. Conclusion

To address the issues of low accuracy in SOC estimation under complex conditions and a sharp increase in SOC estimation error under low power, this paper proposes a GRU model with self-attention mechanism to estimate battery SOC. Three characteristics of this method are summarized by experiments on discharge data under DST and UDDS conditions.

First of all, the diversity of data affects the performance of model. The input of the traditional BP network is only one moment of current and voltage data, which has less data characteristics and poor estimation ability. The GRU model takes in a time series input comprising discharge data across various time points, which greatly increases the information learned by the model. Secondly, the self-attention mechanism enables efficient parallel processing of all positions in a sequence, allowing for better capturing of long-range dependencies compared to traditional RNN that rely on fixed-size local windows. By allocating attention weights, the model can better capture important information within the sequence, thus enhancing the overall estimation capability. Thirdly, the advantages of GRU network combined with self-attention mechanism are particularly obvious in SOC estimation under low power. The combination of both allows for a more comprehensive modeling of the input sequence and effectively extracts key information from the sequence.

However, there is still further work that needs to be perfected. The key to ensuring good model performance is to set the neural network parameters reasonably. Artificially set parameters are influenced by subjective factors, making it challenging to identify the ideal parameter combination. Therefore, the parameter optimization algorithm will be introduced in the future work to solve this issue. Using optimization algorithms to appropriately adjust and balance parameters, optimizing the relationship between model performance, training speed, and memory consumption, while ensuring the stability of the training process.

Acknowledgments

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