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Optimized Deep Convolutional Neural Networks Based State of Charge Estimation for Lithium-Ion Battery

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ABSTRACT

To address the problem of the accuracy decrease of state of charge estimation caused by sudden high current impact, this paper proposes a lithium-ion battery SOC estimation method based on optimized deep convolutional neural network. Firstly, the 18650 battery was tested under actual driving conditions to obtain experimental data, and the experimental data was preprocessed by moving window to fit the two dimensional convolutional neural networks. Secondly, the proposed method was trained and tested, and the model parameters were further optimized. Thirdly, the proposed method is compared with sequence-to-sequence methods such as long short term memory and gated recurrent unit, and the results verify the superiority of the proposed method. This article provides a method to the battery SOC estimation, which is more conducive to practical applications.

Keywords: lithium-ion battery, battery management system, state of charge, deep convolutional neural networks

1. INTRODUCTION

Under the international background of increasing global environmental pollution and double-carbon targets, new clean energy sources have received widespread attention. Lithium-ion batteries have become a representative of new clean energy because of the advantages of low self-discharge rate and long cycle life [1]. And a battery management system is designed to control and manage the battery. Accurate state of charge (SOC) estimation is a prerequisite for other parts of the battery management system, such as state of health estimation, equalization management, and fault diagnosis, so it is of high importance [2].

At present, battery SOC estimation methods are mainly divided into four categories: ampere-hour integration method, look-up table method, model based method, and data-driven method. Among them, the data-driven approach has a better development prospect under the international background of the rapid development of big data. The traditional feedforward neural network is widely used in SOC estimation due to its simple structure, but its robustness and accuracy are low. Then the SOC estimation methods based on recurrent neural networks, such as: recurrent neural network (RNN), long short term memory (LSTM), and gated recurrent unit (GRU), have attracted the attention of many scholars [3], it not only have good interpretability in theory, but also shows a better application in SOC, but when a sudden voltage change caused by large currents occurs, the accuracy of the RNN will decrease significantly. For this reason, this paper proposes a SOC estimation method based on an optimized deep convolutional neural networks (CNN) [4-6]. The average-pooling layer can reduce the impact of input mutation on SOC estimation, and CNN training requires fewer parameters training, which means a better practical applicability.

2. PROPOSED METHOD

2.1 Convolutional neural network

CNN is a feed-forward neural network, which consists of several convolutional layers and pooling layers. In 1989, LeCun combined the back-propagation algorithm and the weight-sharing convolutional neural layer to invent the convolutional neural network, and for the first time successfully applied the convolutional neural network to the handwritten character recognition system of the US Post Office. As shown in Fig. 1, the convolutional layer convolves multiple filters with input layer data and generates features. The input data of CNN is usually two-dimensional data, and data features are learned by convolution layers and pooling layers.

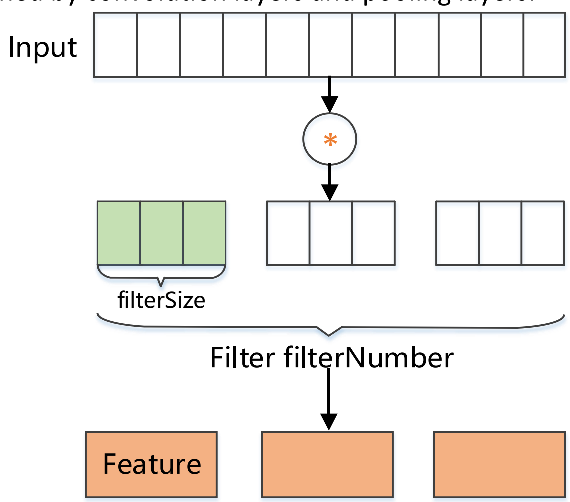

Fig. 1. Schematic of convolution layer

The convolutional layer takes convolution operations on the input information through the convolution kernel and further extracts features. The calculation process is shown in the following formula:

$$z_j^l = \sum_i x_i^{l-1} * k_{ij}^l + b_j^l \qquad (1)$$

Among them, $*$ represents the convolution operation, x_i^{l-1} and z_j^l represents the input and output of the filter, k_{ij}^l and b_j^l represents the weight and bias.

2.2 Data preprocessing by moving window

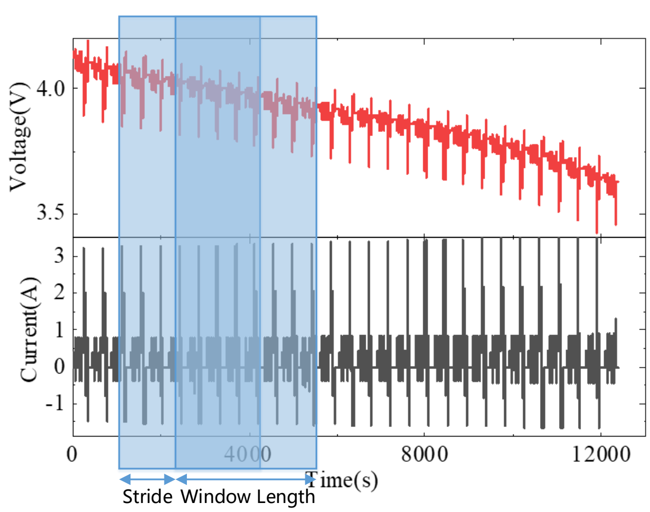

Fig. 2. Data preprocess by moving window

To improve the robustness of the model when the voltage and current changes suddenly, the 2D CNN is adopted in this paper, and the moving window is used to preprocess the input data to take the advantages of the average pooling layer. The preprocessing process of the moving window on the data is shown in Fig. 2.

The window length represents the one-dimensional length of the data processed at a time, and stride represents the one-dimensional distance between adjacent sliding windows.

2.3 Structure of proposed method

The structure of proposed method is shown in Fig. 3, which shows that the proposed deep CNN consists of 1 input layer, 3 convolution layers, 2 average pooling layers, 3 ReLU layers, 1 fully connected layer and 1 regression layer. The model input is preprocessed into a two-dimensional format, the input layer normalizes the data, and further uses the convolutional layer to extract features of the input. Then the ReLU function is used to retain the results of the convolutional layer, and the average pooling layer averages the features to reduce the amount of calculation and prevent overfitting. Finally, the output is calculated by the fully connected layer and regression layer.

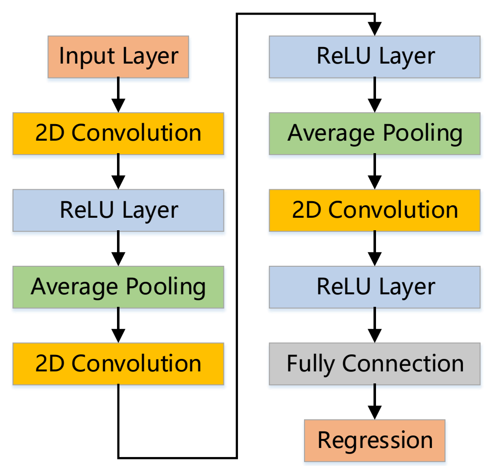

Fig. 3. Structure of proposed DCNN

After each convolutional layer, a layer of non-linear activation function is added. In this paper, ReLU is selected as the non-linear activation function because of its fast calculation speed and good practical application effect. For the input features, ReLU will change the elements less than 0 to 0 and keep other elements unchanged.

Pooling operation is essentially a process of extracting statistical information. Common methods include maximum pooling and average pooling. In this paper, average pooling is used to prevent the phenomenon of SOC accuracy decrease caused by sudden changes of current and voltage.

3. RESULTS AND DISCUSSION

3.1 Test platform

The battery test platform mainly includes a Neware battery test middle computer, a Neware battery test lower computer, a thermal chamber and an upper computer. An NCR18650PF battery was used to charging and discharging to obtain experimental data, and the upper voltage and the lower voltage of the tested battery were 4.2V, and 3.4V. After the initial test, the tested battery was cycled under the dynamic stress test (DST) at 20℃, and the battery data sets from the University of Wisconsin-Madison are used as a supplement to test the proposed method. The batteries datasets, the neural network code and the proposed design method in this work will be shared and made available in the final manuscript if requested.

3.2 Parameters optimization

Hyperparameters have an important influence on the performance of CNN. This article mainly optimizes the following parameters of the proposed method by grid method, the optimized parameters are mainly include: moving window length, maxepochs, and dropout rate. After optimization, the above parameters are determined to be: 40, 256, and 0.1696272.

After optimization, the detailed parameters of the proposed method is shown in the table 1.

Table 1. Detailed parameters of the proposed method

Layers	Parameters
imageInputlayer	inputSize:[40,2,1]
convolutional2dlayer-1	filterSize:[5,2];numFilters:8; Padding:same
relulayer-1	
averagePooling2dLayer-1	poolSize:[5,2];Padding:same
convolutional2dlayer-2	filterSize:[5,2];numFilters:16; Padding:same
relulayer-2	
averagePooling2dLayer-2	poolSize:[5,2];Padding:same
convolutional2dlayer-3	filterSize:[5,2];numFilters:32; Padding:same
relulayer-3	
fullyConnectedLayer	outputSize:1
regressionLayer	

3.3 Model evaluation

In order to verify the superiority of the proposed method, this paper chooses traditional sequence processing methods: LSTM, GRU, to compare with the proposed method. And 20% of the experimental data were used as the test data set, and the remaining data were the training data set. The adam algorithm is used to Iteratively update parameters, and to prevent over-fitting phenomenon, 25% of the training data were randomly selected for real-time verification. The initial learn rate is set to 0.01, and the max epochs is set to 500. The test results are shown in Fig. (4-6) and table 2.

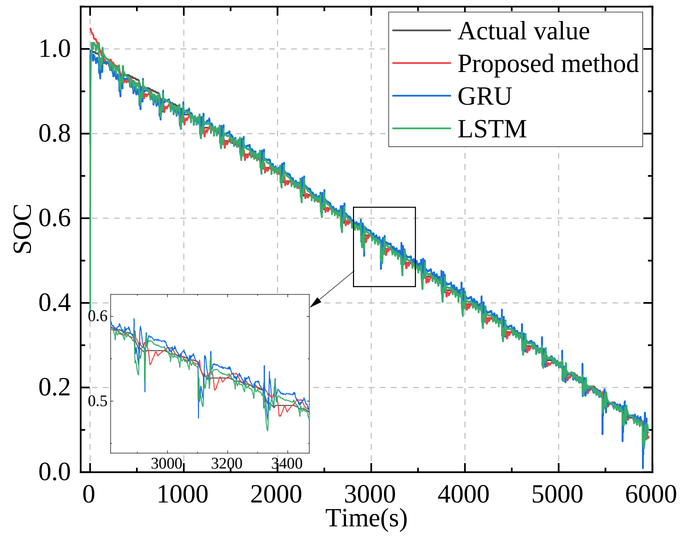

Fig. 4. Results of SOC estimation (DST).

It can be seen from Fig. 4 that the error of the proposed method quickly converges to within 1.5%, while the error of LSTM and GRU fluctuates continuously due to the sudden changes of voltage under DST driving cycles. The MAE of the proposed method is 0.65%, while the MAE of LSTM and GRU are 0.78%, and 1.06%, respectively. It can be seen that LSTM has a large error in the initial stage: greater than 60%, and GRU shows a better performance: the initial error is within 10%.

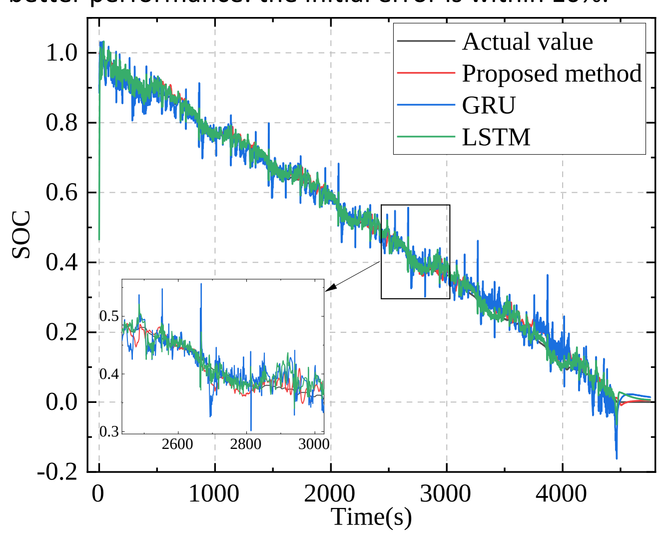

Fig. 5. Results of SOC estimation (US06).

Fig. 5 shows the battery SOC estimation results under US06 driving cycles. Similar to Fig. 4, LSTM has a large error in the initial stage: greater than 50%, but its average error is less than GRU. Among the three methods, GRU performed the worst with a MAE of 2.09%, while the proposed model and LSTM were 1.10% and 1.33% respectively.

To test the generalization performance of the proposed method, battery data from the University of Wisconsin-Madison was used. And the cycle data is used as the test data. The cycle data is composed of a random combination of US06, HWFET, UDDS, LA92 and neural network driving cycle. The driving cycle power curve is calculated for an electric Ford F150 truck with a 35kWh battery pack. The battery pack is scaled according to the proportion of a single 18650PF battery; and the data under US06 driving cycles are selected as the training data. The test result is shown in Figure 6.

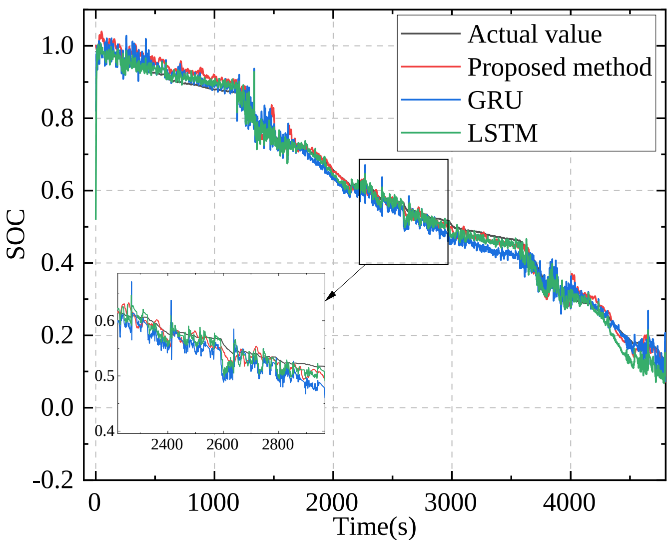

Fig. 6. Results of SOC estimation (Trained by US06 and tested by cycle 4).

It can be seen from Fig. 6 that the proposed method shows a better generalization performance than both the GRU and LSTM method. Similar to Fig. (4. 5), LSTM has a large error in the initial stage: greater than 30%, but its average error is less than GRU. And the test indicators of RMSE, and MAE of three methods are shown in the table 2.

Table 2. Comparison of different estimators

Indicators	Driving cycles	RMSE(%)	MAE(%)
Proposed method	DST	0.87	0.65
	US06	1.41	1.11
	Cycle	2.35	1.99
GRU	DST	1.39	1.06
	US06	2	1.33
	Cycle	9.6	4.84
LSTM	DST	1.48	0.78
	US06	2.8	2.09
	Cycle	5.2	3.2

It can be seen from Fig. (4-6) that the SOC estimation results mainly comes from the non-linear mapping of the voltage signal and current signal. When the battery voltage changes due to sudden changes in the current, the proposed method can better reduce its impact on the SOC estimation, while LSTM and GRU perform generally.

4. CONCLUSION

This paper proposes a SOC estimation method based on optimized deep convolutional neural network. Firstly, the current and voltage are processed to better utilize the advantages of CNN. Secondly, the five hyperparameters of the proposed method are optimized. Finally, the proposed method is compared with traditional sequence processing methods, such as LSTM and GRU, the accuracy is improved by more than 40%, and the model parameters need to be trained is greatly reduced, which means a better applicability.

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