Energy Proceedings
Vol 26, 2022
ISSN 2004-2965

A Random Health Indicator and Deep Learning Approach Based Capacity Estimation for Lithium-Ion Batteries with Different Fast Charging Protocols

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ABSTRACT

Different fast charging protocols will cause different battery aging rates, which will reduce the accuracy and robustness of the capacity estimation. To improve the robustness and accuracy of battery capacity estimation with different fast charging rates, a random health indicator and deep learning approach based capacity estimation framework is proposed in this paper. First, a robust health indicator is proposed to extract the relationship between battery charging data and aging rate, which is a random charging curve segment consist of voltage, current, and charging capacity. Second, a deep convolutional neural network is proposed to estimate capacity based on the robust health indicator with smaller model size, and the field model can be quickly obtained by the pre-trained model and transfer learning. Finally, the proposed framework is verified by the public datasets and experimental datasets with different fast charging protocols. The results show that even the charging protocols of test data are different from that of training data, the average error of capacity estimation is within 0.35%.

Keywords: lithium-ion batteries, capacity estimation, health indicator, deep learning, fast charging

1. INTRODUCTION

The international fossil energy crisis and environmental pollution continue to increase, making the research of clean energy urgent. Lithium-ion batteries have become a representative of clean energy due to their long cycle life, high energy density, and low self-discharge rate. The battery management system (BMS) is an intelligent system that monitors and manages batteries in real time. Battery capacity is one of the key parameters of BMS and is a prerequisite for accurate state of charge (SOC) estimation and state of health (SOH) prediction [1]. However, the nonlinear degradation [2], making accurate capacity estimation challenging.

According to the control theory, the current capacity estimation method can be divided into: open-loop estimation method and closed-loop estimation method. The open-loop estimation method mainly includes: empirical model method, physical model method and data-driven method [3]. The empirical model method uses discrete mathematical models or linear fitting for battery capacity estimation, which is low-cost but cannot be applied due to the difference between laboratory conditions and actual conditions. The physical model method includes equivalent circuit model and electrochemical model, this method relies on an accurate battery model which is difficult to obtain. The data-driven method mainly realizes capacity estimation through nonlinear modeling of charge-discharge features and capacity, which has high accuracy and good generalization. However, it involves too many parameters and is an open-loop estimation with poor robustness. Closed-loop estimation is mainly a fusion of different open-loop estimation methods. For example, the capacity estimation method based on data-driven and empirical model proposed by Zheng et al., which is a cooperation of cloud platform and vehicle BMS [4]. However, the effect of different fast charging protocols on battery capacity decay is rarely studied. A robust health factor is crucial for battery capacity estimation [5], but battery fast charging protocols vary with applicable scenarios. To this end, a health indicator and deep learning enabled capacity estimation framework is proposed in this paper. The proposed health indicator can effectively characterize the battery ageing rates at different charging protocols. And the deep learning and transfer learning enabled framework of pre-trained model to field model helps the model quickly adapt to different scenarios.

2. PROPOSED METHOD

2.1 Robust health indicator

The health indicator proposed is a 2D indicator composed of current, voltage, and capacity, and the schematic diagram of the health indicator generation is shown in Fig. 1.

As can be seen in Fig. 1, the proposed health indicator is a two-dimensional (2D) format input. The current is used to characterize the current feature, the voltage is used to characterize the voltage interval feature, and the capacity is used to characterize the charging rate feature. To further improve the robustness of the proposed health factor, a moving window is used to segment the charging curve. As shown in Fig. 1, the red line represents the current, the black line represents the voltage, the blue line represents the charging capacity, the window length represents the window width, and the stride represents the step between adjacent windows.

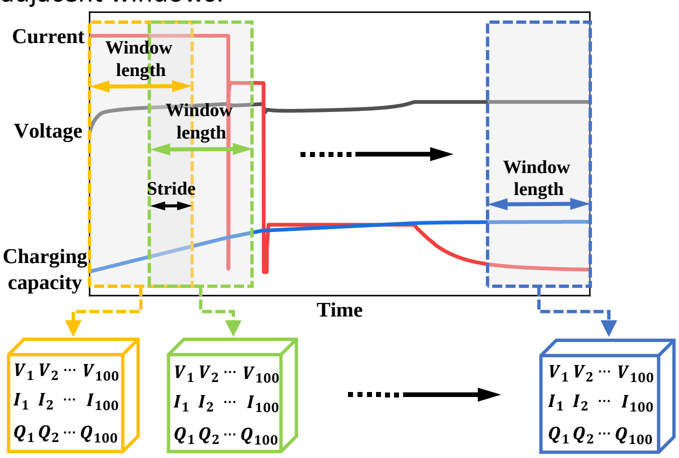

Fig. 1. Schematic diagram of the health indicator generation

2.2 Deep convolutional neural networks

Deep convolutional neural networks (DCNNs) are widely used in data feature extraction, which usually consists of convolutional layers, pooling layers, nonlinear function layers, and fully connected layers. Convolutional layers perform feature extraction on the input data using different mathematical forms of filtering. The pooling layer further maximizes or averages the extracted features. Non-linear functions are used to preserve the extracted features. The fully connected layer uses the weighted summation of the extracted features to obtain the final regression result.

The structure of the DCNN consists of 1 input layer, 3 convolution operations, 1 flatten layer, 2 fully connected layers, and 1 regression layer. The 3 convolution operations include 8 to 32 times of feature extraction, ReLU feature preservation, and max pooling.

2.3 Transferring pre-trained model to field model

The transfer learning technology can help transfer the pre-trained model to the field model, which greatly improves the application value of deep learning model. Thanks to transfer learning, we can train a pre-trained model in laboratory conditions and then get a field model. Fig. 2 shows the schematic diagram of transfer learning based pre-trained model to field model.

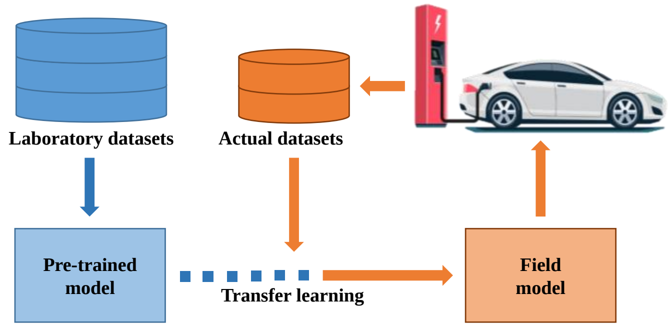

Fig. 2. Schematic diagram of transfer learning based pre-trained model to field model.

3. RESULTS AND DISCUSSION

3.1 Datasets description

The applied datasets include public datasets of 124 A123 commercial lithium-iron phosphate batteries [6] and experimental datasets of 4 Panasonic NCR batteries.

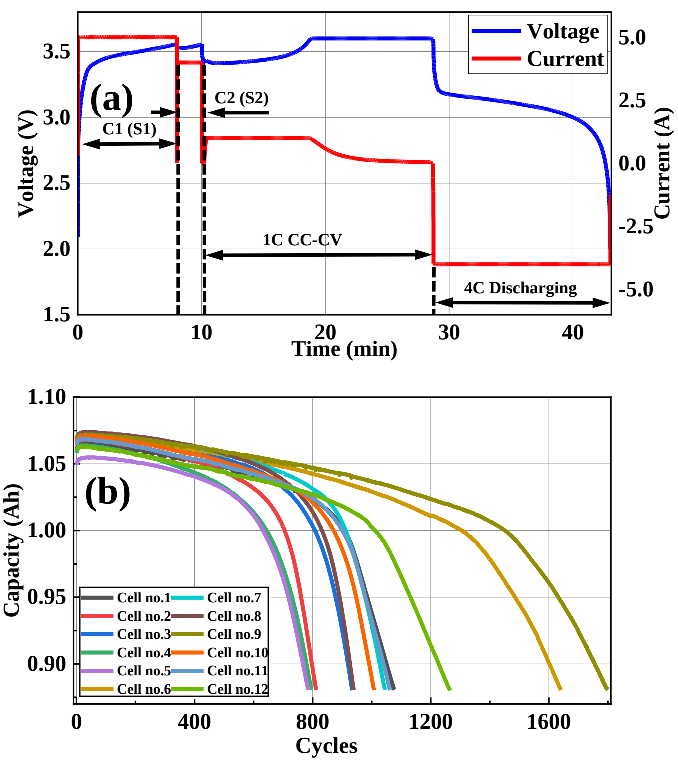

Fig. 3. Degradation of 12 A123 cells: (a) charging to discharging protocols; (b) capacity datasets

All A123 samples were cycled to failure under different fast charging protocols, and the charging-discharging protocols are shown in Fig. 3 (a). First, the test samples were charged at the charge rate of C1, then charged to 80% capacity at the charge rate of C2, and finally charged to full capacity at 1 C under constant current-constant voltage (CCCV). After the batteries were fully charged, the test cells were discharged at a current of 4 C, and the cycle was repeated to battery failure. The data used for pre-trained model training were the first 12 cells in the third group of 48 cells and the capacity data is shown in Fig. 3 (b). The experimental data of No. (5-12) batteries were selected as training datasets, and the experimental data of No. (1-4) batteries were test datasets.

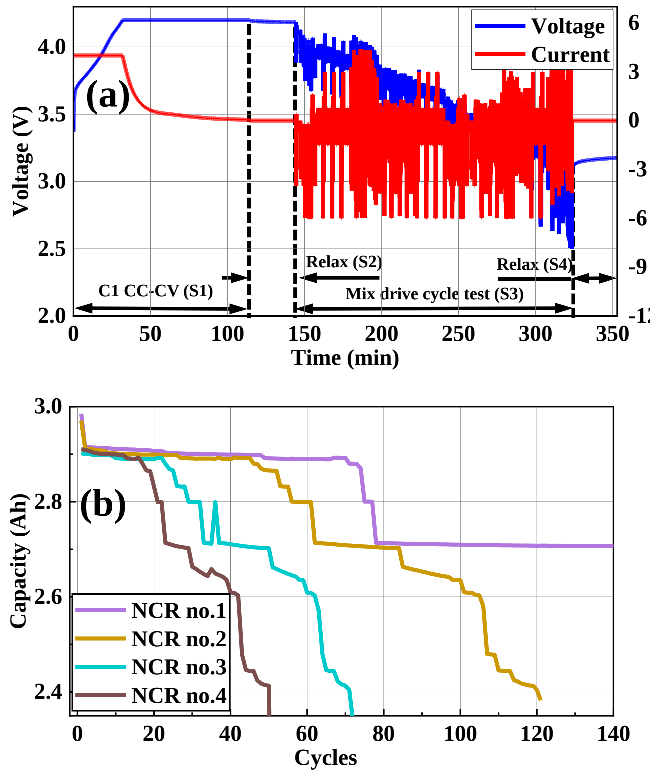

Fig. 4. Degradation of 4 commercial NCR cells: (a) charging to discharging protocols; (b) capacity datasets

4 Panasonic NCR batteries were cycled to failure under different charging protocols and mix drive cycles. As can be seen from Fig. 4 (a), the 4 NCR batteries were firstly charged at CCCV of rate C1. Second, the batteries were relaxed for 30 min to eliminate the polarizing reaction inside the cells. Third, all the test samples were discharged under mix drive cycles. Finally, the batteries were relaxed for 30 min again and be ready for the next charge-discharge cycle. The capacity curves of 4 NCR batteries are shown in Fig. 4 (b), and the datasets were used for field model training.

3.2 Parameters optimization

The hyperparameters of capacity estimation approach are important to the performance of proposed capacity estimation approach. The hyperparameters finally determined is shown in Table 1, and then the robustness, application value of the random health indicator and the generalization of proposed DCNN can be guaranteed.

Table 1. Detailed hyperparameters of the proposed approach

Parameter name	Parameter value
window length	100
stride	5
Image input	Input size: [100,3,1]
convolutional2d-1	Filters size: [5,2]; Filters number: 8; Padding: same
Batch normalization	1000
Relu-1	
Max Pooling2d-1	Pool size: [5,2]; Padding: same
Convolutional2d-2	Filters size: [5,2]; Filters number: 16; Padding: same
Batch normalization	1000
Relu-2	
Max pooling2d-2	Pool size: [5,2]; Padding: same
Convolutional2d-3	Filters size: [5,2]; Filters number: 32; Padding: same
Batch normalization	1000
Relu-3	
Fully Connection Regression	Output size: 1

3.3 Evaluation

To verify the robustness, generalization, and accuracy of proposed capacity estimation approach, experimental datasets of 12 cells with different charging protocols were selected for pre-trained model training. The datasets of cell No. (5-12) were selected as the training data, and the datasets of cell No. (1-4) with random health indicators were the test data. The capacity estimation results of pre-trained model are shown in Fig. 5.

Due to the random health indicator reason, we trained the model 30 times and got a best case and a worst case. As can be seen from Fig. 5, the average error of the capacity estimation results is within 0.35% which verified the robustness and accuracy of the proposed approach. To further prove the application value of proposed approach in real drive cycle, we transferred the pre-trained model to field model by transfer learning technology, and the results are shown in Fig. 6. The average error of best case was 0.15% and the average error of the worst case was 2.2%, which proved the application value of proposed approach. Furthermore, we found that charging data shows a higher correlation with capacity degradation when voltage is higher than 3.5 V, so the capacity estimation is recommended to begin at the charging interval of voltage above 3.5 V. Due to the limitation of 4 pages, further evaluation would be performed on the final manuscript.

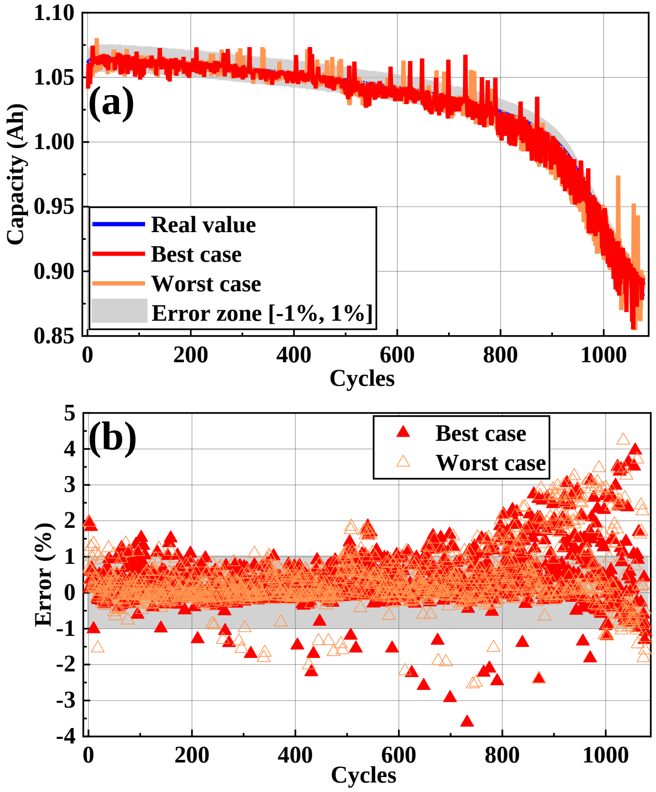

Fig. 5. Capacity estimation results of cell 1: (a) capacity curve; (b) relative error.

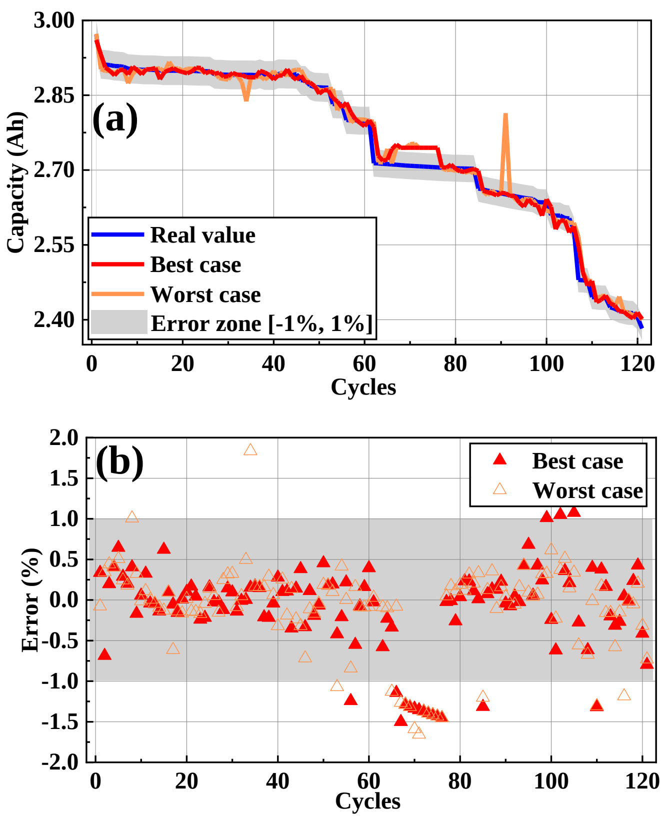

Fig. 6. Capacity estimation results of NCR no.2: (a) capacity curve; (b) relative error.

4. CONCLUSION

This paper proposed a capacity estimation framework for lithium-ion batteries based on random health indicators and deep learning approach. A robustness health indicator was proposed firstly, which was a 2D format input consist of current, voltage, and capacity. With the robustness health indicator to extract the relationship between battery charging rate and aging rate, the capacity can be estimated under different charging protocols. Then, a DCNN was proposed to fit the nonlinear relationship between the health indicator and battery capacity, and the hyperparameters were thoroughly discussed and optimized. Finally, the transfer learning enabled framework of transferring pre-trained model to field model was introduced to improve the application value of proposed approach. The proposed approach was evaluated by the public datasets of 12 A123 cells and experimental datasets of 4 Panasonic NCR batteries with different charging to discharging protocols. The average error of the worst capacity estimation case is within 0.35%. The results verify the robustness, generalization, and accuracy of proposed approach.

In future work, the closed-loop capacity estimation and internal short circuit detection for lithium-ion batteries module will be our main research object.

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