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CNN-based reconstruction of capacity degradation trajectory of lithium-ion batteries

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ABSTRACT

Accurate lithium-ion battery health estimation is crucial to ensure the safe and stable operation of energy storage battery systems. To address the problem of inaccurate battery state of health (SOH) estimation due to low sampling frequency and few stored data in the energy storage battery system, this paper proposes a battery capacity degradation trajectory reconstruction method based on convolutional neural network (CNN). Firstly, the battery capacity increment curves are analyzed to select the voltage segments with obvious differentiation for various degradation states of batteries. Secondly, the selected voltage-capacity segments in the first 30 cycles of batteries are input to a 3-layer CNN. Finally, the life-span capacity degradation curves are directly reconstructed without artificially feature selection and any voltage-capacity data after 30 cycles. The results show that the method has a high accuracy of capacity reconstruction with a mean absolute percentage error (MAPE) within 0.7%.

Keywords: Lithium-ion battery, convolutional neural network, capacity trajectory reconstruction

NONMENCLATURE

Abbreviations	
APEN	Applied Energy
Symbols	
n	Year

1. INTRODUCTION

Lithium-ion batteries have been the main energy source in the field of energy storage, attributed to high energy density, power density, and long lifespan [1][2]. Due to the influence of profiles and the electrochemical properties, batteries can suffer from capacity degradation and increase in internal resistance, which affects the usable energy and power of the battery and results in the battery not being able to meet the performance requirements of the actual profiles [3]. Therefore, accurate estimation of state of health is crucial for the reliability of batteries in energy storage systems.

The SOH estimation methods can be categorized into two types: model-based and data-driven. Model-based methods mainly build various models to simulate the battery behavior, and filtering algorithms and observers, such as Kalman filter (KF) [4] and particle filter (PF) [5], are applied to identify the model parameters to achieve the SOH estimation. One of the widely used models is the electrochemical model, which uses partial differential equations to simulate the material and charge transfer kinetic properties that are closely related to battery degradation [6]. Data-driven methods do not need to rely on models, and directly estimate battery SOH based on a large amount of battery degradation data by machine learning methods, including support vector machines [7], correlation vector machines [8] and Gaussian process regression [9].

Most of the above methods rely on real-time battery data to achieve accurate SOH estimation. However, in practical applications, the battery health state cannot be well estimated owing to lower sampling frequency of the actual battery management system (BMS) with poor data quality, which brings great difficulties in battery SOH estimation. For this reason, this paper proposes a CNN-based capacity degradation trajectory reconstruction method to estimate the SOH of the battery in different cycles. Only part of voltage-current data before the first 30 cycles are required to predict the battery degradation trajectory. Firstly, the battery voltage-capacity intervals that are strongly correlated with the battery aging are analyzed. Then a three-layer CNN for trajectory reconstruction is constructed, and the

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voltage-capacity data are input into the CNN to obtain the capacity degradation trajectory of the battery.

2. METHODS

2.1 Battery incremental capacity analysis

As an in-situ non-destructive analysis method, incremental capacity analysis (ICA) is widely used in the mechanism analysis of lithium-ion battery degradation. The basic principle of ICA is to differentiate the terminal voltage (V)-charge/discharge capacity (Q) curve of lithium-ion batteries to obtain the relationship between capacity increment and terminal voltage. Then the long and flat voltage plateau are transformed on the V-Q curve into the easily recognizable capacity increment peak. Its definition can be expressed by Eq. (1).

$$IC = \frac{dQ}{dV} \tag{1}$$

The data used in this paper is the publicly available lithium iron phosphate (LFP) battery dataset, which consists of 124 LFP/graphite batteries with a rated capacity of 1.1 Ah. The experiments were conducted at 30°C. The charge profiles are set to multi-stage charging. Firstly, all batteries were charged with constant current (CC) until the certain state of charge (SOC). Next, another CC was applied to charge up to 80% SOC. It should be noted that all batteries are charged under various CCs. Finally, batteries were charged to 3.6 V with 1C constant current-constant voltage (CC-CV) mode. As for discharge profiles, 4C rate current is utilized to discharge batteries to 2.0 V. The degradation trajectory curves of all batteries in the dataset are given in Fig. 1. In this paper, the failure threshold is set to 84% SOH.

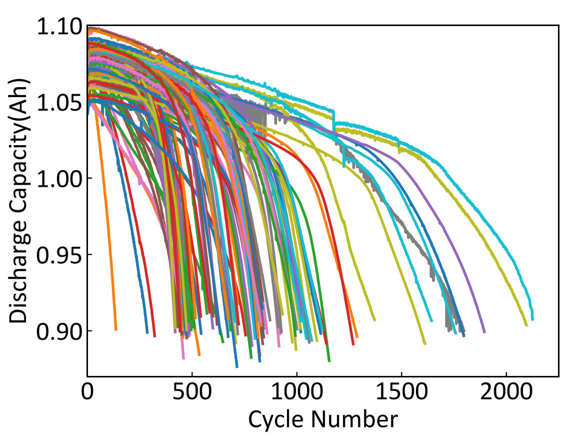
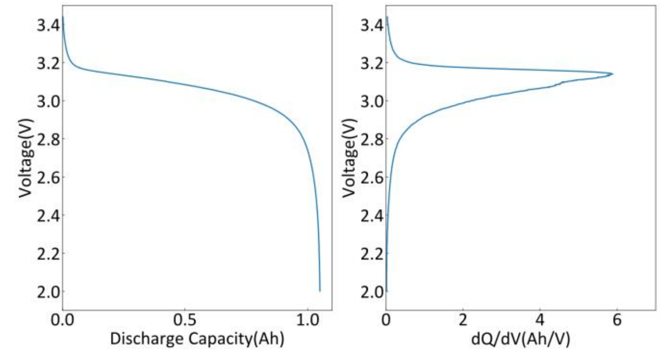


Fig.1 The discharge capacity curves of 124 cells.

In contrast to the other analyses in the literature, this paper does not perform ICA on the OCV curves measured at small currents, but directly analyzes the battery discharge data under diverse high-rate profiles. The discharge curves and IC curve of one of the batteries are shown in Fig. 2. Due to the effect of high-rate profile, there exists only one main peak in the IC curve, which is considered to be related to the internal reaction kinetic properties of the battery.



(a) Discharge voltage-capacity curve. (b) IC curve

Fig.2 The discharge voltage-capacity curve and IC curve of one cell.

The IC curves of this battery at different cycles are shown in Fig. 3. It can be found that the height of the main peak of the IC curve shows a decreasing trend with cycles, which further verifies the strong correlation between the mentioned height of the main peak and capacity degradation. As a result, the voltage-capacity segment corresponding to this peak is selected as the input to the CNN for subsequent trajectory reconstruction. We also noted a peak around 2.5V, but the magnitude of this peak was small and the difference was not significant enough to use it in follow-up.

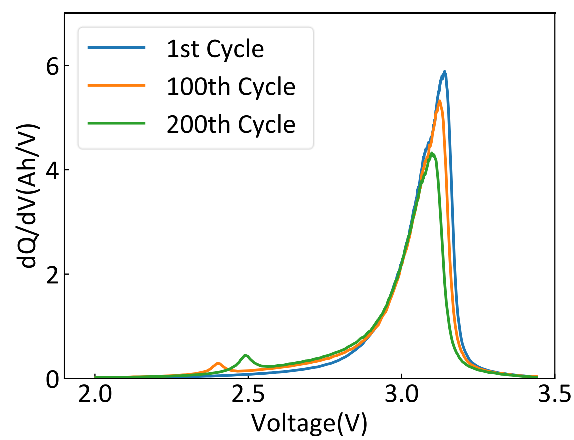


Fig.3 IC curves of one cell under different cycles

2.2 CNN

A typical CNN structure consists of convolutional layer, pooling layer, and fully-connected layer,The convolutional layer extracts high-dimensional features by performing convolutional operations on the input voltage-capacity segments. And the information flow of the input data undergoes the convolutional operation and activation function computation when flowing to the fully connected layer. The mathematical expression is shown in Equation (2):

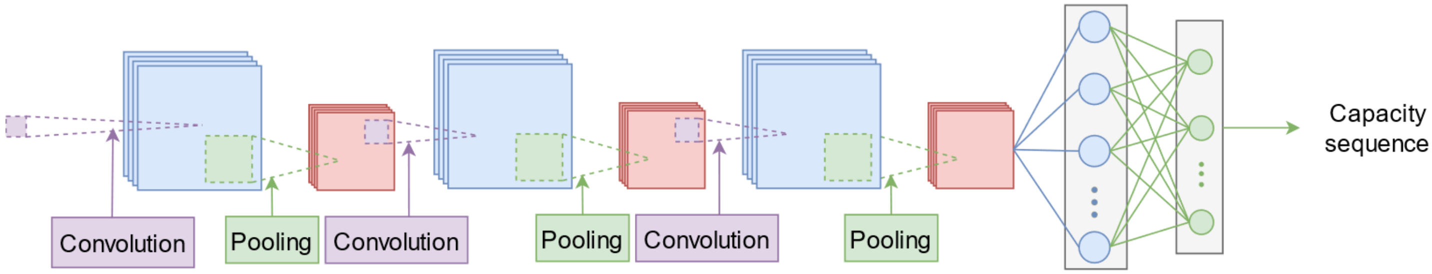


Fig.4 The proposed CNN model.

$$h = \sigma(\omega x + b) \tag{2}$$

where x denotes the input data; w denotes the convolution kernel, i.e., the weight vector; b denotes the bias of the convolution layer, and w and b are acquired and updated during model training; σ is the activation function of the convolution layer, and h is the output data of the convolution layer.

The pooling layer compresses the output features from the convolutional layer based on the pooling size, which is conducive to reducing the computational pressure of the model and discard some irrelevant information. The common methods include average pooling and max pooling. The fully-connected layer mainly aggregates the features of multiple channels and extracts the global features to ultimately output the desired length of the predicted sequence.

In this paper, the model structure is schematically shown in Fig. 4. The first layer is a two -dimensional CNN with 32 channels and 5*5 convolution kernel, and max pooling with a pooling size of 5*5 is employed; the second layer is a two-dimensional convolution with 64 channels and a 5*5 convolution kernel, using max pooling with a pooling size of 2*5; the third layer is a two-dimensional convolution with 128 channels and a 5*5 convolution kernel, also with max pooling of 2*5. After the Flatten layer, the two series fully-connected layers are immediately followed, with 600 and 419 neurons, respectively. ReLU is chosen as the activation function for each layer, and mean absolute error is chosen as the error function during the model training process. The learning rate is 2e-4, and the batch_size is 512. The maximum number of iterations is 150, and the ratio of training set, validation set and test set of the model is 6:2:2, and the data generation and model training are realized in Keras framework.

Since the output of CNN is a constant length sequence, the original battery capacity curves with different end of lives (EOLs) are required to be compressed. Considering that the SOH estimation is based on historical data, the EOL of every battery is known. We compress every capacity degradation curve to the length of 419 that is same to the number of neurons in the last fully-connected layer. Then the output capacity sequences are reduced according to the compression ratio to get the lifecycle capacity degradation trajectories of the batteries with different EOLs.

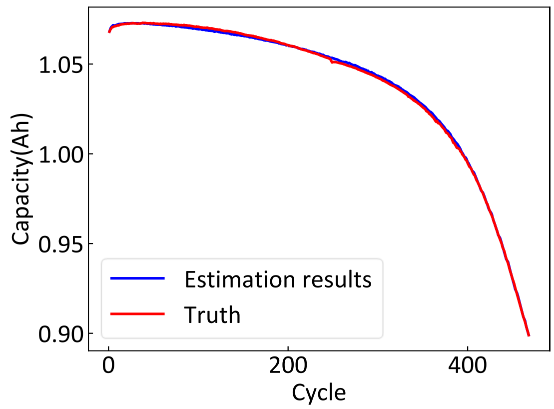
3. RESULTS AND DISCUSSION

Based on the proposed CNN model, the degradation trajectory reconstruction curves of some cells in the test set are shown in Fig.5. Fig.5 (a)(b)(e)(f) show the discharge voltage curves of four cells in test set. The EOLs for the four cells were 468, 837, 1018, 1287, respectively. The red curves in Figures are the true curves of cells, and the blue ones are curves predicted by the CNN model. It is obvious that the two curves of each cell are roughly close to each other. Fig.5 (c)(d)(g)(h) show the capacity relative errors between the estimation results and true values. All maximum relative errors of 4 cells are not more than 0.8%. These results illustrate that the proposed method well predicts the SOH of each cell under different cycles.

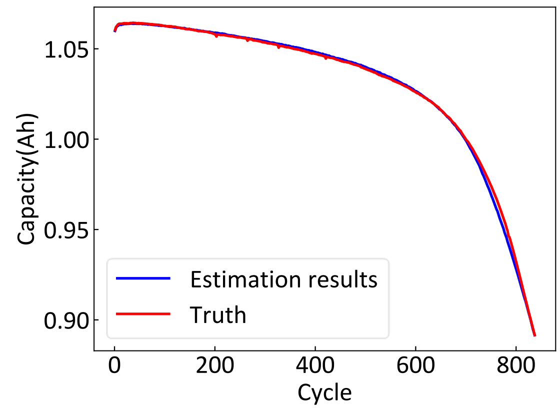
In addition, the MAPEs of 24 test set cells are presented in Fig. 6(a), with the horizontal coordinate being the number of 24 cells and the vertical coordinate being the MAPE. It can be identified that the MAPEs of all 24 cells are less than 0.7%. The box plot of the MAPEs is shown in Fig. 6(b), with the median equals to 0.287%, and the upper and lower quartiles are 0.42% and 0.202%, respectively. These errors are small enough to satisfy actual needs and the proposed method accurately estimates the SOH of the battery under different profiles.

4. CONCLUSIONS

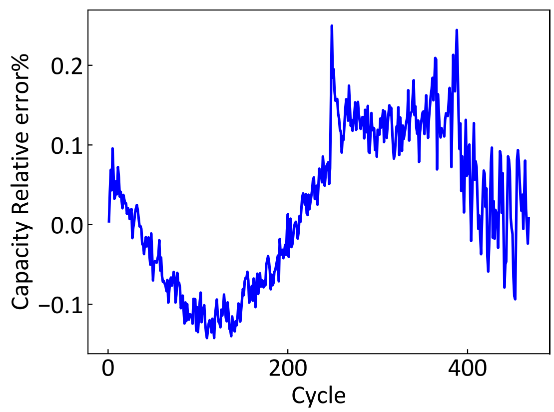
In this paper, a battery capacity degradation trajectory reconstruction method based on convolutional neural network is proposed. Unlike the existing methods for estimating SOH based on real-time data, the proposed method can estimate SOH based on the voltage-capacity segments of the first 30 cycles without collecting real-time data. Firstly, the battery capacity increment curve is analyzed, and voltage-capacity segments that are sensitive to battery aging states are extracted. Secondly, the voltage-capacity segments of the first 30 cycles are inputted into a 3-layer CNN. Finally, the lifespan capacity degradation curve is directly reconstructed without any voltage-capacity data after 30 cycles. The method has high capacity reconstruction accuracy with an MAPE within 0.7%, which is helpful for subsequent battery system fault diagnosis and early warning.



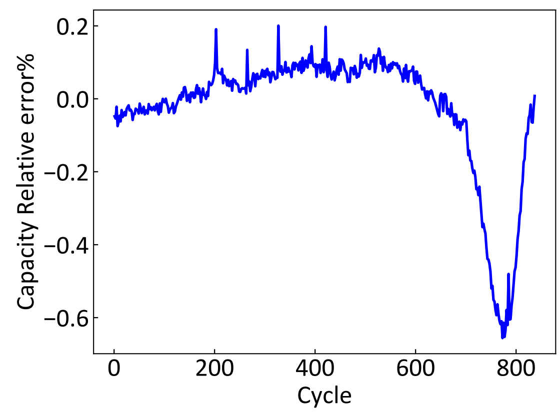
(a) Discharge voltage curves of cell 1.



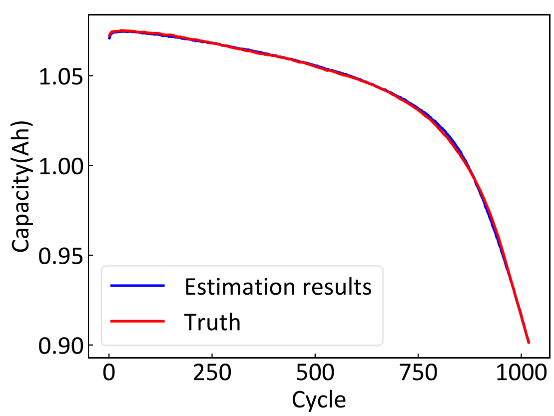
(b)Discharge voltage curves of cell 15



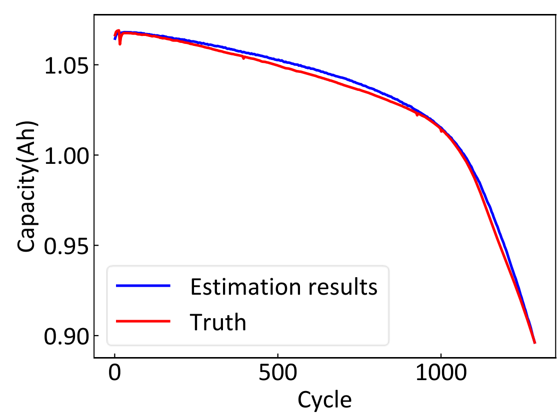
(c) Capacity relative error of cell 1.



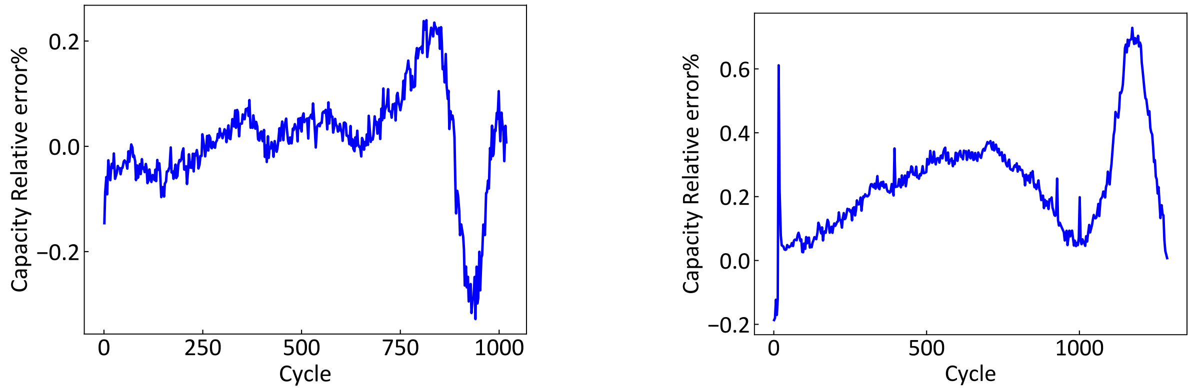
(d) Capacity relative error of cell 15.



(e) Discharge voltage curves of cell 12.

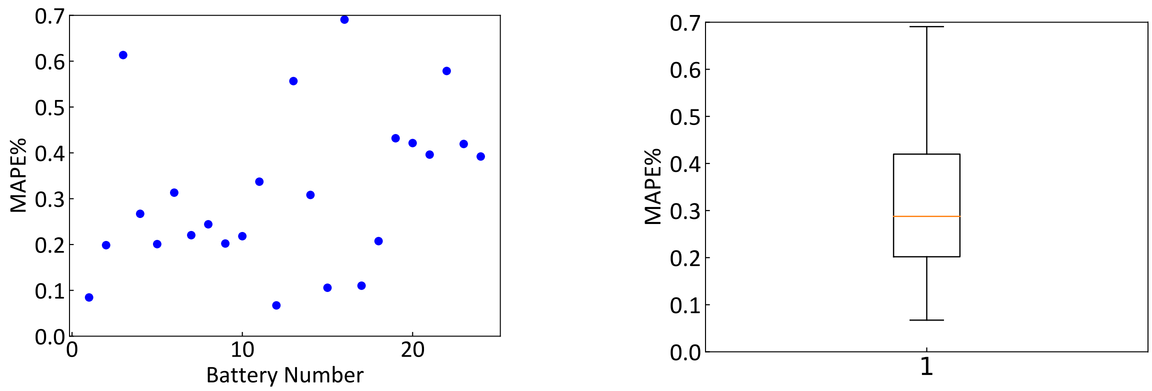


(f)Discharge voltage curves of cell 8.



(g) Capacity relative error of cell 12. (h) Capacity relative error of cell 8.

Fig.5 Degradation trajectory reconstruction results and relative errors.



(a) MAPEs of 24 Cells. (b) The boxplot of MAPEs.

Fig.6 The MAPEs of 24 Cells and the boxplot.

DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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