SOH Estimation Method for Lithium-ion Batteries Based on Partial Charging Voltage Segments

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***Abstract*-- The state of health (SOH) estimation of lithium-ion battery is considered a key component of battery management. A SOH estimation method for lithium-ion batteries, which is based on the partial charging voltage segments, is proposed. The voltage data segments was extracted, and the charging time series corresponding to each mv voltage value was reconstructed by interpolation method, which is used as the input of the RNN network. Finally, the estimated SOH value was obtained. The proposed method was applied to CALCE dataset, and accurate estimation result of SOH can be achieved with only 0.1v voltage segment data.**

***Index Terms*—lithium-ion battery, SOH estimation, voltage data segments**

I. Introduction

Lithium-ion batteries are widely used in energy storage systems, electric vehicles, consumer electronics, mobile portable devices and other fields due to their advantages such as high energy density, high power density, long cycle life and no memory effect. However, the application of lithium-ion batteries still faces many challenges, and battery degradation during operation is one of the most pressing and difficult problems at present. Like any other mechanical or electronic device, lithium-ion batteries undergo a process of performance degradation to failure. Degradation of lithium-ion batteries can lead to equipment failures, even serious accidents. Therefore, it is of great importance to accurately estimate the State of health (SOH) of batteries under various operating conditions.

The battery SOH is used to describe the health or deterioration of a battery, which represents the performance of the battery compared with that of a brand-new battery at a point in its life cycle. According to different research objectives, SOH can be defined in different ways, among which the definition of internal resistance form and the definition of capacity form are the most widely used and are defined as follows [1].

$$SOH = \frac{R_{EOL} - R_{aged}}{R_{EOL} - R_{fresh}} \times 100\% \tag{1}$$

R_{fresh} represents the initial internal resistance of a brand new battery, R_{EOL} represents the internal resistance at end-of-life, and R_{aged} represents the internal resistance of the battery measured at this moment. This definition presents power capability.

$$SOH = \frac{C_{\text{aged}}}{C_{\text{fresh}}} \times 100\% \tag{2}$$

C_{aged} represents the current battery capacity, and C_{fresh} represents the new battery capacity. When the SOH of the on-board battery is less than 80%, which means that the battery capacity is less than 80% of the initial capacity, the battery can be considered to be at the end of its service life and no longer suitable for use in electric vehicles [2]. This definition presents battery energy capability.

The study of battery state of health (SOH) can generally be divided into three kind of methods: experimental-based research, mechanism or equivalent model-driven research, and data-driven research [3]. Experimental-based methods are simple and convenient, but require a large amount of experimentation to obtain resistance and capacity changes during the aging process, and are now less commonly used. For example, in [4], electrochemical impedance spectroscopy (EIS) was used as an analysis tool to observe the degree of battery aging under different operating conditions. In [5], EIS was used to determine the battery's aging parameters. Mechanism-based research typically considers mechanistic factors that affect the internal chemical reactions of the battery, and aims to establish models by mining regularities. Doyle et al. proposed the pseudo-two-dimensional (P2D) model for lithium-ion batteries, which accurately describes the internal electrochemical reaction process and has been widely applied [6, 7]. Ramadas P et al. considered the solid electrolyte interface (SEI) film generated by side reactions and proposed a capacity decay model [8]. BorYann Liaw et al. established a mechanism diagnosis model for lithium-ion battery capacity loss [9], pointing out that the loss of lithium inventory (LLI) and the loss of active material (LAM) are the main mechanisms for lithium-ion battery capacity loss. Xu Jun et al. from Xi'an Jiaotong University used an improved fast Fourier transform (FFT) to decompose and transform the battery's response to step signals, realizing online fast EIS collection, and further established an SOH evaluation model using an extreme learning machine with regularization mechanism [10]. Data-driven prediction methods start with experimental data and use statistical, machine learning, deep learning, and other methods to analyze and summarize the experimental data to derive empirical laws of capacity degradation, which have been widely used in battery research in recent years. Improved algorithms based on data-driven principles such as Kalman filtering [11], particle filtering [12], support vector regression [13], Gaussian process regression [14], neural networks [15], and fuzzy logic have been applied to battery SOH estimation. Among these methods, neural networks have received the most attention [16]. Zhonghua Yun, Wenhu Qin, and others proposed a lithium-ion battery health prediction method based on a mixed scheme, which comprehensively estimates the SOH of the lithium-ion battery [17]. Xiaoqiong Pang et al. combined fusion wavelet decomposition technology and nonlinear autoregressive neural network to effectively capture the phenomenon of battery capacity regeneration [17]. Rui Xiong et al. estimated the complete charging curve by using partial charging curve as input, further estimated SOH, and applied transfer learning techniques to achieve model transfer on different battery datasets [18].

Existing research often uses a wider range of charging voltages to extract features, which is difficult to obtain in practical applications. The method proposed in this paper can achieve battery SOH estimation using only short charging segment data.

II. METHODOLOGY

A. Dataset

The CALCE dataset from University of Maryland[19, 20] is chosen as a case study in this paper. Relevant data contains the aging data of 4 $LiCoO_2$ cells of 1.1Ah nominal capacity, labeled as CS2_35 to CS2_38. All cells underwent a standard constant current-constant voltage (CCCV) protocol until the voltage reaches 4.2V. Then maintain the terminal voltage at 4.2V until the charging current dropped to below 0.05A. In discharge process, cells cycled at constant current of 1C until voltage reaches 2.7V.

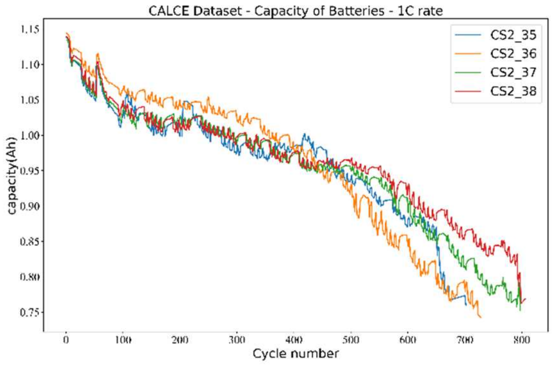

Fig. 1. CALCE dataset

B. Feature Extraction

As lithium-ion batteries age, their charging voltage curves tend to shift. Fig. 2 presents the voltage curve migration of Battery CS2_38. It suggests that the voltage curve of a battery with more cycles and more severe aging tend to shift to the left. The decreasing charging time indicates a reduction in the battery's chargeable capacity.

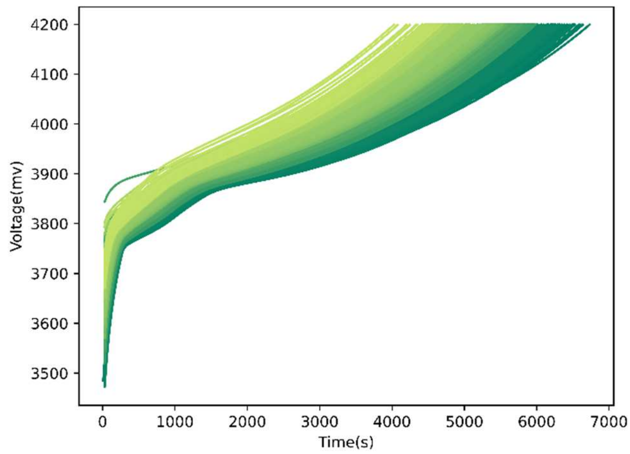

Fig. 2. Charging voltage curve of CS2_38

The incremental capacity (IC) curve of a battery is used as inference techniques capable of revealing battery degradation mechanisms and quantifying the degree of degradation in a cell. The peak size, peak voltage and subpeak area of each IC peak in the IC curve, especially the relevant characteristics of the NO.1 main peak, can well reflect the battery status information. Although drawing IC curve usually requires charging and discharging at low current to obtain OCV curve, the IC curve under normal charging and discharging ratio cannot be quantitatively analyzed, its changing trend can still reflect the hidden information of the battery pack.

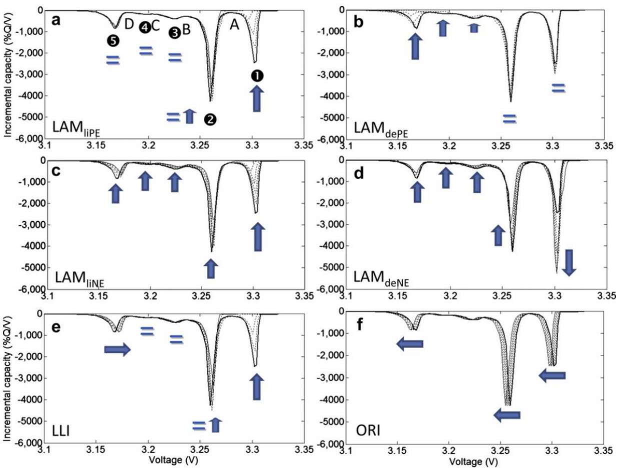

Fig. 3 Mechanism of battery capacity loss represented by IC curve variation[21]

Fig. 4 shows the IC curve of this battery under different cycle times, it reflects the shift more clearly. With the increase of the cycle number, the IC peak is shrunk, and the IC peak moves to the direction of high voltage and the area under the IC curve decreases, indicating that the rechargeable capacity of the battery decreases. Examining the whole curve, the voltage interval near the IC peak contains the most abundant battery aging information, so this voltage interval is selected for feature extraction.

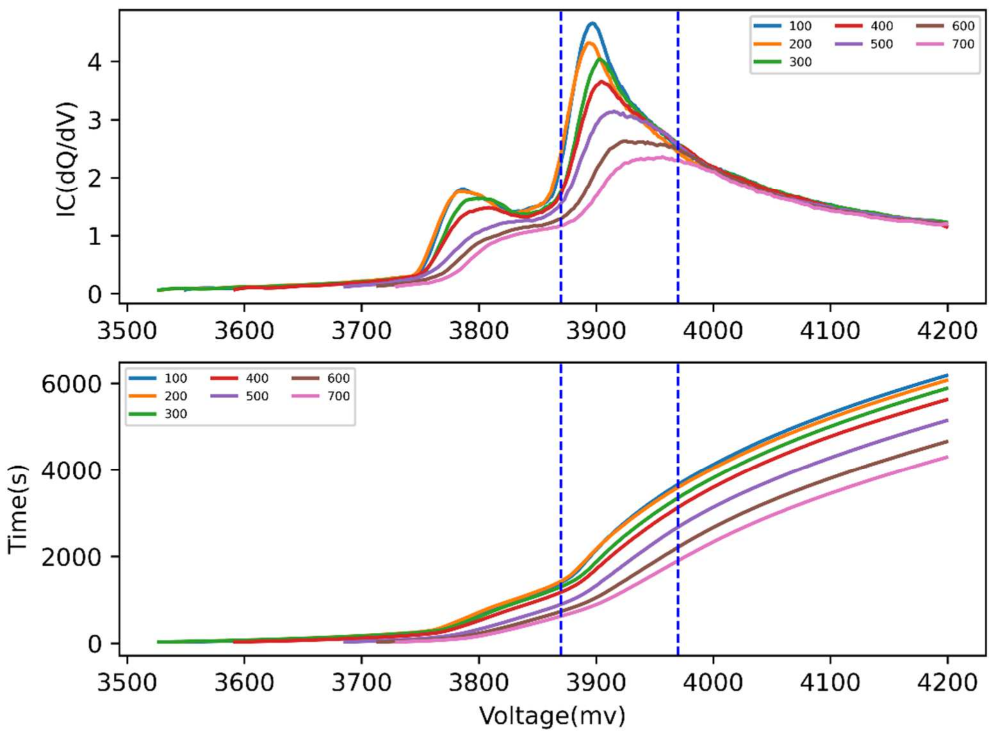

Fig. 4. IC curve and Selection of voltage segments

The [3.87V, 3.97V] interval where the IC peak is located was selected for feature extraction. For constant-current charging batteries, the capacity charged into the battery C_{charge} can be expressed by the formula(3).

$$C_{charge} = I \cdot t_{chargetime} \tag{3}$$

Considering in constant-current charging stage, charging current I remains a constant, charging capacity is determined only by charging time $t_{chargetime}$, the charging time can be used as an equivalent substitute for the charging capacity. Compared with the charging capacity, the charging time can be extracted easily without complex operations such as filtering. Therefore, the charging time is selected as the input feature, the charging voltage curve is used to reconstruct the charging time curve corresponding to each mv by interpolation, and the corresponding time segment information in each voltage segment is selected as the input. That is, $H=[t_0,t_1,t_2,\cdots\cdots,t_{99}]$, where the count starts from 0 to ensure that the input feature only contains the time information within the voltage segment taken.

C. Recurrent Neural Network

Recurrent Neural Networks (RNN) is a neural network that specifically processes sequences. Compared with traditional BP networks, RNN can capture changes in time series and reflect the aging trend of batteries better. Fig. 5 shows the structure of the RNN network.

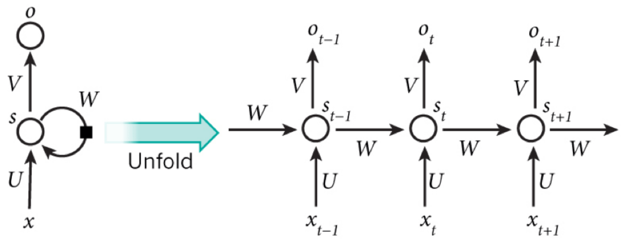

Fig. 5. Structure of RNN network

$$o_t = g(Vs_t) \tag{4}$$

$$s_t = f(Ux_t + Ws_{t-1}) \tag{5}$$

At time t, x_t represents the input, s_t represents the hidden layer value, and the output value is o_t. U represents the weight matrix of input x, V represents the weight matrix of output layer, W represents the last time st-1 is the weight matrix of this input, g and f are the activation function. If Formula (5) is substituted into Formula (4)repeatedly, we can get:

$$\begin{aligned} o_t &= g(Vs_t) \\ &= Vf(Ux_t + Ws_{t-1}) \\ &= Vf(Ux_t + Wf(Ux_{t-1} + Ws_{t-2})) \\ &= Vf(Ux_t + Wf(Ux_{t-1} + Wf(Ux_{t-2} + \cdots)) \end{aligned} \tag{6}$$

The output value o_t of RNN is not only affected by the input x_t at this time, but also by the input x_{t-1}, x_{t-2},… of previous times. Compared with LSTM, RNN focuses more on enhancing the impact of data at similar moments while ignoring the impact of data at distant moments, which is in line with the trend of battery degradation. Therefore, this paper chooses RNN instead of LSTM.

In this paper, the model is trained and tested on a GPU on Windows Sever 2019, the graphics card is Nvidia Quadro RTX4000, the video memory is 8G, and the training environment is python 3.9.12 and Pytorch 1.12.1.

D. Estimation Result and Discussion

In this paper, the previous 400 cycles were used as the training set and the remaining cycles were used as the test set. The capacity form of SOH is chosen as the lable. Selecting Mean Average Error (MAE), Mean Squared Error (MSE) and Root Mean Squared (RMSE) as the criteria for evaluation, the SOH estimation results of this method are as follows.

TABLE I

THE SOH ESTIMATION RESULTS OF CS2 ON CALCE DATASET

Cells No.	MAE(%)	MSE(%)	RMSE (%)
CS2_35	1.30	0.04	1.91
CS2_36	2.12	0.08	2.75
CS2_37	1.31	0.03	1.71
CS2_38	0.71	0.01	1.03

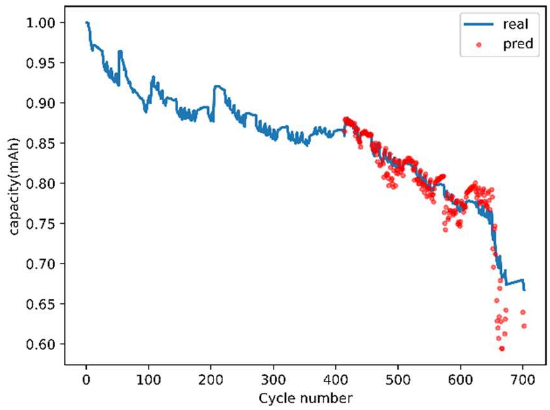

Fig. 6 CS2_35 SOH estimation results

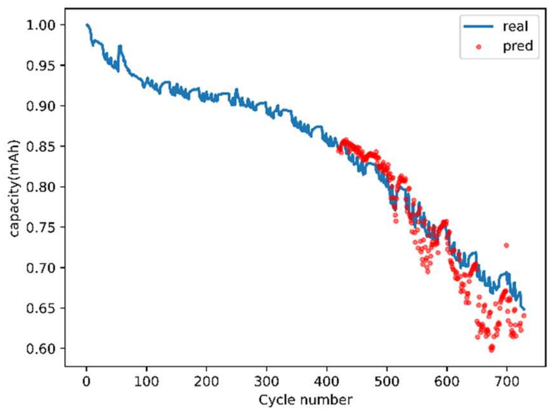

Fig. 7 CS2_36 SOH estimation results

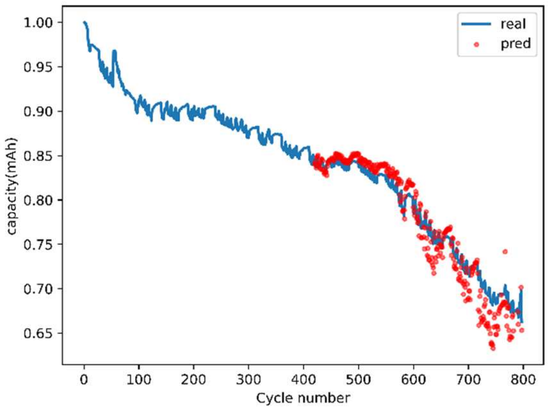

Fig. 8 CS2_38 SOH estimation results

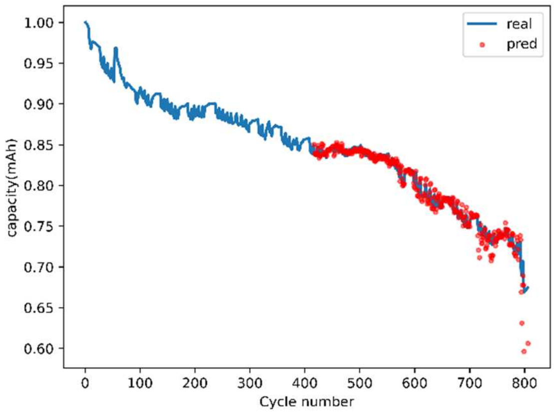

Fig. 9. CS2_38 SOH estimation results

III. Conclusions

A SOH estimation method based on partial charging voltage is proposed in this paper, which using charging time series reconstruction and RNN network .The charging time series corresponding to each mv voltage is used as an input feature. In this method, the battery SOH estimation results can be obtained only from the partial charging voltage segments and time data segments without complicated data operation such as filtering. The proposed method can achieve the MAE of the estimated result within 3%.

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