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Battery Lifetime Prediction and Degradation Reconstruction based on Probabilistic Convolutional Neural Network

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***Abstract*— Capacity degradation of lithium-ion batteries influences their service abilities as energy storage systems. Lifetime prediction, historical degradation curve trajectory, and capacity estimation help prognose the long-term serviceability and timely health status of batteries, which guides early maintenance and intelligent management. This paper proposed a novel method to predict the lifetime, reconstruct the historical degradation curve and estimate the capacity via excavating the information hindered under partially charged capacity and temperature curves. Only partial raw data of temperature and charged capacity are needed for modeling without manual feature engineering. The convolutional neural network is used to build the lifetime prediction and capacity estimation models. In addition, the probabilistic regression is added to the establishment of the capacity estimation model, which could provide the probabilistic estimation results. Finally, transfer learning is adopted to update the model with a few available data of testing batteries. Results show that the predictions are accurate and reliable.**

Keywords— Battery lifetime prediction, degradation trajectory, capacity estimation, probabilistic prediction

I. INTRODUCTION

The electrification of the transportation sector is regarded as an industry trend, where batteries are used as the main energy storage source [1]. However, during long-term operation, the capacity of the battery will fade resulting in a limited lifetime. The aging and damage of lithium-ion batteries can lead to the failure and collapse of the entire system and even cause property damage and casualties [2]. Therefore, lifetime prediction and capacity estimation play a key role in the health management of batteries. Accurate and robust lifetime prediction and capacity estimation help design intelligent management strategies to optimize the battery operation and maximize the battery life [3,4].

Methods for battery health prognostic can be divided into model-based, data-driven, and hybrid methods [5]. Model-based methods mainly establish either empirical or physics-based models to characterize the behavior of battery to estimate the state of health (SOH) or predict lifetime [6]. However, the complexity of modeling and poor generalization are the main drawbacks. Data-driven methods show better generalization higher flexibility and satisfactory accuracy and robustness, making them very appealing for battery SOH estimation and lifetime prediction. The hybrid methods fuse the model-based and data-driven or different data-driven methods to improve the accuracy and robustness, where the data-driven method is the key base.

Data-driven methods for battery health prognostic include three steps, i.e., data preprocessing, model training, and predictive validation [7]. In data preprocessing, the raw data are collected and cleaned up to form the input and output of the machine learning model. Then, the data-driven model is trained using the processed data. Finally, the model is used for capacity estimation when new data are obtained. According to the available literature, three main methods can be used to form the input. The first method uses the capacity sequence for model building, which uses the capacities of a few former cycles as the input [8]. The second method directly uses the raw data of voltage, current, and temperature as the input, then uses deep learning methods such as convolutional neural network (CNN) and recurrent neural network to extract the intrinsic information automatically [9]. The advantage of this method is that only raw data are needed without feature engineering, while the challenge is the effective input parameter selection. In the third method, health indicators (HIs) are extracted from measured parameters to reflect the aging status of the battery and build the relationship between those HIs and capacity via machine learning [10,11]. Online extraction can be achieved while the generalization ability is poor. The second key task is parametrizing ML algorithms in data-driven battery health prognostic. Among various methods, the neural network is one main category to fit the regression model. However, most of them only provide a specific prediction but are not probabilistic. In addition, many data are required for the supervised model training, which is hard to obtain in real applications. Moreover, existing works mainly consider the aging information from charged capacity while ignoring the influence of resistance, which is reflected in the temperature variation during aging.

Therefore, to overcome the problems mentioned above, this paper proposes a probabilistic convolutional neural network (PCNN)-based capacity estimation method, which is achieved through accurate battery lifetime prediction and capacity degradation curve reconstruction. Firstly, temperature and charged capacity data in the partial voltage range are used for data-driven modeling. Then, the lifetime prediction results guide the training of the capacity estimation model. Finally, the transfer learning strategy is adopted to retrain the capacity estimation model only using several checkpoints while satisfactory estimation results can be obtained. The remainder of this paper is organized as follows; the main methods are described in section 2. Then the results are provided and discussed in section 3. Finally, the main conclusion is summarized in section 4.

II. Method

A. Data description

The data from [12,13] are collected to form the data set used in this paper, where 169 battery cells are collected. The cells with wrong temperature signals are removed, which may be caused by the errors of sensors. Therefore, 129 cells remain in total. These batteries are charged under fast charging with different combinations of current rates and discharged under a constant current of 4 C. They are all aged under 35 ℃. The capacity curves of the 129 batteries are shown in Fig. 1.

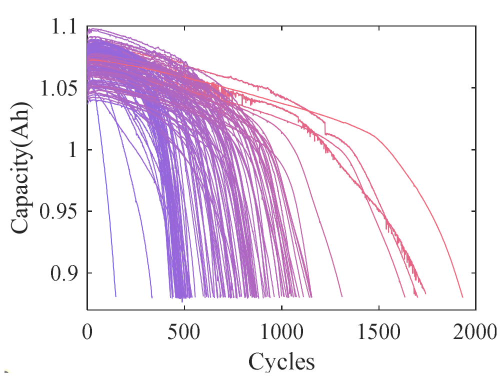

Fig. 1 Capacity fade curves of the 129 battery cells

B. Modeling

It is known that the information hidden in the charged capacity (Q) – voltage (V) curve contains ample aging characteristics because the capacity attenuation will be directly reflected on the charged or discharged amounts [14]. Besides, the temperature is another valuable parameter to be considered when studying the health prognostics for batteries [15]. Because the internal electrochemical reactions of the battery are significantly affected by the temperatures, which directly influence the degradation process [16]. The variations of the Q-V curve and ΔT-V curve of one battery during aging are shown in Fig. 2. The reason for using the ΔT curve instead of the original T curve is that the initial temperatures are different due to the experiment, while the temperature increments can directly reflect the internal electrochemical reaction in the battery during one aging cycle. The color varies from purple to red with the increase in running cycles. It can be seen that the Q-V curve and ΔT-V show regular variations during the aging process. The Q-V curve shows a decreasing trend while ΔT-V shows an increasing trend. Therefore, both Q and ΔT are important inflections of battery aging and need to be considered in the modeling.

In this paper, the capacity and temperature curves measured/obtained during a partial constant current discharging interval (i.e., 2.85 – 3.25 V) are chosen as the inputs considering the requirement of real application. To form the inputs, the partial Q curve, differential Q curve compared to that of the 10$^{\text{th}}$ cycle (used in Ref. [12]), and the T increment (ΔT) curve are included. For battery capacity estimation, the capacity is selected as output to build the PCNN. For battery lifetime prediction, the partial curves of the 100$^{\text{th}}$ cycle are set as inputs, and the end of life (80% of SOH) is the output for the model.

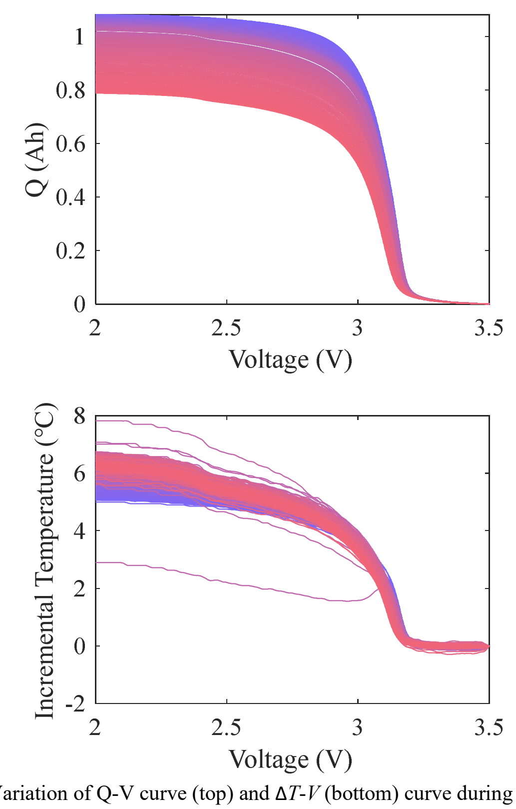

Fig. 2 Variation of Q-V curve (top) and ΔT-V (bottom) curve during the whole lifetime of a battery cell

For automatic hidden feature extraction from the collected charged capacity and temperature curves. The 1D CNN is adopted to extract the hidden characteristic of the raw parameters. Then the fully connected layer is used to output the prediction. The proposed structure of the network is shown in Fig. 3. One-dimensional CNN (1D CNN) has been widely used

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in battery health prognostic recently, and satisfactory predictions could be obtained [17]. The kernel is moved on the time scale to extract the features in 1D CNN. Then, the flatten layer transforms the hidden states, which could be further connected to fully connected layers. The primary function of a neuron in the dense layer is [18],

$$y = activate\_fun(\sum w_i * x_i + b_i) \quad (1)$$

where x and y are input and output, respectively, *activate_fun* is the activation function, and w and b are the weight and bias, respectively. In this paper, the relu activation function is used.

To provide probabilistic predictions, the probabilistic neural network sets the weight and bias as distributions. Consequently, the training process optimizes the distribution instead of one specific value. The loss function between the estimated value (p_y) and real value (y) in the training process is defined as follows,

$$\text{negative\_loglikelihood}(y, p\_y) = -p\_y.\text{log\_prob}(y) \quad (2)$$

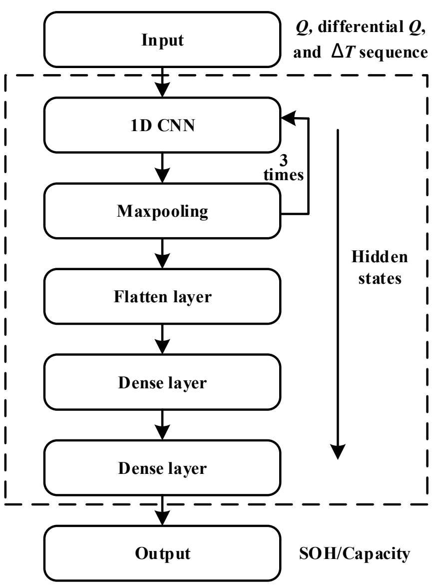

Fig. 3 The proposed NN flowchart

C. Prediction framework

The overall prediction process is shown in Fig. 4. Specifically, the measured data of *V*, *Q,* and *T* are gathered firstly during each aging cycle. Secondly, the data processing is implemented to prepare the inputs for the prediction model, where the interpolation method is used to ensure the same length of the inputs. Because of the same voltage range, the discharge time would decrease during aging. Then, the lifetime model is trained, and the lifetime of the testing battery is predicted. The data of two batteries with close lifetimes to the predicted lifetime are selected for the capacity model training. Next, transfer learning is adopted to continue the model updating process of the testing battery with a few checkpoints. Finally, the prediction of the historical degradation curve and the estimation in the following cycles are obtained by inputting the charged capacity and temperature curves.

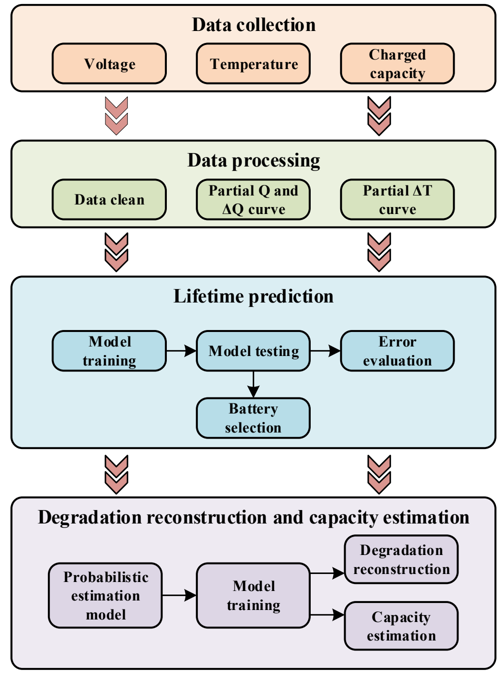

Fig. 4. Flowchart of the proposed prediction method.

III. Results and Discussion

This section presents and discusses the lifetime prediction, capacity degradation curve reconstruction, and capacity estimation results.. To demonstrate the performance of the proposed method, three batteries that have 1/4, 2/4, and 3/4 (cell 35, cell 121, and cell 100, respectively) life ranges of the whole data set, are selected to be the testing batteries for demonstration. The mean absolute error (MAE) and root mean square error (RMSE) is used to evaluate the accuracy of the predicted results. All the results are obtained by Tensorflow and Keras version 2.7.0 and Tensorflow-probability version 0.15.0.

The prediction results are shown in Fig. 5, where the results for the three batteries obtained by retraining the model with the known 10th cycle and 100th cycle are shown in Fig. 5(a), (c), and (e), respectively, and the results when two more checkpoints (50% and 90% SOH) are used for model training are shown in Fig. 5(b), (d) and (f) respectively. The numerical results of the lifetime and capacity predictions are listed in Table I, Table II, and Table III.

Results show that the base model (trained by the source domain but no retrain process is conducted) succeeds in predicting the right trend, but the predictions still have obvious deviations from the real capacities. However, when the model is retrained by the early two checkpoints, the prediction converges more accurately to the real values. But it provides accurate and reliable results in the early stage while a bit large errors in later stages due to the lack of knowledge of testing batteries in these stages. However, when the model is retrained by the four checkpoints, the prediction converges more accurately to the real values, and the predictions nearly cover the real values. The predicted MAE and RMSE are less than 2.1% and 2.9% when using two early checkpoints and reduced to less than 1% when two more checkpoints are used to update the model for the three testing batteries. But the base model has larger errors, which are larger than 5% and 5.4%. The 95% confidence interval is narrow, which means that the predictions are accurate and reliable.

The prediction results for the lifetime indicate that the errors are less than 10%, which helps guide the early maintenance and select adequate data for model training. Moreover, the proposed lifetime prediction and capacity estimation method only needs raw data without feature engineering. The results indicate that the proposed method helps improve the accuracy of prediction significantly with only a few online checkpoints, which has great application properties since the real data rarely has fully charged and fully discharged data.

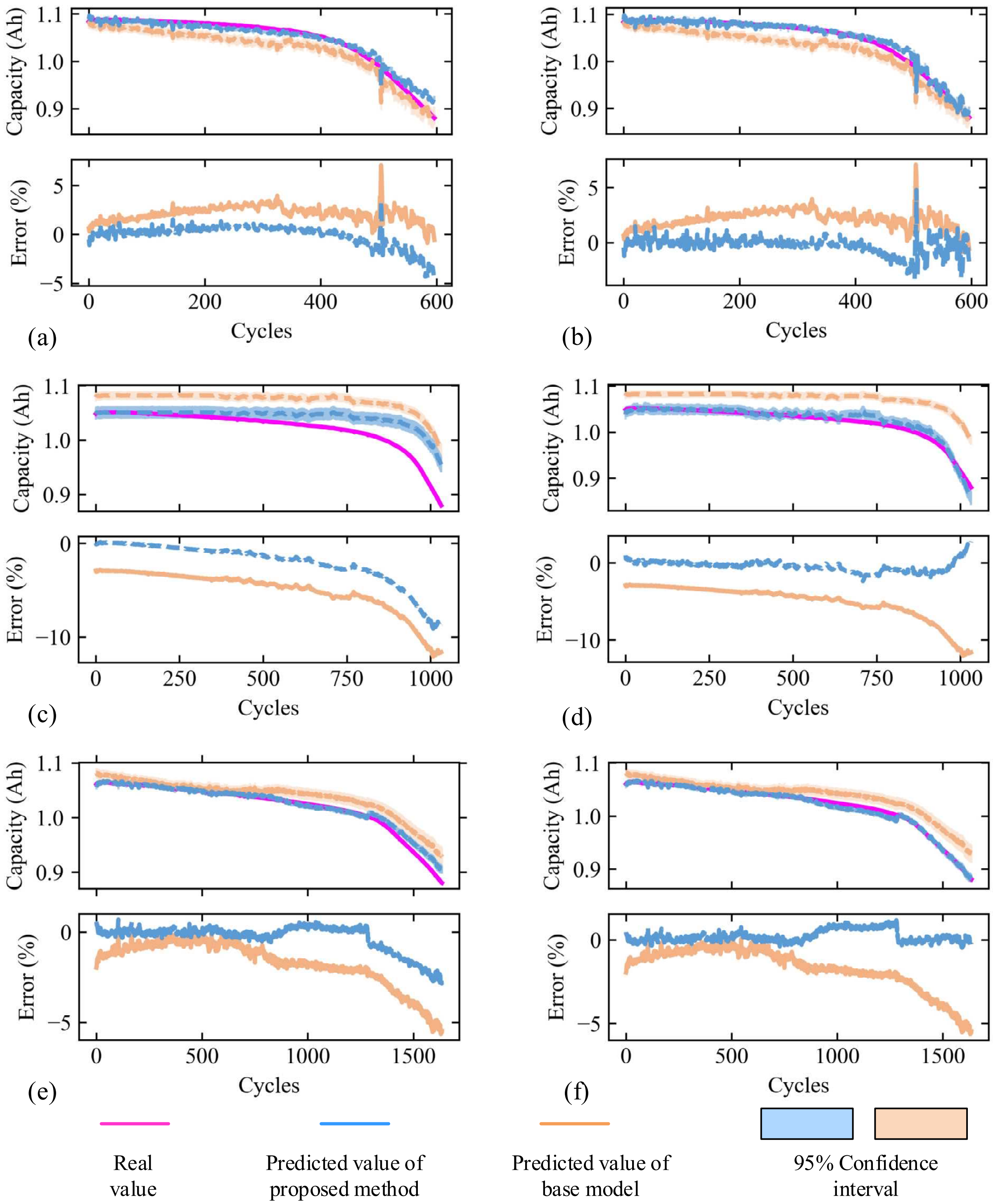

Fig. 5 Capacity degradation recovering and estimation results for battery 35, 121, and 100 with two checkpoints (a), (c), and (e); with four checkpoints (b), (d), and (f).

TABLE I. LIFETIME PREDICTION RESULTS

Value	Cell 35	Cell 121	Cell 100
Real lifetime (cycles)	579	1033	1636
Predicted lifetime (cycles)	531	932	1595
Absolute error (cycles)	-48	-101	-41
Relative error (%)	-8.29	-9.78	1.81

TABLE II. ESTIMATED ERRORS [%] WITH TWO CHECKPOINTS

Method	Cell 35		Cell 121		Cell 100	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Proposed Method	0.79	1.02	2.89	2.06	0.45	0.74
Base model	2.23	2.37	5.04	5.43	1.71	2.05

TABLE III. ESTIMATED ERRORS [%] WITH FOUR CHECKPOINTS

Method	Cell 35		Cell 121		Cell 100	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Proposed Method	0.55	0.84	0.63	0.82	0.29	0.42
Base model	2.23	2.37	5.04	5.43	1.71	2.05

IV. CONCLUSION

This paper proposes a novel method for battery lifetime prediction, capacity curve reconstruction, and estimation. The partial curves are used for formatting the inputs of the 1D CNN framework to learn the hidden features. The probabilistic regression is proposed for the capacity estimation model construction. Additionally, a transfer learning strategy is proposed for the model adaption among different batteries. The results show that lifetime predictions have less than 10% errors with raw data of only two early points. Furthermore, with only four checkpoints, the degradation curve could be accurately reconstructed, and the remaining capacity can be well estimated with errors less than 1%. Future work will focus on the lifetime prediction by the reconstructed capacity curves.

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