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Data-driven lithium-ion batteries capacity estimation based on deep transfer learning using partial segment of charging/discharging data

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A R T I C L E I N F O

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A B S T R A C T

Accurate estimation of lithium-ion battery capacity is crucial for ensuring its safety and reliability. While data-driven modelling is a common approach for capacity estimation, obtaining cycling data during charging/discharging processes can be challenging. Collecting cycling data under various charging/discharging protocols is often unrealistic, and the collected data can be fragmented due to the random nature of working conditions in practice. To address these issues, we propose a deep transfer learning method that uses partial segments of charging/discharging data for battery capacity estimation. The proposed method utilizes capacity increment features of partial charging/discharging segments that is designed to satisfy practical scenarios. A deep transfer convolutional neural network (DTCNN) is trained with both source and target data, and a fine-tuning strategy is employed to effectively eliminate distribution discrepancies between different battery types or charging/discharging protocols, leading the improved estimation accuracy. Experimental results demonstrate that the proposed method accurately estimates the lithium-ion battery capacity, with values of RMSE, MAPE, and MD-MAPE of only 0.0220, 0.0247, and 0.0194, respectively, when using partial segments. These results highlight the promising prospects of the proposed method for lithium-ion battery capacity estimation.

1. Introduction

At present, the problems of fossil energy shortage and environmental pollution are increasingly prominent and serious. For the sustainable development of ecological environment, the world is focusing on reducing carbon emissions and preventing global warming. The use of clean and renewable energy such as solar and wind can effectively meet emissions requirements. Many countries and enterprises are vigorously promoting clean energy and new renewable energy. Lithium-ion batteries can store energy and are easy to use, thus they are widely used in industrial scenarios. Lithium-ion batteries discharge and charge continuously during use. With the charging and discharging process, the performance of lithium-ion battery will gradually decline. In order to ensure the stability and safety of lithium-ion batteries, it is very important to monitor the state of health (SOH) [1–5]. Nowadays, some lithium-ion batteries used in industrial scenarios have to be replaced due to long-term use. In the future, a large number of lithium-ion batteries will be retired. By monitoring the SOH of lithium-ion batteries, the service efficiency will be improved. In addition, with the aging of lithium-ion batteries, the damage of the diaphragm will lead to internal short circuit, which will increase the risk of failure and even lead to potential safety hazards. The SOH of lithium-ion batteries is directly characterized by capacity, and the degradation of lithium-ion batteries occur when the capacity decreases [6–8]. Many researchers have carried out research work on lithium-ion battery capacity estimation.

The methods for estimating lithium-ion battery capacity mainly include model-based methods and data-driven methods [9–13]. Model-based method is to build a model according to the electrochemical reaction mechanism inside the lithium-ion battery. Then the capacity of lithium-ion battery is estimated based on the constructed

Abbreviations: SOH, State of health; ICA, Incremental capacity analysis; GPR, Gaussian process regression; CNN, Convolutional neural network; DTCNN, Deep transfer convolutional neural network; LSTM, Long short-term memory; DBN, Deep belief network; BNN, Bayesian neural network; GCN, Graph convolutional network; MLP, Multilayer perceptron; SVM, Support vector machine; RF, Random forest; ELM, Extreme learning machine; APE, Absolute percentage error; RMSE, Root mean squared error; MAPE, Mean absolute percentage error; MD-MAPE, Mean deviation of mean absolute percentage error.

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model. The commonly used lithium-ion battery models include empirical model, electrochemical model, electrical model, fractional-order model, fusion model, etc. The empirical model is mainly obtained by summarizing and analyzing the previous data. Sadabadi et al. [14] proposed a semi-empirical model to reveal the aging law of batteries. Based on the electrochemical model, the characteristics of the battery can be analyzed. Shao et al. [15] proposed a novel electrochemical model to predict the capacity. For the electrical model, Wang et al. [16] proposed a thermoelectric coupling model, which composed of battery thermal effect and equivalent circuit model. He et al. [17] put forword a multi-time scale variable-order equivalent circuit model. The fractional-order model is also a widely used model, which can optimize the accuracy and complexity between the electrochemical model and the equivalent circuit model. Wang et al. [18] proposes an optimized fractional-order model to study lithium-ion batteries, and achieved accurate calculation results. The fusion model is the fusion of several different models to estimate the state of lithium-ion batteries. Xu et al. [19] proposed a fusion model, which combined the electrochemical model and the equivalent circuit model.

Although the model-based method has a higher accuracy in capacity estimation, it requires professional prior knowledge and can only be used for specific lithium-ion batteries. Therefore, it is not universal and not suitable for wide application. Different from model-based method, the data-driven method does not need to master the complex electrochemical mechanism inside the lithium-ion battery, and the SOH of lithium-ion battery can be accurately estimated only through the data. The commonly used lithium-ion battery data in industrial scenarios include voltage, current, internal resistance, temperature, etc. Many researchers have constructed battery capacity estimation models based on data. Currently, the data-driven methods are developing rapidly. The data-driven methods include neural network method, machine learning method, deep learning method, graph-based method, etc. For the neural network method, Wen et al. [20] proposed a BP neural network model for predicting the SOH of lithium-ion batteries. Zhang et al. [21] put forward a SOH estimation method of lithium-ion battery based on k-means clustering analysis and evolving Elman neural network. For the machine learning method, Ren et al. [22] summarized and analyzed the capacity estimation method of lithium-ion batteries based on machine learning. Richardson et al. [23] proposed a Gaussian process regression (GPR) method to estimate lithium-ion battery capacity. Li et al. [24] utilized the incremental capacity analysis (ICA) and GPR to estimate the capacity of lithium-ion battery. For the deep learning method, Deng et al. [25] proposed a battery capacity estimation method based on long short-term memory (LSTM) network. Han et al. [26] proposed an enhanced LSTM network considering domain adaptation to capacity estimation of lithium-ion battery. Lin et al. [27] proposed an attentional LSTM network to estimate the SOH of lithium-ion batteries. Cao et al. [28] utilized a deep belief network (DBN) to estimate the lithium-ion battery capacity. Zhang et al. [29] proposed a deep Bayesian neural network (BNN) for the SOH estimation. Zhao et al. [30] designed a SOH estimation method based on hybrid attention and deep learning. For the graph-based method, Wang et al. [31] constructed a graph model for lithium-ion battery capacity estimation. Yao et al. [32] prensented a novel graph-based framework for the SOH prediction. Wei et al. [33] proposed the graph convolutional network (GCN) to estimate the SOH of lithium-ion batteries.

The data-driven approach requires a large amount of data to train the model. However, the data is difficult to obtain in industrial scenarios, and the collected data is often only partially segmented. Therefore, it is necessary to study the lithium-ion battery capacity estimation method based on limited segment data. In order to solve these problems, various methods are explored to improve the accuracy of capacity estimation, such as data augmentation, network structure optimization and transfer learning. The data augmentation method is to expand the limited sample data to meet the requirements of data-driven model. For example, Zhang et al. [34] augmented the small training data, and then use the continuous time-varying cascade network based on extreme learning machine (ELM) to estimate the battery capacity. For the network structure optimization method, the accuracy of capacity estimation is improved by optimizing the network structure. Qian et al. [35] proposed a capacity estimation method using convolutional neural network (CNN), and achieved accurate estimation of battery capacity by optimizing hyper-parameters. Deng et al. [36] proposed a sparse Gaussian process regression method to estimate the battery capacity based on the random partial data. Kohtz et al. [37] proposed a physics-informed machine learning model to estimate the capacity of lithium-ion batteries using partial segment data. For the transfer learning method, it improves the accuracy of capacity estimation by training the model on the source domain and then fine-tuning the model with a small amount of data from the target domain. Zhu et al. [38] proposed a transfer learning model to achieve the accurate estimation of battery capacity using the relaxation voltage curve features. Li et al. [39] proposed a CNN method based on transfer learning to estimate the capacity of lithium-ion batteries. Ma et al. [40] using the transfer learning and DBN-LSTM hybrid network for SOH estimation of lithium-ion batteries.

The research goal of this work is to accurately estimate battery capacity using limited segment data in industrial scenarios. The specific idea is to train the model with sufficient source domain data (battery data under laboratory conditions) firstly, and then fine-tune the model with limited data in the target domain to improve the performance of capacity estimation. The difference from the existing capacity estimation based on transfer learning is that this work only uses segment data. The entire charge/discharge cycle data is divided into multiple segments, and only one segment is used for training, which is in line with the fact that only some segments can be obtained in actual industrial scenarios. Another difference is that the model is trained with capacity incremental features instead of voltage and current data. The capacity increment feature is related to the electrochemical reaction inside the battery, which can improve the accuracy of capacity estimation. The contributions of this work are as follows:

(1) A deep transfer learning method, specifically DTCNN, is proposed to accurately estimate the capacity of lithium-ion batteries. Compared with existing deep learning methods, DTCNN method can improve the accuracy of capacity estimation by using the inherent information in both sufficient source domain data and limited target domain data.
(2) The measured voltage and current data are converted into capacity increment features. The capacity increment features are utilized to train the deep learning model. Compared with directly using the voltage and current data to train the model, using the capacity increment feature can more effectively reflect the degradation law of lithium-ion batteries, and has a better capacity estimation effect.
(3) Due to randomness in industrial scenarios, it is often impossible to obtain the entire charging/discharging cycle data. By training the deep learning model with partial segment data, a satisfying capacity estimation performance is achieved. The use of partial segment data meets the actual requirements of industrial scenarios.

The reminder of this work is organized as follows. In section 2, the proposed methodology is introduced. In section 3, the experiments are designed. The results and discussion are analyzed in detail in section 4. Finally, the conclusions are summarized in section 5.

2. Methods

To meet the practical requirements of capacity estimation of lithium-ion batteries, we aim to design the method by considering the following two aspects. First, the voltage, current, and temperature data are usually measured during charging/discharging cycle. The estimated accuracy will be influenced by the used features, and the capacity increment feature is explored in this work to achieve superior performance. Due to the fact that the entire charging/discharging cycle data is difficult to obtain, the proposed method only use the capacity increment features extracted from partial charging/discharging data to train the deep learning model. More importantly, the proposed method considers the domain discrepancy between the training data and testing data, and presents a transfer learning strategy, which incorporates pre-training and fine-tuning.

2.1. Capacity increment feature

In order to improve the performance of model training, the capacity increment feature is used here. Unlike voltage and current, the capacity increment feature is related to the internal parameters of lithium-ion batteries. The lithium-ion battery voltage is the difference between the positive and negative voltages of the battery, which is

$$V_B = V_p - V_n \tag{1}$$

where V_B, V_p and V_n are the battery voltage, battery positive voltage and battery negative voltage.

The charge/discharge capacity of the battery is Q. The functional relationship between capacity and battery voltage, positive voltage and negative voltage are $V_B(Q)$, $V_p(Q)$, $V_n(Q)$, respectively. Then according to formula (1), the following formula can be obtained.

$$V_B(Q) = V_p(Q) - V_n(Q) \tag{2}$$

Assume that q_p and q_n are the discharge capacities per unit mass of the positive and negative active materials, respectively. Then formula (2) can be converted into the following formula.

$$V_B(Q) = V_p(q_p) - V_n(q_n) \tag{3}$$

The relationship between the discharge capacity Q, q_p and q_n is as follows.

$$Q = m_p q_p - \delta_p = m_n q_n - \delta_n \tag{4}$$

where m_p and m_n are the masses that participate in the electrochemical reaction and affect the discharge capacity, respectively. δ_p and δ_n are constants.

Differentiating both sides of formula (2), and then combining formulas (3) and (4), the following formula can be obtained.

$$\begin{aligned} \frac{\mathrm{d}Q}{\mathrm{d}V_B(Q)} &= \frac{\mathrm{d}Q}{\mathrm{d}V_p(Q) - \mathrm{d}V_n(Q)} \\ &= \frac{m_p \mathrm{d}q_p - m_n \mathrm{d}q_n}{\mathrm{d}V_p(Q) - \mathrm{d}V_n(Q)} \end{aligned} \tag{5}$$

It can be seen from formula (5) that the capacity increment $\mathrm{d}Q/\ \mathrm{d}V_B(Q)$ is related to the internal parameters (m_p, q_p, m_n, q_n) of the battery. The above analysis analyzes the internal electrochemical mechanism of the battery, and verifies that the battery capacity increment can reflect the battery degradation process. The capacity increment feature takes into account the external data characteristics of the battery and the internal electrochemical reaction mechanism, thus it can be used to analyze the battery capacity degradation state. The capacity increment feature can be calculated according to the external parameters of the battery, and they are as follows.

$$Q = \int_{t=1}^{T} I \mathrm{d}t \tag{6}$$

$$\frac{\mathrm{d}Q}{\mathrm{d}V} = \frac{I \times \mathrm{d}t}{\mathrm{d}V} \tag{7}$$

where I is the charge/discharge current. V is the constant current charge/discharge voltage. T is the constant current charge/discharge time. Taking the NASA randomized battery usage data set as an illustration [41], Fig. 1(a) and Fig. 1(b) shows the charging current and charging voltage curves of the lithium-ion battery under different cycle numbers, respectively. Meanwhile, the smoothing process of the capacity increment features and the corresponding capacity increment curve are illustrated in Fig. 1(c) and Fig. 1(d).

2.2. Deep convolutional neural network

After extracting the capacity increment feature from original monitoring current and voltage of lithium-ion battery, a capacity estimation model need to be established to map the extracted features into the remaining capacity. In this work, the CNN is used and its input is the capacity increment feature of lithium-ion battery. CNN is essentially a feedforward neural network with deep structure. This type of deep model is composed of multiple convolutional layers, pooling layers and fully-connected layers, which is used to learn hierarchical and abstract features, and finally estimate the capacity.

The input layer of CNN can process multi-dimensional data. For the capacity estimation of lithium-ion battery, the input layer is one-dimensional capacity increment data. The hidden layer of CNN includes convolution layer, pooling layer and fully-connected layer. The convolution layer can extract features from input data, and it contains multiple convolution kernels. Each element of the convolution kernel corresponds to a weight coefficient and a bias. The convolution kernel can sweep the input features regularly, multiply and sum the matrix elements of the input features in the receptive field, and add up the bias. The calculation formula of convolution kernel is as follows:

$$Z_{i,j}^{l+1} = \mathrm{ReLU}\left(Z_{i,j}^{l} \otimes \omega_{i,j}^{l+1} + b\right) \tag{8}$$

where $Z_{i,j}^{l}$ and $Z_{i,j}^{l+1}$ are the input and output of $l-$ th convolutional layer, respectively. $\omega_{i,j}^{l+1}$ denotes the weight vector of convolutional kernel. b is the bias. The convolutional layer output is further processed by using rectified linear unit (ReLU) as the activation function. Commonly used activation functions are sigmoid function, hyperbolic tangent function, rectified linear unit, etc. The activation function usually follows the output of convolution kernel.

After operation in the convolution layer, the output feature maps will be transmitted to the pooling layer. The max-pooling operation is then used to down-sample the convolutional output to avoid over-fitting caused by excessive dimension. For each region in the feature map, the maximum value of the neurons in this region is used as the output of max-pooling layer, and the formula is given as follows:

$$P_i^{l+1}(j) = \max_{(j-1)W+1 \le t \le jW} \left\{P_i^l(t)\right\} \tag{9}$$

where W is the length of the max-pooling region, $P_i^l(t)$ is the value of the $t-$ th neuron in the $l-$ th pooling layer, and $P_i^{l+1}(j)$ denotes the output value of the $j-$ th region.

The fully-connected layer of CNN is located at the last part of the deep model and is finally used to map the features into the corresponding capacity of lithium-ion battery. Fig. 2 shows the structure of the designed CNN model.

2.3. Deep transfer learning for batteries capacity estimation

In order to accurately estimate the capacity of lithium-ion batteries, the deep model, which maps the extracted capacity increment features from charging/discharging data to the capacity of lithium-ion batteries, need to be trained with sufficient aging data. However, it is difficult to obtain enough charging/discharging data of lithium-ion batteries in industrial scenarios. The internal physicochemical mechanism of different types of lithium-ion batteries and charging/discharging protocols is not exactly the same. This leads to the domain discrepancy

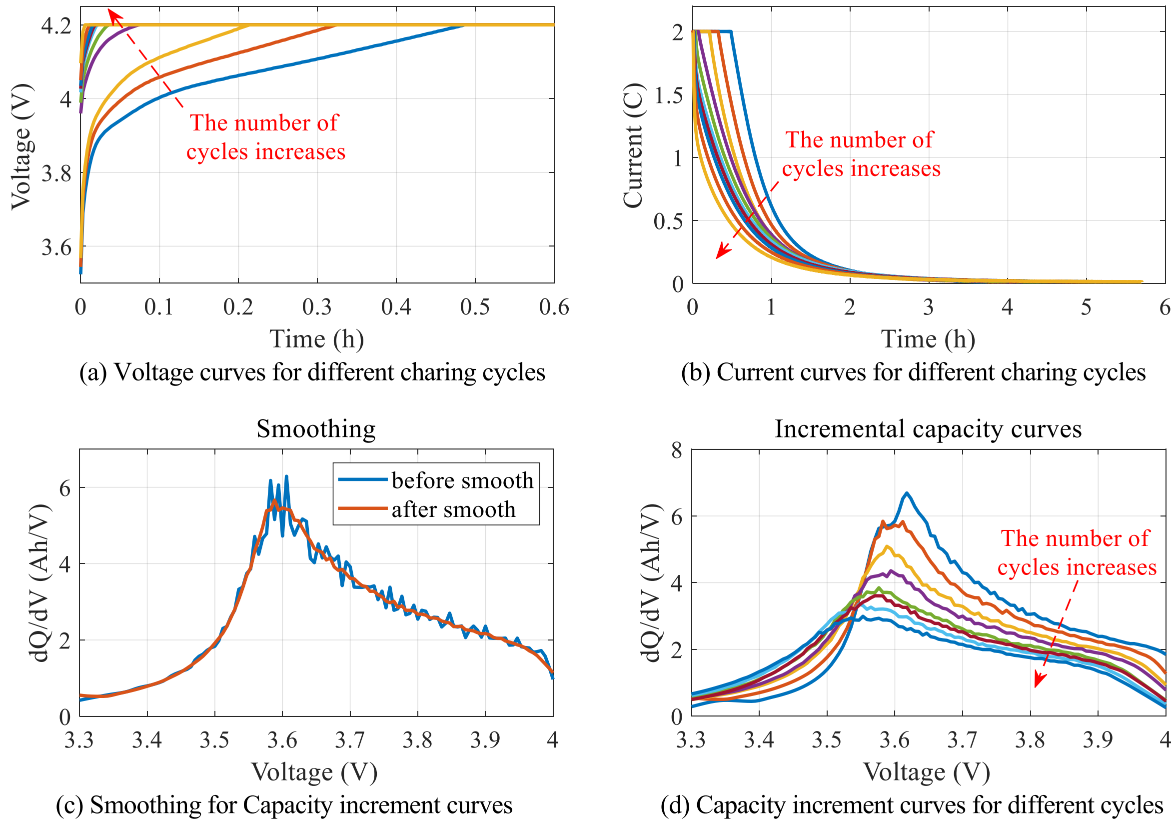


Fig. 1. Illustrations of the raw voltage and current curves, and the capacity increment features.

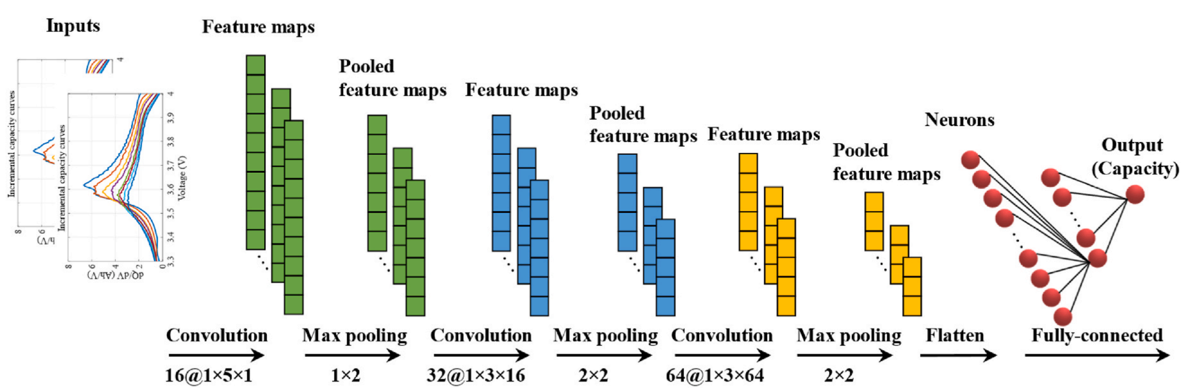


Fig. 2. Structure of the designed CNN model.

problem between the source domain D^s (where the model is trained) and the target domain D^t (actual industrial deployment applications), resulting in inaccurate capacity estimation.

Generally, the source domain data are assumed to be sufficient, as the charging/discharging process can be simulated and extensive battery aging data can be collected in the experimental environment. The aging data in practical target domain are limited. Although the deep model trained with source data suffers from domain discrepancy in target domain, the relevant information is useful and can be transferred for target tasks, so that improving the performance of capacity estimation with limited target data. To this end, a deep transfer learning scheme with fine-tuning strategy is presented for batteries capacity estimation.

The deep transfer learning scheme mainly contains the model pre-training with source charging/discharging data, and the parameter transfer and fine-tuning with few target data. The sufficient battery aging data in source domain are denoted as $\{(x_i^s, y_i^s)\}_{i=1}^{N_s}$. The (x_i^s, y_i^s) is a training sample, consisting of the extracted features or raw monitoring signal x_i^s. The y_i^s is the corresponding battery capacity in this charging/discharging cycle. The limited aging data in target domain is denoted as $\{(x_i^t, y_i^t)\}_{i=1}^{N_t}$. The $N_t \ll N_s$. The pre-training of deep capacity estimation model with respect to source data can be formulated as:

$$\underset{\boldsymbol{\theta}}{\operatorname{argmin}} \sum_{i=1}^{N_s} L\left(y_i^s, f\left(x_i^s, \boldsymbol{\theta}\right)\right) \tag{10}$$

where $\boldsymbol{\theta}$ is the parameters of deep model, $f(x_i^s, \boldsymbol{\theta})$ represents the battery capacity predicted by deep model, and $L(\cdot)$ represents the errors between the predicted battery capacities and real ones.

To solve the domain discrepancy problem, the pre-trained parameters of source model are transferred to target domain, and are reused to initialize the target model. Note that only the parameters of the shared architecture in source and target models are transferred. Then, the target model is fine-tuned with the limited target data. In different fine-tuning strategies, the parameters that need to be fine-tuned are distributed in different layers or positions of the deep architecture. The fine-tuning with respect to target data can be formulated as:

$$\boldsymbol{\theta}^{(l)} = \boldsymbol{\theta}^{(l)} - \alpha \frac{\partial E\left(L\left(y_i^t, f\left(x_i^t, \boldsymbol{\theta}\right)\right)\right)}{\partial \boldsymbol{\theta}^{(l)}} \tag{11}$$

where α is the learning rate, and $\boldsymbol{\theta}^{(l)}$ represents the model parameters in l layer that need to be fine-tuned.

With the above deep transfer learning scheme, the final deep model is adapted to estimating the battery capacity in target domain, and is used to monitor health state of lithium-ion battery. This work utilizes the CNN as the baseline deep model, and the presented transfer learning model is referred as deep transfer convolutional neural network (DTCNN).

2.4. Overall framework of the proposed method

The overall framework of the proposed method is illustrated in Fig. 3, including four main parts.

1) The raw physical variables, such as voltage and current, are monitored for the lithium-ion batteries. Due to the randomness of charging/discharging process, it is unrealistic to collect whole cycle data in practical application. The partial charging/discharging data are used for further analysis.
2) The partial segments of raw monitoring data are preprocessed by resampling, smoothing, and normalizing. Then, the capacity increment features are calculated through partial segments of voltage and current data.
3) Supposing sufficient source domain data (voltage, current, capacity, etc.) are obtained in the laboratory. The deep learning model is firstly designed and pre-trained with the capacity increment features of source data. Then, the pre-trained model parameters are transferred to target model. Limited target domain data are used for fine-tuning, which aims to eliminate the distribution discrepancy of lithium-ion batteries with different types or different operating conditions.
4) Based on the above process, a deep transfer learning model is obtained for target capacity estimation tasks. The health states of lithium-ion batteries in the target domain can be monitored using the deep transfer learning model, and the capacity estimation performance is further analyzed.

3. Experimental descpritions

A wide range of experiments were conducted in this study, including transfer experiments, comparison experiments of different methods, comparison experiments of different input features, and comparison experiments of different partial segments. The transfer experiments aimed to compare the conventional deep learning model with the proposed DTCNN, thus validating the necessity of transfer learning in the scenarios of domain shift and limited training data. The superiority of the proposed DTCNN was further confirmed in the comparison experiments of different deep methods. Additionally, comparison experiments of different input features were carried out to verify the superiority of the used capacity increment features in comparison to the popular voltage and current. Furthermore, experiments using different partial segments were performed to assess the effectiveness and superiority of the proposed method, as the partial fragments of data are more common and more accessible in practical applications. The results of these comprehensive experiments effectively confirmed the effectiveness and superiority of the proposed method.

3.1. Battery aging data

In this study, we utilized the publicly available lithium-ion battery aging data set from NASA randomized battery usage data set [41], which was obtained through numerous experiments conducted by professional researchers, thereby ensuring its accuracy and reliability. There are multiple sets of lithium-ion batteries. Specifically, we selected eight batteries from the NASA battery data set, namely, RW1, RW2, RW7, RW8, RW9, RW10, RW11, and RW12, for our analysis and research. The validity of our results can be ensured by utilizing this high-quality and established data set.

Source domain: The source domain consisted of four batteries with serial numbers RW1, RW2, RW7, and RW8. These batteries underwent continuous discharge to 3.2 V using random discharge sequences with current ranging from 0.5A to 4A. Following each discharging cycle, the batteries were randomly selected for charging for a duration between 0.5 and 3 h. To establish a reference baseline of battery state health, a series of reference charging/discharging cycles were performed after every 50 random walk cycles [41].

Target domain: The target domain in this study comprised of the lithium-ion batteries data from RW9, RW10, RW11 and RW12. These batteries underwent continuous operation using a range of charge and discharge currents between −4.5A and 4.5A. Each loading cycle lasted for 5 min, and a series of reference charge and discharge cycles were performed after 1500 cycles to provide a baseline for battery state health assessment [41].

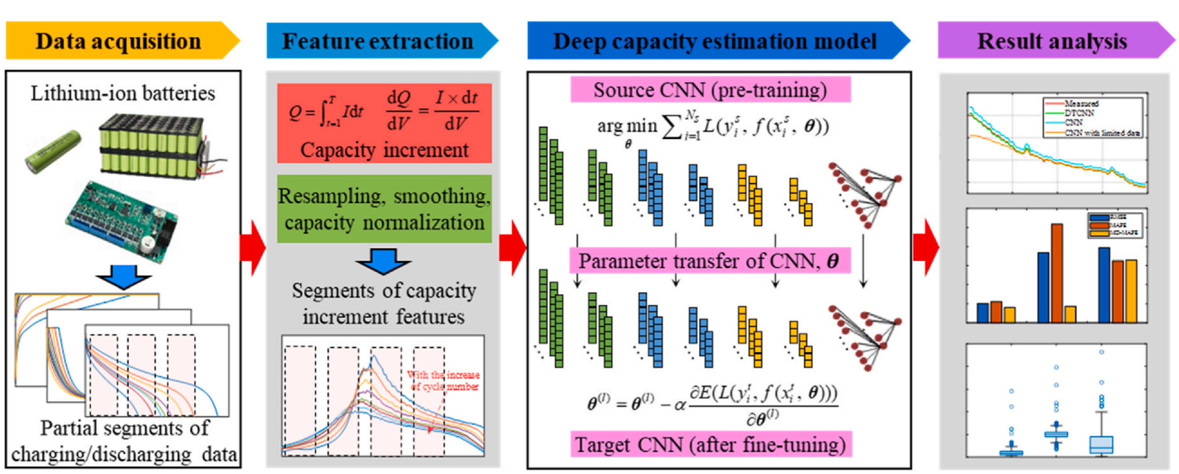


Fig. 3. The overall framework of this proposed method.

The source domain and the target domain selected for this study represent different operating conditions for the lithium-ion batteries. The batteries in the source domain were subject to continuous discharge with random sequences, while the batteries in the target domain were subjected to continuous operation with a range of charge and discharge currents. The differences in the operating conditions between the source and target domains could result in variations in the capacity degradation, namely the distribution shift. The success of conventional data-driven method relys on the independently identically distribution between training data (source data) and testing data (target data). Consequently, further investigation is required to understand how the distribution shift is addressed in the proposed method.

3.2. Data preprocessing

Firstly, both voltage and current data were measured for each battery in the NASA randomized battery usage data set. Then, the capacity increment feature was calculated from the measured voltage and current data in our proposed method. Finally, the resulting feature was used to train the deep models for capacity estimation, since the capacity increment feature is more effective in capturing the internal electrochemical mechanism of lithium-ion batteries and reflecting their degradation state than using the raw voltage and current data directly.

It should be noted that data preprocessing is a crucial step for improving the accuracy of battery capacity estimation. The preprocessing steps include resampling and smoothing of the measured voltage and current data. Resampling is performed using the pchip interpolation algorithm with 120 resampling points. The smoothing method adopts a 5-point moving average to reduce the impact of interference noise. Next, the capacity increment feature is calculated using formulas (6) and (7), and the capacity is normalized to the range of [0, 1]. In the proposed deep transfer learning framework, all cycling data from the source domain batteries are utilized for pre-training the deep model, whereas only one to several cycles of the target domain batteries are utilized for fine-tuning the pre-trained model.

3.3. Transfer experiments

In this section, we conduct transfer experiments to investigate the effectiveness and superority of the proposed DTCNN method. We compare three methods in these transfer experiments:

DTCNN: This method involves three steps: (i) training a CNN model using sufficient source domain data with an architecture and model parameters as shown in Fig. 2, (ii) fine-tuning the trained CNN model with limited target domain data (only 6 aging cycles), and (iii) utilizing the fine-tuned model to estimate the battery capacity in the target domain data and evaluate its performance.

CNN trained in source domain: In this method, only source domain data are used to train the CNN model. The trained model is then used directly to estimate the battery capacity in the target domain.

CNN with limited target data: This method involves training the CNN model with only limited target domain data, followed by utilizing the trained model to estimate the battery capacity in the target domain.

3.4. Comparison experiments of different methods

In this study, we conducted a comprehensive evaluation of the performance and effectiveness of various methods for estimating the capacity of lithium-ion batteries. To this end, we trained several models, including Long Short-Term Memory (LSTM) [42], Multilayer Perceptron (MLP) [43], Support Vector Machine (SVM) [44], Random Forest (RF) [45] and AdaBoost [46], using only sufficient source domain data. The trained models were then used to estimate the battery capacity in the target domain data. Finally, the effectiveness of the different methods was compared based on their performance in estimating the lithium-ion battery capacity.

3.5. Comparison experiments of different input features

This study examines the effects of using capacity increment features versus voltage current features as inputs to the CNN model. The experiment involves training the CNN model on the input data from either the capacity increment or voltage current features in the source domain, followed by evaluating the accuracy of capacity estimation in the target domain using the trained CNN model. The results are then compared to assess the relative accuracy of capacity estimation with each type of input feature.

3.6. Comparison experiments of different partial segments

In the transfer experiments, it is necessary to investigate the effects of the DTCNN method under different segmentation scenarios since the practical monitoring data is often partially segmented in battery management systems due to the randomness of operating conditions. Two scenarios are considered where the capacity increment curve is divided into two or three parts.

For the scenario where the capacity increment curve is divided into two parts, the following implementation process is employed. Firstly, the entire capacity increment feature curve is segmented into two parts, and only the first part is utilized to train the CNN model. Secondly, the trained CNN model is fine-tuned with limited target domain data. Finally, the fine-tuned model is used to estiamte the capacity of the target batteries.

For the scenario where the capacity increment curve is divided into three parts, the following implementation process is employed. Firstly, the entire capacity increment feature curve is segmented into three parts, and only the second part is utilized to train the CNN model. Secondly, the trained CNN model is fine-tuned with limited target domain data. Finally, the fine-tuned model is used to estiamte the capacity of the target batteries.

3.7. Evaluation index

To quantitatively assess the effectiveness of the proposed method, three evaluation indexes, namely the root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean deviation of mean absolute percentage error (MD-MAPE), are utilized. Notably, the MD-MAPE is computed by employing the absolute percentage error (APE) and MAPE. The calculation formulas for these metrics are provided as follows:

$$\mathrm{APE} = \left|\frac{\widehat{y}_{i,n} - y_{i,n}}{y_{i,n}}\right| \tag{12}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{y}_{i,n} - y_{i,n}\right)} \tag{13}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{\widehat{y}_{i,n} - y_{i,n}}{y_{i,n}}\right| \tag{14}$$

$$\mathrm{MD-MAPE} = \frac{1}{N}\sum_{n=1}^{N}\left(\mathrm{APE}_n - \mathrm{MAPE}\right) \tag{15}$$

where $\widehat{y}_{i,n}$ represents the estimated capacity of nth cycle, and $y_{i,n}$ denotes the measured capacity of nth cycle. Larger values of RMSE, MAPE, and MD-MAPE indicate greater deviations between the predicted capacity and the actual capacity, indicating reduced accuracy of the predictions.

4. Results and discussions

4.1. Capacity estimation results in transfer experiments

The capacity estimation results for the four target batteries are presented in Fig. 4. It is evident that the DTCNN method provides the closest estimation of the measured capacity, while the CNN method shows a significant error between the estimated and measured capacities. Overall, the CNN method exhibits a large error. The CNN trained with limited target data performs better in the later stages of the cycle, but produces large errors in the initial stages of the cycle. This is due to the inadequate training data, resulting in poor performance in the front part. The quantitative results of the evaluation indexes are listed in Table 1.

According to Table 1 and Fig. 4, the DTCNN method demonstrates the smallest error, indicating a higher accuracy of capacity estimation. Specifically, the DTCNN method exhibits RMSE, MAPE, and MD-MAPE values of only 0.0102, 0.1111, and 0.0081, respectively. In comparison, the CNN method exhibits a higher MAPE value of 0.0518, and a larger RMSE value of 0.0367. The CNN method with limited data displays RMSE, MAPE, and MD-MAPE values of 0.0394, 0.0325, and 0.0329, respectively, indicating the largest error results. This can be attributed to the utilization of only 6 cycles of data in the target domain, which is insufficient for accurate capacity estimation. The direct application of a model trained using source data to target domain would lead to poor capacity estimation results due to domain distribution shift. However, the DTCNN method utilizes sufficient source data to train the model, followed by fine-tuning the model using a small amount of target data. This approach eliminates the impact of domain shift and improves the accuracy of capacity estimation. Therefore, the experimental results demonstrate the effectiveness and superiority of the DTCNN method.

Table 1
Result comparisons of different methods in transfer experiments.

Methods	RMSE	MAPE	MD-MAPE
DTCNN	**0.0102**	**0.0111**	**0.0081**
CNN	0.0367	0.0518	0.0087
CNN with limited data	0.0394	0.0325	0.0329

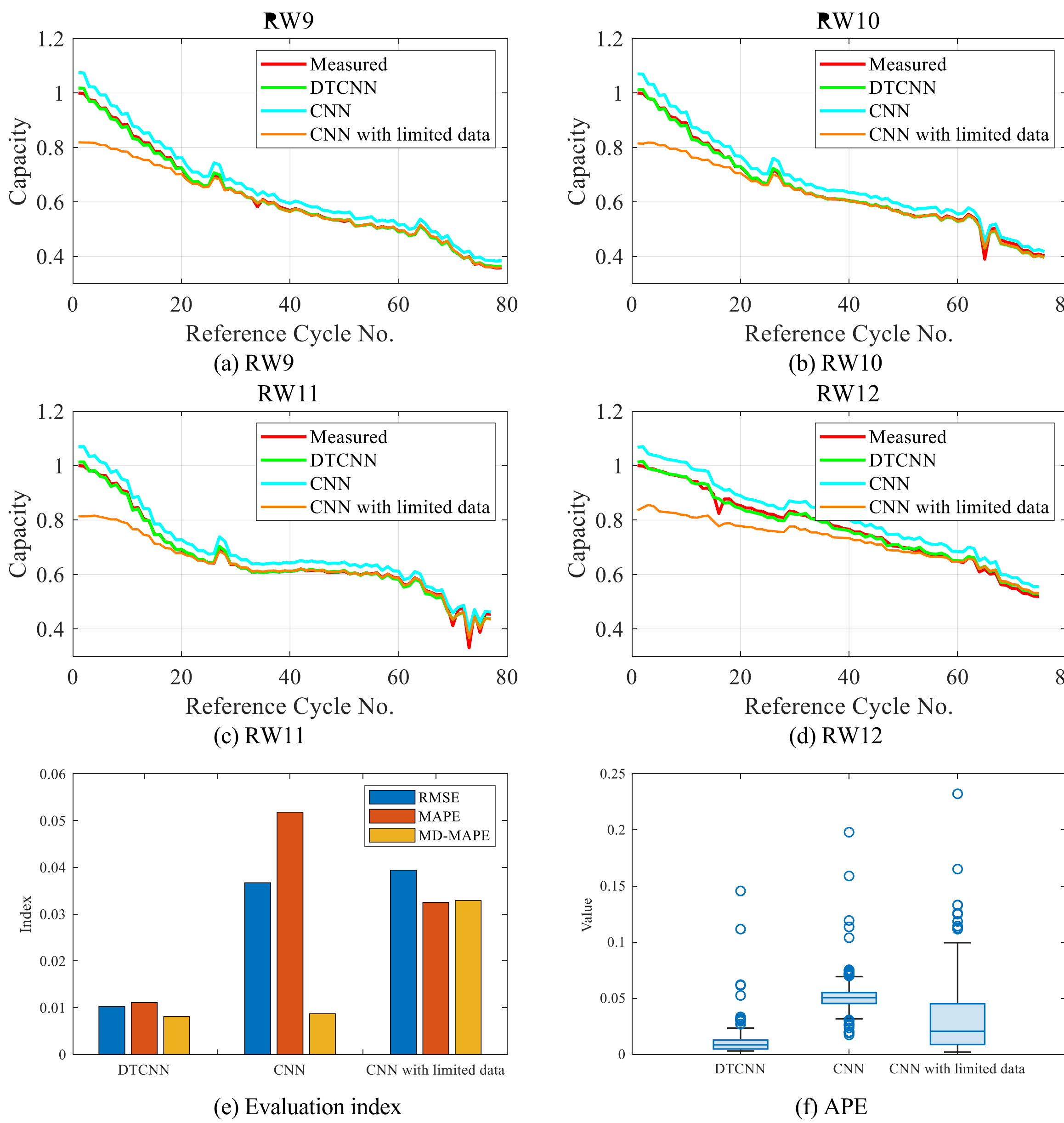


Fig. 4. The capacity estimation results for the four target batteries.

The Table 1 highlights the minimum values of these indicators, which are shown in bold font.

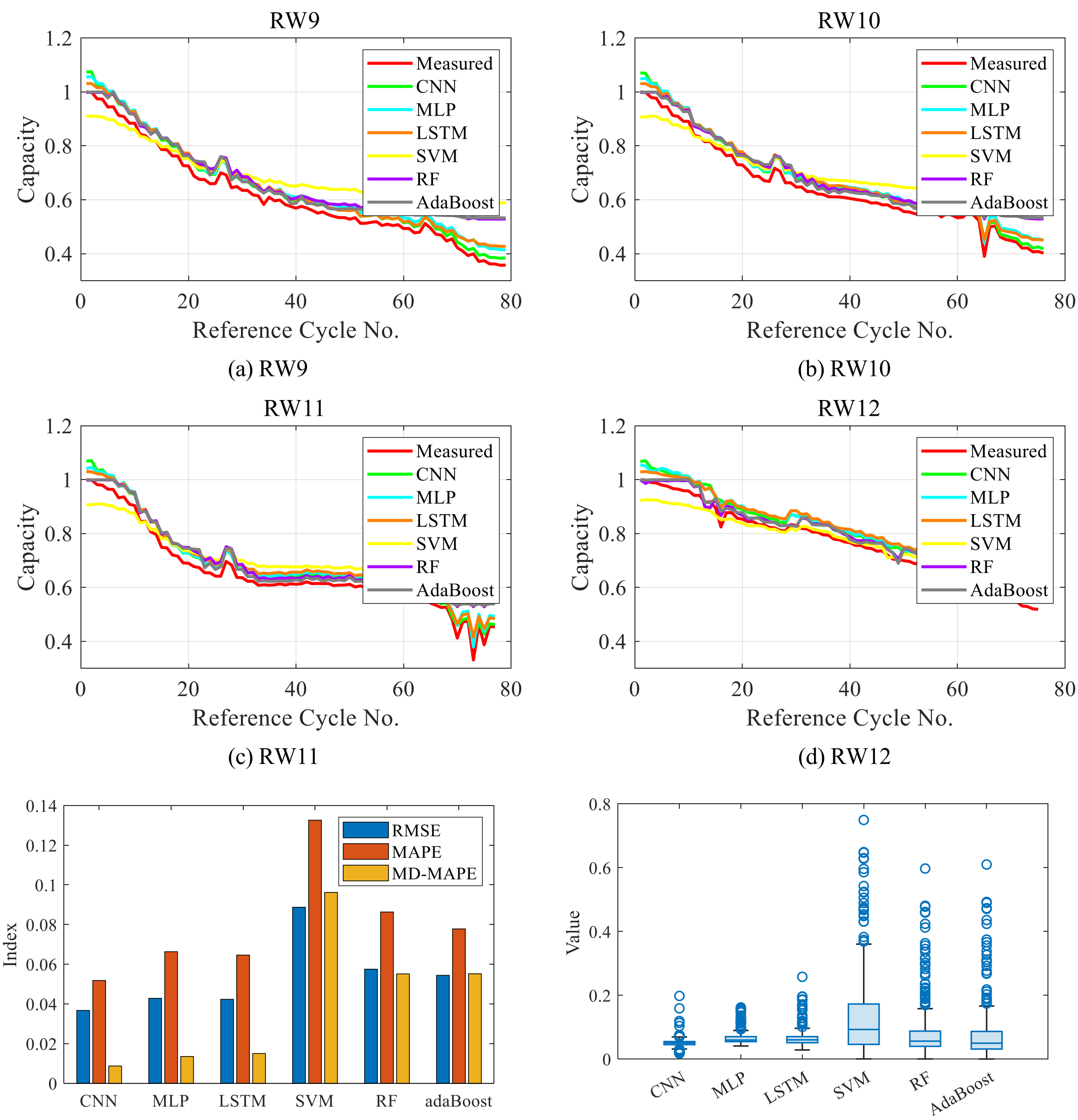
4.2. Comparison results of different methods

In this section, the deep CNN model, which is the benchmark model of the proposed DTCNN, is compared with other machine learning models. The purpose is to demonstrate the advantages of this deep learning model. The estimated battery capacity results of the MLP, LSTM, SVM, RF and AdaBoost models and the deep CNN model are shown in Fig. 5. It is evident from the results that the capacity estimation results of the MLP, LSTM, SVM, RF and AdaBoost methods have larger errors with respect to the measured capacity. The quantitative results of the evaluation indexes are reported in Table 2.

Based on the results presented in Table 2 and Fig. 5, it can be observed that the CNN model outperforms other machine learning models in terms of estimation accuracy. The CNN model achieves the smallest error among all the tested methods. In terms of the RMSE index, the SVM method shows the largest error with a value of 0.0887, while the RF and AdaBoost methods exhibit errors of 0.0575 and 0.0544, respectively. The MLP and LSTM methods achieve errors of 0.0428 and 0.0423, respectively, while the CNN method attains the smallest error of 0.0367. With respect to the MAPE index, the SVM method presents a large error of 0.1326, while the CNN method again shows a lower error than the other methods. In terms of the MD-MAPE index, the error of the CNN method is merely 0.0087, while the other methods yield errors

Table 2
Result comparisons of different machine learning methods.

Methods	RMSE	MAPE	MD-MAPE
CNN	**0.0367**	**0.0518**	**0.0087**
MLP	0.0428	0.0663	0.0135
LSTM	0.0423	0.0646	0.0150
SVM	0.0887	0.1326	0.0962
RF	0.0575	0.0863	0.0551
AdaBoost	0.0544	0.0778	0.0552



(a) RW9 (b) RW10
(c) RW11 (d) RW12
(e) Evaluation index (f) APE

Fig. 5. The capacity estimation results of different machine learning methods.

greater than that of the CNN method. Thus, the CNN method surpasses other tested methods for the capacity estimation of lithium-ion battery.

4.3. Comparison results of different input features

Based on the analysis in section 2.1, the capacity increment feature was found to be an effective measure to reflect the electrochemical mechanism of lithium-ion batteries and their capacity change patterns. In this work, the capacity increment feature is used to estimate the capacity of the batteries. To investigate the influence of using other features, the battery capacity estimation is performed by using voltage and current features, and the results are presented in Fig. 6.

From the results of Fig. 6, it can be observed that using the capacity increment feature for training the model leads to better capacity estimation compared to using only voltage and current features. This is because the capacity increment feature takes into account both external data characteristics of the battery and the internal electrochemical reaction mechanism, which can accurately reflect the degradation state of the battery. In contrast, the voltage and current features alone cannot effectively capture the internal degradation law of lithium-ion batteries, resulting in larger errors, particularly in the latter part of the battery's life. These observations are further supported by the quantitative analysis presented in Table 3, where the capacity estimation error for models trained with capacity increment feature is significantly smaller than that of models trained with voltage and current features.

When using the capacity increment feature, the RMSE, MAPE, and MD-MAPE values are 0.0367, 0.0518, and 0.0087, respectively. However, for voltage and current features, the corresponding values are 0.0868, 0.1329, and 0.0819, respectively. A higher value for these error indices indicates a worse capacity estimation result. Thus, it can be

Table 3
Result comparisons of different input features.

Feature	RMSE	MAPE	MD-MAPE
Capacity increment	**0.0367**	**0.0518**	**0.0087**
Voltage and current	0.0868	0.1329	0.0819

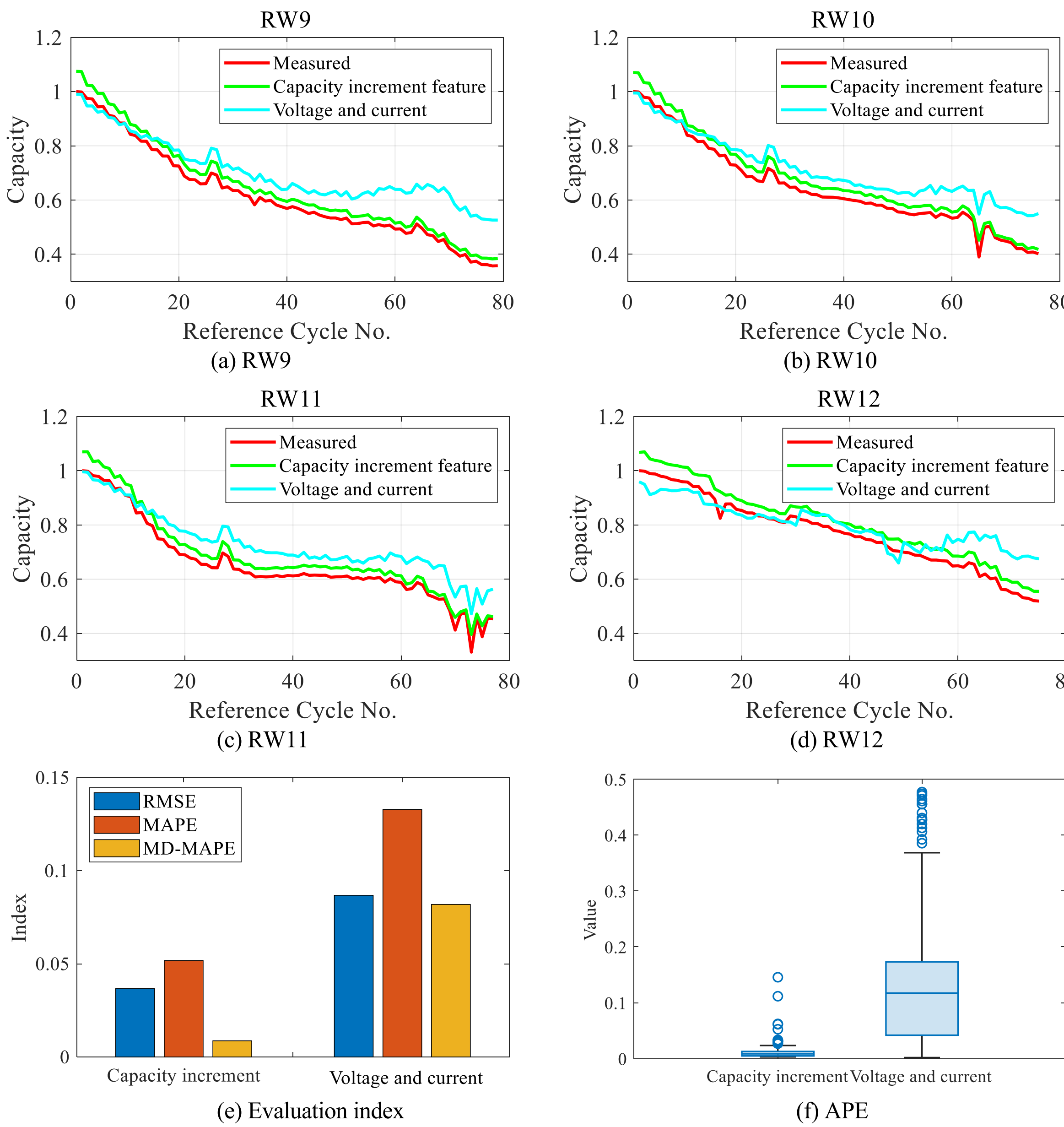


Fig. 6. The capacity estimation results with different input features.

concluded that the capacity increment feature outperforms the voltage and current features for reflecting the battery's degradation state.

4.4. Comparison results of different partial segments

In practical industrial scenarios, it is often difficult to obtain the entire capacity increment curve during the charging/discharging process, and collecting the entire capacity increment curve under various charging/discharging protocols is unrealistic. Furthermore, the collected data may be composed of segmented charging/discharging cycles due to the randomness of working conditions. Therefore, it is necessary to use only partial segment data in the charging/discharging cycle. In this study, only one segment data is used after dividing the entire capacity increment curve into two or three segments. When the entire capacity increment curve is divided into two segments, the segment containing more feature information is selected, which is the latter segment. When the whole cycle is divided into three segments, the middle segment is selected for calculation. The capacity estimation results using partial segment data are shown in Fig. 7. Based on the results shown in Fig. 7, the capacity estimation using only partial segment data is demonstrated to be consistent with the measured capacity, indicating the suitability of the proposed DTCNN method for partial segment data. The quantitative estimation errors are reported in Table 4.

The quantitative estimation errors presented in Table 4 further support this observation, showing that the RMSE index values for capacity estimation are 0.0102, 0.0203, and 0.0220, respectively, when the entire capacity increment curve and different partial segments are used. The corresponding MAPE index values are 0.0111, 0.0222, and 0.0247, and the MD-MAPE index values are 0.0081, 0.0177, and 0.0194. The error of capacity estimation gradually increases as the whole cycle data is divided into two and three segments. The error is highest when

Table 4
Result comparisons of different partial segments.

Segmentation settings	RMSE	MAPE	MD-MAPE
Entire capacity increment curve	0.0102	0.0111	0.0081
Two segments	0.0203	0.0222	0.0177
Three segments	0.0220	0.0247	0.0194

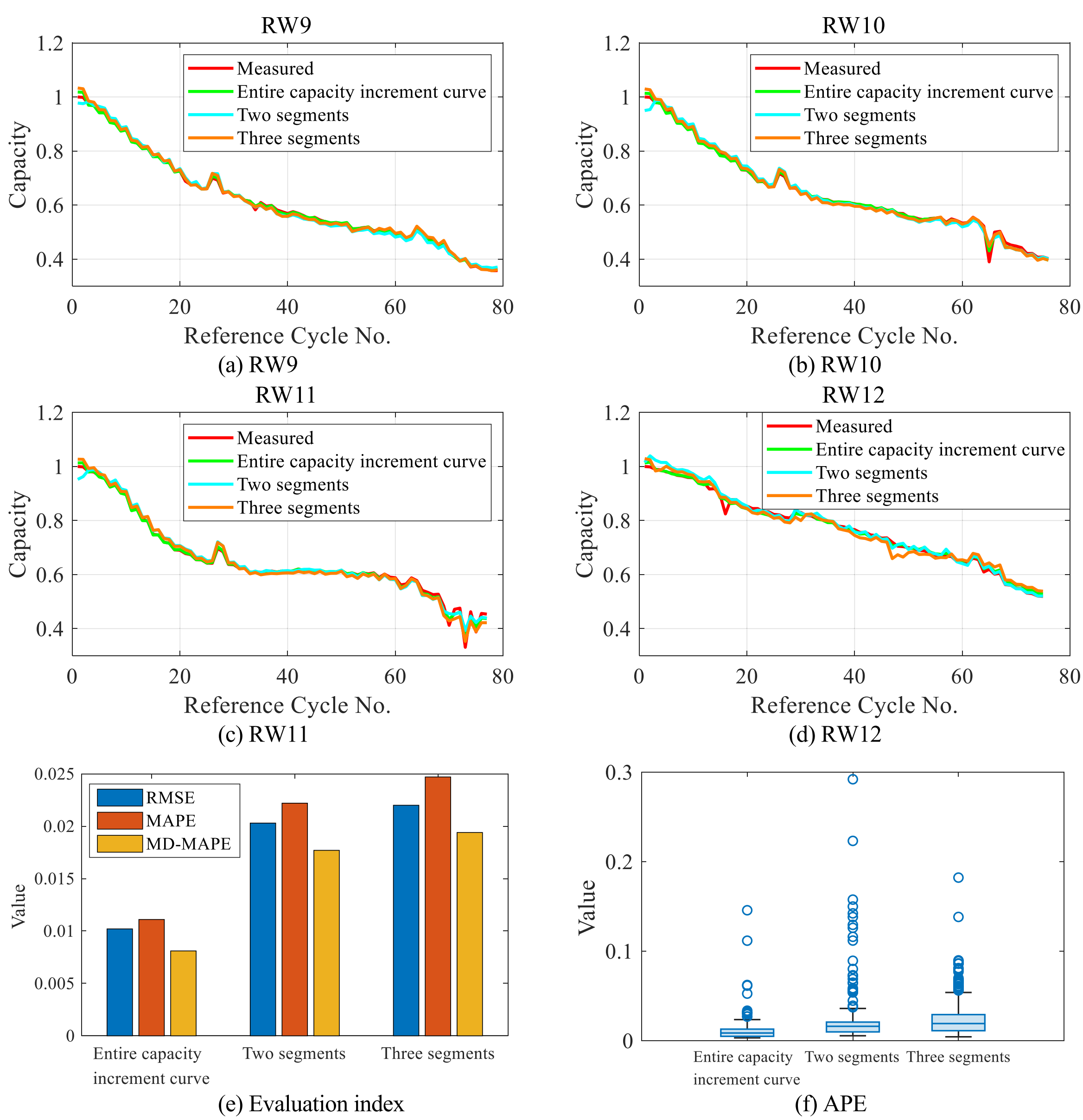


Fig. 7. The capacity estimation results of different partial segments.

the entire capacity increment curve is divided into three segments. Nevertheless, even when the entire capacity increment curve is divided into three segments, the error of capacity estimation is still only about 2%. Overall, the experimental results demonstrate the effectiveness and feasibility of the proposed DTCNN method for capacity estimation using partial segment data.

4.5. Discussion

The results of transfer experiments in section 4.1 demonstrate the feasibility and effectiveness of the proposed DTCNN method. The error in capacity estimation is found to be large when the CNN model is trained solely on either source domain data or limited target domain data due to the statistical distribution shift between the two domains. This discrepancy is attributed to the inherent unique characteristics of the target domain data, which cannot be captured using only source data or a small amount of target data. To address this challenge, the proposed method trains the model with sufficient source data and fine-tunes it with limited target data to obtain a deep transfer learning model named DTCNN. This approach successfully reduces or eliminates the distributional discrepancy between different data sets, resulting in improved accuracy in capacity estimation. The experimental results demonstrate that the proposed DTCNN method has superior performance and is a suitable solution for capacity estimation of lithium-ion batteries in practical industrial settings.

The results of the experiments in section 4.2 demonstrate that the benchmark model of the proposed method, namely the CNN, exhibits superior capabilities in feature extraction and mapping compared to other commonly used models such as MLP, LSTM, SVM, RF, and AdaBoost. Additionally, the experiments conducted in section 4.3 confirmed that the capacity increment feature outperforms the voltage and current features in capacity estimation due to its relationship with the external data characteristics of lithium-ion batteries and the internal electrochemical reaction mechanism. Using the capacity increment feature can effectively reflect the degradation law of lithium-ion batteries and lead to more accurate capacity estimation.

It is worth noting that the aforementioned analysis is based on complete charging/discharging cycle data. However, in practical industrial scenarios, only parital segment during one cycle data may be available due to working condition randomness. Nevertheless, the experiments carried out in section 4.4 demonstrate that the proposed DTCNN method can accurately estimate lithium-ion battery capacity even with only partial segment data, providing robustness and flexibility to the proposed method in real-world applications.

4.6. Advantages and limitations

Based on the above discussion, the proposed method for estimating the remaining capacity of lithium-ion batteries has several strengths. Firstly, the method utilizes a partial capacity increment feature for more efficient and accurate capacity estimation, especially in industrial scenarios where only partial fragments of data can be obtained. The capacity increment feature can both reflect the external data characteristics of the lithium-ion batteries and the internal electrochemical aging mechanism. Secondly, the proposed method utilizes a data-driven approach and incorporates a deep transfer learning strategy to account for the domain discrepancy between the training and testing data. The used deep learning models are trained with an end-to-end manner, regardless of expert experience and priori knowledge. More importantly, the capacity estimating method for lithium-ion batteries is highly accurate, with an error rate of only 2% using partial segment data, making it well-suited for industrial applications.

Although our proposed method shows significant advantages with respect to other deep learning methods, it is important to acknowledge some of its limitations. One limitation is that the proposed method only takes current and voltage as external parameters to calculate the capacity increment feature. Incorporating other external parameters, such as temperature, humidity, and usage pattern, could potentially improve the accuracy of our method for estimating the capacity of lithium-ion batteries. We have added this limitation to our paper and will consider it for future work. Additionally, the proposed method was only evaluated using lithium-ion battery aging data from NASA, and further experiments are needed to evaluate its generalization ability to different types of batteries or energy storage systems. Finally, the computational efficiency is a significant topic, and the proposed DTCNN model may be complex and computationally expensive. In practical applications, the battery capacity estimation is often conducted in real-time or online. Future work can explore the feasibility of implementing the proposed method on low-cost and low-power edge devices, such as microcontrollers and embedded systems, to enable real-time capacity estimation of batteries.

5. Conclusions

This study presents a novel approach for estimating the remaining capacity of lithium-ion batteries based on deep transfer learning and partial capacity increment feature. The capacity increment feature is computed by taking into account the external measurements of the battery such as the current and voltage. A convolutional neural network (CNN) model is trained to learn the mapping between the input feature and the predicted capacity. Furthermore, the proposed method incorporates a transfer learning strategy to address the domain shift issue between the training and testing data. Specifically, the deep model is first pre-trained and then fine-tuned to optimize its performance. The experimental evaluation is conducted using the NASA lithium-ion battery aging data to ensure the effectiveness and superiority of the proposed method. The experiments include transfer learning, comparisons with other deep learning models, and variations of input features and partial segments. The experimental results demonstrate that the proposed DTCNN method outperforms other state-of-the-art deep learning models, achieving an error of only about 2% in capacity estimation using partial segment data. This promising performance makes the proposed DTCNN method well-suited for practical industrial scenarios.

Three potential areas for future work include: (i) investigating the benefits of incorporating additional external parameters beyond current and voltage to improve the estimated accuracy, such as temperature, humidity, and usage pattern, (ii) evaluating the generalization ability of the proposed method to different types of batteries or energy storage systems, and (iii) exploring the feasibility of implementing the proposed method on low-cost and low-power edge devices for real-time capacity estimation of batteries.

Credit author Statement

Jiachi Yao: Conceptualization, Investigation, Methodology, Software, Writing - original draft. **Te Han:** Supervision, Conceptualization, Methodology, Writing-review &editing.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

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