Online Estimation of Lithium-Ion Battery Capacity Using Transfer Learning

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***Abstract*-Producing satisfactory accuracy in capacity estimation of lithium-ion (Li-ion) rechargeable batteries based on a small size of charge-discharge cycling data is a challenging task, since the cycling data may not cover high cell-to-cell variability in the aging process. However, in real-world applications, collecting long-term cycling data from a large number of cells is a costly and time-consuming process. This paper presents a transfer learning-based method for cell-level capacity assessment while only having access to a relatively small dataset. Transfer learning is a knowledge learning method that leverages knowledge learned from a source task to improve learning on a related but different target task. In this study, ten-year daily cycling data from implantable Li-ion cells is used as the source dataset to pre-train a deep convolutional neural network (DCNN). The parameters of this pre-trained DCNN are then transferred to a new DCNN model named deep convolutional neural networks-transfer leaning (DCNN-TL). The DCNN-TL model is then fine-tuned and re-trained to produce accurate capacity estimation on a target dataset (NASA data). Compared with the Gaussian process regression method and DCNN without transfer learning, the proposed DCNN-TL method is demonstrated to reduce the RMSE in capacity estimation by 63.09% and 17.57%, respectively.**

I. Introduction

Due to the nearly continuous improvements in cycling efficiency and power density and reduction in cost, lithium-ion (Li-ion) rechargeable batteries have been increasingly used as energy storage devices in various applications, such as cell phones, laptops, hybrid and electric vehicles, and grid-scale energy storage systems. In such applications, it is of great importance to online estimate the capacity of a battery cell, an important measure of the cell's state of health (SOH), for ensuring the safety and reliability of the cell operating in the field.

In recent years, literature has reported a variety of machine learning methods for online estimating the capacity of a Li-ion battery cell [1][2]. Most of these machine learning methods focus on improving the accuracy of capacity estimation assuming the availability of large training datasets. However, in many real-world applications, gathering long-term cycling data from a large number of battery cells is often time-consuming and costly. On the other hand, there may exist large *source* aging datasets that have been collected under cell chemistries and aging conditions similar to those of the *target* application. The question now becomes how to accurately estimate the cell capacity on a specific *target* application with a small amount of *target* aging dataset by leveraging much larger *source* datasets on different but similar applications.

This study answers the aforementioned question by employing two deep learning methods, named deep convolutional neural network (DCNN) and transfer learning (TL). First, a DCNN model is pre-trained based on a large *source* dataset (i.e., ten-year daily cycling data from implantable Li-ion cells [3]). Then, the parameters of this pre-trained DCNN model are transferred to a new DCNN model named DCNN-TL. With fine-tuning and retraining, the DCNN-TL model is shown to yield accurate capacity estimation on a *target* dataset (i.e., a publicly available aging dataset with five group of battery cells from the NASA Prognostics Data Repository [4]). The results suggest that the proposed DCNN-TL method can provide accurate capacity estimation with a small size of training dataset and outperform a traditional machine learning method named Gaussian process (GP) regression and DCNN without transfer learning.

II. Methodology

A. Input and Output Structures

The input of a DCNN-TL model are measured cell voltage, current, and capacity curves during a partial charge cycle. It is worth mentioning that the voltage and current can be directly measured from the cell, whereas the capacity is required to be calculated using the coulomb counting method, which integrates the charge current with respect to time for the partial charge cycle [3]. Each of the the voltage, current, and capacity curves of a battery cell for one partial charge cycle is discretized into 25 segments and the discretized values of voltage, current, and capacity are used as the input to the DCNN-TL model. As such, the input to the model is a matrix with fixed size 25×3, of which the first, second, and third columns are associated to the discretized values of voltage, current, and capacity, respectively [5].

Each partial charge cycle has a corresponding discharge capacity that serves as the true output of the DCNN-TL model. The discharge capacity is calculated using the coulomb counting method, which integrates the discharge current over

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time for the entire full discharge cycle that immediately follows the partial charge cycle.

B. Transfer Learning

In this study, we first train (or pre-train) a DCNN model with a *source* dataset, and then transfer learned parameters of this pre-trained DCNN model to a new DCNN model (i.e., the DCNN-TL model) that will be re-trained with a *target* dataset. The pre-trained DCNN model contains five convolutional layers and three fully-connected layers. This network depth has been proven to achieve satisfactory performance in capacity estimation of implantable cells [5]. When re-training the DCNN-TL model, we follow the strategy described in [6] for fine-tuning the network and adopt a learning rate that is 90% smaller than the original learning rate used to pre-train the DCNN model. The learning rate is selected to maximize the *target* task performance with the same number of epochs as pre-training the DCNN model. This learning rate is used to learn all layers of the DCNN-TL model except the first layer, which uses 5x the original learning rate.

Fig. 1 shows the use of transfer learning to build a DCNN-TL model that approximates the complex mapping from the multi-dimensional time-series input (i.e., voltage, current, and partial charge capacity) to the one-dimensional discharge-capacity output.

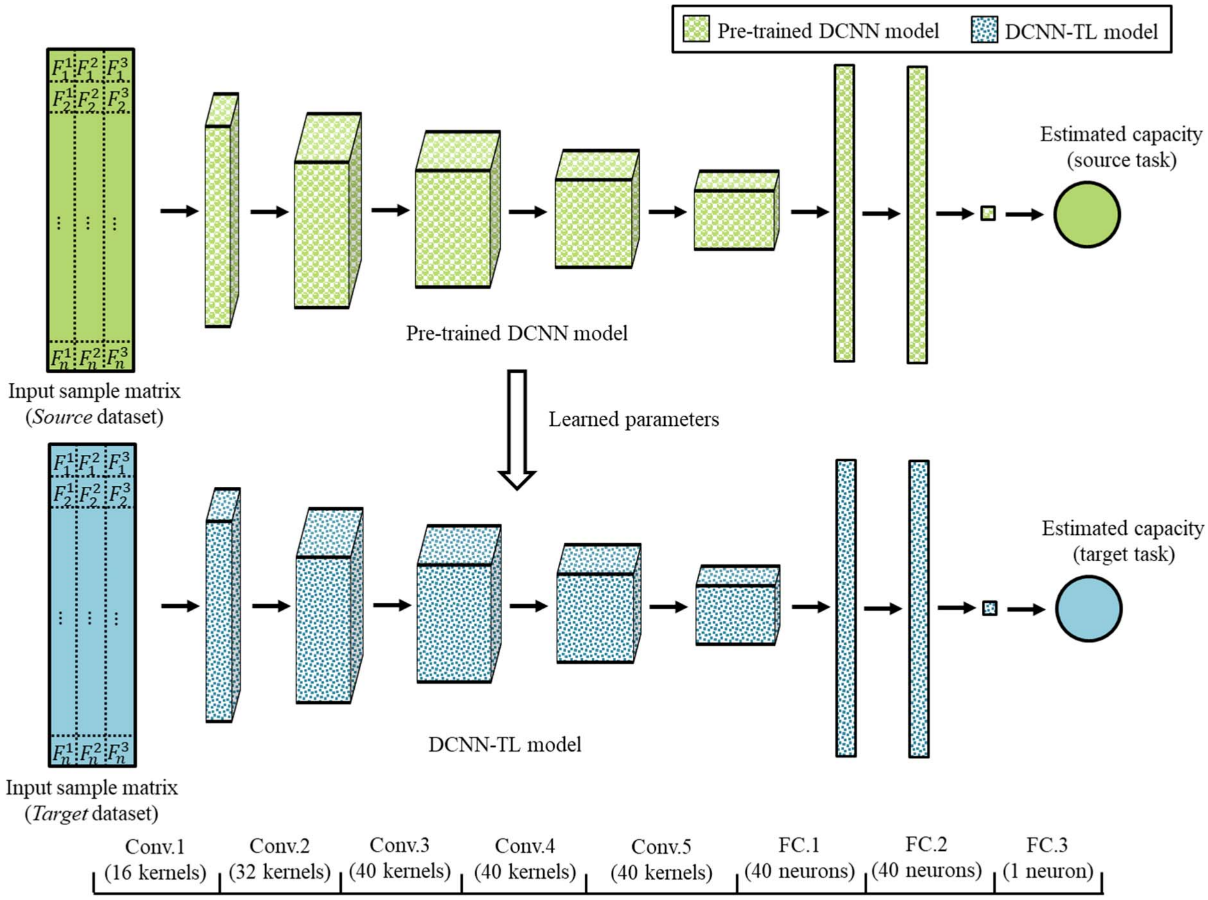

Fig. 1. Overview of the proposed transfer learning approach to battery capacity estimation. Top: A DCNN model is pre-trained based on the *source* dataset. Bottom: The DCNN-TL model is trained using transfer learning based on the *target* dataset. The color indicates the dataset that the model was originally trained on (green denotes *source* dataset and blue denotes *target* dataset). The filled pattern distinguishes the pre-trained DCNN model from the DCNN-TL model. A rectangular solid represents the kernels learned for a convolutional layer and a rectangle represents the neurons learned for a fully-connected layer.

III. RESULTS AND DISCUSSION

A. Cycling Data

This study employs two different datasets, a *source* dataset (long-term cycling data from implantable cells) and *target* dataset (short-term cycling data from the NASA Prognostics Data Repository). The *source* dataset is a large dataset, which has about 76,000 samples (or cycle-cell observations). The test duration for collecting the source data was more than ten years. The *target* dataset is of a small size and only has about 500 samples. It took approximately five months to collect the target data. The information regarding the sample size and test duration for the *source* and *target* datasets are summarized in TABLE I. Compared with the *source* dataset, the *target* dataset presents a greater challenge for capacity estimation since it includes cells cycled with five different cycling protocols and a time-varying charge-discharge profile within each protocol group (as opposed to only a single protocol and profile for the *source* dataset).

TABLE I
SUMMARY OF SOURCE DATA AND TARGET DATA

Dataset	*Source* data	*Target* data
Sample size	76,014	525
Test duration	More than ten years	Approximately 5 months

B. Definition of Error Measures

The accuracy of the proposed DCNN-TL method is evaluated by using the five-fold cross validation (CV), as shown in Fig. 2. The complete *target* dataset consisting of 20 Li-ion cells is first split into five mutually exclusive folds or subsets. Each fold consists of four different cells. Subsequently, five CV trials of training, validation, and test are performed such that within each CV trial a fold of the data is held out for test, while the remaining four folds are pulled together, randomly shuffled, and divided into a training dataset (80% of all samples in the four folds) and a validation dataset (20%). After performing all the five CV trials, the overall test error $\varepsilon_{\text{RMS}}^{\text{All}}$ by DCNN is estimated by taking the average of the individual test errors $\varepsilon_{\text{RMS}}^{k}$ across the eight trials.

$$\varepsilon_{\text{RMS}}^{k} = \sqrt{\frac{1}{N_k}\sum_{i=1}^{N_k}\left(y^k(\mathbf{x}_i^k) - \hat{y}^k(\mathbf{x}_i^k)\right)^2} \tag{1}$$

$$\varepsilon_{\text{RMS}}^{\text{All}} = \sqrt{\frac{1}{\sum_{k=1}^{5} N_k}\sum_{k=1}^{5}\sum_{i=1}^{N_k}\left(y^k(\mathbf{x}_i^k) - \hat{y}^k(\mathbf{x}_i^k)\right)^2} \tag{2}$$

where N_k is the number of samples used for the test in the k^{th} trial, $\hat{y}^k(\mathbf{x}_i^k)$ and $y^k(\mathbf{x}_i^k)$ are the estimated and measured (or true) capacities for the i^{th} sample in the k^{th} trial, respectively, and $\mathbf{x}_i^k$ is the i^{th} sample matrix in the k^{th} trial. The performance of the proposed DCNN-TL model is reflected by the overall test error in (2).

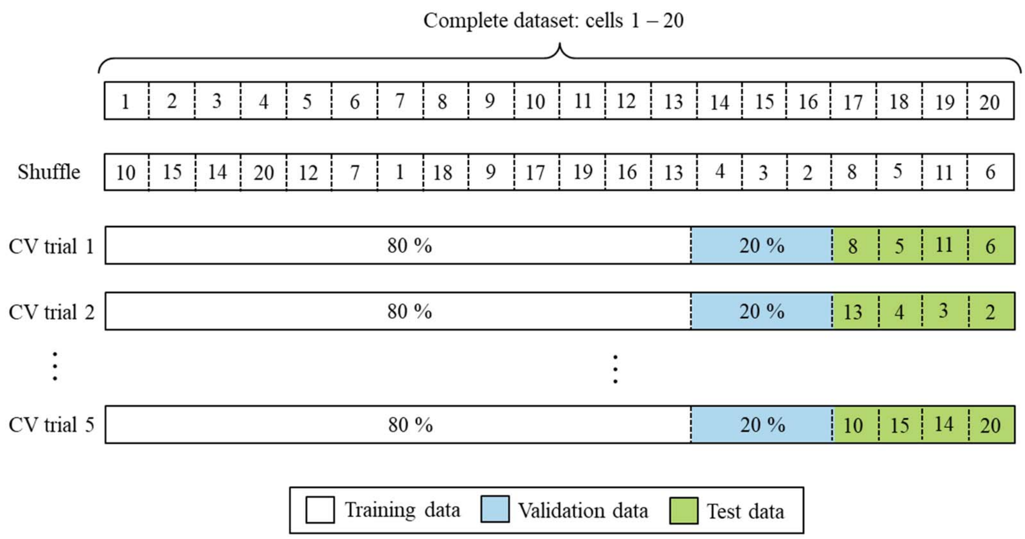

Fig. 2. Procedure of five-fold cross validation. The training dataset in each CV trial consisted of 80% of all samples randomly drawn from the dataset of sixteen cells, and the remaining 20% of the samples were used to form the validation dataset.

The performance of the proposed DCNN-TL method is compared to a widely used machine learning method (i.e., GP regression [7]) and a deep learning method (i.e., DCNN [5]). TABLE II shows the comparison results in terms of the RMSE and maximum (Max) error. The DCNN-TL model produces an overall RMSE of 1.218%, which implies that the proposed transfer learning method can provide accurate capacity estimation with a small number of training samples. Both deep learning methods, DCNN-TL and DCNN, produce higher accuracy in capacity estimation than the traditional machine learning method, GP regression, in all CV trials. The DCNN-TL model performs slightly better than the DCNN model.

TABLE II
CAPACITY ESTIMATION RESULTS BY GP, DCNN, AND DCNN-TL

Model	Item	CV trial 1	CV trial 2	CV trial 3	CV trial 4	CV trial 5	Overall
GP	RMSE	2.328	4.714	2.700	3.198	3.561	3.300
	Max error	4.949	20.328	7.215	20.763	12.737	20.763
DCNN	RMSE	1.405	1.305	1.628	1.683	1.365	1.477
	Max error	8.403	9.479	7.207	**6.567**	4.973	9.479
DCNN-TL	RMSE	**0.954**	**1.143**	**1.174**	**1.530**	**1.289**	**1.218**
	Max error	**2.520**	**3.214**	**4.357**	8.200	**4.891**	**8.200**

IV. CONCLUSIONS AND FUTURE WORK

In this study, we have proposed and implemented a transfer learning approach to battery capacity estimation. The proposed deep convolutional neural networks-transfer learning (DCNN-TL) model was demonstrated to outperform a traditional machine learning method, Gaussian process regression, and the DCNN model without transfer learning. Our future work will examine the benefit of transfer learning with respect to accelerating the training process as well as investigate how the number and locations of transferred layers affects the accuracy of the DCNN-TL model.

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