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*Article*

# Health-Conscious Vehicle Battery State Estimation Based on Deep Transfer Learning

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**Abstract:** Establishing an accurate mathematical model is fundamental to managing, monitoring, and protecting the battery pack in electric vehicles (EVs). The application of the deep learning algorithm-based state estimation method can significantly improve the accuracy and stability of the battery model but is hindered by the great demand for training data. This paper addresses the challenge of health-conscious battery modeling by utilizing multi-source data based on a novel deep transfer learning method. Firstly, a cloud-based battery management framework is designed, which is able to collect and process battery operation data from various EVs and provide a foundation for deploying the transfer learning method. Battery healthy state information in the collected dataset is labeled by a generic perception model, which can be commonly used to quantify the aging state of different battery packs and facilitate the knowledge transfer process. Additionally, a deep transfer learning method is developed to boost the training process of the battery model, where the operation data from different types of EVs can be used for establishing state estimators. The method is verified by the battery operation data collected from two types of electric buses. With the developed healthy state perception model and transfer learning method, battery model error can be limited to 2.43% and 1.27% in the whole life cycle.

**Keywords:** Transportation electrification, electric vehicles, battery energy storage, deep transfer learning, battery management system, battery state estimation.

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## 1. Introduction

Vehicle is an essential part of modern transportation and energy system, and the improvement of its efficiency is of great significance to alleviate global warming and achieve carbon-neutral ambition [1, 2]. Electrification, intelligence, and networking

have been recognized as the three most important development directions of future transportation systems [3, 4]. The adoption of electric vehicles (EVs) makes it possible to reduce greenhouse gas emissions and fossil fuel consumption fundamentally, while the promotion of intelligent connected vehicles can further boost the operational efficiency of integrated transportation and energy system. As the main energy storage device, the lithium-ion battery pack is one of the most important and expensive devices in EVs [5]. The establishment of an accurate mathematical model is fundamental to managing, monitoring, and protecting the battery [6, 7]. Kalman filters are the most commonly used method to estimate battery state. In [8], the model-adaptive Kalman filter is used to estimate the State of Charge (SoC) of lithium-ion batteries; experimental results validate the accuracy and robustness of the established battery model. However, the lithium-ion battery is a complex electrochemical system and its characteristics change with capacity degrades [9-11]. The accuracy and stability of conventional model-based and data driven battery state estimation methods can no longer satisfy data quality requirements from advanced vehicle control and intelligent transportation systems [12, 13].

Recently developed internet of vehicle and artificial intelligence technologies bring a bright perspective to improve the performance of battery models. Many research has been conducted to study big-data-driven battery modeling and healthy estimation methods [14-17]. A deep belief network-based battery model is established in [18], and the model is trained by battery historical operation data with SoC as output. Experimental results indicated that the deep learning model has good estimation accuracy under vehicle dynamic working conditions. Paper [19] proposes an intelligent battery State of Health (SOH) estimation method based on fast impedance measurements. The data analysis and clustering method are used in their study to establish the battery SOH estimation model, and the experimental results validate the accuracy and real-time performance of the developed method. The big data analysis methods and artificial intelligence technologies are further employed in [17] to monitor the operation state and detect the fault and defect of the vehicle battery system.

With big data technology and deep learning algorithms, the performance of the established battery model can be significantly improved compared to conventional onboard battery modeling methods [20, 21]. However, the training and calibration of the model need a large volume of data, which burden the data collection and preparation process [22-25]. According to [26], feature engineering, which means constructing features and data representations from raw data, is the main reason why deep learning algorithms outperform other data driven methods. Nevertheless, the training of feature extractors needs a large volume of high-quality data that can evenly cover the definition domain of all independent and dependent variables. For example, technology corporations such as Google, YouTube, and Uber usually use exabyte or larger datasets to establish deep learning-based recommender systems to achieve the best performance.

Similar to recommender systems, the establishing of the battery model also needs a large volume of high-quality training data [27, 28]. On the one hand, the battery is a complex electrochemical system that contains multi-features: the single cell is already an independent system with its own chemical and electrical features, each of them has a completed unique mathematical model; while the battery pack contains thousands of cells with non-uniform characteristics (e.g., SoC, state of power, and temperature) [29–32]. On the other hand, the degradation phenomenon and the capacity change make the situation even worse: the battery owns different external characteristics at different healthy states [33–35]. The complex group effect and aging mechanism make the modeling process hard. Without sufficient training data, the established model always shows limited extrapolation capability for cases that are out of the prescribed dataset. According to [14], machine learning algorithm-based battery models own better performance under battery stable working conditions. However, model accuracy decreases greatly under high current working conditions because of the underfitting phenomenon caused by lacking training data. Therefore, it is difficult to guarantee the reliability of derived model under complex dynamic working conditions.

However, it is hard to collect a comprehensive dataset that can reflect the overall battery characteristics, which introduces challenges for model training. Different vehicle types are with different battery packs that consist of varying numbers and types of battery cells. In conventional artificial intelligence-based methods, the establishment of the battery model in these vehicles needs independent datasets, which means that several large battery datasets are required to guarantee the model performance [36, 37]. Nevertheless, collecting the battery operation data for various EVs throughout the life cycle is hard and costly, especially for some of the latest models. In recent years, the development of transfer learning brings a bright perspective to boost the performance and reduce the training cost of deep learning algorithm-based battery models [38–40]. Transfer learning algorithms are designed for applying knowledge and skills learned in previous tasks to novel domains and have been proved effective in reducing the size of the training dataset in many fields, such as intelligent translator [41], visual tracking [42], and image classification [43]. However, to the best of the author's knowledge, no published works have studied the use of deep transfer learning methods in vehicle battery state estimation.

This paper addresses the challenge of accurate battery modeling by utilizing multi-source data based on a novel deep transfer learning method. A cloud-based health-conscious battery modeling and management framework is designed to collect and process the operation data from different EVs, which provides a foundation for deploying the transfer learning method. Furthermore, on the basis of the established big data platform, an easily transferred battery healthy state estimation model is established to label the collected battery data with aging information for improving the performance of the battery model. Additionally, since establishing and training the health-conscious

battery model for new EVs is impractical due to the significant data volume requirement, we propose a deep transfer learning method to boost the battery modeling process by using a multi-resources dataset. The main contribution of this paper is summarized as follows:

- 1) To the authors' best knowledge, this paper is the first effort to study the reduction of training dataset size when establishing battery state estimation models by the deep transfer learning method.
- 2) A cloud-based health-conscious battery modeling and management framework is designed, which is able to collect and process the battery operation data. The collected and processed battery operation data can be flexibly used for training battery state estimators in different EVs.
- 3) A novel generic battery healthy state perception model is established, which can automatically extract and analyze the irregular battery aging cycles in the collected battery dataset. The battery healthy state label can be universally used for analyzing the aging state of different battery packs, which facilitates the establishment of the transfer learning model. With the developed health-conscious method, battery model error can be limited to 2.43% in the whole life cycle.
- 4) A deep transfer learning method is developed for boosting the training process of the battery model, where the operation data from different types of EVs can be universally used for establishing state estimator for new type EVs. With the developed transfer method, the battery model can be further limited to 1.27% by only utilizing operation data of three EVs.

The rest of the paper is organized as follows: The developed cloud-based health-conscious battery modeling and management platform are described in Section 2. Section 3 presents the established generic battery healthy state perception model. The proposed deep transfer learning method for battery state estimation is in Section 4. The performance of the developed battery modeling method is illustrated in Sections 5, followed by concluding remarks in Section 6.

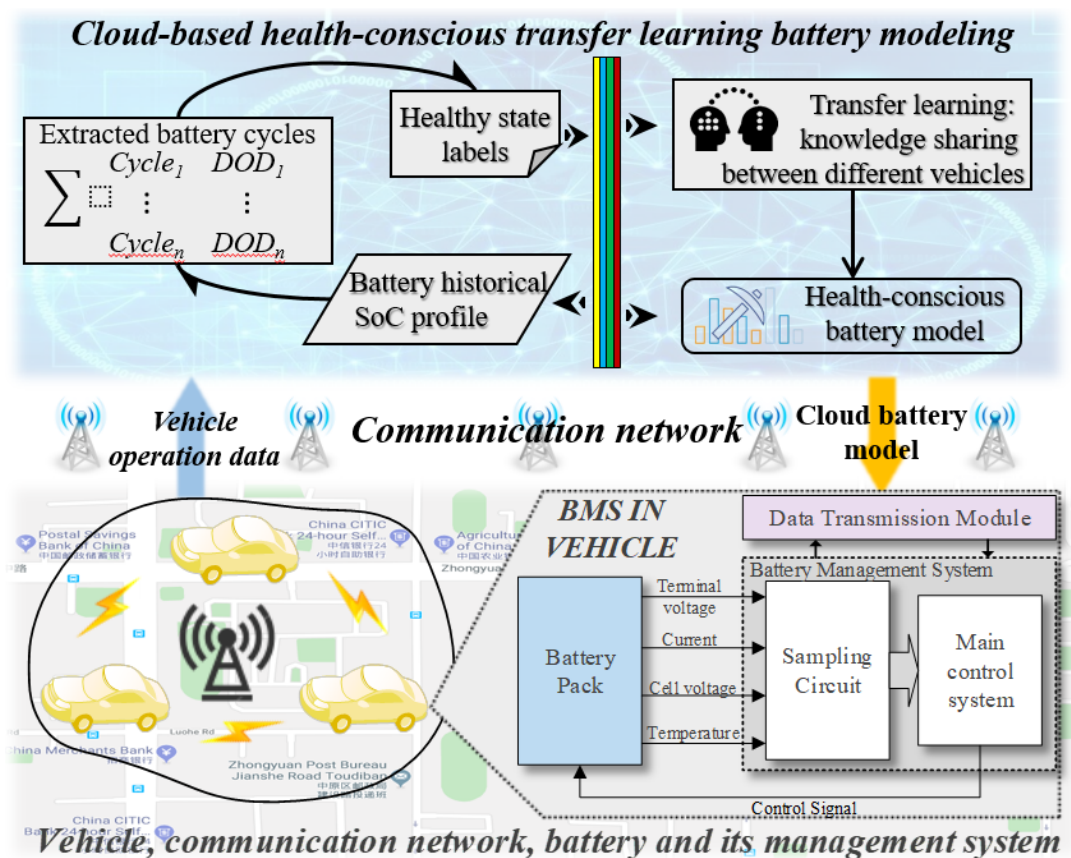
## **2. Cloud-based health-conscious battery modeling and management platform**

A cloud-based health-conscious battery modeling and management framework (CHBMF) is built to collect, process, integrate, and analyze the operation data from various EVs, providing a foundation for deploying the transfer learning battery modeling method. As shown in Fig. 1, the whole CHBMF consists of two parts: the onboard battery management system and the cloud battery management platform.

### **➤ Onboard battery management system**

The battery pack of EVs consists of hundreds of battery cells with different characteristics, so it is necessary to monitor and manage these battery cells and the battery pack in real-time. The onboard battery management system (OBMS) is one of

the most commonly used battery management devices in conventional EVs [44, 45]. However, the battery pack is a complex electrochemical system and its characteristics change with the healthy state, and a mass of operation data is indispensable for establishing an accurate and stable model. It is hard to establish an accurate health-conscious battery model just by utilizing the data provided by OBMS. Therefore, on the basis of conventional vehicle configuration, a data transmission module that enables the bi-directional linkage between the OBMS and the cloud data center is installed. The OBMS still works to manage the battery pack in EVs directly but can also upload its data to cloud data center for further analysis. As shown in Fig. 1 (down), a vehicle battery information communication network is built within the EVs cluster, and the battery operation data of different EVs can be sharing in the cloud battery center.



**Fig. 1.** Cloud-based health-conscious battery modeling and management framework.

### ➤ Cloud battery data center

The developed transfer learning algorithm-based health-conscious battery modeling method is deployed in the cloud battery management platform.

As shown in Fig. 1, the whole platform can be divided into three parts: battery operation database, battery healthy state perception model, and the transfer learning-based battery model. The battery database is built to collect and process the battery operation data of various EVs uploaded by the OBMS, and the battery operation from the same EVs is aggregated together for analyzing its healthy states. Meanwhile, a

generic battery healthy state estimation model is used to extract the battery number of cycles (NOC) and depth of discharge (DOD) information from the collected battery data. The generated battery healthy state labels are stored back in the database for further data mining process. At last, based on the collected battery operation data with healthy state indexes, a transfer learning algorithm-based battery model is established in the cloud platform. Benefiting from the knowledge transfer process, the battery model can be built under the data-scarce condition by sharing using the operation data from various EVs. The established cloud battery model can work jointly with OBMS as the battery state estimator to monitor and manage the operation of EVs, such as energy management, route planning, and fault detection, which has been studied in our previous work [46].

The communication network is a bridge between the OBMS and the cloud data center in the developed CHBMF. The onboard battery management system and the vehicle communication network has been well studied in previous literature. Accordingly, this paper mainly focuses on the cloud battery management platform, including the establishment of the generic battery health state perception model and the transfer learning method.

### 3. Generic battery healthy state perception model

On the basis of the built cloud-based battery management platform, the battery operation data from various vehicles can be collected and stored. The battery health state changes with EV usage, and the battery data is collected under different aging states. Perceiving the healthy state in the collected battery dataset is of great significance for improving the accuracy of the established battery model. Conventional battery aging models, including equivalent circuit models [47] and electrochemical models [48], are specifically designed for a type of EVs and cannot adapt to different EVs or battery types. To facilitate the deployment of transfer learning method, it is necessary to unify the used battery healthy state index. In this section, a generic battery healthy state perception model is developed. Sum number of cycles and depth of discharge, the two most remarkable battery aging performance indexes that are in common use for all types of battery, are used to label the healthy state of the collected data. Firstly, the SoC trajectory is got out from the established cloud battery database:

$$S_i = [SoC_1 \quad \cdots \quad SoC_i \quad \cdots \quad SoC_n] \quad (1)$$

$$S = [S_1 \quad \cdots \quad S_2 \quad \cdots \quad S_3] \quad (2)$$

Where:  $S_i$  is the battery SoC profile of an EV in  $i^{th}$  travel,  $S$  is the complete battery SoC trajectory in the whole life cycle. The rain-flow cycle-counting (RCC) algorithm [49] is usually used for analyzing the fatigue data and was firstly used in

metal fatigue estimation. In this research, this method is used to extract the irregular charging and discharging cycles from the EVs' SoC trajectory.

Basically, the cycle counting can be achieved by analyzing the adjacent points in SoC profiles, as shown in Fig. 2. Firstly, the data (for the battery data is the SoC profile that presents the charging/discharging cycles) is pre-processed by searching for adjacent data points with the reverse polarity. The difference between local maxima and minima values found in adjacent searching are labeled as sub-cycle. Secondly, battery full cycles are composed by analyzing the turning points and summing up the amplitudes of each sub-cycle. The extracted battery number of full cycles and DoD are recorded as  $N_i^C$  and  $DC_i$ . Then, the remaining adjacent points in the battery SoC profile, which cannot form full cycles, are further labeled as half-cycles. The extracted battery number of half-cycles and the corresponding DoD are recorded as  $N_i^{HC}$  and  $DHC_i$ . Based on the extracted battery cycles and DoD information, the following functions are built to reflect aging states of the battery of EV in  $n$  times travel:

$$f_1 = \sum_{i=1}^n N_i^C + N_i^{HC} \quad (3)$$

$$f_2 = \sum_{i=1}^n DC_i + DHC_i \quad (4)$$

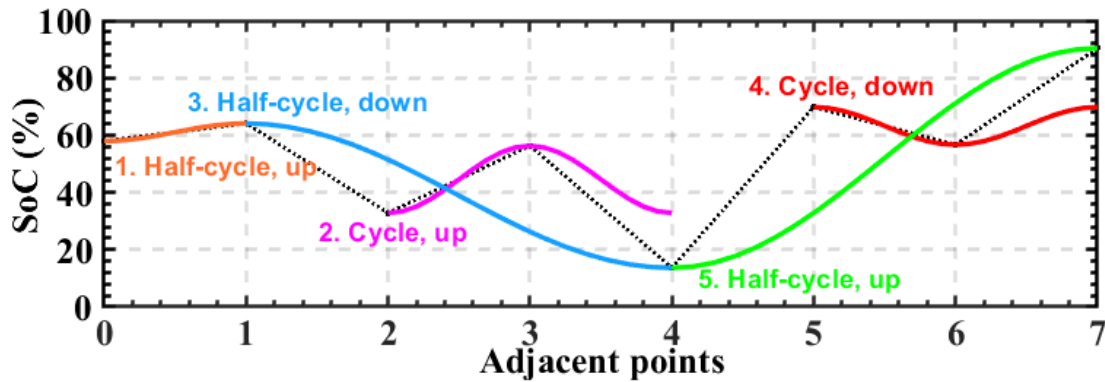


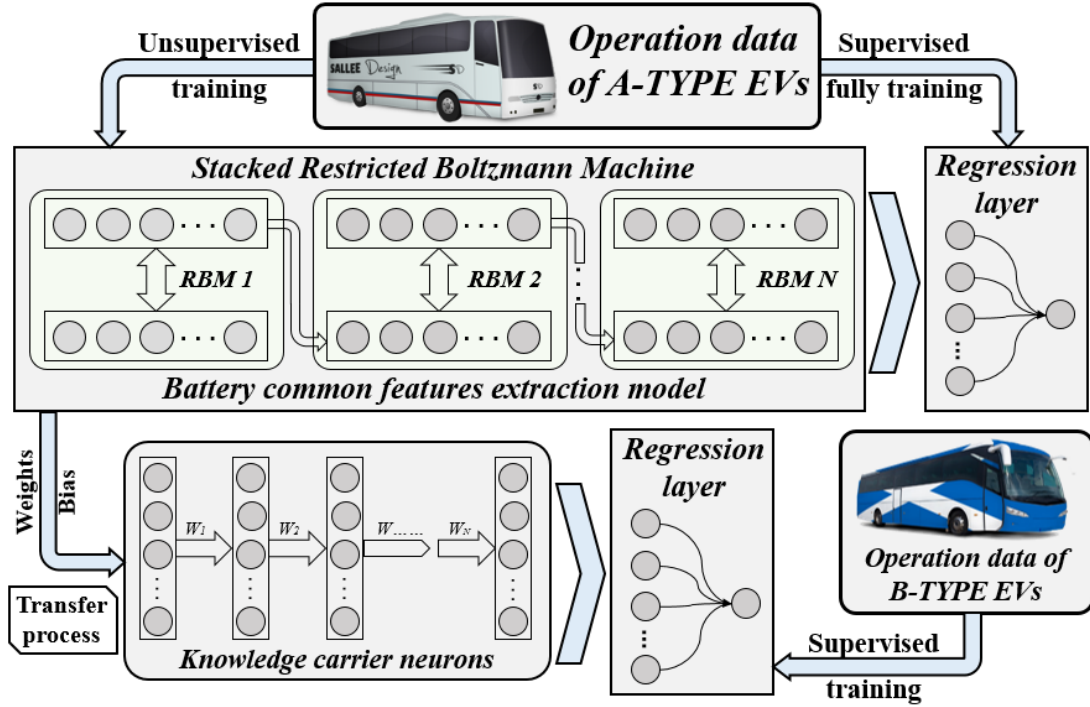
Fig. 2. Extracted number of cycles and depth of discharge from battery SoC trajectory.

#### 4. Deep transfer learning method for battery state estimation

A large volume of data is usually indispensable for establishing an accurate battery model. The more the training data is available, the higher the model accuracy can be achieved. The situation may be even worse when the healthy state is considered in battery models. This section develops a health-conscious battery modeling method by utilizing multi-sources data based on a novel deep transfer learning method.

The knowledge transfer between two EVs labeled A-type and B-type is studied in this paper. As shown in Fig. 3, two learning models are established in the developed transfer learning framework: the original learning model, which is trained by the operation data of A-type EVs that has been put into use for a long time and the training

dataset is sufficient; and the transfer learning model, which is trained with operation data from B-type EVs that has just been put into use and the dataset is poor.



**Fig. 3.** Deep transfer learning algorithm-based battery modeling method by utilizing multi-sources data.

The training objective of the original learning model is to extract the common features within the battery dataset. Based on the sufficient battery dataset from the A-type EV, an unsupervised feature extractor is established. The battery operation data in the whole life cycle of A-type EVs, including terminal voltage, SoC, current, temperature, and healthy labels  $f_1$  and  $f_2$ , are used to train the SBRM model. The model training input can be derived as:

$$\mathbf{Tr}(t) = [\mathbf{SoC} \quad \mathbf{I} \quad \mathbf{U} \quad Tp(t) \quad f_1(t) \quad f_2(t)] \quad (5)$$

Where:  $\mathbf{Tr}(t)$  is the training input vector;  $\mathbf{SoC}$ ,  $\mathbf{I}$ , and  $\mathbf{U}$  are the battery SoC, current, and terminal voltage series;  $Tp(t)$  is the battery temperature at  $t$ ;  $f_1(t)$  and  $f_2(t)$  are the sum of NOC and DOD at  $t$ , which is used to represent battery healthy state. The Restricted Boltzmann Machine (RBM) [50] is used to learn the common features between different battery datasets, and the training process can be derived as:

$$E(v, h | \theta) = \sum_{i=1}^n a_i v_i - \sum_{j=1}^m b_j h_j - \sum_{i=1}^n \sum_{j=1}^m v_i w_{ij} h_j \quad (6)$$

$$p(v, h | \theta) = \frac{e^{-E(v, h | \theta)}}{\sum_{v, h} e^{-E(v, h | \theta)}} \quad (7)$$

$$p(h_j = 1 | v, \theta) = \frac{1}{1 + e^{-(b_j + \sum w_{ij} v_i)}} \quad (8)$$

$$p(v_i = 1 | h, \theta) = \frac{1}{1 + e^{-(a_i + \sum_j w_{ij} h_j)}} \quad (9)$$

$$\frac{\partial \log P(v | \theta)}{\partial \theta} = \sum_{t=1}^T \frac{\partial (-E(v^{(t)}, h | \theta))}{\partial \theta} - \sum_{t=1}^T \frac{\partial (-E(v, h | \theta))}{\partial \theta} \quad (10)$$

Equation (6) gives the energy function of RBM network, which is used to evaluate the feature extraction ability.  $v$  and  $h$  are the state of visible and hidden layers of RBM, which is relevant to training data.  $\theta = \{w_{ij}, a_i, b_j\}$  is the RBM parameters, including weights and biases of network units.

With the sufficient data set from A-type EVs, the established feature extractor can fully expose the hidden features in the dataset, including battery internal and aging characteristics after the training. Meanwhile, the unsupervised training mechanism employed in the SRBM model enhances its robustness and compatibility to batteries with different sizes, group structures, and even types. Therefore, when the new B-type EV is put into use, whose available training dataset is relatively poor, the knowledge carrier neurons in the SRBM model are directly transferred used for establishing its external characteristics simulation models. As shown in Fig. 3, the weights and biases in the SRBM model are directly used to form a feed-forward neural network (FFNN), which served as a data feature analyzer for B-type EV.

The FFNN transferred from the SRBM model can analyze the common features of the battery packs without any training process, which will help boost the battery model training process. However, the SRBM model is not able to simulate battery external characteristics because no definite outputs are defined during the training process. In this study, a regression layer (RL) is put on the top layer of the FFNN model in the transfer learning process to simulate external characteristics of the B-type batteries, as shown in Fig. 3. The battery terminal voltage is used as the output to fine-tune model parameters, and the Error Back Propagation method [51] is used to fine-tune the parameters of the whole network:

$$E = \frac{1}{2} \sum_{p=1}^P (t_p - y_p)^2 \quad (11)$$

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial net_j} \frac{\partial net_j}{\partial w_{ji}} = \frac{\partial E}{\partial net_j} \frac{\partial}{\partial w_{ji}} \left( \sum_{i=0}^n w_{ji} x_{ji} \right) = \frac{\partial E}{\partial net_j} x_{ji} \quad (12)$$

Where:  $E$  is the network feedback error vector, which is calculated based on network output  $y_p$  and observation value  $t_p$ , as described in equation (11). The error backpropagation process is given in equation (12), where the network weights  $w$  are adjusted based on the output errors. It is worth noting that benefiting from the battery common features provided by the knowledge transfer process, only a small volume of data is required to fine-tune the parameters in FFNN-RL model to achieve the best model performance.

With the above transfer learning framework, an accurate battery model can be easily established by utilizing multi-source data. The built FFNN-RL model can be used to directly model the battery of B-type EVs.

## 5. Results and discussion

### 5.1. Model training data preparation

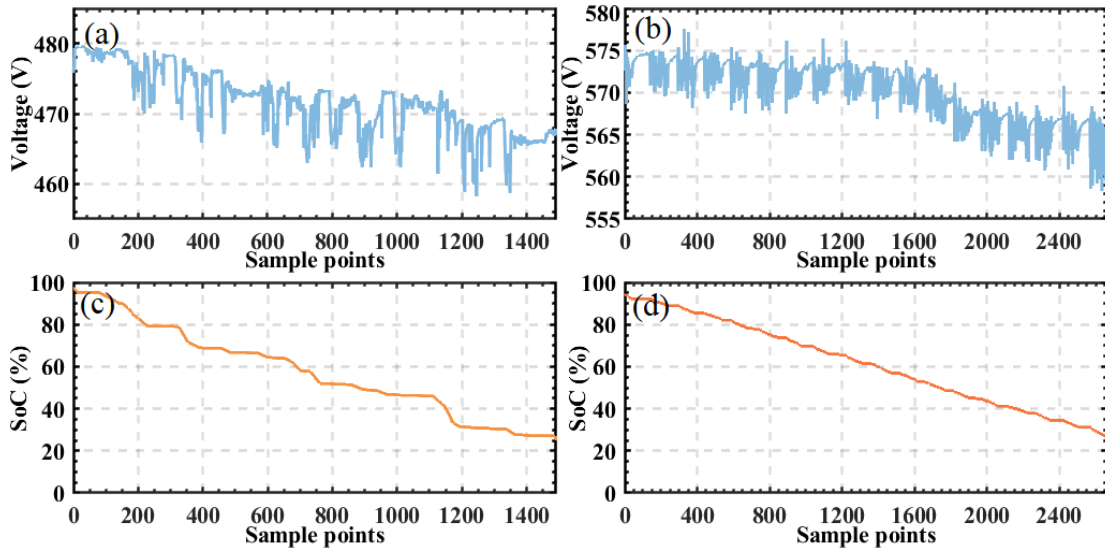
The real battery operation data of electric buses in Zhengzhou, China, which is collected by the cloud-based battery monitoring platform established in our previous work [46], is used here to verify the performance of the proposed methods. In this study, we prepare the operation data from two types of electric buses to verify the effectiveness of the developed transfer learning method. The detailed vehicle and battery system parameters of the studied buses are provided in Table I. Type-A electric buses weigh 13750 kg with a driving range of 220 km, while Type-B buses weigh 18000 kg with an extended range of 240 km. The battery pack in both EVs consists of Lithium iron phosphate cells. The rated capacity and voltage of the battery system in Type-A buses are 260 kWh and 480 V, and its maximum discharging current reaches 400 A. Compared with Type-A buses, Type-B buses' battery pack has higher capacity and voltage. The rated capacity and voltage of the battery system are 304 kWh and 580 V, and the maximum current reaches 480 A for satisfying the power requirement of vehicle driving systems. To fully train the established feature extractor, battery operation data in the whole life cycle of the A-type fleet, which consists of 50 buses, are collected and served as the source dataset to train the initial learning model. Benefiting from knowledge transfer process, only a small volume of data is required to establish battery models for B-type fleet. Therefore, the target dataset, which is used to fine-tune the parameters, consists of only operation data from three electric buses in the B-type fleet.

**Table I.** Vehicle and battery system parameters of the studied buses.

Parameters	Type-A	Type-B
<b>Vehicle mass</b>	13750 kg	18000 kg
<b>Range</b>	220 km	240 km
<b>Fleet size</b>	50	3
<b>Battery cell type</b>	Lithium iron phosphate	Lithium iron phosphate
<b>Rated capacity</b>	260 kWh	304 kWh
<b>Rated voltage</b>	480 V	580 V
<b>Maximum current</b>	400 A	480 A

Battery operation data for training the initial learning model and transfer learning model in one discharging cycle are shown in Fig. 4 as a typical example. Terminal voltage under different SoC levels of Type-A battery is illustrated in (a) and (c). Battery terminal voltage drops from 480 V to 465 V with the decrease of SoC value in the discharging cycle. Under the same SoC level, the higher the discharging current, the

lower the battery terminal voltage level. A large amount of operation data from Type-A buses are used to train the unsupervised learning model by learning the common features and the relationship between SoC state, current state, temperature state, SoH state, and terminal voltage. B-type batteries show different characteristics compared to A-type batteries, and their voltage fluctuates within the range of 575 V to 555 V when the SoC value drops from 95% to 25%. The corresponding terminal voltage data under different SoC levels are provided in (b) and (d), which are used to train the transfer learning model. The terminal voltage is selected as the output of the model to evaluate and compare the performance of different methods.

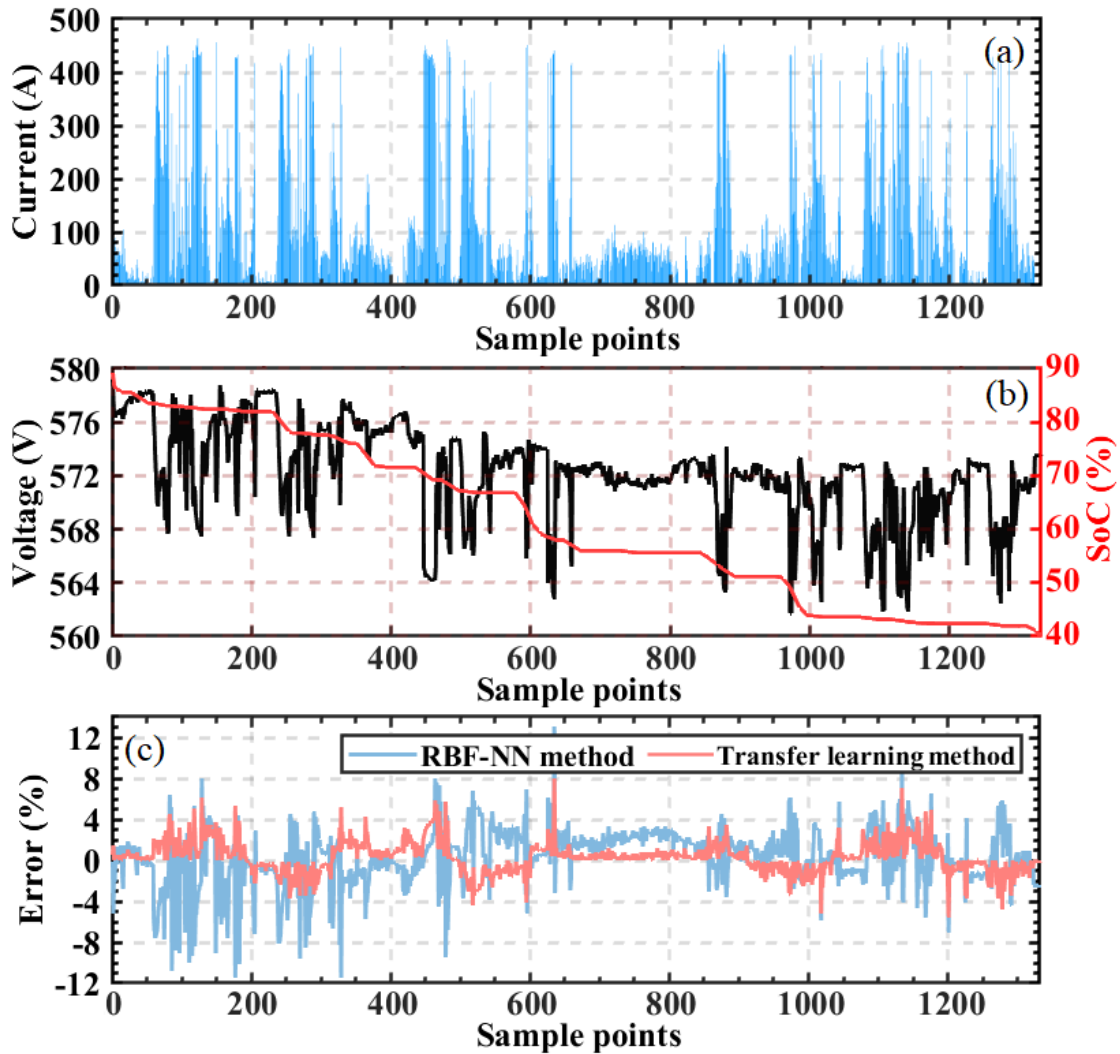


**Fig. 4.** Battery operation data for model training in one complete discharging cycle. (a, c) battery terminal voltage and SoC profile of A-type buses; (b, d) battery terminal voltage and SoC profiles of B-type buses.

## 5.2. Model performance evaluation

The performance of the developed battery state estimation method in one complete discharging cycle is compared with the conventional Radial Basis Function Neural Network (RBF-NN) method [52] in Fig. 5. As shown in (a) and (b), battery SoC value decreases from 85% to 40% in the studied operation cycle. Battery discharging current varies from 0 A to 480 A according to vehicle power requirement, and the corresponding terminal voltage estimation errors are shown in (c). Under large discharging current states, battery external characteristics cannot be accurately simulated by the RBF-NN model because of lacking training data. As shown in Area A, the average estimation error reaches 3.74% in this period. The developed transfer learning method can excavate the hidden battery model features by utilizing datasets from different types of EVs. The estimation error can be limited to 1.62% after the transfer learning mechanism is deployed, which validates that the accuracy of the established battery model is significantly improved. Meanwhile, the developed method can also enhance battery model accuracy under stable working states. As shown in Area

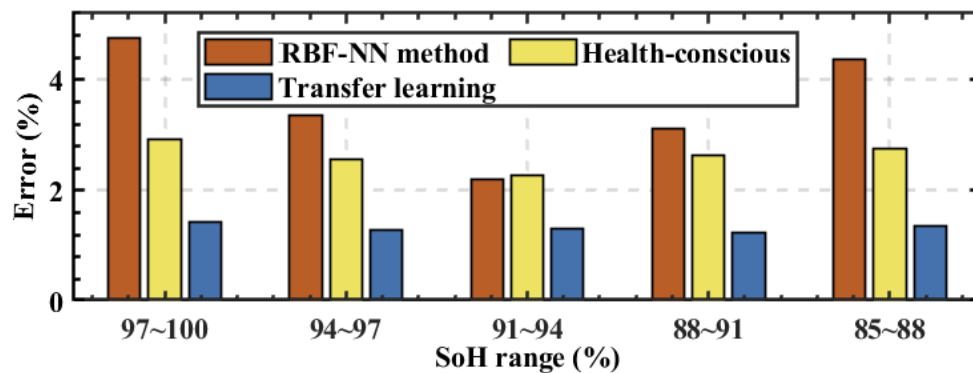
B, battery static characteristics can hardly be accurately simulated by the conventional RBF-NN method, and the average estimation error is still as high as 2.24%. With the developed method, the above number is successfully reduced to 0.53%, which validates the effectiveness of the transfer learning method in improving model accuracy under low current states. In summary, the established transfer learning algorithm-based battery model can simulate battery external characteristics accurately and stably under dynamic working conditions.



**Fig. 5.** Accuracy of battery model in one complete discharging cycle. (a) current profile; (b) terminal voltage and SoC profiles; (c) estimation errors.

Fig. 6 further compares the performance of different methods under various battery SoH states. Battery healthy state is divided into five stages: 97%~100% (high), 94%~97% (medium-high), 91%~94% (medium), 88%~91% (medium-low), and 85%~88% (low) in its whole life cycle. Battery external characteristic change caused by aging cannot be reflected in the RBF-NN-based method, thus model performance under high and low SoH ranges is unsatisfactory. The average model errors reach 4.71% and 4.32% under high and low battery SoH states, respectively. Compared to the RBF-NN method, the

generated battery healthy state index significantly improves model accuracy under the whole life cycle. Under high and low SoH states, battery terminal voltage estimation error can be reduced to 2.84% and 2.75%, which indicates that the influence of aging on battery external characteristics can be successfully learned by the developed method. The transfer learning method further improves model performance in the whole life cycle. Compared to the health-conscious method, battery model accuracy can be further reduced by 45.4% on average. As a result, the average battery terminal voltage estimation error can generally be limited to 1.3% under different SoH ranges, which validates the effectiveness of the developed method.



**Fig. 6.** Performance comparison of different battery modeling methods under various SoH states.

The performance of different battery modeling methods in the whole life cycle is quantitatively compared in Table II. RBF-NN method shows limited capability when simulating battery external characteristics. The mean absolute error (MAE) and mean absolute percentage error (MAPE) are as high as 1.16 V and 3.31%. Meanwhile, the RBF-NN model also shows limited stability under the variety of battery SoH states and working conditions. The maximum percentage error (MPE) and prediction error standard deviation (STD) reach 12.44% and 1.5421, respectively. The developed healthy state perception method significantly improves battery model accuracy. Compared with the conventional RBF-NN method, model MAPE and MPE are reduced by 26.6% and 14.4%, respectively. Furthermore, estimation error STD can also be reduced by 30.5%, which validates that model stability is significantly enhanced by the developed health-conscious method. The deployment of the transfer learning mechanism further improves battery model performance by utilizing datasets from different types of EVs. In the battery's whole life cycle, terminal voltage estimation MAPE and MPE can be limited to 1.27% and 8.83%, respectively. Meanwhile, estimation error STD can also be limited to 0.7461, which validates the stability of the developed transfer learning method.

**Table II.** Quantitative performance comparison of different battery modeling methods.

Methods	MAE(V)	MAPE (%)	MPE (%)	STD
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<b>RBF-NN method</b>	1.16	3.31	12.44	1.5421
<b>Health-conscious method</b>	0.85	2.43	10.65	1.0752
<b>Transfer learning method</b>	0.45	1.27	8.83	0.7461

## 6. Conclusion

The transfer learning method is employed in the paper to address the challenge of accurate battery modeling issues by utilizing multi-sources data. A cloud battery management framework is established to collect and process the battery operation data of various EVs in the whole life cycle. The battery operation data collected from two types of electric buses are downloaded to verify the developed transfer learning battery modeling method. Through extensive simulations, the key findings are as follows: (1) The generic battery health state estimation model can provide a label to reflect the battery aging state in the battery dataset. With the battery healthy state label, the accuracy of the established battery model can be improved by 26.6% on average. (2) The transfer learning method can effectively boost the training process of the deep learning algorithm-based battery model by utilizing the operation data from other types of EVs. The model accuracy can be improved by 47.7% after the transfer learning technology is adopted. In summary, with the developed knowledge transfer method, the battery model can be established under data-scarce conditions, which is more practical in reality. The mean absolute battery terminal voltage estimation error can be limited to 1.27% in the whole life cycle under different working conditions.

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