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Article

Edge Computing for Vehicle Battery Management: Cloud-based Online State Estimation

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Abstract: The adoption of electric vehicles (EVs), including battery EVs and hybrid EVs, makes it possible to reduce fossil fuel consumption and greenhouse gas emission. However, an accurate battery model and an effective battery management system should be established to enable this benefit. This paper proposes a novel cloud-assisted online battery management method based on artificial intelligence and edge computing technologies. Integration of cloud computation and big data resources into real-time vehicle battery management is realized by establishing a novel cloud-edge battery management system (CEBMS). A deep learning algorithm-based cloud data mining and battery modeling method is developed to estimate the voltage and energy state of the battery. The accuracy of the established cloud battery model outperforms the onboard battery management system by utilizing multi-sources information from different EVs. Meanwhile, a cloud-assisted battery management method is established at edge nodes in the onboard battery management unit to realize real-time state estimation locally. By using precise battery state estimation provided by the cloud platform, vehicle battery model accuracy can be significantly improved. The performance of the proposed battery management method is verified by a vehicle big data platform and battery pack experimental test bench. Experimental results justify the effectiveness of the proposed method in battery state estimation, which can help the EVs use and manage the battery more effectively.

Keywords: Electric vehicle, battery management system, edge computing, deep learning, battery energy storage, and state estimation.

Nomenclature

$U_{ter,k}$	Battery terminal voltage state time series.
I_k	Battery current state time series.
Tem_k	Battery temperature state time series.
SoC_k	Battery SoC state time series.
IN_k	Training input of RBM model.
b, a, W	The bias and weight matrixes of RBM unit.

θ	Parameter set of RBM unit.
\mathbf{F}_T	Extracted battery feature from the original dataset.
$U_{t,k+1}^{cloud}, SoC_{k+1}^{cloud}$	Estimated battery terminal voltage and SoC in the cloud.
f_t, f_{soc}	Mapping functions in cloud terminal voltage and SoC estimators.
$\mathbf{x}, \mathbf{u}, \mathbf{y}$	System state, input, and output vectors.
f, h	System state transfer functions.
ω, ν	System measurement and observation noises.
$U_{oc,k}^{cloud}, f_{ocv-soc}$	Estimated battery OCV in cloud and SoC to OCV function.
\mathbf{e}_k, f_{potter}	Error feedback signal and potter measurement update function.
\mathbf{K}, M	Kalman gain and length of the observation window.
$\mathbf{Q}, \mathbf{R}, \mathbf{P}$	Covariance of system noise, measurement noise, and state estimation error.

I. Introduction

Increased electrification of the automotive industry has been identified as a key solution to resolve environmental and energy issues [1]. The adoption of electric vehicles (EVs), including battery EVs and hybrid EVs, makes it possible to reduce fossil fuel consumption and greenhouse gas emission [2, 3]. However, although EVs bring great benefits to society, their safety, endurance mileage, and costs still concern consumers [4]. The battery system is one of the most important and expensive components in EVs, and its management method has direct impacts on the safety and costs of EVs [5, 6]. Therefore, developing an effective battery management method has become a vital issue in recent years.

The core of battery management is to build an accurate battery model to estimate the State of Charge (SoC) and monitor its operation [7, 8]. Researchers have developed various battery modeling and state estimation methods to enhance the efficiency of battery management system (BMS). The equivalent circuit model and least-square algorithm (LSA) were employed in [9] to estimate the state of series-connected battery packs in EVs. The proposed method was validated under various scenarios, and results showed that the SoC estimation error could be constrained within 5%. As an improvement, an adaptive sigma-point extended Kalman filter (EKF) algorithm was used in [10] to estimate the battery SoC in real-time. The battery-in-the-loop experiment results indicated the satisfactory performance of the proposed algorithm. However, limited by the computational capability and data quantity of onboard BMS, the accuracy and stability of LSA and EKF method always shows unsatisfactory performance in real-world.

The development of cloud platforms [11], data transmission technology [12], and artificial intelligence algorithms [13, 14] provide a possible solution to solve the issues of vehicle battery management. Cloud-based EV management was used in [15] to monitor the operation of battery systems and predict endurance mileage based on a

deep-learning algorithm. Experiment results in a real transportation system showed that the cloud platform could predict battery SoC and vehicle endurance mileage more accurately (error within 3.33%). Paper [16] and [17] propose an intelligent battery SoC and State of Health (SOH) estimation framework based on EVs' big data platform. The deep feedforward neural network is used in their study to establish a battery state estimation model, and the experimental results on a real vehicle monitoring dataset indicated that the developed method could estimate battery energy and life state accurately. However, to the authors' best knowledge, no research has been dedicated to integrating cloud state estimation information to real-time battery management issues yet. The vehicle and battery are both dynamic systems with high requirements on control system real-time performance [18]. However, the unavoidable data transmission delay between the cloud and vehicles makes it challenging to deploy cloud battery state estimation results in real-time battery management.

In recent years, edge computing technology has brought a promising prospect to solving the problem discussed above [19, 20]. Edge computing is a multi-resource integration technology specially designed for solving complex system control problems and has been proved effective in smart cities [21], industrial applications [22], and intelligent transportation systems [23], etc. Cloud and edge computing technologies have also been successfully deployed in vehicle energy management. Hong Wang and Amir Khajepour proposed a cyber-physical energy management system for off-road and through-the-road hybrid EVs in [24] and [25]. Experiment results validated that the energy management strategies can schedule power system operation in real-time and improve vehicle energy efficiency at the same time. Edge computing is a bridge between the cloud platform and distributed sub-controllers, with which both system real-time performance and high accuracy can be realized.

This paper aims to bridge the above research gap and construct a novel cloud-assisted online battery management method based on artificial intelligence and edge computing technologies for improving vehicle battery state estimation accuracy. Firstly, a CEBMS framework is established to integrate cloud computation and big data resources into online vehicle battery management. A deep learning algorithm-based cloud data mining and battery modeling method is developed to estimate the voltage and energy state of the battery. The accuracy of the established cloud battery model outperforms the onboard battery management system by utilizing multi-sources information from different EVs. Meanwhile, a cloud-assisted battery management method is established at edge nodes in the onboard battery management unit to realize real-time state estimation locally. By using precise battery state estimation provided by the cloud platform, vehicle battery model accuracy and real-time performance can be simultaneously ensured. The vehicle big data platform is used to validate the performance of the developed cloud battery data modeling method, and a battery pack experimental test bench verifies the performance of the cloud-assisted battery

management method. The main contributions of this paper can be summarized as follows:

- 1) To the best of authors' knowledge, this paper is the first effort to study the use of cloud battery state estimation information in real-time online vehicle battery management.
- 2) A novel CEBMS framework is designed. As a bridge between the cloud computation center and sub-controller, the CEBMS realizes real-time battery management locally with onboard BMS while successfully integrating cloud big data and computation resources.
- 3) A novel cloud battery data mining method is developed based deep-learning algorithm. With the developed method, an accurate and stable battery state estimator can be established in the cloud data platform by utilizing big data resources. The derived high accuracy state estimation results can be further used to improve the performance of online battery management at edge nodes.
- 4) It realizes real-time online vehicle battery management at edge nodes by a cloud-assisted online battery state estimation model. Compared to conventional methods, battery state estimation accuracy can be significantly improved by utilizing information provided by the cloud platform.

Furthermore, the theoretical and practical significance of the developed methods can be summarized as follows:

- 1) The designed CEBMS framework provides a data-sharing platform between different EVs, which can significantly enrich the available dataset in battery modeling issues and improve vehicle battery management system performance.
- 2) The established cloud-assisted online battery state estimation model brings a bright perspective for improving the accuracy and stability of onboard vehicle battery management. It further boosts the practical application of big data driven vehicle management technologies.

II. Cloud-edge vehicle battery management framework

To integrate cloud computation resources in onboard battery management and thus improve the performance and stability of onboard, a CEBMS framework is developed based on cloud platform and edge computing technology in this section. As shown in Fig. 1. the developed cloud-edge vehicle battery management framework consists of three components: i) the edge nodes, including battery, vehicle and its battery management system; ii) the cloud platform, including the vehicle battery database and cloud battery model; iii) the edge network, which is responsible for bidirectional data transmission between the cloud platform and edge nodes.

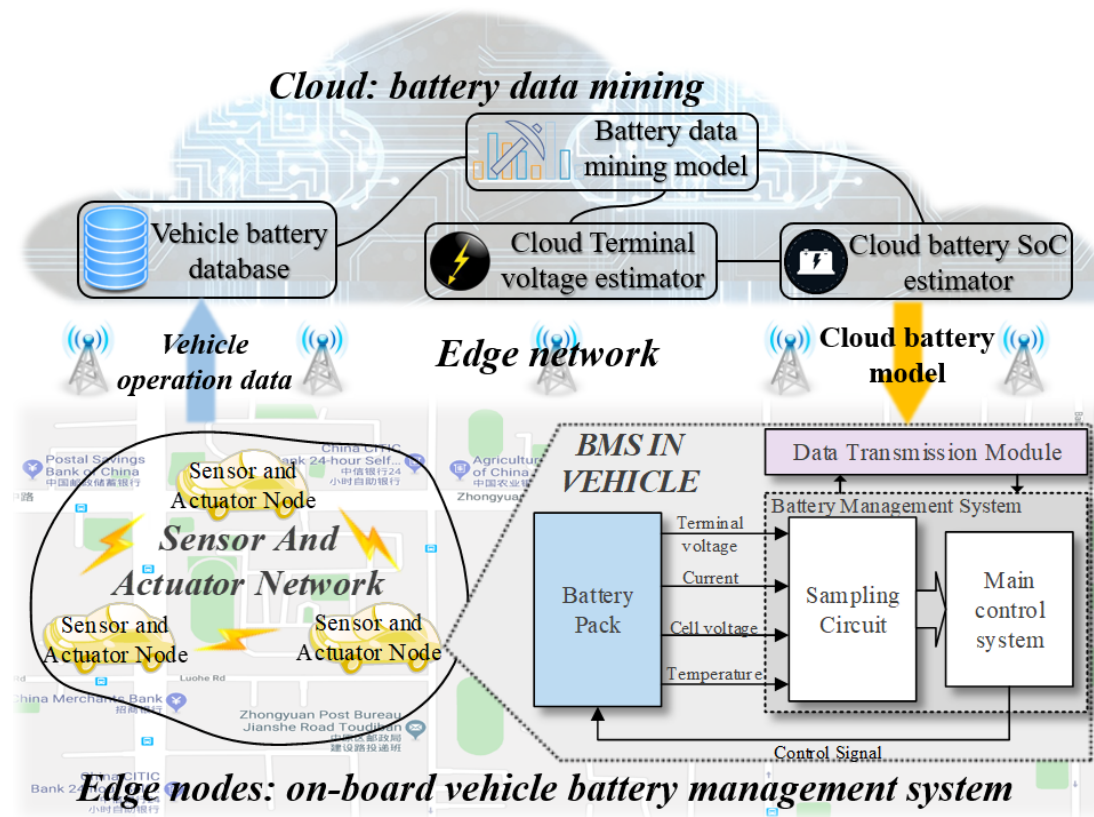


Fig. 1. The developed CEBMS framework for online vehicle battery management.

a) Edge nodes: onboard battery management system

In the basic concept of edge computing, the edge nodes are mainly responsible for real-time information perception and system control through distributed sensors, actuators, and sub-controllers [26]. Similar to the classical edge computing framework, the edge nodes are the cornerstone of the whole CEBMS framework, and real-time battery management and data communication are realized at this level. As shown in Fig. 1, based on the real-time sampled battery external data, the equivalent circuit model and the Kalman filter algorithm are used to estimate battery SoC and manage the battery and vehicle online. However, the electrochemical reactions of the battery and the working condition of the vehicles are very complex, and thus onboard BMS can hardly achieve a satisfactory performance because of its limited calculation capability and data volume. Therefore, a data processing module with bi-directional sending and receiving functions is employed in the developed CEBMS framework to provide cloud-assisted service: the accurate battery state estimation results derived in the cloud center is used to provide prior information for onboard system identification and state estimation, thus improving the efficiency and performance of onboard BMS. Additionally, the data transmission module also uploads battery operation data to the cloud for further data mining and enriching the battery database. Therefore, all the grid-connected EVs in a district are integrated together through the communication network, and each can be regarded as a virtual sensor and edge node.

b) Cloud platform: battery data center and state estimation model

The cloud platform is responsible for building the cloud battery data mining model and providing accurate battery reference state information for all grid-connected EVs. As shown in Fig. 1, a database is built to collect EV battery operation data and a data mining process is carried out to establish cloud battery terminal voltage and SoC estimators. Nevertheless, although the accuracy and stability of the cloud battery model are much higher than that of the onboard BMS, it still cannot be directly used for online battery management because of the information transmission delay between vehicles and the cloud. Therefore, in the proposed CEBMS framework, the estimated battery terminal voltage and SoC information in the cloud are transmitted to onboard BMS and serve as a reference calibration value for improving its performance.

c) Edge network

In the CEBMS framework, the communication network is the bridge between the cloud platform (data mining model) and edge nodes (BMS in vehicles). With the link services between vehicles and the cloud, the bi-directional parameter transmission between road EVs and the cloud platform can be realized. The operation data of EVs can be uploaded to the cloud platform for data mining, and the battery state estimation from the cloud battery model can be sent back to the EVs to improve the real-time state estimation accuracy of onboard BMS. The communication mechanism in cloud-edge computing has been well studied in previous literature and applications, and thus the rest of the paper mainly focuses on the cloud battery data mining technologies and cloud-assisted online battery management in onboard BMS.

III. Vehicle battery modeling method based on data mining technology

This section proposes a data mining method to establish terminal voltage and SoC estimator by utilizing the collected battery data in a cloud platform based on a deep learning algorithm.

A. Data mining for vehicle battery big data in cloud platform

The Restricted Boltzmann Machine (RBM) and Deep belief network [27] are the most popular data mining method and has been proved effective in image identification, renewable energy forecasting, and machine translation. In this part, a battery data mining method is developed by using the DBN algorithm. As shown in Fig. 2 (a), based on the RBM algorithm, the deep features are firstly extracted from the dataset.

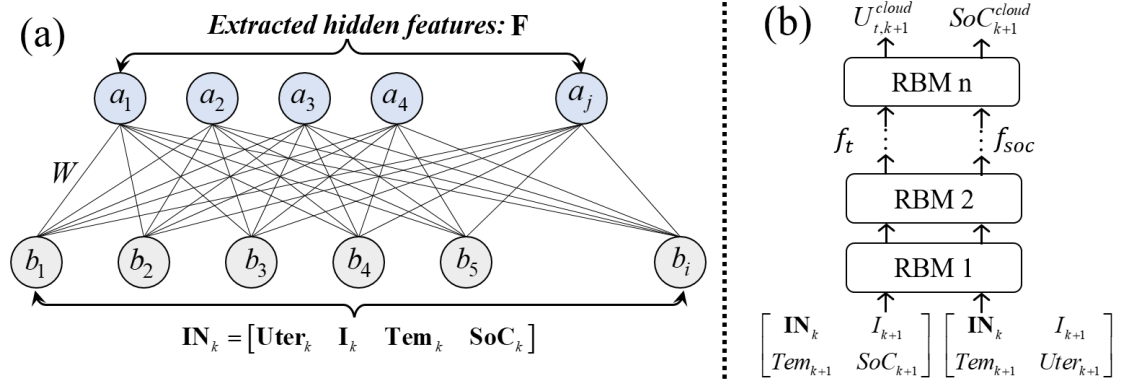


Fig. 2. The data mining-based vehicle battery modeling method. (a) structure of RBM unit; (b) battery external characteristics simulation model.

The external characteristics of the battery are mainly reflected by the terminal voltage, current, temperature, and SoC. Therefore, the input of the RBM module \mathbf{IN}_k is designed as a combination of the above four sequences to excavate the deep temporal and model features in the cloud dataset:

$$\mathbf{IN}_k = [\mathbf{Uter}_k \quad \mathbf{I}_k \quad \mathbf{Tem}_k \quad \mathbf{SoC}_k] \quad (1)$$

Where: \mathbf{Uter}_k , \mathbf{I}_k , \mathbf{Tem}_k , and \mathbf{SoC}_k are the historical terminal voltage, current, temperature, and SoC state of the battery.

The core of RBM is an energy-based generation model [28], and for battery data mining issues, the state of RBM is:

$$E(\mathbf{IN}, \mathbf{F}, \boldsymbol{\theta}) = -\mathbf{b}^T \mathbf{IN} - \mathbf{a}^T \mathbf{F} - \mathbf{F}^T \mathbf{W} \mathbf{IN} \quad (2)$$

Where: $\boldsymbol{\theta}$, \mathbf{b} , \mathbf{a} , and \mathbf{W} are the hyperparameter of the RBM unit. \mathbf{IN} is the original battery data, and \mathbf{F} is the extracted battery feature from the original dataset. The training target of RBM is to optimize the hyperparameters in RBM to achieve the most stable state [29], expressed as maximizing the joint probability distribution of RBM parameters:

$$\max \{P(\mathbf{IN}, \mathbf{F} | \boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} e^{-E(\mathbf{IN}, \mathbf{F}, \boldsymbol{\theta})} = \frac{1}{Z(\boldsymbol{\theta})} e^{\mathbf{b}^T \mathbf{IN} + \mathbf{a}^T \mathbf{F} + \mathbf{F}^T \mathbf{W} \mathbf{IN}} \quad (3)$$

Where: $Z(\boldsymbol{\theta}) = \sum_{\mathbf{F}, \mathbf{IN}} e^{-E(\mathbf{IN}, \mathbf{F}, \boldsymbol{\theta})}$ is the normalization factor. The Contrastive Divergence algorithm [30] is employed in the paper to train the established battery features extraction model.

To enhance the efficiency and performance of the established data mining model, RBMs are stacked layer by layer and end to end to generate a multi-layer network, i.e., a DBN model in the paper. As shown in Fig. 2 (b), the hidden layer output of the first RBM is used as the input of the next RBM's visible layer. The training method of the upper layer RBM is the same as the first RBM. The RBMs are trained layer by layer from bottom up, and the deeper features in battery data are extracted and excavated effectively. Finally, the output of the top-layer RBM is used as the battery data mining results.

B. Battery external characteristics simulation model

The DBN and RBM algorithms can effectively excavate the hidden features in the battery dataset; however, the whole DBN model is trained in an unsupervised way and can only be used as a data mining model. The characteristics of the batteries are not possible to simulate and model because no definite outputs are defined in training. Therefore, in this section, a fine-tuning method is proposed to build state estimators in the cloud battery data platform.

Firstly, the structure of the RBM model is simplified to adapt to the battery modeling: the visible layer offset b is abandoned and the network weight matrix \mathbf{W} degenerates to one-way mode. In this way, as shown in Fig. 2 (b), the whole DBN model can be regarded as a forward neural network. Then, the whole model is retrained with labeled battery data. In the terminal voltage estimator, the input of the network is constructed as a combination of battery historical working state, current, terminal voltage, and SoC. The mapping relationship can be represented as:

$$U_{t,k+1}^{cloud} = f_t(\mathbf{IN}_k \quad I_{k+1} \quad Tem_{k+1} \quad SoC_{k+1}) \quad (4)$$

Similar to the terminal voltage estimator, the mapping relationship in the battery SoC estimator is constructed as:

$$SoC_{k+1}^{cloud} = f_{soc}(\mathbf{IN}_k \quad I_{k+1} \quad Tem_{k+1} \quad U_{ter_{k+1}}) \quad (5)$$

The Error Back Propagation algorithm [31] is employed to retrain the network with cloud battery data.

IV. Cloud-assisted online battery management in onboard BMS

The built data mining model in the cloud can estimate the battery state information accurately, but its real-time performance is not satisfactory. In this section, a cloud-assisted method is developed to integrate cloud battery state estimation results into real-time management.

A. Vehicle battery mathematical model

A mathematical that accurately describes the external characteristics of the battery pack is indispensable for realizing real-time battery management in the onboard BMS unit. The electrochemical reactions in Li-ion power batteries are very complex and it is difficult to construct detailed electrochemical models. Therefore, this paper uses a 2-order RC equivalent circuit model to simulate the external characteristics of lithium-ion batteries.

Fig. 3 shows the circuit topology of the 2-order RC equivalent battery model, which consists of three resistances and two capacitors [32]. The state and output equations of the second-order RC equivalent circuit model are represented by the following formulas:

$$\dot{U}_d = -\frac{U_d}{C_d R_d} + \frac{I_L}{C_d} \quad (6)$$

$$\dot{U}_c = -\frac{U_c}{C_c R_c} + \frac{I_L}{C_c} \quad (7)$$

$$U_t = U_{oc} - U_d - U_c - R_0 I_L \quad (8)$$

Where: U_{oc} and R_0 are the electromotive force and ohmic internal resistance of the power battery; R_d and C_d are polarization resistance and capacitance that reflect battery electrochemical polarization effect; R_c and C_c are concentration resistance and capacitance that reflect the concentration polarization effect in the battery. U_t is the terminal voltage of the battery.

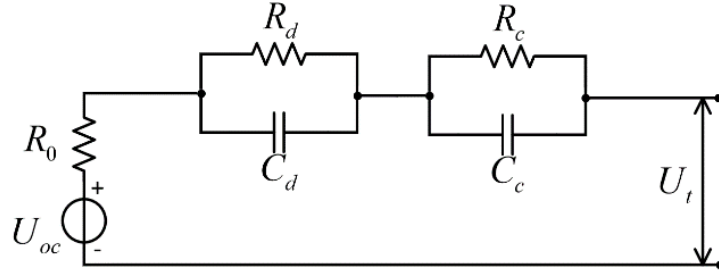


Fig. 3. The Restricted Boltzmann Machine-based battery data mining method.

Based on the established battery mathematical model, system state and output equations are constructed in the following form:

$$\begin{cases} \mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k) + \omega_k = \mathbf{A}_k \mathbf{x}_k + \mathbf{B}_k \mathbf{u}_k + \omega_k \\ \mathbf{y}_k = h(\mathbf{x}_k, \mathbf{u}_k) + \nu_k = \mathbf{C}_k \mathbf{x}_k + \mathbf{D}_k \mathbf{u}_k + \nu_k \end{cases} \quad (9)$$

Where: \mathbf{x} , \mathbf{u} , and \mathbf{y} are system state, input, and output vectors, respectively. f and h are system state transfer functions; ω and ν are the system and observation noise matrixes. \mathbf{A} , \mathbf{B} , \mathbf{C} , and \mathbf{D} are system transformation matrixes that reflect battery external characteristics [33].

B. Cloud-assisted vehicle battery state estimation method

The parameters in 2-order RC equivalent circuit model should be accurately identified to establish an observation system mathematical model for realizing battery state estimation. The extended Kalman filtering method has been commonly used in vehicle battery parameter identification and SoC estimation issues for its high computational efficiency. It can be easily deployed to vehicle onboard BMS hardware to realize real-time battery state estimation. However, limited by data quantity and quality, the robustness and convergence of the conventional EKF method are always unsatisfactory. This part improves the performance of the EKF algorithm by developing a cloud-assisted vehicle battery state estimation method.

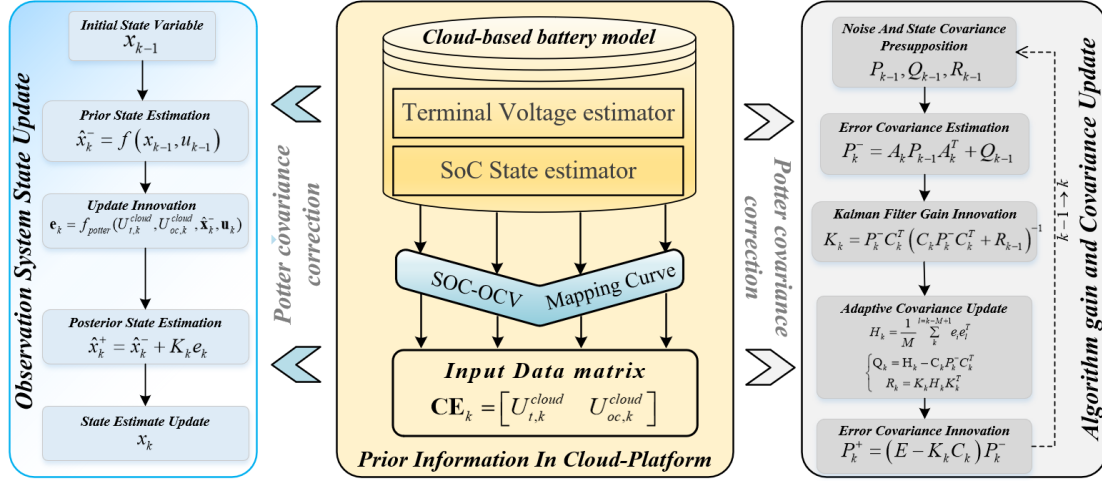


Fig. 4. The information flow in the proposed cloud-assisted vehicle battery SoC estimation method.

The flowchart of the proposed cloud-assisted vehicle battery SoC estimation method is shown in Fig. 4. The battery state estimation results provided by the cloud platform are combined into onboard BMS as extra system observation error prior information to improve the adaptability and robustness of the conventional EKF algorithm. Based on the estimated battery SoC value in the cloud platform, the corresponding open circuit voltage (OCV) state of the battery $U_{oc,k}^{cloud}$ can be calculated as:

$$U_{oc,k}^{cloud} = f_{ocv-soc}(SoC_k^{cloud}) \quad (10)$$

Where: $f_{ocv-soc}$ is the OCV to SoC mapping relationship function [34]. Combining with the terminal voltage, the prior information provided by the cloud platform is arranged in the following vectors:

$$CE_k = \begin{bmatrix} U_{t,k}^{cloud} & U_{oc,k}^{cloud} \end{bmatrix} \quad (11)$$

The difference between the estimated battery terminal and open circuit voltage states in the onboard BMS and cloud platform is used as the error feedback signal to improve the performance of EKF estimator. The potter measurement update method [35] is employed in this study to generate the corresponding error signal:

$$e_k = f_{potter}(U_{t,k}^{cloud}, U_{oc,k}^{cloud}, \hat{x}_k^-, u_k) \quad (12)$$

The observation system state is updated from the initial state x_{k-1} to x_k by the following two steps: prior state estimation and posterior state estimation, which can be represented by the following equations:

$$\hat{x}_k^- = f(x_{k-1}, u_{k-1}) \quad (13)$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k e_k \quad (14)$$

The Kalman gain and observation system noise information are updated by the following five steps: noise and state covariance presupposition, error covariance estimation, Kalman gain innovation, covariance update, and error covariance innovation [36]. The update process is realized by the following equations:

$$\mathbf{P}_k^- = \mathbf{A}_k \mathbf{P}_{k-1} \mathbf{A}_k^T + \mathbf{Q}_{k-1} \quad (15)$$

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{C}_k^T (\mathbf{C}_k \mathbf{P}_k^- \mathbf{C}_k^T + \mathbf{R}_{k-1})^{-1} \quad (16)$$

$$\mathbf{Q}_k = \mathbf{H}_k - \frac{1}{M} \sum \mathbf{e}_k \mathbf{e}_k^T + \mathbf{C}_k \mathbf{P}_k^- \mathbf{C}_k^T \quad (17)$$

$$\mathbf{R}_k = \mathbf{K}_k \left(\frac{1}{M} \sum \mathbf{e}_k \mathbf{e}_k^T \right) \mathbf{K}_k^T \quad (18)$$

$$\mathbf{P}_k^+ = (\mathbf{I} - \mathbf{K}_k \mathbf{C}_k) \mathbf{P}_k^- \quad (19)$$

Where: \mathbf{K} is Kalman gain; \mathbf{Q} , \mathbf{R} , \mathbf{P} are the covariance of system noise, measurement noise, and state estimation error, respectively. M is the length of the observation window.

V. Experimental platform and results

The vehicle and battery monitoring cloud platform established in our previous work is used to monitor the operation state and collect the battery data [37]. The operation of the battery pack on 45 EVs (same type) within three months is collected and downloaded from the cloud platform to verify the performance of the developed battery data mining method. It should be figured out that the abnormal samples, including the noise polluted data and missing value, are removed and restored from the dataset during the data collection process to avoid their impact on the establishment cloud battery model. The corresponding data cleaning scheme employed in the cloud platform is provided in [38]. The typical battery data within one complete discharging cycle is in Fig. 5. The terminal voltage (a), current (b), SoC (c), and temperature (d) are collected by sensors installed on the battery pack and uploaded to the cloud data center. Compared to system real-time performance, accuracy and stability are more significant for cloud-based battery management platforms. Therefore, the data uploading frequency is set as 3hz in this study.

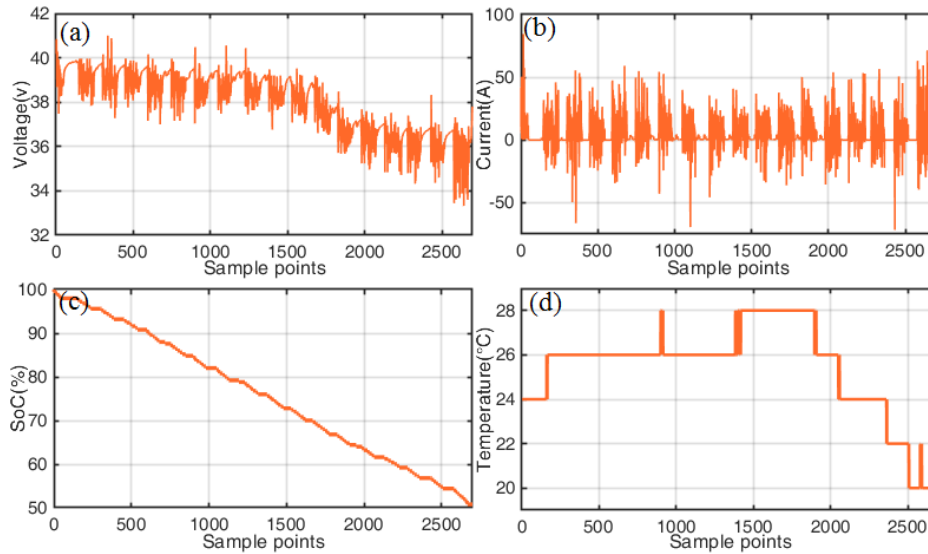


Fig. 5. The collected battery operation data from electric buses.

As described in section III, the battery data mining model is trained by the unlabeled dataset in an unsupervised way, and the battery state estimators are trained with labeled datasets in fine-tuning process. Two independent battery state estimators are generated, and their performance is evaluated by comparing with the conventional neural network method [39] and time-series analysis method [40] in this study.

The accuracy of the established cloud battery terminal voltage estimator is illustrated in Table I. Conventional neural network method shows very limited capability in vehicle battery modeling issues. The model Mean Absolute Percent Error (MAPE) is as high as 4.16% (0.54V), which indicates that the big data environment is failed to be effectively utilized. Meanwhile, the model also shows limited stability in the operation period, and the Standard Deviation (STD) of estimation error reaches 1.3621. The time-series method can better utilize the time dependence information in the battery dataset. Model accuracy and stability are improved by 34.6% and 39.6% compared with the neural network method. However, model dependence information is ignored in time-series analysis, which limits battery model performance dramatically. With the developed data mining method and DBM algorithm, the overall performance of the battery terminal voltage estimator is significantly improved, and the MAE is limited to 1.55% (0.20v). Meanwhile, the model estimation error STD is reduced to 0.6819 after the DBN algorithm and the data mining process are adopted, which indicates that the stability of the model is also significantly improved.

Table I. Accuracy and stability comparison of different cloud-based battery state estimation methods.

Methods	Terminal voltage estimation		SoC estimation	
	MAPE (%)	STD	MAPE (%)	STD
Neural network method	4.16	1.3621	0.64	0.4899
Time-series analysis method	2.72	0.8232	0.33	0.2357
Data mining method	1.55	0.6819	0.17	0.1342

In terms of SoC estimation, the developed data mining method also shows satisfactory performance. As shown in Table I, the MAE of and error STD of the estimated SoC in the conventional neural network method are as high as 0.64% and 0.4899, which is not precise enough to guide real-time battery state estimation in onboard battery management. The time-series analysis method improves model accuracy and stability greatly by excavating the temporal dependence in the dataset. Compared to the neural network method, model MAPE and STD are reduced by 48.4% and 51.9%, respectively. With the developed data mining method, the battery SoC estimation MAPE is reduced to 0.17%, which indicates that the accuracy of the cloud battery SoC estimator is improved significantly. Furthermore, with the unsupervised feature extraction process provided by the DBN model, the stability of the established battery SoC estimator can be significantly improved. The estimation error STD is

limited to 0.1342, which indicates that the established model can stably work in the whole SoC range.

For verifying the performance of the developed cloud-assisted battery modeling method, a battery test bench shown in Fig. 6 is set up to collect real-time accurate battery operation data. The whole test system consists of 4 parts: a battery testing system (Arbin BT2000), which is used to control the state of the battery; a thermal chamber, which is responsible for providing battery test environments; a battery management unit (MPC5644A), which is used to manage and control the behavior of the battery, and at last, a host computer is used to collect and analyze the battery test and experimental data. The connection and communication mechanism between the above four equipment are also illustrated in Fig. 6. The battery operation data in different test cycles are collected to verify the proposed cloud-assisted battery management method.

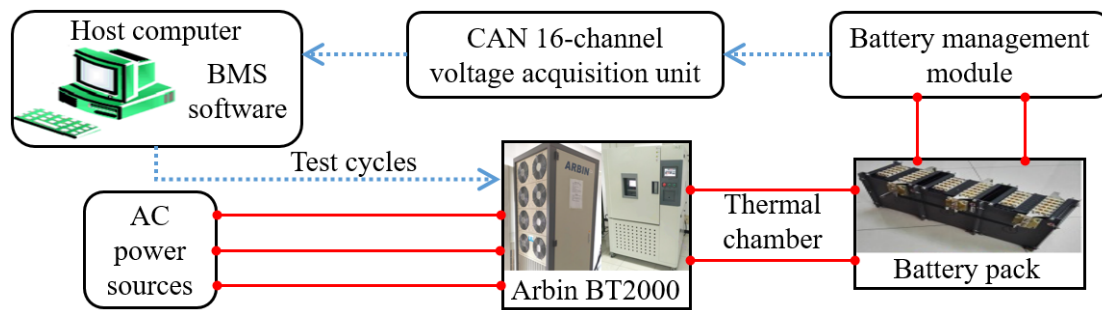


Fig. 6. The hardware and connection of the battery test bench.

In the developed cloud-assisted battery state estimation method, the derived battery terminal voltage and SoC estimation results in the cloud platform are used as additional prior information to improve the accuracy of the battery model in onboard BMS. In this part, the performance of the proposed methods is qualitatively evaluated through system identification and SoC estimation experiments, respectively.

The Hybrid Pulse Power Characteristic (HPPC) test [41] is firstly employed to qualitatively analyze the effectiveness of the proposed cloud-assisted method in parameter identification. Fig. 7 (a) shows the battery operation conditions in 10 cycles, where the battery is tested under 1C, 2C, and 3C working conditions to better reflect its characteristics. As shown in (b), the developed cloud-assisted method accurately follows the change of battery terminal voltage in the whole tested cycle, which validates its effectiveness. The performance of the developed method is further compared with offline [42], EKF[43], adaptive EKF (AEKF) [44], and cooperative co-evolutionary differential evolution (CCDE) [45] methods. The bounds of absolute percent error (BAPE) reaches 4.34% in the conventional offline method. The online identification method shows better accuracy, the estimation BAPE is reduced by 17.7% and 48.2% after the EKF and AEKF methods are deployed. Under the same dataset, the CCDE method shows the best performance, the estimation error is limited to 1.41%. Compared

to the conventional EKF and AEKF methods, the prior information provided by the cloud platform significantly improves parameter identification model accuracy. The terminal voltage estimation error is reduced by 76.5% and 62.7%. Meanwhile, the accuracy of the cloud-assisted method is also better than the CCDE method by 40.4%, which indicates that the knowledge improvement is more effective than the algorithm.

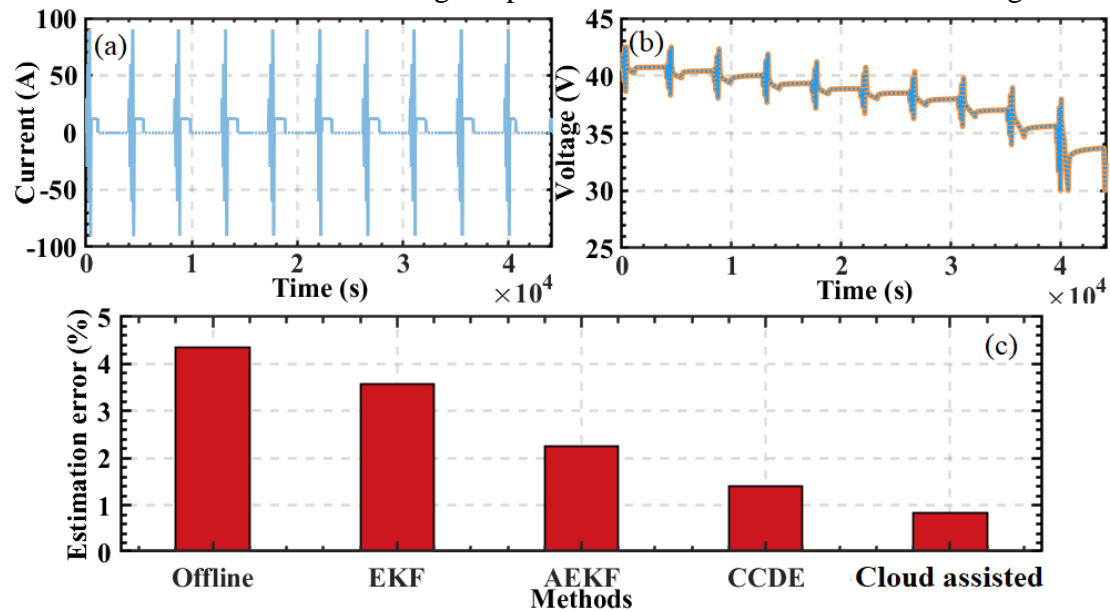


Fig. 7. Performance comparison of different battery parameter identification methods.

Table. II further compares battery SoC estimation error of different methods in a hybrid of DST, FUDS, and UDDS working conditions. The conventional EKF method achieves an inferior result, the bounds and root mean square (RMS) errors reach 7.81% and 1.462 in the simulation. The performance of the EKF method is effectively improved after the adaptive rules are adopted. Battery SoC estimation bounds error and RMS error are reduced by 61.5% and 43.5%, which indicates that model accuracy is significantly improved. Meanwhile, model stability is also enhanced, and the estimation error STD is reduced by 51.7%. Compared to the AEKF method, the developed CEBMS method achieves a more remarkable accuracy and stability improvement by utilizing the prior information provided by the cloud platform. Model bounds error and RMS error are further limited to 1.25% and 0.473, which validate its accuracy in SoC estimation. Meanwhile, SoC estimation STD is also reduced by 53.9% compared to the AEKF method, which indicates that model stability is also significantly improved.

Table II. Battery SoC estimation accuracy and stability comparison of different methods.

Methods	Bounds error (%)	RMS error	STD
EKF method	7.81	1.462	1.681
AEKF method	2.97	0.826	0.812
Cloud-edge combination method	1.25	0.473	0.374

VI. Conclusion

The cloud platform and edge computing technologies are employed in the paper to integrate the cloud computation resources into real-time vehicle battery management. The vehicle big data platform and battery pack experimental test are used to validate the performance of the cloud-assisted battery management method. Through extensive simulations, the key findings are as follows:

- The designed CEBMS framework provides a data-sharing platform between different EVs, which can significantly enrich the available dataset in battery modeling issues and improve vehicle battery management system performance. The proposed data mining method could model the battery accurately, and the mean absolute error of the estimated terminal voltage and SoC in the cloud can be limited to 1.55% and 0.17%. Meanwhile, the estimation error standard is also limited to 0.6819 and 0.1342, guaranteeing cloud battery model stability.
- The performance of battery parameter identification and SoC estimation is improved significantly with the implementation of cloud reference battery state information. The battery terminal voltage identification and SoC estimation error can be limited to 0.89% and 1.25%, respectively. Meanwhile, the SoC estimation error standard deviation is successfully limited to 0.374, which validates that model stability is also significantly improved.

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Reference

- [1] J. Kim, J. Lee, S. Park, and J. K. Choi, "Battery-Wear-Model-Based Energy Trading in Electric Vehicles: A Naive Auction Model and a Market Analysis," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, pp. 4140-4151, 2019.
- [2] Z. Su, Y. Wang, Q. Xu, M. Fei, Y. Tian, and N. Zhang, "A Secure Charging Scheme for Electric Vehicles With Smart Communities in Energy Blockchain," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 4601-4613, 2019.
- [3] A. Chu, A. Allam, A. Cordoba Arenas, G. Rizzoni, and S. Onori, "Stochastic capacity loss and remaining useful life models for lithium-ion batteries in plug-in hybrid electric vehicles," *Journal of Power Sources*, vol. 478, p. 228991, 2020/12/01/ 2020.
- [4] J. Chen, C. Xu, C. Wu, and W. Xu, "Adaptive Fuzzy Logic Control of Fuel-Cell-Battery Hybrid Systems for Electric Vehicles," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 292-300, 2018.
- [5] J. He, Z. Wei, X. Bian, and F. Yan, "State-of-Health Estimation of Lithium-Ion Batteries Using Incremental Capacity Analysis Based on Voltage-Capacity Model," *IEEE Transactions on Transportation Electrification*, vol. 6, no. 2, pp. 417-426, 2020.

- [6] S. Li, P. Zhao, C. Gu, J. Li, S. Cheng, and M. Xu, "Battery Protective Electric Vehicle Charging Management in Renewable Energy System," *IEEE Transactions on Industrial Informatics*, pp. 1-10, 2022.
- [7] C. Jiang, S. Wang, B. Wu, C. Fernandez, X. Xiong, and J. Coffie-Ken, "A state-of-charge estimation method of the power lithium-ion battery in complex conditions based on adaptive square root extended Kalman filter," *Energy*, vol. 219, p. 119603, 2021/03/15/ 2021.
- [8] X. Ding, D. Zhang, J. Cheng, B. Wang, and P. C. K. Luk, "An improved Thevenin model of lithium-ion battery with high accuracy for electric vehicles," *Applied Energy*, vol. 254, p. 113615, 2019/11/15/ 2019.
- [9] H. Dai, X. Wei, Z. Sun, J. Wang, and W. Gu, "Online cell SOC estimation of Li-ion battery packs using a dual time-scale Kalman filtering for EV applications," *Applied Energy*, vol. 95, pp. 227-237, 2012/07/01/ 2012.
- [10] Y. Bi and S.-Y. Choe, "An adaptive sigma-point Kalman filter with state equality constraints for online state-of-charge estimation of a Li(NiMnCo)O₂/Carbon battery using a reduced-order electrochemical model," *Applied Energy*, p. 113925, 2019/11/23/ 2019.
- [11] W. Li *et al.*, "Physics-informed neural networks for electrode-level state estimation in lithium-ion batteries," *Journal of Power Sources*, vol. 506, p. 230034, 2021/09/15/ 2021.
- [12] F. Tramarin, A. K. Mok, and S. Han, "Real-Time and Reliable Industrial Control Over Wireless LANs: Algorithms, Protocols, and Future Directions," *Proceedings of the IEEE*, vol. 107, no. 6, pp. 1027-1052, 2019.
- [13] L. Yang, Y. Cai, Y. Yang, and Z. Deng, "Supervisory long-term prediction of state of available power for lithium-ion batteries in electric vehicles," *Applied Energy*, vol. 257, p. 114006, 2020/01/01/ 2020.
- [14] S. Li, P. Zhao, C. Gu, J. Li, S. Cheng, and M. Xu, "Online Battery Protective Energy Management for Energy-Transportation Nexus," *IEEE Transactions on Industrial Informatics*, pp. 1-1, 2022.
- [15] C.-H. Lee and C.-H. Wu, "A novel big data modeling method for improving driving range estimation of EVs," *IEEE Access*, vol. 3, pp. 1980-1993, 2015.
- [16] D. Liu, L. Li, Y. Song, L. Wu, and Y. Peng, "Hybrid state of charge estimation for lithium-ion battery under dynamic operating conditions," *International Journal of Electrical Power & Energy Systems*, vol. 110, pp. 48-61, 2019/09/01/ 2019.
- [17] M. Jiao, D. Wang, and J. Qiu, "A GRU-RNN based momentum optimized algorithm for SOC estimation," *Journal of Power Sources*, vol. 459, p. 228051, 2020/05/31/ 2020.
- [18] M. Dubarry and D. Beck, "Big data training data for artificial intelligence-based Li-ion diagnosis and prognosis," *Journal of Power Sources*, vol. 479, p. 228806, 2020/12/15/ 2020.
- [19] Z. Tian *et al.*, "Real-time lateral movement detection based on evidence reasoning network for edge computing environment," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, pp. 4285-4294, 2019.
- [20] S. Nastic *et al.*, "A serverless real-time data analytics platform for edge computing," *IEEE Internet Computing*, vol. 21, no. 4, pp. 64-71, 2017.

- [21] Y. Liu, C. Yang, L. Jiang, S. Xie, and Y. Zhang, "Intelligent edge computing for IoT-based energy management in smart cities," *IEEE network*, vol. 33, no. 2, pp. 111-117, 2019.
- [22] A. H. Sodhro, S. Pirbhulal, and V. H. C. De Albuquerque, "Artificial intelligence-driven mechanism for edge computing-based industrial applications," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, pp. 4235-4243, 2019.
- [23] J. Lin, W. Yu, X. Yang, P. Zhao, H. Zhang, and W. Zhao, "An edge computing based public vehicle system for smart transportation," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 11, pp. 12635-12651, 2020.
- [24] H. Wang, Y. Huang, and A. Khajepour, "Cyber-physical control for energy management of off-road vehicles with hybrid energy storage systems," *IEEE/ASME Transactions on Mechatronics*, vol. 23, no. 6, pp. 2609-2618, 2018.
- [25] H. Wang, Y. Huang, A. Soltani, A. Khajepour, and D. Cao, "Cyber-Physical Predictive Energy Management for Through-the-Road Hybrid Vehicles," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3246-3256, 2019.
- [26] M. Wang, M. Zhan, K. Yu, Y. Deng, Y. Shi, and J. Zeng, "Application of Bit Interleaving to Convolutional Codes for Short Packet Transmission," in *2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS)*, 2019, pp. 425-429.
- [27] N. Le Roux and Y. Bengio, "Representational power of restricted Boltzmann machines and deep belief networks," *Neural computation*, vol. 20, no. 6, pp. 1631-1649, 2008.
- [28] N. Zhang, S. Ding, J. Zhang, and Y. Xue, "An overview on restricted Boltzmann machines," *Neurocomputing*, vol. 275, pp. 1186-1199, 2018.
- [29] A. Fischer and C. Igel, "An introduction to restricted Boltzmann machines," in *Iberoamerican congress on pattern recognition*, 2012, pp. 14-36: Springer.
- [30] Y. Bengio and O. Delalleau, "Justifying and Generalizing Contrastive Divergence," *Neural Computation*, vol. 21, no. 6, pp. 1601-1621.
- [31] L. Wang, Y. Zeng, and T. Chen, "Back propagation neural network with adaptive differential evolution algorithm for time series forecasting," *Expert Systems with Applications*, vol. 42, no. 2, pp. 855-863, 2015.
- [32] Q. Zhang, Y. Shang, Y. Li, N. Cui, B. Duan, and C. Zhang, "A novel fractional variable-order equivalent circuit model and parameter identification of electric vehicle Li-ion batteries," *ISA Transactions*, vol. 97, pp. 448-457, 2020/02/01/ 2020.
- [33] H. He, R. Xiong, H. Guo, and S. Li, "Comparison study on the battery models used for the energy management of batteries in electric vehicles," *Energy Conversion and Management*, vol. 64, pp. 113-121, 2012.
- [34] S. Lee, J. Kim, J. Lee, and B. H. Cho, "State-of-charge and capacity estimation of lithium-ion battery using a new open-circuit voltage versus state-of-charge," *Journal of power sources*, vol. 185, no. 2, pp. 1367-1373, 2008.
- [35] D. Simon, *Optimal state estimation: Kalman, H infinity, and nonlinear approaches*. John Wiley & Sons, 2006.

- [36] R. Xiong, H. He, F. Sun, and K. Zhao, "Evaluation on state of charge estimation of batteries with adaptive extended Kalman filter by experiment approach," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 1, pp. 108-117, 2012.
- [37] S. Li, H. He, and J. Li, "Big data driven lithium-ion battery modeling method based on SDAE-ELM algorithm and data pre-processing technology," *Applied energy*, vol. 242, pp. 1259-1273, 2019.
- [38] S. Li, H. He, P. Zhao, and S. Cheng, "Data cleaning and restoring method for vehicle battery big data platform," *Applied Energy*, vol. 320, p. 119292, 2022/08/15/ 2022.
- [39] L. Kang, X. Zhao, and J. Ma, "A new neural network model for the state-of-charge estimation in the battery degradation process," *Applied Energy*, vol. 121, pp. 20-27, 2014/05/15/ 2014.
- [40] Z. Xi, R. Wang, Y. Fu, and C. Mi, "Accurate and reliable state of charge estimation of lithium ion batteries using time-delayed recurrent neural networks through the identification of overexcited neurons," *Applied Energy*, vol. 305, p. 117962, 2022/01/01/ 2022.
- [41] W. H. Zhu and B. J. Tatarchuk, "Characterization of asymmetric ultracapacitors as hybrid pulse power devices for efficient energy storage and power delivery applications," *Applied Energy*, vol. 169, pp. 460-468, 2016.
- [42] R. Ahmed, S. Rahimifard, and S. Habibi, "Offline parameter identification and soc estimation for new and aged electric vehicles batteries," in *2019 IEEE Transportation Electrification Conference and Expo (ITEC)*, 2019, pp. 1-6: IEEE.
- [43] S. Zhang and X. Zhang, "A comparative study of different online model parameters identification methods for lithium-ion battery," *Science China Technological Sciences*, vol. 64, no. 10, pp. 2312-2327, 2021.
- [44] T. Mao, A. Zhiguo, C. Xing, Z. Lin, L. Yakun, and S. Xin, "SOC estimation of lithium battery based online parameter identification and AEKF," *Energy Storage Science Technology*, vol. 8, no. 4, p. 745, 2019.
- [45] C. Wang *et al.*, "Cooperative co-evolutionary differential evolution algorithm applied for parameters identification of lithium-ion batteries," *Expert Systems with Applications*, vol. 200, p. 117192, 2022/08/15/ 2022.