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Data driven battery modeling and management method with aging phenomenon considered☆

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HIGHLIGHTS

- A novel aging trajectory extraction method is proposed to process the battery data.
- An aging index generation model is designed to provide life state for the battery.
- A new aging phenomenon considered battery modeling method is developed.
- Data in cloud battery management platform is used to validate the proposed method.

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ABSTRACT

The battery is one of the most important parts of electric vehicles (EVs), and the establishment of an accurate battery state estimation model is of great significance to improve the management strategy of EVs. However, the battery degrades with the operation of EVs, which brings great difficulties for the battery modeling issue. This paper proposes a novel aging phenomenon considered vehicle battery modeling method by utilizing the cloud battery data. First of all, based on the Rain-flow cycle counting (RCC) algorithm, a battery aging trajectory extraction method is developed to quantify the battery degradation phenomenon and generate the aging index for the cloud battery data. Then, the deep learning algorithm is employed to mine the aging features of the battery, and based on the mined aging features, an aging phenomenon considered battery model is established. The actual operation data of electric buses in Zhengzhou is used to validate the practical performance of the proposed methodologies. The results show that the proposed modeling method can simulate the characteristic of the battery accurately. The terminal voltage and SoC estimation error can be limited within 2.17% and 1.08%, respectively.

1. Introduction

With the development of modern society, the vehicle has become an important and indispensable part of the world [1]. The popularity of vehicles brings great convenience to people's daily life, but the ensuing energy consumption and environmental pollution problems also concern the sustainable development of society a lot [2]. The emerging of EVs provides a possible solution for the energy and environment problem, and in recent years, many countries and governments have set a serious of policies to promote the adoption of EVs [3,4]. The battery pack is one of the bottleneck components in EVs, and the performance of the battery management system (BMS) influences the operation state of the battery pack directly [5,6]. The efficiency of battery management strategy affects the economy and dynamic performance of EVs greatly. Therefore, it is necessary to develop an effective battery management method to encourage the promotion of EVs [7–9].

The State-of-Charge (SOC) is the basic parameter of the vehicle batteries. The accurate estimation of SoC is of great significance to the battery management issue [10]. However, the battery degrades with the operation of the EVs, and the actual battery capacity gradually changes with the life of the battery [11], which brings great difficulties for the accurate estimation of SOC [12,13]. The accumulative error of SOC not only leads to the chaos of the control system of EV but also may cause the misconception of the energy management information for EV

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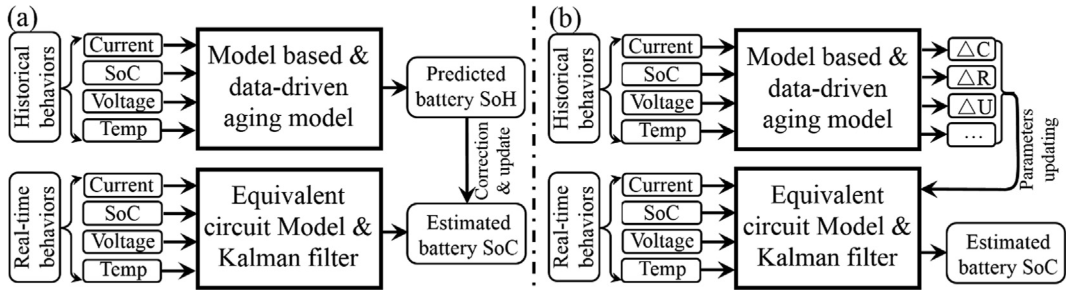

Fig. 1. Two conventional aging considered battery SoC estimation method.

drivers [14]. Therefore, the development of the aging considered battery modeling method has become one of the most crucial issues in recent years [15,16].

In most existing literature, the aging considered battery SoC estimation method can be divided into two categories: the SoC correction method and the parameter correction method, as shown in Fig. 1. In the SoC correction method, as shown in Fig. 1 (a), the battery Remaining Useful Life (RUL) is evaluated by the model-based or data-driven method, and the predicted battery RUL information is used to correct the estimated battery SoC value directly [17–19]. Yongzhi Zhang proposed a Box-Cox transformation and Monte Carlo simulation algorithm based vehicle battery RUL prediction method in [20], and the experiment results showed that the predicted error of battery RUL could be limited within 4%, which can provide an accurate correction for the battery SoC estimation issue. The battery equivalent circuit model and the recursive least squares algorithm are used in QuanqingYu's work [21] to estimate the battery remaining capacity, and the experiment results validated the effectiveness of the proposed method. However, even though the battery RUL prediction technology is almost well-rounded in recent years, the performance of SoC correction method-based battery SoC estimation still has promotion space. There is a gap between the battery RUL prediction and SoC estimation, and the RUL predictor and SoC estimator are always two independent parts of the BMS [22]. The introduction of estimated battery remaining capacity does not improve the accuracy of the battery model, so the estimation error may accumulate with the operation of the BMS [23].

To overcome the weaknesses of the SoC correction method, the parameter correction method is proposed in recent years. As described in Fig. 1 (b), the parameter correction method is a joint estimation method: the aging model provides parameters updating services for the battery state estimation model, but not corrects the estimated battery SoC directly [24–26]. On the basis of this principle, a battery SoC and State of Health (SOH) co-estimation method was developed in Xiaosong Hu's research [27] based on the Fractional-Order Calculus model. Extensive experimental results showed that the maximum steady-state errors of SOC and SOH estimation could be achieved within 2%, even in the presence of initial deviation, noise, and disturbance, which indicated the high stability and robustness of the proposed method. However, the models in the parameter correction method are always very complex, and there are many battery parameters that need to be identified [28]. The existing parameter identification method can hardly deal with the time-varying complex state-space model [29]. As a result, the system stability and practical performance are limited, especially under some dynamic conditions.

The vehicle is a dynamic system with strong nonlinear characteristics and various road conditions in some metropolises are very complex [30–32]. The battery may experience several irregular cycles in a journey, and these irregular cycles affect the battery life span in different ways and degrees [33]. Therefore, it is difficult to quantify the battery degradation phenomenon with the operation of EVs. Recently, the development of the Deep Learning algorithm [34,35] brings a bright prospective to raise practical aging considered battery model. Compared to the neural network algorithm, the deep learning algorithm has the ability to effectively simulate highly nonlinear mapping between the input and output [36]. At present, deep learning algorithms are widely used in many fields, for example, electric load forecasting [37], traffic speed prediction [38], and fault diagnosis systems [39]. In [40], a Deep Learning algorithm based battery energy state estimation method was proposed to help the drivers overcome the range anxiety problem. The Deep Learning algorithm has also been applied to the degradation mechanism learning issue. Rui Ma studied the aging mechanism of proton exchange membrane fuel cells based on the Deep Long Short-Term Memory algorithm in [41], the experiment results showed that the Deep Learning algorithm could analyze the degradation features of the fuel cell effectively. The Deep Learning algorithm is also a powerful tool to analyze the battery degradation features of EVs. However, to the author's best knowledge, there is no published research about applying Deep learning algorithm into the aging phenomenon considered battery model until now.

Keeping in view of above issues, on the basic of the cloud battery management platform established in our previous work [42], this paper proposes a novel aging phenomenon considered vehicle battery modeling method. The key contributions are as follows: A battery aging trajectory extraction method is developed based on the RCC algorithm to quantify the battery degradation phenomenon and generate the aging index for the cloud battery data. To integrate the battery aging index into the battery modeling method and thus improve the accuracy of the cloud battery model, a deep learning algorithm-based aging phenomenon considered battery modeling method is developed. The cloud battery monitoring platform is used in this paper to provide a more complete and adequate data resources for verifying the proposed aging considered battery modeling method.

The rest of the paper is organized as follows: Section 2.1 presents the proposed battery aging trajectory extraction method. The developed battery aging index generation model is provided in Section 2.2, and the built aging phenomenon considered battery modeling method is presented in Section 2.3. Results and discussions are provided in Section 3, followed by concluding remarks in Section 4.

2. Methodology

2.1. The Rain-flow cycle counting algorithm-based battery aging trajectory extraction method

Before establishing the battery state estimator, it is necessary to quantify the battery degradation phenomenon in the battery data set. The RCC algorithm has been identified as one of the most effective methods in the mechanical fault diagnosis and identification issue [43,44]. In this research, based on the RCC algorithm, a battery aging trajectory extraction model is established to extract the irregular charging and discharging cycles that the battery experienced during the vehicle operation.

The process of the proposed RCC algorithm-based battery aging trajectory extraction method is shown in Algorithm 1. The whole model

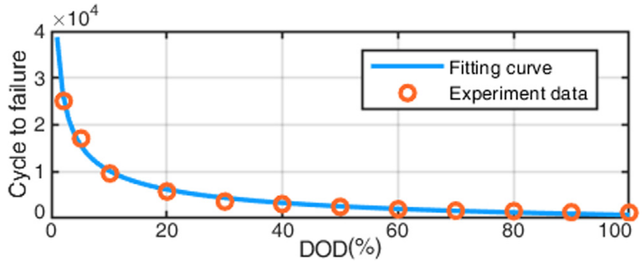

Fig. 2. The Cycles to Failure profile of the battery used in our work.

can be divided into three parts: ***SoC data reconstructing***, which is used to pre-process the battery data by searching for adjacent data points with the reverse polarity so that the local maxima and minima can be found and stored in a matrix. ***Full-cycle judging,*** which is used to compose full cycles by analyzing the turning points and combine these sub-cycles to get full-cycles together with the summing up of the amplitudes. ***Amplitude calculation of the full cycles,*** which is used to extract and count the number of cycles in varying amplitudes and store them for later use.

Algorithm 1 (*Rain-flow counting algorithm-based battery aging trajectory extraction method*).

```
Input: Battery SOC trajectory in the whole vehicle operation period
Output: Battery cycles, corresponding DODs
Part one: SoC data reconstructing
    Store SOC data in A matrix and B matrix, and the length of the SOC data is
  donated as m
      for i = 2 to m-1 do
        if (A (i − 1) − A (i)) * (A (i) − A (i + 1)) > 0 then
          A (i) ← Ø
          B ← A
        end if
      end for
Part two: Definition the function of judging full cycle flag(X)
    n ← length of matrix B
    for j = 1 to n-4 do
      s1 ←|B (j + 1) – B (j + 2) |
        s2 ←|B (j + 3) – B (j) |
          if s1 < = s2 do
            flag ← 1, break
          else
            flag ← 0, continue
          end if
      end for
    return flag
Part three: Calculate the amplitude of each full cycle
    Store the cycle amplitude matrix F.
    while flag (B) = = 1 or flag(B) = = 0 do
      if flag (B) = = 1 do
        for j ← 1 to n-4 do
          s1 ← |B (j + 1) − B (j + 2)|
          s2 ← |B (j + 3) − B (j)|
        if s1 < s2 do
          F ← S1
          B(j + 1) ←∅
        else
          Continue
      end if
    end for
  else if flag (B) = = 0
    Continue
  end if
end while
```

2.2. The battery aging index generation model

To provide an accurate and specific reference battery life state information for the cloud battery model, the extracted battery cycle information in above section should be further processed to generate a quantitative label that can reflect the battery degradation information. Therefore, an integrated battery aging model is developed in the paper to quantify the aging phenomenon, in which the battery number of cycles, DODs and Crate information are taken into consideration.

For most of the Lithium-ion batteries, the consumption of the active substance is proportional to the range of discharging in each cycle. The depth of discharge impacts the battery life span mostly, and the deeper the battery is discharged, the more battery capacity will be consumed. Therefore, the battery DODs are mainly considered factor in the proposed aging model. The manufacturer usually provides an experiment profile to describe the degradation character of the battery, and the relationship between maximum life cycles and the DOD of the battery can be derived. In our work, the Cycles to Failure (CTF) profile is used to transform the quantified battery cycle information to the corresponding capacity degradation degree. The CTF profile of the battery used in our work is shown in Fig. 2.

To make the CTF profile continuous, hereinafter, a Gaussian function is used to approximate the relationship between the CTF and the battery DODas shown in Eqn 1:

$$CTF = f_{CTF}(DOD) = a_1 \cdot e^{-\frac{DOD-b_1}{c_1}^2} + a_2 \cdot e^{-\frac{DOD-b_2}{c_2}^2} \tag{1}$$

where a_1 to c_2 are the curve fitting coefficients, the values of which are a1 $=4.254 \times 10^{43}$, b1 = -10.16, c1 = 1.07, a2 $=2.134 \times 10^{29}$, b2 = -63.13, c2 = 8.235.

According to the previous literature, the battery discharging current also impacts battery life greatly. Therefore, in this paper, the Crate is also considered in the proposed battery aging index generation model. The larger the current battery is discharged, the more lifetime will be consumed. According to the experiment results, the relationship between the capacity retention and the Crate can be described as following Eqn 2:

$$CapR = f_{CC}(Crate) = d_0 + d_1 \cdot e^{-\frac{Crate-d_2}{d_3}^2} \tag{2}$$

where d_0 to d_3 are the curve fitting coefficients, the values of which ared_0 = 0.9032, d_1 = 0.097, d_2=-0.064, d_3=-1.378. When the *Crate* is 0, the value of *CapR* is 1. The value of *CapR* decreases with Crate rises, which reflects the influence of discharging current on battery equivalent cycle. As a result, the equivalent battery cycles CTF_E can be derived as Eqn 3:

$$CTF_E = f_{CTF}(DOD) \cdot f_{CC}(Crate) \tag{3}$$

Fig. 3 shows the 3D mapping relationship between DOD, Crate and equivalent cycles in the established aging model. The battery may

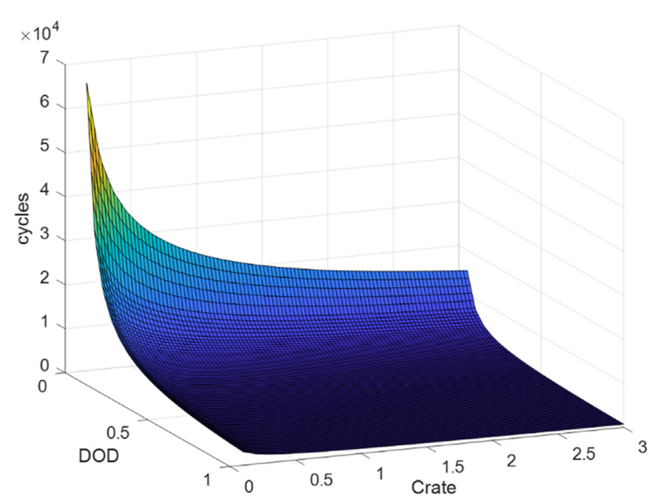

Fig. 3. The mapping relationship between DOD, Crate and equivalent cycles.

experience several cycles in the whole the life span, to enable the additivity of the quantified battery equivalent battery cycles, the equivalent battery aging factor η, which reflects the relationship between the battery experienced cycles and life state is defined as Eqn 4:

$$\eta(k) = \frac{1}{CTF_E(k)} \tag{5}$$

where k means the index of the extracted battery cycles. According to the total number of cycles and DOD data obtained by the RCC algorithm, the total battery aging index can be calculated as Eqn 5:

$$TBA = \sum_{k=1}^{k=n} \eta(k) \tag{6}$$

The value of TBA is between 0 and 1, and when the value of *TBA* is close to 1, the battery should be marked as out of service and replaced. In this paper, the value of *TBA* is used as the aging index for the cloud battery modeling process.

2.3. The aging-considered battery modeling method

As it is difficult to simulate the degradation phenomenon and chemical reaction of Lithium-ion battery directly, this research develops a novel data driven battery modeling method based on the deep learning algorithm and RCC model. The specific modeling process is shown in Fig. 4.

The proposed aging phenomenon considered battery modeling method consists of the following three parts:

Part one. The cloud battery database and the battery aging index generation model: as shown in Fig. 3, first of all, to improve the data foundation of the battery model, a vehicle battery database is built in the cloud to collect and store the battery operation data. Then, to provide a degradation index for the collected battery data, the RCC algorithm is used to extract the battery aging trajectory, and a battery aging index generation model is established to label the battery degradation state information. The labeled battery operation data is sent back to the battery database and served as the training data of the cloud battery model.

Part two. The battery degradation analyzer: to deeply excavate the degradation features in the battery database and thus improve the accuracy of the established battery model, the Deep Stacked Denoising Auto Encoder (DSDAE) algorithm is used to unsupervised extract and analyze the deeply hidden degradation features in the labeled battery operation data and thus improve the stability and accuracy of the battery model.

Step three. The battery external characteristic simulator: To simulate the battery external characteristics and thus establish the corresponding terminal voltage estimator and SoC estimator, the Extreme Learning Machine is applied to the cloud battery model.

The mathematical principle of the proposed methodologies is detailed in the following part of this section.

DSDAE is one of the most popular unsupervised learning models [45] and has widely used in the field of language modeling [46], speech processing [47] and image identification [48]. The Denoising Automatic Encoder (DAE) is the basic unit of DSDAE [49], the essence of which is a single hidden layer neural network. Based on the principle of the DSDAE algorithm, this paper proposes a novel battery aging features mining method. Firstly, the four battery basic characteristics variables: the terminal voltage $Uter_T$, current I_T, State of Charge SoC_T, and temperature Tem_T are serialized as Eqn 6–9

$$Uter_T = [Uter_{t-n} \ \cdots \ Uter_{t-1} \ Uter_t] \tag{7}$$

$$I_T = [I_{t-n} \ \cdots \ I_{t-1} \ I_t] \tag{8}$$

$$Tem_T = [Tem_{t-n} \ \cdots \ Tem_{t-1} \ Tem_t] \tag{9}$$

$$SoC_T = [SoC_{t-n} \ \cdots \ SoC_{t-1} \ SoC_t] \tag{10}$$

Furthermore, to represent the battery aging characteristics, the generated battery aging index is also used as the input of the established battery data mining model. During the model training process, the battery degradation degree index *TBA* can associate the battery external characteristics to the battery degradation degrees and thus improve the accuracy of the battery model. In summary, the input of the battery data mining module can be described as Eqn 10:

$$DM_T = [Uter_T \ \ I_T \ \ Tem_T \ \ SoC_T \ \ TBA] \tag{11}$$

To mine the battery internal characteristics and associate the battery external characteristics to the battery degradation degrees, the battery external variables are used as both the model input and output to train the DAE model. Furthermore, to strengthen the model robustness, the DAE is trained with the polluted data, the Gaussian White Noise is added to the input data of DAEas shown in Eqn 11:

$$\begin{aligned} \rho &= DM_T + w_k, \ \ w_k \sim (0, Q_k) \\ \hat{\rho} &= DM_T = [Uter_T \ \ I_T \ \ Tem_T \ \ SoC_T \ \ TBA] \end{aligned} \tag{12}$$

where: ρ represents the input data of the DAE and $\hat{\rho}$ represents the output target of neurons. w_k is the Gaussian White Noise added in the training data, which obeys the Gaussian distribution $(0, Q_k)$. The relative entropy method is used as sparsity restrictions in our work to extract the deep hidden features in the battery data, and it is as depicted below as Eqn 12:

$$KL(\rho \| \hat{\rho}) = \rho \log \frac{\rho}{\hat{\rho}} + (1-\rho) \log \frac{1-\rho}{1-\hat{\rho}} \tag{13}$$

When $\rho = \hat{\rho}$, the value of the relative entropy function is 0, and the loss function of the DAE model can be represented as Eqn 13:

$$J_{sparse}(W, b) = J(W, b) + \beta \cdot KL(\rho \| \hat{\rho}) \tag{14}$$

where: W and b are the weights and bias of the network, $J_{sparse}(W, b)$ is the loss function. After training, the state of the hidden layer of the DAE

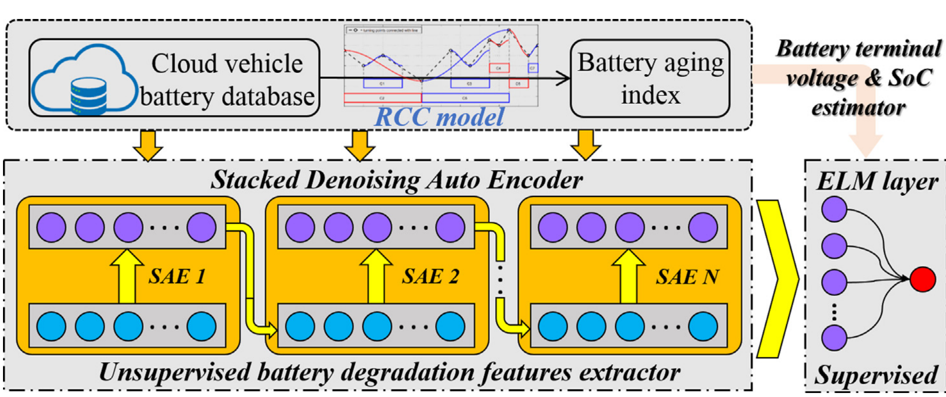

Fig. 4. The aging phenomenon considered battery modeling method.

is used as the output of the data mining module.

Since the battery degradation effect is a complex chemical reaction process and can hardly be simulated by a single DAE. To enhance the ability of the established battery degradation feature extractor, the DAE is stacked to generate an SDAE model [50] in our work. During the training process, the training data is used as the input data of the first DAE. Then, the output (state of the hidden layer) of the first DAE is used as the input of the next DAE again. By analogy, the DAE is unsupervised trained by turn, and the hidden layer output of the top-level DAE is used as the final extracted features of the original battery dataset.

The Extreme Learning Machine (ELM) model [51] is used to build the cloud battery terminal voltage estimator and SoC estimator in our work. The mapping relationship of the ELM can be described as Eqn 14:

$$\sum_{i=1}^{L} \beta_i x_{ij} = o_j \tag{15}$$

where: L and β are the numbers of neurons and the weights in ELM; X represents the hidden layer input, which is the output result of the DAE model. The target of the ELM is to find the optimal β to minimize the output error as shown in Eqn 15:

$$\min_{\beta} ||X\beta - Tu|| \tag{16}$$

where: Tu represents the expected output of the model. In battery terminal voltage estimator, the Tu is the observed battery terminal voltage; in battery SoC estimator, the Tu is the observed battery SoC value. The linear system least-squares solution method is used to find the optimal β in our work, and the weight matrix can be directly obtained by the following equation Eqn 16:

$$\hat{\beta} = X^{+}Tu \tag{17}$$

With the above operation principle, the electrochemical characteristics and the degradation effect of the battery in EVs can be extracted by the DSDAE model, and the battery external characteristics can be simulated by the ELM model.

3. Result and discussion

3.1. Experiment platform and dataset description

The Lithium Iron Phosphate Battery with rated capacity of 199.4kWh is used in this paper to verify the effectiveness of the proposed modeling method. It is the battery pack of a 10 m electric bus designed by Yutong bus Co., Ltd [42]. As shown in Fig. 5, to monitor the operation of the produced EVs and collect data for further product improvement, a cloud battery monitoring system is established. Furthermore, a battery monitor interface is also designed to enable flexible data download and analysis.

The real operation data of 50 electric buses in Zhengzhou, China, is used to verify the effectiveness of the proposed methodology. We kept downloading the operation data of these electric vehicles within one year (from June 2018 to June 2019). This paper only uses battery data collected while the vehicle is running on the road. Because when the vehicle is turned off, the discharging current of the battery is very small, and the impact on battery degradation is almost negligible. Compared to system real-time performance, the accuracy of the collected data is more valued when verifying the proposed method. Therefore, the sampling interval of data collection is set as 10 s to mitigate the working pressure of the communication network. The collected data include the Terminal voltage, the SoC, the temperature and the current of the battery during normal driving of EVs. The example of the battery data used in our work in 1 complete discharging cycle is described in Fig. 6. Subfigure (1)–(4) demonstrates the collected battery terminal voltage, current, SoC and temperature data, respectively.

In the collected data set, the observed SOC value of electric buses is calculated based on Adaptive Extended Kalman Filter algorithm [52]. The aging phenomenon is considered through battery capacity testing and calibration process. The battery is discharged to the lower limit protection voltage (0% SoC) firstly, and then charged to the upper limit protection voltage (100% SoC). After charging, the charged capacity C is recorded as the nominal capacity of the battery. With the updated battery capacity information, the aging phenomenon can be reflected in vehicle battery SoC estimator and the collected data set. Compared to normal commercial vehicles, the capacity testing and calibration process is carried out more frequently: the battery capacity is calibrated per week during the data collection period in this paper. On average, each battery experiences two discharging cycles daily, the remaining capacity of a battery in our experiment is shown in Fig. 6(e). The capacity of battery degrades with the operation of electric vehicles, so it is necessary to take the battery degradation phenomenon into consideration in battery modeling issue.

3.2. Aging considered battery modeling result

With the proposed battery degradation quantification method, the battery number of cycles and the corresponding depth of discharge during the operation of EVs can be extracted successfully. As shown in Fig. 7, (a) is the battery aging trajectory extracted by the RCC algorithm in a journey, (b) is the corresponding charge/discharge cycle statistics by the RCC algorithm. In the illustrated example, the battery experienced 4 half-cycles and 4 full-cycles, and the battery aging information can be reflected by the above-extracted battery cycles. The extracted battery cycles are further processed by the battery aging index generation model and used as the input of the cloud-based battery model to

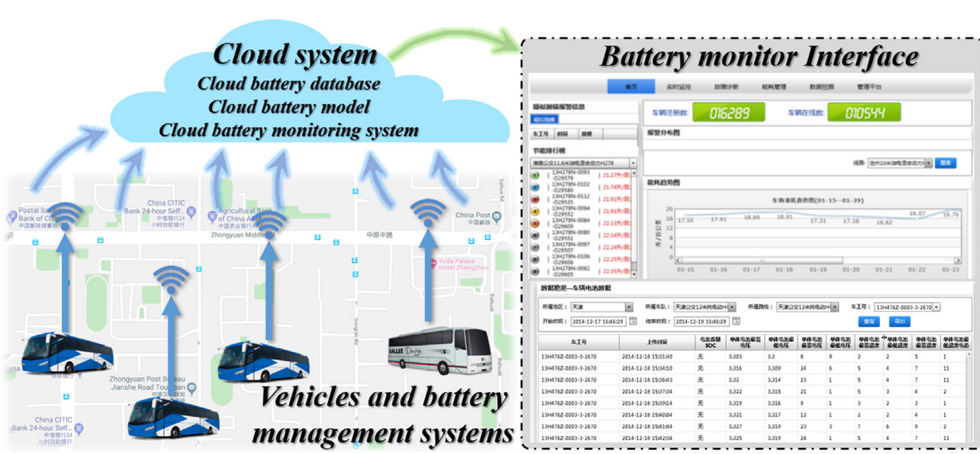

Fig. 5. The vehicle battery monitoring platform used for battery data collection.

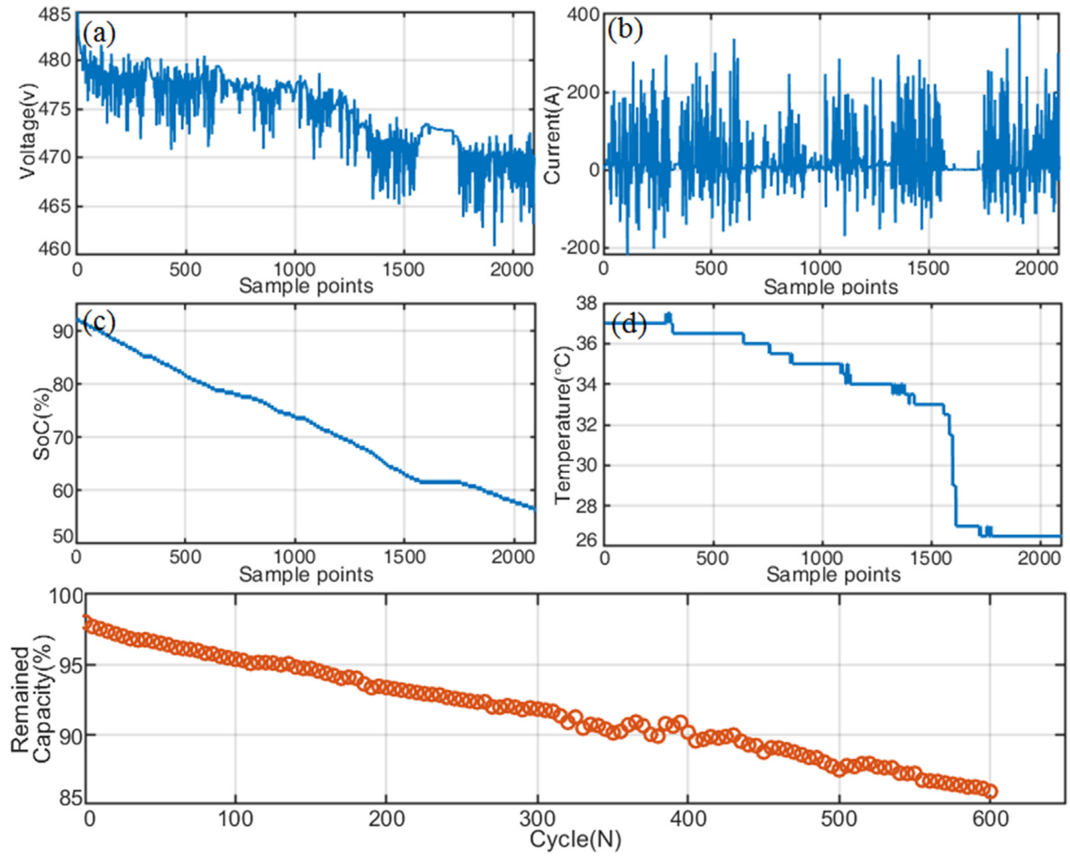

Fig. 6. The battery operation data of electric buses used in our work. (a) Voltage data, (b) current data, (c) SoC data, (d) temperature data and (e) battery remaining capacity within 600 cycles.

improve accuracy.

The aging considered battery modeling method proposed in Section 2.3 is used to build the battery model. The operation data of 45 EVs are used for model training, and data from the other 5 EVs are used for model verification. To better reflect the effectiveness of the proposed method, the battery terminal voltage is used as the model output firstly to evaluate the model dynamic performance, and the corresponding results are shown in Fig. 8. Then, the battery SoC estimator is established, and the battery SoC is used the model output to test the practical model performance, and the corresponding result is shown in Fig. 9.

Since the batteries of the EVs owns different dynamic characteristics in different degradation degrees, to improve the efficiency of the battery management issue, the established battery should be able to capture the degradation features in different degradation degrees. In this paper, to verify the effectiveness of the proposed battery degradation phenomenon considered modeling method, the performances of the established battery model are verified under different life states. Firstly, three different battery life states are selected as the test points: $TBA = 0.2$, $TBA = 0.5$ and $TBA = 0.8$ (TBA is the defined battery aging index in Section 2.2, the value of which is between 0 and 1). The battery model accuracy under different life states is compared in Fig. 8.

In the initial period of use ($TBA = 0.2$), the battery degradation phenomenon is not obvious, so both the traditional model and aging considered model can simulate the battery dynamic characteristics vibrantly. As compared in (a) and (b), the modeling error of two methods is all satisfactory. With the use of the battery, the degradation phenomenon becomes more serious ($TBA = 0.5$). The reduction of battery capacity results in the change of the battery external characteristics, the battery terminal voltage drops with the decrease of the battery open-circuit voltage. However, the traditional neural network algorithm-based battery model is not able to reflect these changes, so the battery terminal voltage estimation result is generally higher than the accurate value, as shown in (c). Compared to traditional method, the battery aging trajectory can be extracted and utilized in the proposed method, so the estimation error is reduced significantly, as illustrated in (d). When $TBA = 0.8$, the battery external characteristics change dramatically. The traditional method can hardly simulate the battery in this situation, as shown in (e), the maximum estimation error is up to 8.3v

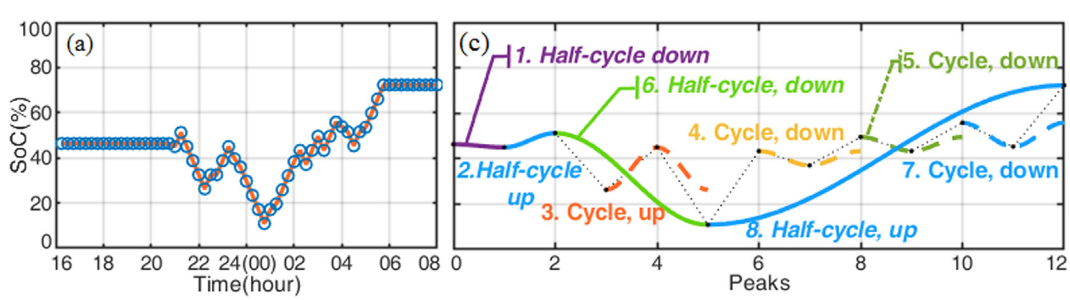

Fig. 7. The RCC algorithm-based battery aging trajectory extraction result.

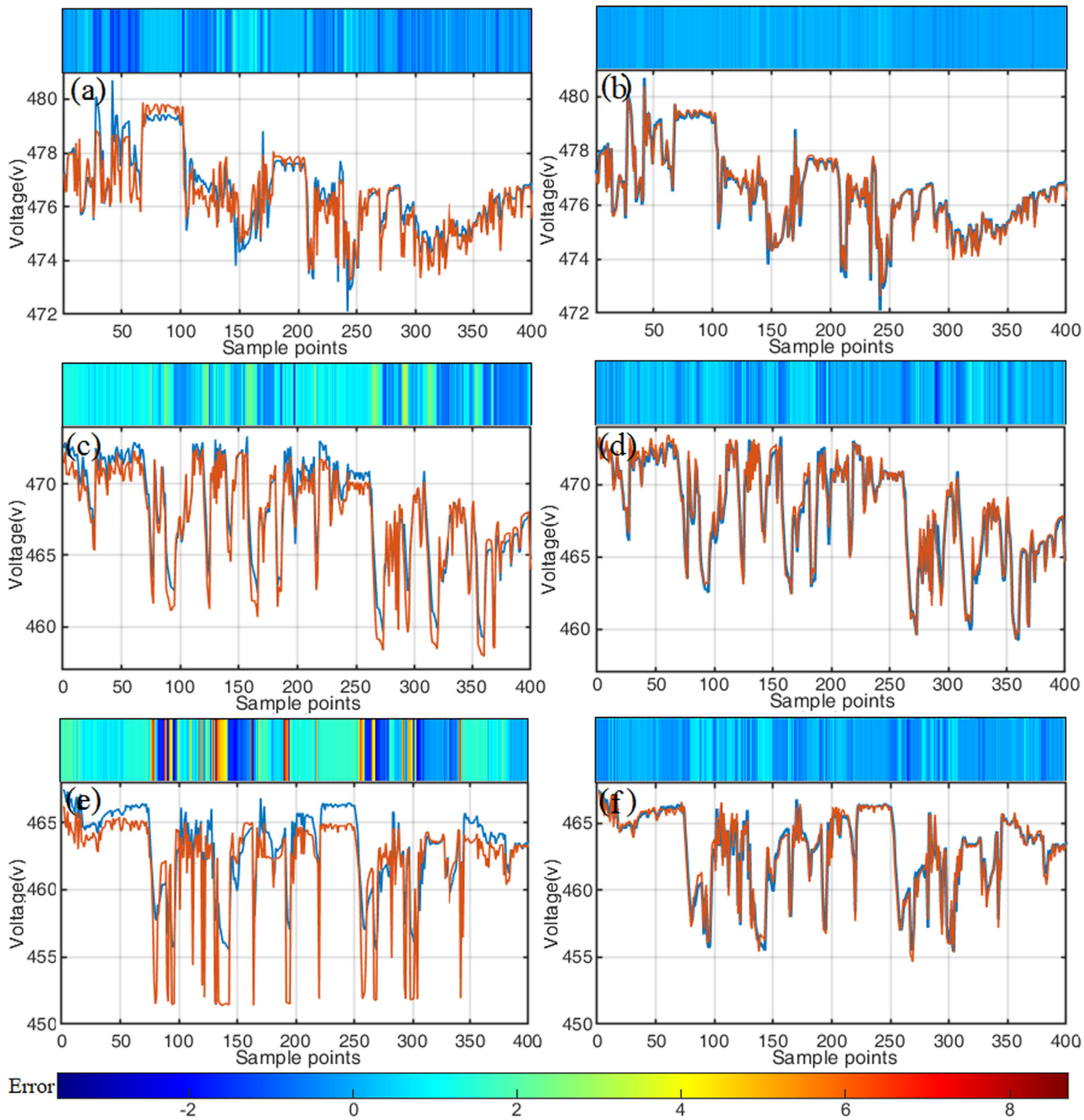

Fig. 8. The battery model accuracy under different life states. Conventional battery modeling method under cycles: (a) $TBA = 0.2$, (c) $TBA = 0.5$, (e) $TBA = 0.8$; aging considered modeling method under cycles: (b) $TBA = 0.2$, (d) $TBA = 0.5$, (f) $TBA = 0.8$.

(27.6%). The effectiveness of the aging considered method is more evident under this scenario, the generated battery aging index can improve the accuracy and stability of the established battery model significantly, as described in (f).

The performance of the proposed deep-learning algorithm-based battery aging features extraction method is verified in Table 1.

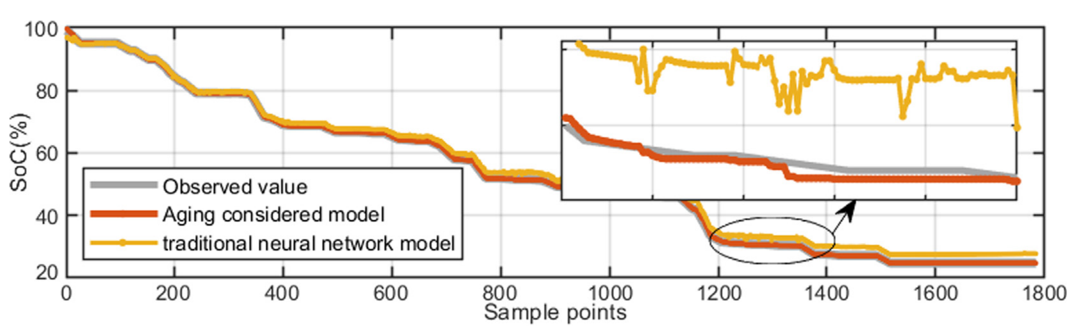

Fig. 9. The SoC estimation result of the aging phenomenon considered battery modeling method.

Table 1
The error comparison of different battery modeling algorithms.

Model	MAE(V)	MAPE(%)	BAE(V)	BAPE(%)
Neural network	3.54	11.80	11.32	37.73
Aging considered method + neural network	2.62	8.73	10.45	34.83
Aging considered method + DSDAE	0.65	2.17	3.14	10.47

Although the battery aging quantification model can provide the battery degradation index for the battery model, the accuracy of the conventional neural network battery modeling method is not satisfactory. The model mean absolute error (MAE) and bounds of absolute error (BAE) is as high as 2.62v (8.73%) and 10.45v (34.83%), respectively. The reason can be attributed to the poor fitting ability of the traditional neural network algorithm, and the battery aging information is not able to be used deeply. The proposed aging phenomenon considered battery modeling method can use the battery degradation index thoroughly, thus the model accuracy and stability can be improved significantly. As shown in Table 1, model MAE and BAE are reduced to 0.65v (2.17%) and 3.14v (10.47%), respectively, which validates the effectiveness of the developed aging phenomenon considered battery modeling method.

Regardless of the methods, the essential goal of the battery modeling issue is to accurately estimate the SOC of the battery. Therefore, the practical performance of the proposed battery modeling method is also evaluated by the SoC estimation experiment. Fig. 9 compares the model accuracy in a complete discharging cycle, and before which the battery has experienced about 300 cycles. The accuracy of the traditional neural network method is not satisfactory, and the maximum SoC estimation error is as high as 4.25%. The reason is that the battery degradation phenomenon is not considered in the traditional method, and the capacity error accumulates with the operation of the SoC estimator. Compared to the conventional neural network method, similar to terminal voltage estimation results, the accuracy of the proposed aging phenomenon considered battery SoC estimator is improved significantly. As shown in Fig. 9, the battery SoC estimation error in the proposed method can be limited within 1.08%, which highlights the importance and effectiveness of the introduction of the battery aging index.

4. Conclusions

This paper develops a novel aging phenomenon considered battery modeling method for the electric vehicles based on the RCC method and deep learning algorithm. The proposed Rain-flow cycle counting algorithm-based battery degradation quantification method can extract the battery aging trajectory effectively, and the generated battery aging trajectory provides an aging index for the battery model to improve its accuracy. With the proposed DSDAE algorithm based aging phenomenon considered battery modeling method, the established battery model can adapt the change of battery life and capacity with the operation of EVs. The cloud battery management platform is used to integrate the battery data resources and provide a good data foundation for verifying the proposed aging considered battery modeling method. The results showed that compared to the traditional neural network method, the proposed aging considered battery modeling method could improve the accuracy of the battery model significantly. The terminal voltage estimation error and the SoC estimation error were reduced by 6.56% and 3.17%, respectively. The battery SoC estimation error can be limited within 1.08%, which revealed that the effectiveness of the proposed method.

There are still some limitations in this study. (1) The proposed method is only verified on Lithium Iron Phosphate Battery of electric buses in this paper. Nevertheless, different batteries have different aging characteristics. To further guarantee the performance of the proposed modeling method, tests should be conducted on different platforms in future work. (2) Limited by experimental conditions, the influence of the temperature and consistency on battery model is ignored in this paper. The battery owns different aging characteristics at different temperatures, especially under low-temperature environments. Meanwhile, the battery pack of EVs consists of hundreds of battery cells, and different battery cell has different external characteristics and aging degrees. The performance of the battery model may be further improved by taking the temperature and consistency into consideration in future works.

CRediT authorship contribution statement

Shuangqi Li: Conceptualization, Methodology, Validation, Writing - original draft. **Hongwen He:** Methodology, Data curation, Resources, Supervision. **ChangSu:** . **Pengfei Zhao:** Visualization, Investigation.

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