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Big data driven Deep Learning algorithm based Lithium-ion battery SoC estimation method: A hybrid mode of C-BMS and V-BMS

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Abstract—Batteries are the bottleneck technology of electric vehicles (EVs), which hosts complex and hardly observable internal chemical reactions. This paper presents a big data-driven battery management method utilizing the deep learning algorithm, with the ability to work stably under dynamic conditions and whole battery life cycle. First, a Deep Belief Network-Extreme Learning Machine (DBN-ELM) algorithm-based battery model is established to extract the deep structure features of battery data, and in which the rain-flow cycle counting algorithm is used to reflect the battery degradation phenomenon. Next, to improve real-time performance of Battery Management System (BMS), a conjunction working mode between the Cloud-based BMS (C-BMS) and BMS in vehicles (V-BMS) is proposed, and a battery State of Charge (SoC) estimation method based on the interaction between C-BMS and V-BMS is also presented. Using the battery data to verify the model effectiveness and accuracy, the error of the battery SoC estimation is within 3%.

Keywords—electric vehicle, battery energy storage, battery management system, big data, deep learning

I. INTRODUCTION

The battery and its management system are the most important components of EVs[1]. Reasonable data collection and analysis are the foundation for state estimation and fault diagnosis of the battery, and accurate battery state estimation is the premise of durability and safety management[2].

Currently, research on the battery and its management system mainly focuses on the parameter identification[3], SoC estimation[4] and fault detection[5] based on the equivalent circuit model and electrochemical model[6]. However, there are still two main factors that limit the accuracy of the battery model: Data volume & system real-time performance and algorithm performance.

A. Data volume and system real-time performance

Currently, BMS in vehicles is the most commonly used instrument for battery modeling and state estimation. The data of which are generally derived from a single vehicle [7]. The data volume and available calculating ability in the V-BMS is limited, but the chemical reaction process of the battery is affected by factors such as temperature, battery life state, dynamic conditions, etc. [8]; it is difficult to accurately model the battery in the case of insufficient data.

Cloud data centers have advantages including high storage capacities, high calculating abilities, etc[9]. Therefore, this paper proposes a cloud-based battery management system.

The real-time performance of the system usually conflicts with system accuracy and adaptability, which is especially evident in the battery management system. The equivalent circuit model is one of the most commonly used models of lithium-ion batteries in EVs. Rui Xiong et al.[10] used an equivalent circuit model to simulate and model the external characteristics of the battery, and the adaptive extended Kalman filtering (AEKF) algorithm is also used in their work to estimate the battery SoC. The experimental results show that the established model can accurately simulate the characteristics of the battery, and the error of estimated SoC is within 2%. The $H\infty$ filter algorithm is used in Jingyu Yan's work[11] to estimate the SoC of EV, and the simulation experiment based on a typical battery model is used in their work to verify the availability and efficiency of the method. The equivalent circuit model and Kalman filtering algorithm is able to realize high accuracy battery modeling and SoC estimation under standard conditions. However, considering the complex working condition of EVs including variable temperatures and the battery aging phenomenon, the mentioned methods appear to be incompetent, with sharp increasing error or model divergence.

The data-driven battery modeling method can achieve high-precision simulation for battery characteristics, thereby obtaining a higher SoC estimation accuracy. Hicham Chaoui came up with a neural network based approach for lithium-ion battery modeling and SoC estimation[12], the experimental results highlighted the high modeling accuracy. However, the training and updating of the model requires large amount of computing resource and time, which makes it impossible to be applied in V-BMS.

To improve the accuracy and stability of battery modeling and SoC estimation while ensuring the system real-time performance, a conjunction working mode between C-BMS and V-BMS is proposed in our work, and a battery SoC estimation method based on the interaction between C-BMS and V-BMS is also presented.

B. Algorithm performance

The neural network algorithm has a strong nonlinear mapping ability, which can automatically learn useful knowledge from the data without an accurate mathematical model. However, the chemical reaction in lithium-ion battery is complex, and the volume of training data is large, so the training process of the black box model turned out to be rather difficult. While most of the algorithms used to model the battery can be regarded as shallow structure networks[13, 14], whose performance on approximation of complex functions is limited under limited computing units. Kang L W et al.[15] made estimation on battery open circuit voltage or SoC using BP neural network algorithm, but it's hard to simulate the reaction inside the battery when the neural network has few hidden layers, which results in rather unstable regression with larger error. Haq I N et al.[16] established a battery model using Support Vector Regression algorithm. However, although the model has low requirement on training data, and achieved effective results with considerable robustness in experimental stage, with the amount of training data increasing, the training time of the model increases explosively, making it difficult to handle those training samples with large volume of data.

In contrast to neural network algorithm, deep learning algorithms could effectively simulate the highly nonlinear mapping between the input and output. At present, deep learning algorithms have been widely used in electric load forecasting, traffic speed prediction, energy management system, etc.

To tackle the deficiency of the black box model with shallow neural network algorithm, we make the first attempt to apply the DBN-ELM algorithm to battery modeling issues. The idea is to fully excavate the hidden features in battery data, so as to utilize the battery big data effectively and improve the battery modeling accuracy.

II. BATTERY MODELING METHOD BASED ON RAIN FLOW COUNTING ALGORITHM AND DBN-ELM MODEL

The degradation phenomenon of lithium-ion battery is mainly affected by the number of cycles and the depth of discharge. Therefore, it is important to take the number of cycles and the depth of discharge into consideration to improve the model accuracy when establishing the battery model.

A. Rain-flow counting algorithm

The rain-flow cycle-counting algorithm is usually used for analyzing the fatigue data and was firstly used in metal fatigue estimation[17]. In this research, this method is used to extract the irregular charging and discharging cycles that the battery experienced during the simulation period.

Basically, the cycle counting can be achieved by the following three steps. Firstly, the data (for the battery the data is the DOD that presents the battery charge/discharge cycles) is pre-processed 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. Secondly, full cycles are composed by analyzing the turning points and combining these sub-cycles to get full-cycles together with the summing up of the amplitudes. Thirdly, the number of cycles is extracted and counted in varying amplitude, and stored for later use.

B. Lithium-ion battery modeling with battery degradation considered

The chemical reaction and degradation phenomenon in Lithium-ion battery is complex and difficult to be monitored directly, so this paper established a battery model which simulated the internal state with neural network and quantified the battery degradation with rain-flow cycle counting algorithm.

In the previous battery modeling method, the current, temperature and terminal voltage are the inputs, and the SoC is the output. However, to take the impact of battery degradation on the battery model into consideration, the total number of cycles (TNOC) and the total depth of discharge (TDOD) are used as additional model inputs. The purpose of the neural network is to approximate the function:

$$SoC_k = f\left(SOC_{k-1}, I, T, U, TNOC, TDOD\right) \tag{1}$$

C. Deep belief network

The Restricted Boltzmann Machine (RBM) is the basic unit of the DBN[18]. It is essentially an energy-based generation model, which can be regarded as an undirected graph model. The nodes in different layers are fully connected, and there is no connection between nodes in the same layer. The structure of RBM is shown in Fig. 1.

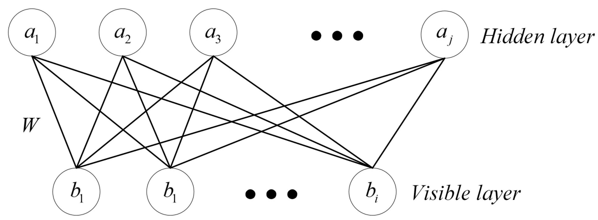

Fig. 1. The structure of Restricted Boltzmann Machine.

A DBN can be regarded as a network composed of several Restricted Boltzmann Machine. As shown in Fig. 2, a DBN is formed by stacking three RBMs in this paper.

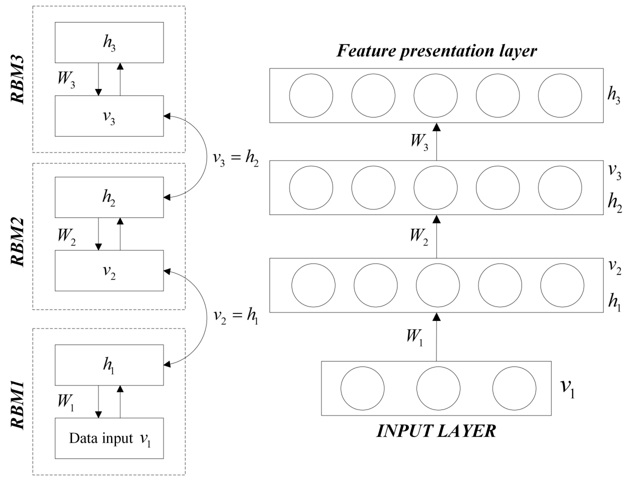

Fig. 2. The structure of Deep belief network.

Each layer of the DBN is a separate RBM, which consists of a visible layer v and a hidden layer h. During training, the training data is used as the input of the visible layer h_1 of the first RBM. Then, the output of the hidden layer of the first RBM is used as the input of the visible layer v_2 of the next RBM. Analogously, the RBM is trained unsupervised from the bottom up, and the output of the hidden layer h_3 of the top-level RBM is the abstract expression of the input data.

After the training process is completed, the weight and offset of the entire network are saved. At this time, for a single restricted Boltzmann machine, the offset a of the visible layer v is no longer used, and the connection weight W becomes one-way, as shown in Fig. 4, the structure is the same as the forward neural network.

D. The DBN-ELM model

Extreme Learning Machine (ELM) is a machine learning algorithm that solves the problem of regression, the core of the ELM algorithm is the linear regression layer, in which the regression problem is converted to the problem of finding least-squares solution for linear system [19].

DBN-ELM is a commonly used algorithm in deep learning[20]. The DBN model is trained unsupervised from the bottom-up by unlabeled data, and it is used as a feature extractor. The output of the DBN model is used as the ELM's input; afterwards, the ELM is trained directly by labeled data and is used as the output layer of the DBN-ELM model.

Aiming at the battery terminal voltage prediction problem in this paper, the feature extraction process in DBN can be regarded as the simulation of complex chemical reactions inside the battery, that is, the internal characteristics of the battery are excavated with a large amount of battery data, so that the subsequent modeling process is more stable and accurate.

III. THE CONJUNCTION WORKING MODE BETWEEN C-BMS AND V-BMS

For the reason that the data volume which can be used for battery modeling from a single electric vehicle is insufficient, the V-BMS has difficulty working stably under multi-variable environments and dynamic conditions. Cloud data centers have advantages including high storage capacities, high calculating abilities, etc. Therefore, this paper proposes a cloud-based battery management system. For a single electric vehicle, a C-BMS with a data transmission module is established based on the V-BMS, and the battery data are uploaded to the cloud in real-time for further analysis. The cloud receives and stores the data of all EVs that share the same specification, and a multidimensional, multistate, multifactor complex data space is provided for battery modelling and SoC estimation. Combined with the DBN-ELM algorithm, the established model can comprehensively reflect the influence of temperature, aging, dynamic conditions and so on, improving the accuracy of battery state estimations and optimizing battery management strategies.

However, in the one hand, due to the existence of remote communication process, C-BMS has limited real-time performance; on the other hand, the deep learning-based battery modeling method is not able to effectively utilize the recursive relationship of time series in SoC estimation process, and its accuracy is limited. As such, in this section, a conjunction working mode between C-BMS and V-BMS is proposed to make better use of big data stored in the cloud, as shown in Fig. 3.

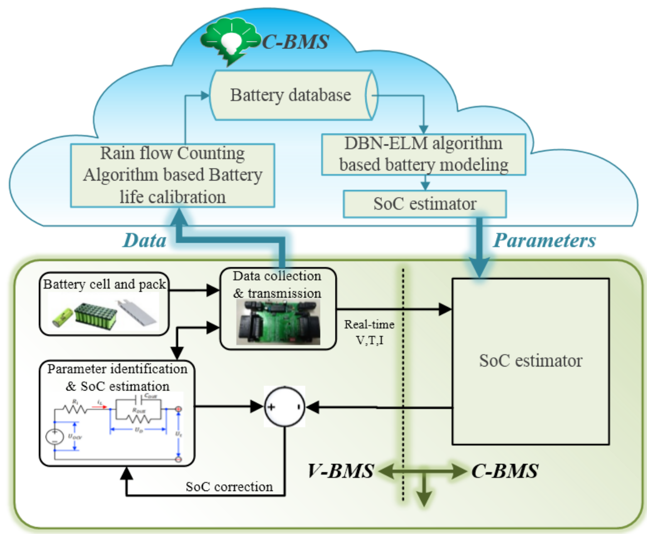

Fig. 3. The conjunction working mode between C-BMS and V-BMS.

Step 1. The battery data is calibrated based on the rain-flow counting algorithm first, and based on the C-BMS, a database containing integral battery status information is established to provide a good data foundation for battery modeling.

Step 2. A black box model is established for the battery in the cloud based on deep learning algorithm, the SoC is used as the model's output as shown in formula 1.

Step 3. The V-BMS monitors and controls the battery directly. The equivalent circuit model and the least squares algorithm or the Kalman filtering algorithm are used to model the battery and estimate the SoC. At the same time, the C-BMS builds a big data driven SoC estimator that can work stably under multi-variable environments and dynamic conditions in the cloud. However, due to the data exchange delay between the V-BMS and the C-BMS, the

SoC estimator in the C-BMS cannot be directly used in battery management or vehicle energy management. Therefore, in this step, the cloud-based SoC estimator is used to work in conjunction with the V-BMS. C-BMS regularly provides accurate SoC sequences for V-BMS, based on these SoC sequences, on the one hand, the V-BMS adaptively modifies the equivalent circuit model parameters, and on the other hand, it adaptively corrects the real time SoC estimation result in the Kalman filter.

IV. BATTERY SOC ESTIMATION METHOD BASED ON C-BMS AND V-BMS INTERACTION

A. Lithium-ion battery model and parameter identification

The equivalent circuit model is one of the most commonly used methods in battery modeling. Although the higher-order equivalent circuit model has better accuracy, it will bring about greater difficulties to the model parameter identification process. Therefore, the equivalent circuit model selected in this paper is a second-order RC model, as shown in Fig. 4[21].

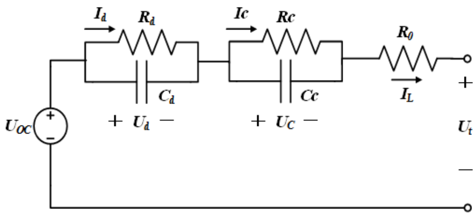

Fig. 4. Equivalent circuit model.

The state equation of the equivalent circuit model is as follows:

$$\begin{cases} \dot{U}_d = -\dfrac{U_d}{C_d R_d} + \dfrac{I_L}{C_d} \\ \dot{U}_c = -\dfrac{U_c}{C_c R_c} + \dfrac{I_L}{C_c} \\ U_t = U_{oc} - U_d - U_c - R_0 I_L \end{cases} \tag{2}$$

Where U_d, U_c is voltage of R_d, R_c respectively, I_L is the charge and discharge current, U_t represents battery terminal voltage, U_{oc} is the open circuit voltage (OCV).

To realize online estimation of battery model parameters, the forgetting factor recursive least squares (FFRLS) method is used in our work. In the parameter identification process, the most important process is to continuously update SoC value during the identification. The current mainstream method is to obtain the SoC update based on the ampere-hour integral method, but it will directly lead to error accumulation, which will result in model divergence; Another method is combined with SoC estimation based on Kalman filtering algorithm to obtain a relatively accurate SoC in identification process, but it also will lead to the error passing between two algorithms, thereby increasing the modeling error. In order to overcome the above difficulties, we propose a battery parameter identification method based on the conjunction working mode between C-BMS and V-BMS.

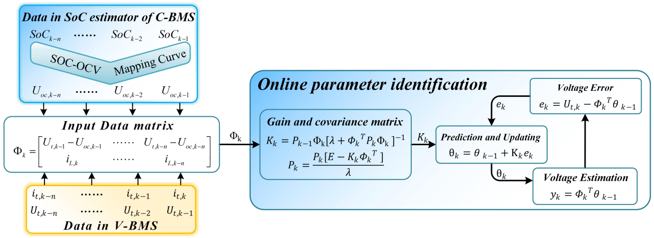

Fig. 5. Battery parameter identification method based on the conjunction working mode between C-BMS and V-BMS.

The flowchart of FFRLS algorithm-based battery parameter identification method is shown in Fig. 5. To avoid the error accumulation in SoC estimation, the historical SoC is obtained from C-BMS, and transformed into open circuit voltage data based on the SoC-OCV curve. Then the open circuit voltage data are combined with the current and terminal voltage measured in V-BMS to form the input matrix for parameter identification.

To obtain the parameters of the power battery model, the equation (2) is transformed into a transfer function expression as follows:

$$\frac{U_t(s) - U_{oc}(s)}{I_L(s)} = \frac{U_{rc}(s)}{I_L(s)} = -\left(R_0 + \frac{R_c}{1 + R_c C_c s} + \frac{R_d}{1 + R_d C_d s} \right) \tag{3}$$

Based on the FFRLS algorithm, the historical battery data can be used to identify the battery parameters in the above transfer function, thereby completing battery modeling.

B. AEKF algorithm based SOC estimation

Kalman filtering algorithm is one of the most commonly used algorithms in the field of battery SoC estimation. It has many advantages such as high precision, high efficiency and easy hardware implementation. However, the ordinary Kalman filter algorithm has poor robustness and convergence speed. In comparison, the AEKF algorithm can adaptively correct the system noise covariance and the measurement noise covariance, with higher robustness and convergence speed.

However, the traditional AEKF algorithm-based battery SoC estimation method has poor adaptability, and it is prone to non-convergence under dynamic and complex conditions, thereby its accuracy is inferior to the ampere-hour integral method. On the other hand, the SoC estimation method based on AEKF algorithm relies too much on the accuracy of the equivalent circuit model, and there is frequent parameter transferring between it and the equivalent circuit model, which inclines to cause error diffusion. Finally, due to the battery aging phenomenon, and the AEKF algorithm is not able to effectively identify the SoH change, the SoC estimation error tends to increase with battery degradation. In order to solve the above problems, we propose a SoC estimation method based on AEKF algorithm and the conjunction working mode between C-BMS and V-BMS in this section.

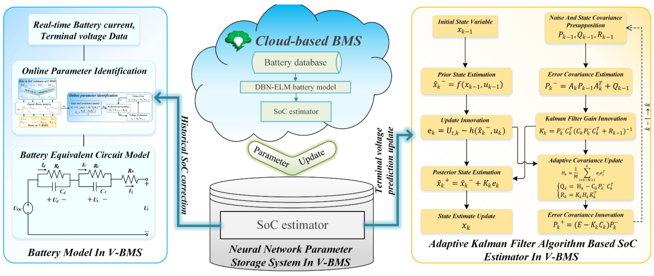

Fig. 6. Battery SoC estimation method based on the conjunction working mode between C-BMS and V-BMS.

The flowchart of proposed battery SoC estimation method based on the conjunction working mode between C-BMS and V-BMS is shown in Fig. 6. To improve the adaptability and robustness of the AEKF algorithm, we combine the SoC estimation results in C-BMS as an additional system observation variable, reducing its dependence on the accuracy of equivalent circuit model and thereby improving algorithm accuracy. The details of improved AEKF algorithm are as follows. First, a discrete state space equation[22] which reflects the change of state is established:

$$\begin{bmatrix} SOC(k) \\ U_{R_cC_c}(k) \\ U_{R_dC_d}(k) \end{bmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \exp(\frac{-T}{\tau_c}) & 0 \\ 0 & 0 & \exp(\frac{-T}{\tau_d}) \end{pmatrix} \times \begin{bmatrix} SOC(k-1) \\ U_{R_cC_c}(k-1) \\ U_{R_dC_d}(k-1) \end{bmatrix} + \begin{bmatrix} \frac{-\eta T}{C} \\ R_c(1-\exp(\frac{-T}{\tau_c})) \\ R_d(1-\exp(\frac{-T}{\tau_d})) \end{bmatrix} \times i(k-1) + w(k-1) \quad (4)$$

Where C is the current battery capacity; T is sampling period; τ_c and τ_d are the time constants in RC loops; i is battery current; w represents the system noise.

We use $f(x_k,u_k)$ to represent system state equation, $h(x_k,u_k)$ to represent the observation equation of system, then the system state transition equation can be represented as follows:

$$\begin{cases} x_{k+1} = f(x_k,u_k) + \omega_k \\ y_k = h(x_k,u_k) + \upsilon_k \end{cases} \quad (5)$$

Where x is system state matrix, u is system input matrix, y is system observe matrix, υ_k is observe noise matrix, ω_k is system noise matrix.

The equation of linearized model is as follows:

$$\begin{cases} x_{k+1} \approx A_k x_k + [f(\hat{x}_k,u_k) - A_k \hat{x}_k] + \omega_k = A_k x_k + B_k u_k + \omega_k \\ y_k \approx C_k x_k + [h(\hat{x}_k,u_k) - C_k \hat{x}_k] + \upsilon_k = C_k x_k + D_k u_k + \upsilon_k \end{cases} \quad (6)$$

The above formula is a standard expression of the AEKF algorithm. According to the AEKF flow shown in Figure 5, the system state can be continuously updated by iteration, thus realizing SoC estimation.

V. Result and Discussion

In this paper, the actual operation data of the EVs are used as the experimental data, and the terminal voltage, SOC, battery temperature and discharge current of the battery are collected during normal driving. Totally 15000 sets of battery data are collected, and the data distribution is shown in Fig. 7.

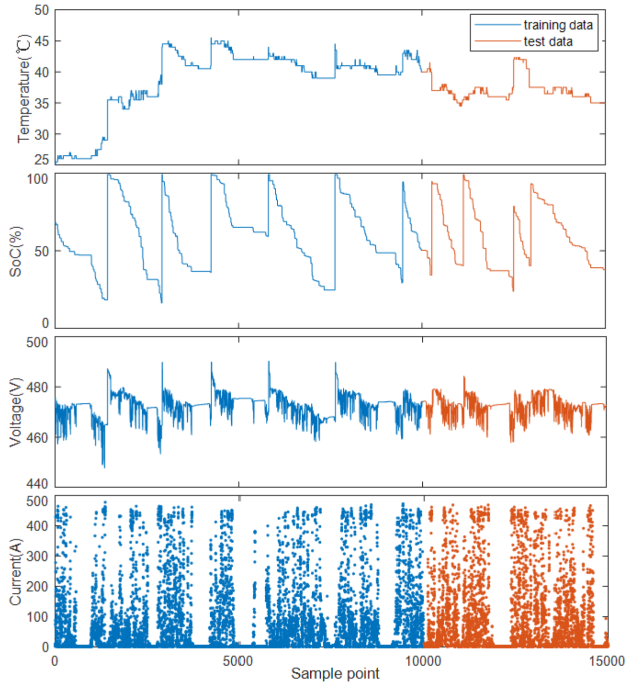

Fig. 7. The data used in this paper.

A. Battery modeling result

To establish an accurate battery model, it is necessary to properly quantify the power battery degradation. Based on the battery degradation quantification method proposed in Section II.A, we quantify the degradation phenomenon in the battery historical discharge curve before modeling.

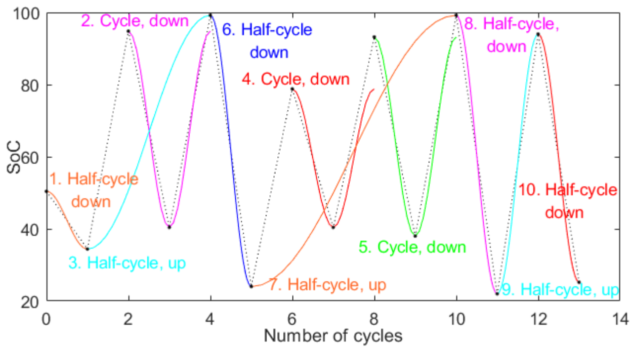

Fig. 8. The result of rain-flow cycle counting algorithm based battery degradation quantification method.

Fig. 8 shows the result of rain-flow cycle counting algorithm-based battery degradation quantification method. After battery SoC profile is given, all the discharge cycles experienced during the whole battery life time can be extracted and the depth of discharge for each cycle is recorded.

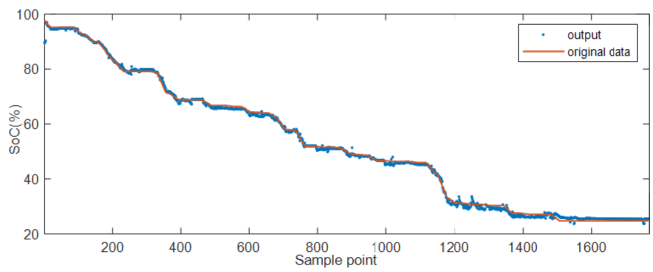

Fig. 9. The accuracy of the DBN-ELM model in a discharge cycle.

The accuracy of the DBN-ELM model in a discharge cycle is shown in Fig. 9. The battery model based on the DBN-ELM algorithm can accurately estimate the battery terminal voltage under dynamic conditions, and the error is within 3%.

In order to verify the proposed conjunction working mode between C-BMS and V-BMS, we performed a charge and discharge experiment on a single battery pack. The experimental scheme is as follows: the battery is placed in a 25ºC chamber, loaded with Urban Dynamometer Driving Schedule conditions.

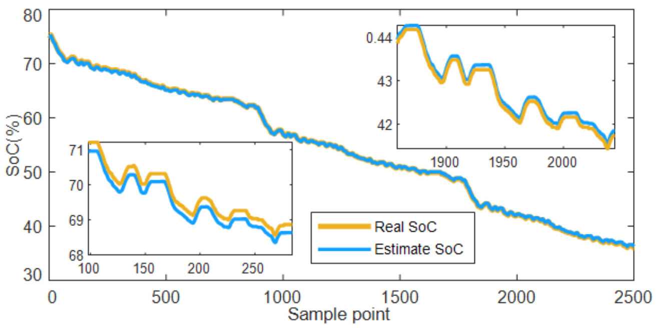

Fig. 10. The accuracy SoC estimation based on the proposed conjunction working mode between C-BMS and V-BMS.

Fig. 10 illustrates the results of SoC estimation based on the proposed conjunction working mode between C-BMS and V-BMS. It is apparent that the SoC estimators can work stably, and the model accuracy is significantly improved compared with cloud based SoC estimator. The mean absolute error is within 1% and the maximum relative error is within 3%.

VI. Conclusion

This paper presents a big data driven battery management method utilizing the deep learning algorithm, with the ability to work stably under dynamic conditions during whole battery life cycle. The rain-flow cycle counting algorithm is able to reflect the battery degradation phenomenon effectively, and the battery modeling method based on DBN-ELM algorithm is able to extract the deep structure features of the data effectively, and the results show that the deep-learning algorithm is able to reduce model error and achieve a high-precision simulation for the dynamic characteristics of the battery effectively, and error of the SoC estimation result is within 3%. The proposed C-BMS is able to effectively deal with big data resources and can reduce the calculation burden of the V-BMS. It provides a multidimensional, multistate, multifactor complex data space for battery modeling and SoC estimation. The presented conjunction working mode between C-BMS and V-BMS is able to improve the accuracy and stability of battery modeling and SoC estimation while ensure the system real-time performance.

Acknowledgments

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