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An online state of charge estimation method with reduced prior battery testing information

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ABSTRACT

An online State of Charge (SOC) estimation method with reduced prior battery testing information is proposed in this paper, in which no testing data obtained in laboratory is needed, including the relationship between the open circuit voltage (OCV) and the SOC. The first order RC battery model is utilized to interpret the characteristics of the lithium-ion battery. The genetic algorithm is introduced to carry out the online identification for the battery model. Parameters obtained by the identification are applied to the joint SOC estimation method to estimate the SOC of the battery. An experimental battery test workbench is established to validate the proposed method. Several drive cycle current profiles are scaled down and applied to the battery. The experiment results show that the parameters obtained by the proposed method could characterize the battery well, even for different drive cycles, and accurate SOC of the battery could be obtained online.

Introduction

Considered as the only viable solution at present for Electric Drive Vehicles (EDVs), such as Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs)., lithium-ion (li-ion) batteries have drawn more and more attentions worldwide. However, as complex electrochemical systems with strong nonlinearities, li-ion batteries are sensitive to overcharge and overdischarge. If overcharge or overdischarge occurs, the cycle life of the battery could be dramatically reduced, and the battery could catch fire or even have an explosion. Measures should be taken in battery management systems (BMS) to avoid these situations and assure the safety of EDVs.

Defined as the ratio of the remaining capacity over the nominal capacity, the State of Charge (SOC) is considered as one of the key parameters that could be used to solve the problems stated above. Besides, accurate SOC is also needed as one of the important parameters in EDVs for the concern of control engineering, remaining range of the EDV, and so forth. If accurate SOC could be obtained, the useable SOC range could be extended. A smaller battery pack would be able to satisfy the demand of an EDV that right now is equipped with a larger battery pack. Thus the price for the battery pack could be dramatically decreased, further helping the market penetration of EDVs.

The coulomb counting method (CCM) [1] is the most straight forward method to estimate the SOC of a battery, according to the definition of the SOC. The CCM has actually been widely used in practical BMS for its easy implementation and simple computation. However, the CCM heavily relies on the prior knowledge of the initial SOC of the battery. If the initial SOC were unknown or not accurate, the estimated SOC would always have a bias. Besides, the accumulative error problem could not be ignored, especially for long-term SOC estimations.

The model based SOC estimation method (MBSEM) [2–6] is considered as one of the most popular SOC estimation methods in recent years. Comparing with the CCM, the MBSEM takes advantage of both the measured current and voltage signals, and thus forms a close loop estimation method, leading to a more accurate estimation. For this reason, the MBSEM does not rely on the accurate initial SOC, and the accumulative error problem could also been solved. Such MBSEMs could be the Kalman filter method [2,3], the sliding mode method [7–10], the Luenberger observer method [11–13], the proportional integral observer method [5,6], etc.

Some attempts have been made to evaluate the models for the states and parameters estimations of li-ion batteries, such as the Rint Model [14–16], the first order RC model [17–19], the impedance model [2]. More models have also been researched derived

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from the models mentioned above, such as hysteresis model [14]. Different models have its own unique features, but all the models should be identified to obtain the parameters of the model. Normally, such identification procedures are carried out offline with specially defined data obtained in laboratory. To obtain such testing data, different testing procedures such as the OCV test, the Hybrid Pulse Power Characterization (HPPC) test [20], and so forth, should be carried out and complex battery test workbenches should be established, which could be expensive and time consuming. Furthermore, the obtained data may only suit for the tested battery and even only for the certain state of the battery. If the battery has been used for a long time, the parameters may vary, and the laboratorial data could be useless.

To solve the problems stated above, this paper proposed a new thought, a joint online parameter identification and SOC estimation method. In such a joint method, no testing data obtained in laboratory is needed, including the OCV–SOC relationship. All the identification processes are carried out online. By this way, batteries could be equipped to the EDVs directly, and the parameters of the model could be obtained automatically. The MBSEM and the CCM are jointly utilized to estimate the SOC, taking advantage of each method and making up their own defects. In Section 'Principle of the joint method', the principle of the proposed joint online parameter identification and SOC estimation method would be interpreted. In Section 'Experiment and validation', the experimental workbench would be established to validate the proposed method. The conclusions would be drawn in Section 'Conclusion'.

Principle of the joint method

In this section, the principle of the joint online identification and SOC estimation method for li-ion batteries is analyzed in detail. Although, a battery pack would be used for a real EDV application, the whole battery pack could be treated as a big battery cell by taking advantage of battery balancing methods [21–23] and some other measurements. Therefore, for the sake of simplicity, a battery cell is studied in this paper instead of a battery pack, and the method proposed in this paper could be easily applied to battery pack.

As is known to all, the only information for a given battery is from its datasheet, which includes the capacity, the cut-off voltage, etc. If no laboratorial experiment were carried out, the parameters for the battery, such as the internal resistance, would be unknown. However, it would always take long time to excite the characteristics of the battery in laboratorial experiments, such as the HPPC testing profile [24]. Besides, battery test equipment for such experiments is often very expensive and difficult to operate. A better way should be configured out to solve such problems. The principle of the proposed method is depicted in Fig. 1.

As shown in Fig. 1, since the capacity of the battery is given in the datasheet, the only information needed for the proposed joint method is the initial SOC. As far as the initial SOC of the battery is concerned, it is easy to be known when the battery is brand new. Even if the initial SOC of the battery is unknown, it could also be easily obtained by a full charge before its first use.

The voltage and the current signals are measured for the battery used in practical applications, as shown in Fig. 1. With the measured current signals and the given initial SOC, the SOC of the battery could be calculated by the CCM for a short time, e.g. one drive cycle. In this short time, the accumulative error of the CCM could be small and be ignored. The voltage signals, the current signals and the estimated SOC are recorded by the data logging device. After a certain interval, the recorded data are selected to identify the parameters of the battery model according to some criterions. To simplify the calculation, such criterions should meet the requirement that the SOC would vary little for the selected data, which would be explained in detail in 'Data selection'.

When the data selection is finished, such selected data are applied to the online identification algorithm to calculate the unknown parameters of the battery model. When these parameters are obtained, they are substituted to the model to determine whether the obtained parameters are accurate enough or not. If so, such set of parameters are stored for further usage in the model to estimate the SOC. If not, the online identification processes would be carried out repeatedly until the parameters could fit the data well enough. The obtained parameters are stored such that the piecewise technology could be used and the parameters for other SOC could also be calculated. Finally, the parameters of the battery model could be obtained for each SOC interval, and could be applied to the model based SOC estimation method to correct the SOC estimation. Since these procedure would carried out all the time and the parameters of the battery model would update accordingly, the method could always obtain the latest parameters of the battery and have a good estimation of the SOC even the properties of the battery changes with time.

To further understand the proposed joint method, several key links of the procedure are explained in detail in following sections.

Battery model

Li-ion batteries have been widely used in EDV applications, and plenty of battery models [14–19] have been proposed and studied. However, li-ion batteries are complex electrochemical systems with strong nonlinearity, and no unique model could fully characterize the real battery. Besides, it is believed that, the more accurate, the more complex the battery model would be. Since the online identification is a complex procedure, the computation complexity should be carefully considered. To reduce the computation complexity of the online identification, the battery model should be the simpler the better. Take such aspects into consideration, the first order RC model [17–19] is introduced in this paper.

The first order RC model is divided into three parts: the open circuit voltage (OCV) part $E_o(z)$, the internal resistance R_1 and the parallel RC network. The SOC is denoted as z in the figure and equations, the OCV part $E_o(z)$ is used to interpret the nonlinear part of the voltage response and it is also a function of SOC, the resistance R_1 is used to interpret the internal resistance of the battery, and the parallel RC network is used to represent the high frequency response of the battery. V_o is the terminal voltage of the battery, I is the denotation of the current applied to the battery and it is assumed to be positive when the battery is charged.

According to the circuit theory, the terminal voltage could be calculated as follows:

$$\begin{cases} \dot{V}_2 = -\frac{1}{R_2C_2}V_2 + \frac{I}{C_2} \\ V_o = E_o(z) + V_2 + R_1 I \end{cases} \tag{1}$$

Data selection

As stated above, the main criteria of the data selection is to make sure that the OCV would maintain constant. Through prior experiments, it is found that in a short period of time, e.g. less than 30 s, if the battery charges/discharges within 2C rate, the OCV could be regarded as unchanged, where C denotes the battery rated capacity in ampere-hours. It is assumed in this paper that the battery parameters, including the internal resistance and the OCV, would remain unchanged during this time interval. Besides, in order to fully excite the characteristics of the battery, the battery should be charged and also be discharged in this time interval. So the limitations for the selected data should be as follows:

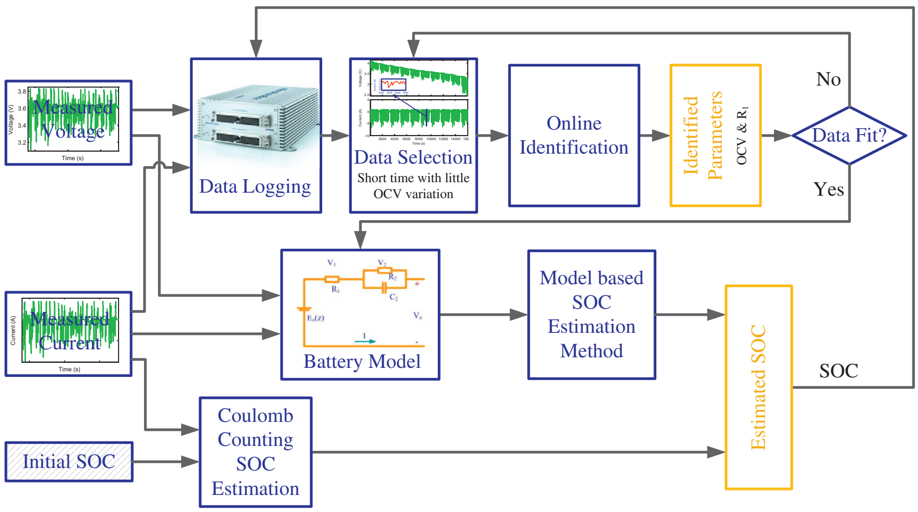

Fig. 1. Flowchart of the proposed method.

a. Time interval should be short enough, e.g. less than 30 s.
b. The charge or discharge current should be not too large, e.g. less than 2C rate.
c. There should be enough current excitation. Maximum current deviation (the maximum current minus the minimum current) of these data should be larger than a certain value, e.g. 0.5C rate.

Fig. 2 shows an example of the data selection. In this example, the capacity of the battery is 2.95 Ah. The time interval is set to be 30 s, the maximum discharge current is less than 2C rate (about 1C rate in this example), and the maximum current deviation is also large enough. So, these data could be used in the online identification process to obtain the parameters of the model.

Online identification

As an effective tool to estimate the model parameters of nonlinear systems and a unique algorithm owning the whole range optimum properties, the genetic algorithm (GA) has been widely applied in bioinformatics, computational science, engineering, mathematics, physics, and other fields. GA has also been successful applied to parameter identification in our previous work [25]. For the whole range optimum properties, GA is introduced in this paper to perform the online identification.

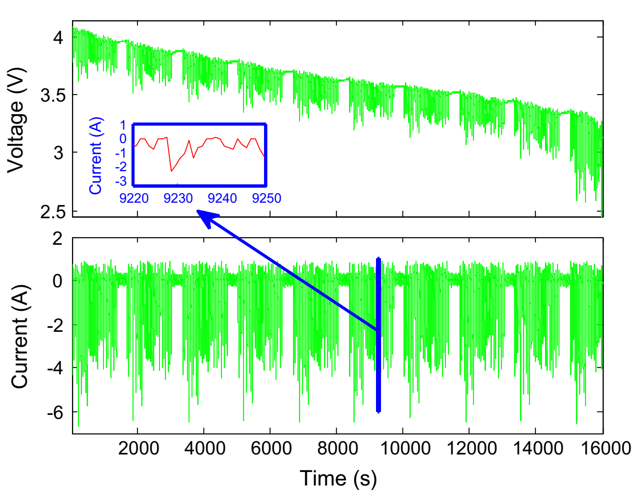

Fig. 2. Online identification data selection with zoom-in selected current data.

For the online identification, the battery model (1) is applied to calculate the voltage response. As stated above, the parameters $E_o(z)$, R_1, R_2, C_2 are assumed to be constant in this process. The errors between the calculated voltage and the measured voltage are presented as follows:

$$e = V_{\text{calculated}} - V_{\text{measured}} \tag{2}$$

Parameters of the battery could be obtained by minimizing the following equation:

$$[\widetilde{E}_o, \widetilde{R}_1, \widetilde{R}_2, \widetilde{C}_2] = \arg \min_{[E_o, R_1, R_2, C_2]} \sum_{i=1}^{n} e_i^2 \tag{3}$$

where $[\widetilde{E}_o, \widetilde{R}_1, \widetilde{R}_2, \widetilde{C}_2]$ is the identified parameters of the model, n is the samples in the selection time interval. The GA is applied to find the whole range optimal values of $[\widetilde{E}_o, \widetilde{R}_1, \widetilde{R}_2, \widetilde{C}_2]$ for the selected data.

Joint online model based SOC estimation

The choice of SOC estimation methods

According to the analysis above, the CCM and the MBSEM are jointly applied and a joint SOC estimation method is proposed based on the online identification method. Fig. 3 shows the strategy determining which SOC estimation method should be used.

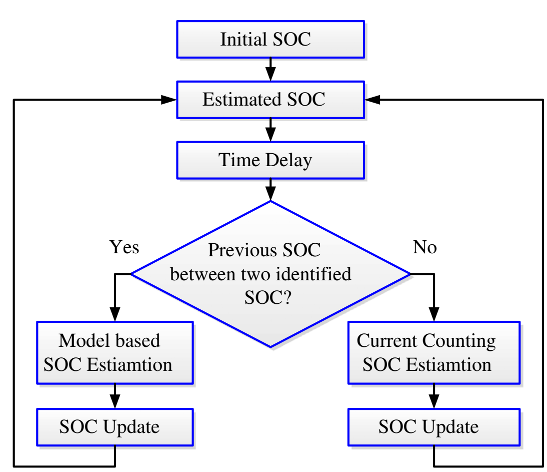

Fig. 3. Flowchart to determine which SOC estimation method should be used.

It is assumed that the initial SOC for the first use is known (it could be fully charged before the first use if the initial SOC is unknown).

The time delay means time interval between two SOC estimation calculations. As shown in the figure, if the SOC of the previous sampling time is between two identified SOC, the parameters for such two SOC are known, and the MBSEM would be utilized. For example, if the parameters of 40% SOC and 50% SOC are known, and the SOC of the previous sampling time is between 40% and 50% (45% for example), the MBSEM would be applied since the parameters could be inferred from the parameters of the two identified SOC. If not, the CCM would be used to calculate the SOC since there is no parameter available for the model based SOC estimation method. Although the CCM suffers the accumulative error problem discussed above, estimation error caused by such problem could be acceptable if the time range is short enough. According to prior experiment results, in a short time range, e.g. one or several drive cycles, the SOC estimation accuracy of the CCM is accurate enough. In this case, the previous SOC is treated as the initial SOC for this process. And these SOC, together with the current and voltage signals are recorded for the further usage of online identification.

Brief explanation of the MBSEM used in this paper

The proportional integral observer SOC estimation method [5,6] is introduced as the MBSEM in this paper. Other MBSEMs could also be utilized if necessary, such as the Kalman filter method.

According to the definition of SOC, following relationship could be rewritten:

$$\dot{z} = \frac{\eta_i}{C_n} I \tag{4}$$

where z is battery SOC, I is the instantaneous battery current, η_i is the battery Coulombic efficiency, and C_n is the nominal battery capacity.

Taking SOC as the state, the state space function could be written as follows:

$$\begin{cases} \dot{z} = \frac{\eta_i}{C_n} I \\ V_o = E_o(z) + R_1 I \end{cases} \tag{5}$$

However, the output equation of the above state space function is not expressed directly with the state z, but with $E_o(z)$. The relationship between SOC and E_o is nonlinear and it is not easy to draw a mathematical interpretation for it. To deal with this problem and simplify the computation, a gain scheduling method [26] is introduced, which typically employs an approach whereby the nonlinear system is decomposed into a number of linear subsystems. For a given nonlinear system, the relationship between SOC and $E_o(z)$ can be divided into several sections, and the subsystem in each section is considered to be linear. So the relationship can be written in the short SOC interval as follows for the ith SOC interval $(i-1)\cdot\Delta_z \leqslant z_i \leqslant i\cdot\Delta_z$:

$$E_o = a_i \cdot z_i + b_i \tag{6}$$

where Δ_z is the SOC interval length. For the ith SOC interval $(i-1)\cdot\Delta_z \leqslant z_i \leqslant i\cdot\Delta_z$, the corresponding set (a_i, b_i) can be calculated from the curve and will maintain constant in the ith SOC interval. To consider the online identification application, Δ_z is the SOC interval between two identification processes. If two identification processes have been taken, the parameters between these two SOCs could be piecewise calculated.

Combine (5) and (6), the state space function of the battery model could be depicted as follows:

$$\begin{cases} \dot{z} = \frac{\eta_i}{C_n} I \\ V_o = a_i \cdot z_i + b_i + R_1 I \end{cases} \tag{7}$$

According to the definition of the proportional integral observer SOC estimation method, following equations could be obtained:

$$\begin{cases} \dot{\tilde{x}} = A\tilde{x} + Bu + K_p(y-\tilde{y}) + K_{i2} w \\ \dot{w} = K_{i1}(y-\tilde{y}) \end{cases} \tag{8}$$

where variable w is defined as the integral of the difference $(y-\tilde{y})$. Vectors $K_p \in \mathbb{R}^{2\times1}$ and $K_{i1} \in \mathbb{R}^{1\times1}$ $K_{i2} \in \mathbb{R}^{2\times1}$ are the proportional and integral gains respectively.

Experiment and validation

Experimental battery test workbench establishment

To validate the performance of the proposed method, an experimental battery test workbench is established. The structure of the workbench is shown in Fig. 4 and the established battery test workbench is shown in Fig. 5. In this workbench, a charger and an electronic load are connected in parallel to the terminals of the battery. A Hall current sensor is utilized to measure the main current of the battery. The voltage of the battery is measured by the analog to digital converter (ADC) of the MicroAutobox, and the current of the battery by another channel of the ADC. The charger and the electric load are controlled by the MicroAutobox through RS232 signals. The MicroAutobox is controlled by a computer to simulate some current profiles applied to the battery, and the current profiles are sent out by RS232 signals to the charger and the electronic load, and finally applied to the battery. These current profiles could be constant current charge, constant voltage charge, constant current discharge and drive cycles, such as Environmental Protection Agency (EPA), Urban Dynamometer Driving Schedule (UDDS), EPA Supplemental Federal Test Procedure (SFTP) and Highway Fuel Economy Test (HWFET). The MicroAutobox is also used to record the data and perform the proposed joint method stated above.

Experimental scenario for the proposed method

To verify the online identification method, the experiment is established and a li-ion battery is tested on the workbench. The UDDS drive cycle is applied to the li-ion battery, and the current and the voltage signals are recorded. On the online identification stage, the SOC is calculated by the CCM and also be recorded. After a certain time interval, 30 s in this experiment, the data selection method is applied to select the data to identify the model parameters from the recorded data and the online identification would be carried out to obtain the parameters of the battery model.

While the proposed method could be applied to any scenario according to practical driving habits. However, to fully validate the proposed method, a special scenario is set up in this paper as follows: The battery is assumed to be equipped to an EDV and it is the first use. All the parameters for this battery model are

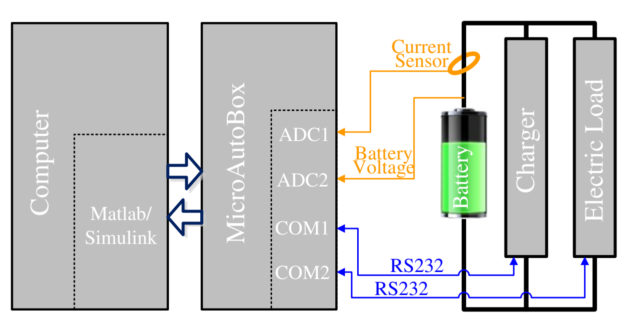

Fig. 4. The structure of the experimental battery test workbench.

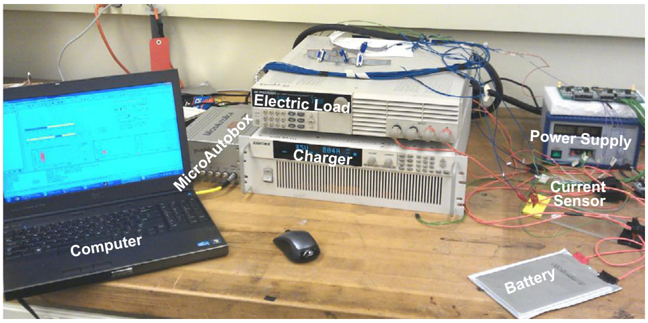

Fig. 5. Experimental battery test workbench.

unknown except the initial SOC. Firstly, the EDV is applied to several UDDS drive cycles. At this time, the SOC is assumed to be 50% (could be any other value actually) and the EV is back home and being fully charged. Secondly, the EDV is applied to another several UDDS drive cycles again and the battery is almost exhausted. The final SOC is assumed to be about 15% at this time. The EDV would be charged to a certain SOC but not fully charge, 83% in this case. Finally, the EDV is applied to another several drive cycles until it is home and the finally SOC is about 20%. At this final step, to validate the identified parameters used in MBSEM, the initial SOC for the MBSEM is assumed to be unknown and it is reset to 50%. Fig. 6 shows the procedures and the results of the scenario.

As shown in the figure, in Fig. 6(a), the SOC is always be calculated by the CCM, since for this first run, the parameters of the battery model are unknown. In this first run, the data are recorded, including the SOC, the voltage and the current signals. Besides, during this time period, the data are selected and the online identification processes are carried out. According to procedure of the proposed method, the identified parameters are subscribed to the battery and calculate the voltage to compare with the measured voltage. If the value of fitness function is bigger than a certain value, 98% for example, this set of parameters would be recorded. If not, the data selection process would be done again and the identification process would also be carried out again until the criteria meets.

In Fig. 6(b), the processes are separated into two parts. In the first part, in the time range from 0 to around 9000 s, the parameters have been identified by the first run as shown in Fig. 6(a). While in the second part, in the time range after around 9000 s, the parameters are unknown. So in the first part, as shown in Fig. 6(b), the SOC are estimated by the MBSEM, and the calculated voltage could be almost the same as the measured voltage, which indicates that the model parameters identified by the first run cycle could characterize the battery well. The parameters of the first order RC model are shown in following table: (see Table 1).

In the second part, the SOC are calculated by the CCM and the initial SOC for the CCM is the final SOC estimated by the MBSEM. In this part, the data are recorded to be used by the online identification.

In Fig. 6(c), the initial estimated SOC is assumed to be unknown. Since the parameters for the whole range are known, the MBSEM is utilized. As shown in the figure, the initial error could be compensated in a short time and the estimation errors are small.

Identification results

Further studies are also carried out by the comparison between the measured voltage and the calculated voltage with the identified model. The voltage comparison results are given in Fig. 7.

As shown in the figure, the voltages calculated by the identified model are almost the same as the measured voltages, which indicates that the identified parameters could fully interpret the characteristics of the battery. The voltage errors between the measured voltages and the calculated voltages are also given in the figure. Most of the voltage errors are less than 0.03 V, which is less than 1%, further proving the good accuracy of the battery model obtained by the online identification method.

SOC estimation results with the identified parameters

The proportional integral observer SOC estimation method is introduced as the MBSEM. For the first cycle, the CCM is utilized to calculate the SOC as stated in above sections. When the parameters for the battery model are known, the MBSEM is applied. The results for the MBSEM are depicted in Fig. 8. The figure shows that the initial SOC estimation error could quickly be compensated and the estimated SOC could converge to the reference SOC in a short time. The estimation errors are also very small for the whole SOC range, within ±2% error bound. It could be concluded that the identified parameters could work well for the MBSEM method, and the proposed joint method could work well as long as the initial SOC is known, but without any other laboratorial data of the battery.

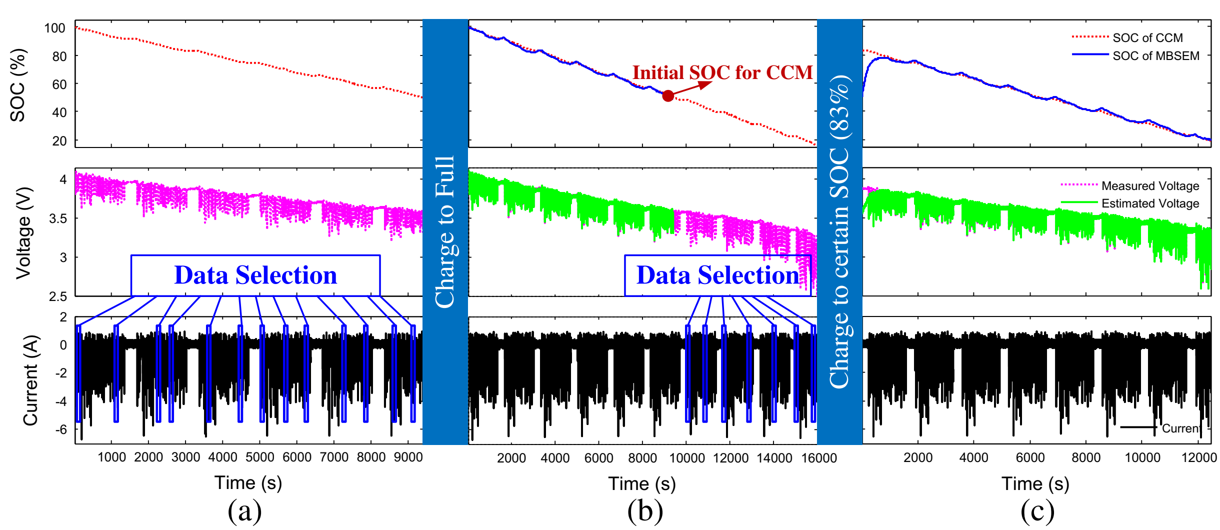

Fig. 6. The results of the validation: (a) data recorded for the first run; (b) data recorded for the cycle in which the SOC range is out of the first run; (c) data recorded for the cycle in which the parameters are identified by former cycles.

Table 1
Identified parameters of the first order RC model.

R_1 = 0.057			R_2 = 0.085			C_2 = 50,430		
SOC (%)	100	99.4	94.57	90.1	80.2	70.5	60.5	49.8
OCV (V)	4.093	4.0927	4.039	3.966	3.863	3.774	3.673	3.605

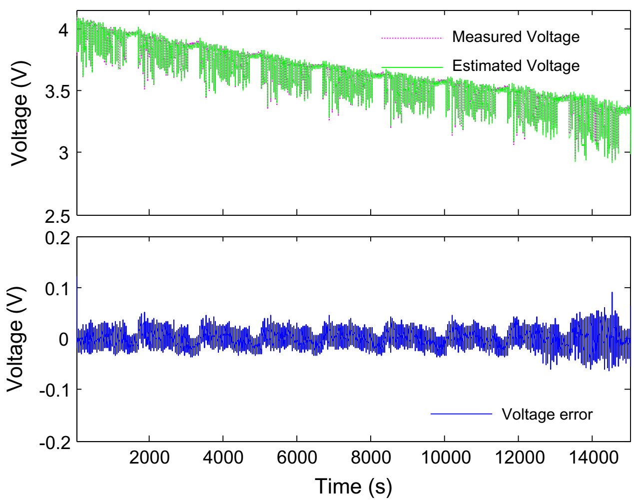

Fig. 7. Online identification results.

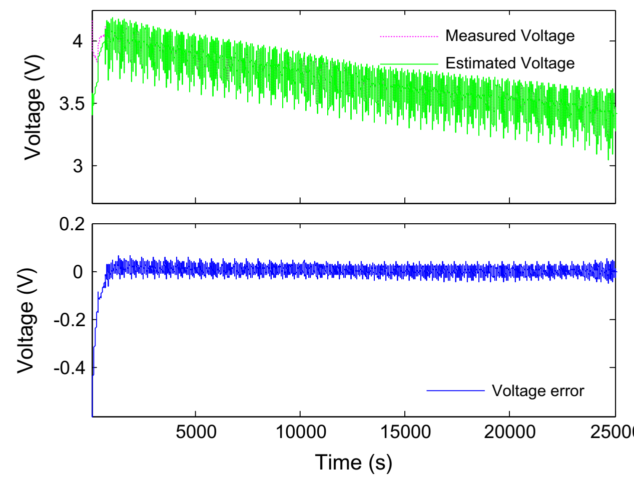

Fig. 9. Voltage response of SFTP drive cycles with parameters identified by UDDS.

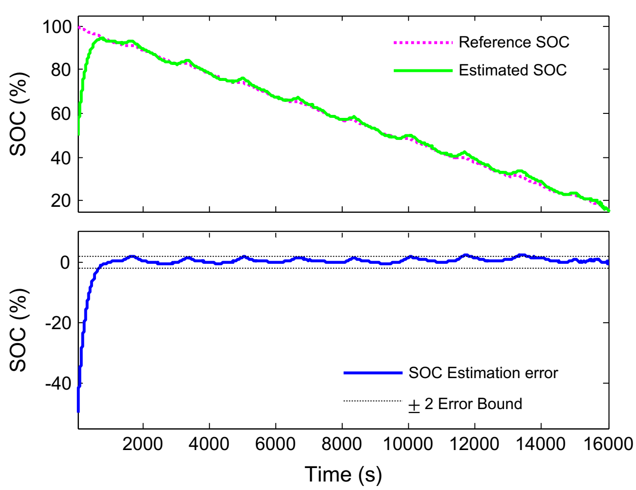

Fig. 8. Estimation results with the joint estimation method.

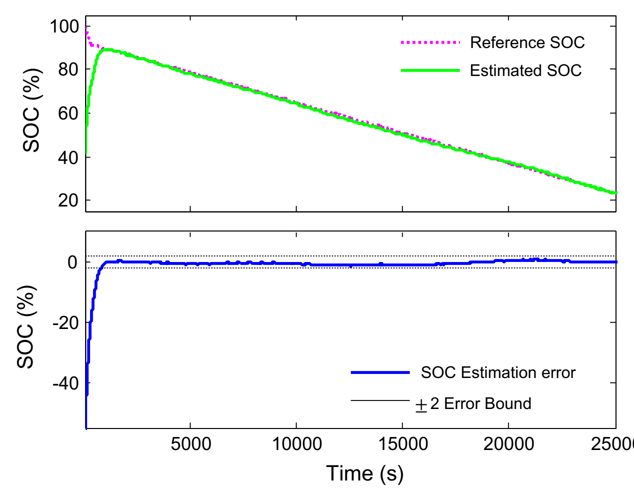

Fig. 10. SOC estimation results of SFTP drive cycles with parameters identified by UDDS.

Validation with other drive cycles

To further validate the proposed joint method, the parameters identified by UDDS drive cycles are applied to SFTP drive cycles. Fig. 9 shows the voltage response of the measured voltage of the battery applied with the SFTP drive cycles, comparing to the voltage response calculated by the battery model with the parameters obtained by the UDDS drive cycle. It is obvious in the figure that the voltage errors are still very small, which indicates that the parameters identified by the proposed method could work well, even for different drive cycles.

Fig. 10 shows the SOC estimation results for SFTP drive cycles. The results show that the parameters identified by the proposed method could work well even for different drive cycles, and the estimated SOC could also quickly converge to the reference SOC, compensating the initial SOC error. Besides, the estimation errors are also very small, mostly be confined in ±2% error bound. The results further prove that the proposed method is robust to different drive cycles, and it is suitable to be implemented to practical applications, such as EDV applications.

Conclusion

This paper proposed an online SOC estimation method with reduced prior battery testing information. The main highlight of the proposed method is that it could work well without testing data obtained in laboratory, including the OCV–SOC relationship. The principle of the proposed method was described and analyzed in detail. To further take advantage of the merits of both the CCM and the MBSEM, a joint SOC estimation method has been proposed in this paper. To validate the proposed method, an experimental battery test workbench was established according to the validation requirements. The online identification results were firstly validated, in which the identified parameters could characterize the tested li-ion battery well. The errors between the voltage response of the battery model and the measured voltage were less than 0.03 V, which was less than 1%. The joint SOC estimation method was also validated based on the identification method, in which initial SOC errors were compensated and the estimation results were accurate. The proposed method were applied to different drive cycles and also worked well, proving the robustness of the proposed method and the possibility to be implemented to practical applications, such as EDV applications.

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