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A Novel Real-Time State-of-Health and State-of-Charge Co-Estimation Method for $LiFePO_4$ Battery *

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The state of charge (SOC) and state of health (SOH) are two of the most important parameters of Li-ion batteries in industrial production and in practical applications. The real-time estimation for these two parameters is crucial to realize a safe and reliable battery application. However, this is a great problem for $LiFePO_4$ batteries due to the large constant potential plateau in the charge/discharge process. Here we propose a combined SOC and SOH co-estimation method based on the experimental test under the simulating electric vehicle working condition. A first-order resistance-capacitance equivalent circuit is used to model the battery cell, and three parameter values, ohmic resistance (R_s), parallel resistance (R_p) and parallel capacity (C_p), are identified from a real-time experimental test. Finally we find that R_p and C_p could be utilized to make a judgement on the SOH. More importantly, the linear relationship between C_p and the SOC is established to make the estimation of the SOC for the first time.

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Due to the advantages of high voltage, light weight, long cycle life and high energy density, lithium ion batteries are widely used as a power source in the field of electric vehicles (EV), and shows very good application prospects.[1−3] The accurate estimation of battery state of charge (SOC) and state of health (SOH) is crucial to realize a safe and reliable battery application. The overcharge or deep discharge due to the inaccuracy of SOC estimation may bring irreversible damage to the battery cell, as well as the whole system. A battery in bad SOH which has not been replaced in time would lead to capacity loss, rapid warming, even a potential safety incident.[4−7]

Battery SOC is the ratio between remaining available capacity and the maximum available capacity.[8] Battery SOH represents the battery health status, and can be defined as the ratio between the maximum available capacity and the rated capacity.[9] They are generally expressed in percentage (%). To date, a number of studies on the SOC and SOH estimation methods for lithium ion batteries have been carried out. Typically, there are several methods to derive the SOC. The Coulomb counting method[10] and the open circuit voltage (OCV) method[11−14] are widely used in battery management systems of EV due to the simple and direct characteristics. However, the uncertainty of initial SOC and accumulated errors seriously affect the accuracy of the Coulomb counting method. The OCV method requires the battery remaining unused for a long time to monitor terminal voltage, which limits the online usage. For $LiFePO_4$ (LFP) batteries, typical charge/discharge platform enlarges the measuring error of the OCV method.[15] The Kalman filter,[16−19] the sliding mode[20−22] and some intelligent methods, such as neural network,[23−25] fuzzy logic,[26,27] were introduced to enhance the precision of battery SOC estimation. The disadvantage of the former two is that they are computationally expensive, and that of the latter two is that they are too sensitive to the amount and quality of training data. Table 1 summarizes the advantages and disadvantages of these SOC estimation methods.

Compared with the SOC estimation, less attention has been paid to the SOH estimation, and few results can be directly used for EV. According to the definition, SOH can be directly measured through a fully charge/discharge process at a low current rate. However, this method cannot be utilized in practical applications due to the fact that most batteries are operated in a range of 20–80% SOC to protect the battery from irreversible damage.[28]

In this Letter, a discharge experiment at variable current rates is designed to simulate the working condition of LFP batteries in the EVs. By using an optimal first-order resistance-capacitance (RC) equivalent circuit model as the equivalent circuit model, three parameters are calculated, including ohmic resistance R_s, parallel resistance R_p, and parallel capacity C_p. Finally, we find that R_p and C_p could be used to judge the SOH. Moreover, the linear relationship between C_p and battery SOC is established to evaluate the SOC. Accordingly, a real-time co-estimation method

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to evaluate the SOC and SOH is built. The method has a higher precision than the OCV method, and could be combined with other methods to reduce the complexity and to improve the accuracy of the estimation work.

Table 1. Advantages and disadvantages of SOC estimation methods.

Method	Advantage	Disadvantage
Coulomb counting[10]	Simple and fast	Uncertain to initial SOC, affected heavily by the accumulated error
OCV method[11–14]	Simple and fast	Unsuitable for LFP batteries with flat OCV-SOC curve and requires a sufficient rest period, unsuitable for real-time SOC estimation
Kalman filter method[16–19] Sliding mode method[20–22]	Accuracy, closed-loop	Computationally expensive and highly depend on the model accuracy
Neural network method[23,25] Fuzzy logic method[26,27]	Good nonlinearity, mapping approximation	Sensitive to the amount and quality of training data, slow to converge

LFP-32650 batteries (cathode: $LiFePO_4$, anode: graphene, electrolyte: a mixture of EC and DMC with 1 M $LiPF_6$ dissolved, size: diameter 32 mm×height 65 mm, rated capacity: 5 Ah) were adopted in our test. According to their SOH, batteries are divided into four categories A, B, C and D, respectively. Each category contains four cells. Table 2 lists the SOH of these batteries. Here the SOH is defined from the aspect of capacity fading, that is,

$$\mathrm{SOH} = C_{\mathrm{aged}}/C_{\mathrm{new}}, \tag{1}$$

where C_{aged} is the capacity of the battery after certain cycles, and C_{new} is the original capacity of the brand new battery. When the SOH of a battery is less than 80%, we call it a 'bad battery', and it should be replaced.[29]

Table 2. The SOH of four categories of batteries under test.

Battery categories		Charge/discharge cycles in the past	SOH
Healthy batteries	A	500	> 90%
	B	1000	> 90%
Bad batteries	C	400	< 80%
	D	1200	< 80%

The working condition test is programmed according to the standard stipulated in the IEC 61982–3–61982. The output power of each cell is converted into the output current, the maximum is 19.5 A (about 4 C). As shown in Fig. 1(a), each discharge stage contains three sections of working condition to be simulated according to the real applications in city driving and one of working condition to be simulated according to the real applications in country driving. A braking energy recovery process (rechargeable) is also included. A fully discharge process includes about 18 discharge stages. Thus we could use the SOC to represent the whole discharge procedure.

A general battery model to describe the electrical behavior is usually derived from an equivalent circuit. As shown in Fig. 1(b), R_{s} represents the bulk resistance of the battery, which reflects the electrical conductivity of the electrolyte, the separator, and the electrodes. The parallel connection of R_{p} and C_{p} is used to describe the effects caused by activation polarization and Li-ion diffusion while the battery is charged or discharged. Here U_{p} denotes the terminal voltage of the parallel R_{p} and C_{p}. The parameterization values of the resistances and capacitances greatly depend on the particular operating point of the battery and the cell degradation. Therefore, they will change with time, temperature, power demand, the SOC and SOH.[30]

All tests in this work are performed under a constant ambient temperature. In the whole test process, we monitored the voltage and current data of each battery by using a battery charge/discharge instrument (Maccor MC16) with the interval time of 1 s. Based on the ohm law, the value of R_{s} could be estimated by Eq. (2). Simultaneously, the values of R_{p} and C_{p} could be calculated by fitting the polarization voltage curve with Eq. (3). Three parameters were calculated by the data of section 1 marked in Fig. 1(a). Section 1 represents a current step from 0 C to 0.5 C, and its zoom-in graph was presented in Fig. 1(b)

$$R_{\mathrm{S}} = \frac{U_1 - U_2}{I_2 - I_1}, \tag{2}$$

$$U_{\mathrm{P}} = I \cdot R_{\mathrm{P}} \cdot (1 - e^{\frac{-t}{R_{\mathrm{P}} \cdot C_{\mathrm{P}}}}), \tag{3}$$

As shown in Fig. 2(a), all the values of R_{s} are calculated according to the above analysis. The calculated R_{s} values for four types of LFP batteries (A, B, C, D) mainly fall in the ranges of 17.9–25.3, 23.5–27.8, 24.2–28.0 and 24.6–29.9 mΩ, respectively. According to the statistical result shown in Fig. 2(a), the R_{s} values of healthy and bad batteries seriously overlap, although the R_{s} values of healthy batteries (A and B) are slightly lower than those of bad batteries (C and D). Thus we could not judge the SOH of LFP batteries according to R_{s}. In addition, for healthy batteries, R_{s} of battery B (1000 cycles) do have a slight increase compared with that of battery A (500 cycles). The similar phenomenon is observed in the bad batteries, indicating that R_{s} will increase with the cycle numbers. This is consistent with the previous report.[31]

Moreover, R_s almost remains unchanged with the decrease of SOC except in the early stage of the discharge for four types of LFP batteries, which makes no sense for the SOC estimation. Consequently, R_s could not be used to estimate the SOC and SOH well and accurately.

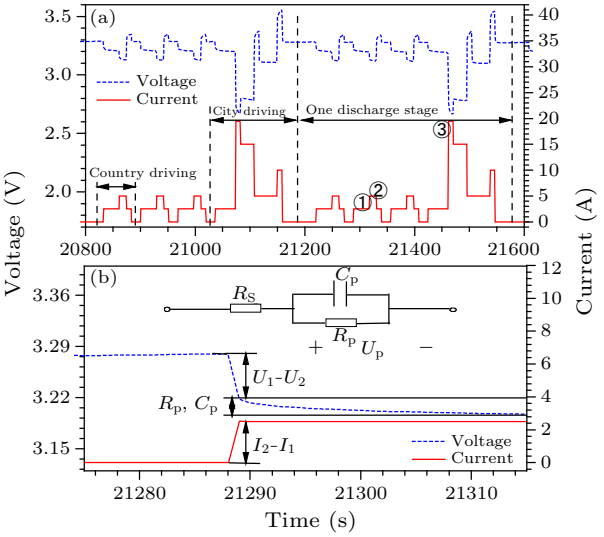

Fig. 1. (a) Current and voltage profiles of LFP batteries in the test dataset; (b) the first-order RC equivalent circuit model for LFP batteries (inset), and a zoom-in current and voltage stage in the test dataset.

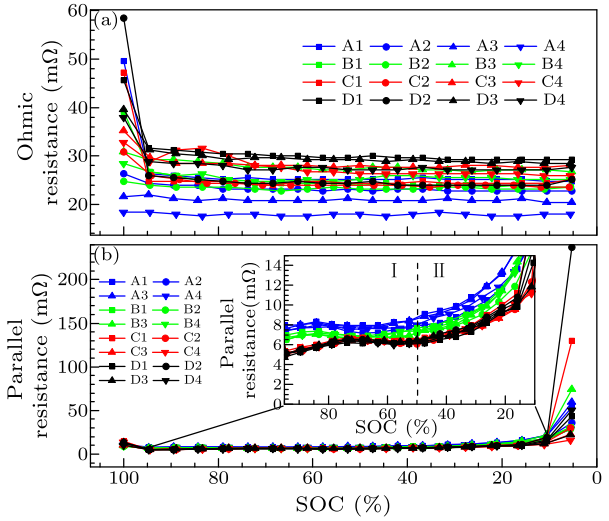

Fig. 2. (a) The calculated R_s as a function of the SOC for four types of LFP batteries (A, B, C and D); (b) the calculated R_p as a function of the SOC for four types of batteries: A, B, C, D.

The R_p values are also calculated and plotted versus the SOC in Fig. 2(b). As shown in the inset of Fig. 2(b), the R_p values of healthy batteries (A and B) are relatively dispersive and slightly higher than that of bad batteries (C and D) in the main part (10–95%) of the whole SOC window. For example, when SOC is 50%, R_p of the healthy batteries (A and B) fall in the range of 6.8–8.3 mΩ, and the values of the bad batteries (C and D) fall in the range of 6.0–6.3 mΩ. They are not overlapped. Thus the R_p value could be acted on as a criterion to distinguish healthy batteries from bad batteries. According to the variation trend of R_p versus the SOC, the inset could be divided into two regions, regions I and II. In region I (50–95%), R_p almost remains unchanged, while in region II (10–50%), the R_p value increases slowly with the discharge depth. The SOC in the range of 10–50% can be estimated by the R_p value. Here R_p steeply rises in the end of the discharge period. Based on the above analysis, it is concluded that the SOH could be partly judged by the R_p value, which is not an ideal criterion to estimate the SOC.

As shown in Fig. 3(a), the C_p values are calculated and plotted versus the SOC. The C_p values of healthy batteries (A and B) are significantly lower than that of bad ones within the whole SOC range. The C_p curves of healthy batteries and bad batteries also do not overlap. In this light, C_p can act as an outstanding SOH estimator. Notably, the C_p value decreases linearly with the decrease of the SOC for all the batteries when the SOC is less than 60%. This result is obviously different from the plateau characteristic presented in R_p and the OCV for LFP batteries. When the SOC is larger than 60%, C_p changes slowly without any obvious rising or reducing tendency. Based on the above analysis, C_p can be used to fully estimate both the SOH and the SOC concurrently.

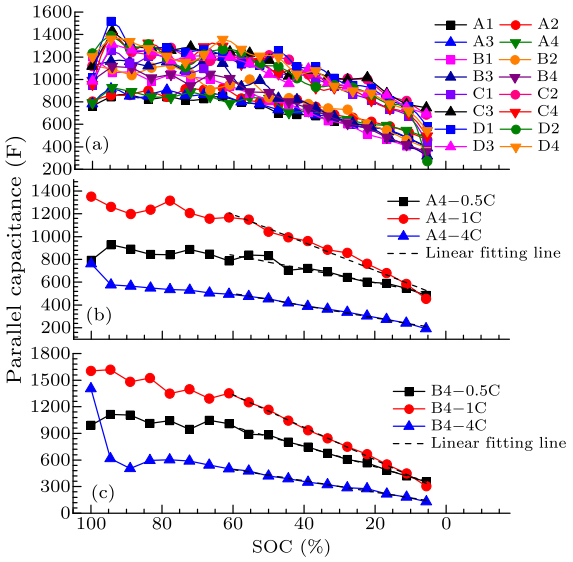

Fig. 3. (a) The calculated C_p as a function of the SOC for four types of batteries (A, B, C and D); (b) and (c) comparison of curves for C_p versus SOC between A4 and B4 at different current rates.

According to the above discussion of three parts, we could conclude that R_p and C_p could be utilized in a two-dimensional way to judge the SOH, and C_p could be an ideal parameter to estimate the SOC for LFP batteries. To further confirm the reliability of this method, parameter values at another two current

rates (1 C and 4 C marked as 2 and 3 in Fig. 1(b)) are calculated. Particularly, we plot the C_p values versus the SOC of healthy batteries (A4 and B4) in Fig. 3(b) and Fig. 3(c). The C_p values at these current rates all show excellent linear relationship with the SOC in the range of 0–60%. There seemingly is consistent change rule in the values from 0.5 C to higher current rates, which shows that C_p value identified from higher current rates could also be used to judge the SOH.

Linear regression models are established to verify the accuracy of this SOC estimation method for healthy batteries and bad batteries, respectively. The significance test of regression equation (F), correlation coefficient (R) and 95% confidence interval are calculated and listed in Table 3. The values of F_c and R_c are obtained by look-up table.

Table 3. Analysis results of regression model and estimation error.

Battery categories	F	F_c	R	R_c	95% confidence interval
Healthy batteries	744.13	3.92	0.94	0.21	[SOC_0-6.33%, SOC_0+6.33%]
Bad batteries	544.30	3.92	0.92	0.21	[SOC_0-7.20%, SOC_0+7.20%]

Here SOC_0 represents the estimation value of SOC, $F > F_c$, indicating that the regression models established are effective, R is close to 1, and $R > R_c$, showing a highly linear correlation between SOC and C_p. The absolute errors of the estimated SOC values for healthy and bad batteries are 6.33% and 7.20%, respectively, further confirming the accuracy of this estimation method.

In summary, we have designed and performed the discharge experiments of healthy and bad LFP batteries to simulate various working conditions of EV. Based on a first-order RC equivalent circuit, we systematically investigate the relationship of three parameters (R_s, R_p and C_p) and the SOC, SOH. Lastly, we find that R_p and C_p could be used to judge the SOH. Moreover, C_p is found to be linearly correlated with the SOC for the first time. Thus the novel method based on R_p and C_p to co-estimate the SOC and SOH can be herein established, which is more precise than the traditional OCV method. The internal mechanism of this method and the physical meanings of three parameters (R_s, R_p and C_p) would be further studied based on the finding. We could predict that the combination with this method and other reported methods, such as the Kalman filter, neural network and fuzzy logic, would greatly reduce complexity and improve the accuracy of the estimation work.

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