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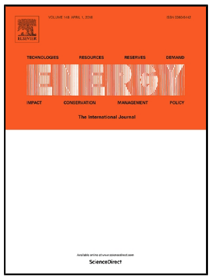

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Adaptive Sliding Mode Observers for Lithium-ion Battery State Estimation Based on Parameters Identified Online

Bo Ning[a,b], Binggang Cao[a,b], Bin Wang[a,b], Zhongyue Zou[a,b]

[a] State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China

[b] School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China

*Correspondence should be addressed to Bo Ning: ningxjtu@163.com

Highlights

An adaptive battery model with parameters estimated online is proposed.

Parameter adaptive sliding mode observers are proposed for battery states estimation.

Lyapunov stability criterion has been employed to verify the robustness of the proposed method.

The proposed approach is verified by lithium-ion battery experiment.

The proposed method could improve the battery estimation results of state of charge and state of health.

Abstract

Simplicity and accuracy are both important factors in real-time battery states estimation applications. However, a battery model initialized with static parameters which are identified in ideal laboratory conditions will not be able to get an accurate estimation in various actual applications. Besides, it is time-consuming and complex in implement. To solve the above problem, a new battery states estimation method is proposed. Firstly, an adaptive battery model is proposed according to a new online parameter estimation algorithm. Based on it, the parameter adaptive sliding mode observer for state of charge is proposed. Thus, the state of charge systematic error led from various work environments could be effectively reduced. The parameter adaptive sliding mode observer for state of health is proposed by tracing the derivative of open circuit voltage estimated online. As the reference open circuit voltage is estimated based on measurable inputs and outputs, rather than conventional observer with an assumed constant capacity. The estimated battery capacity could converge to the actual value while the error of battery open circuit voltage converges to zero. The proposed method is verified through the urban dynamometer driving schedule driving cycle. The results indicate that:1) parameters estimated online are accurate, 2) the absolute error of state of charge is less than 2%, 3) the estimated lithium-ion battery capacity could converge to the actual value with small capacity error.

Keywords

Lithium-ion battery; Parameters estimation online; Adaptive sliding mode observer; State of charge estimation; State of health estimation

Nomenclature

E_0	open circuit voltage
$\hat{E}_0$	estimation of open circuit voltage
E_{Cn}	filtered output of $\hat{E}_0$
$\hat{E}_{Cn}$	estimation of filtered output of $\hat{E}_0$
R_1	ohm resistance
$\hat{R}_1$	estimation of ohm resistance
R_2	polarization resistance
$\hat{R}_2$	estimation of polarization resistance
C_2	polarization capacitor
$\hat{C}_2$	estimation of polarization capacitor
V_0	terminal voltage
$\hat{V}_0$	estimation of terminal voltage
I	current
V_2	polarization voltage
$\hat{V}_2$	estimation of polarization voltage
z	SOC
$\hat{z}$	estimation of SOC
C_{n}	nominal capacity
$\hat{C}_{\mathrm{n}}$	estimation of capacity
α_{n}	system parameter
β_{n}	system parameter
$\boldsymbol{\theta}$	a matrix consist of the slow time-varying parameters
$\boldsymbol{\mu}$	a matrix consist of the parameters could be measured through sensors
$\boldsymbol{\Lambda}$	positive definite matrix
$\omega_i (i=1,2,3)$	noises
$\delta_i (i=1,2,3)$, h_1	positive feedback coefficients
Δf	modeling errors and uncertainties
e	error states

BMS	battery management system
EKF	extended Kalman filter
EV	electric vehicle
UDDS	urban dynamometer driving schedule
HPPC	hybrid pulse power characterization
SOC	state of charge
SOH	state of health
PASMO	parameter adaptive sliding mode observer
MAE	mean absolute error
RMSE	root mean square error

1. Introduction

Due to the merits in high energy and power density, long cycle life, broad operating temperature range and extremely low self-discharge rate [1], Lithium-ion battery has been regarded as the most promising energy storage solution to electrify the transportation sector and reduce the air pollution in urban areas [2]. To improve both the operating performance and cycle life of batteries in EVs (electric vehicles), an accurate estimation of the battery states are of great importance. The states emphasized here refer to the SOC (state of charge) and the SOH (state of health).

The SOC of a battery is the ratio of remaining capacity to nominal capacity. As an key output of BMS (battery management system), the SOC has an extremely considerable effect on safety and reliability [3]. If a more accurate SOC can be obtained, the SOC range we can use will extends compared with before [4]. It means the actual available energy of the same battery pack could be improved without promoting the risk of battery damage caused by over-discharge. Thus, a smaller battery pack will be able to satisfy the power demand of EVs. Accordingly, the cost of the battery pack could be significantly reduced by the saving parts. It will be an useful effort to handle the contradiction between a better mileage and a cheaper price of EVs [5].

A variety of SOC estimation techniques have been proposed, which could be divided into the non-model based methods and the model-based methods. The model-based SOC estimation methods have become the research hotspot gradually for the ability of self-correct under unexpected disturbances [3]. In existing studies, three factors are regarded as the key to obtain an accurate SOC, namely an accurate battery model, accurate battery internal parameters and a robust SOC observer. Thus, a variety of battery models are proposed and used in implementing, for instance, the Rint model, the RC model, the Thevenin model, the PNGV model, the nonlinear equivalent circuit model model and the electrochemical model [6]. HPPC (hybrid pulse power characteristic) and EIS (Electrochemical impedance spectroscopy) methods are used to identify the parameters. Bizhong Xia proposed an improved parameter identification method to analyze the polarization characteristics of lithium-ion batteries [7]. Based on these methods, many SOC observers have been built to optimize the robustness and reduce negative impacts of the estimation. Fuli Zhong proposed a SOC estimation approach based on an adaptive sliding mode observer and a fractional order equivalent circuit model for lithium-ion batteries [8]. Xue Li analyzed the effects of different initial SOC errors and parameters variation on SOC estimation accuracy and robustness with H-infinity observer [9]. Jun Xu proposed a proportional-integral observer to estimate the SOC of lithium-ion batteries in EDVs under unknown initial SOC cases [10]. Di Li proposed a SOC estimation method based on the Strong Tracking Sigma Point Kalman Filter algorithm, which has the advantages of tracking the variables in real-time and adjusting the error covariance by taking the Strong Tracking Factor into account [11]. However, the static battery models initialized with parameters identified in ideal laboratory conditions are unable to satisfy various actual applications. Thus, keeping the coherence of a battery model and its actual characteristics becomes the key to ensure the accuracy of SOC estimation.

The SOH is defined as the ability of a cell to store energy, source and sink high currents, and retain charge over extended periods, relative to its nominal capabilities. An accurate SOH estimation could help to optimize the operation, extend the cycle life and avoid a sudden failure of batteries. The actual capacity variation is the most important and obvious indicator of battery SOH.

The existing researches on SOH estimation are based on chemical analysis or electrical circuits [12]. However, there are still some drawbacks of the chemical analysis methods: 1) Implement to EVs is hard, 2) A lot of history data is needed. Thus, the electrical circuit methods become the research hotspot. Since Plett proposed a dual extended Kalman filter method to estimate the SOC together with the SOH of a battery [13], a series of researches based on the cyclic-state-estimation method have been proposed. Haifeng Dai et al. improved the cyclic-state-estimation method with dual time-scale theory to lithium-ion battery packs. [14] Song et al. proposed a dual sliding mode observer [15]. Lei Pei et al. proposed a real-time peak power/SOP prediction method for lithium-ion batteries based on DEKF [16]. However, some serious issues are ignored in the cyclic-state-estimation based methods. 1) The error propagation between parameter estimation and battery state estimation is ignored. As we know, The inputs and the outputs are interdependent in cyclic-state-estimation methods. It means accurate initial battery parameters are needed to prevent an inaccurate battery state estimation. Similarly, an accurate battery state estimation is necessary for battery parameters estimation. However, it is hard to guarantee. 2) The estimated battery capacity will fluctuate around the assumed constant capacity, rather than converge to its actual value. Because the actual capacity is estimated according to a closed-loop based on a quantitative relationship of SOC error. However, the actual SOC value needed in the SOH observer is estimated based on an assumed constant capacity.

To solve the problem stated above, a new electrical circuit based battery state estimation method is proposed in this paper. In the first place, a new online parameter estimation algorithm is proposed. Additionally, parameters estimated online are filtered by moving average filter to update the battery model. Based on it, two independent PASMOs (parameter adaptive sliding mode observers) for SOC and SOH estimation have been proposed. As parameters estimation, model updating and SOC estimation are almost synchronous, the system error of adaptive battery model can be eliminated effectively. Combined with sliding mode observers for battery states estimation, many significant advantages are performed: 1) online estimation of parameters, 2) no need of accurate initial parameters, 3) simple mathematical operation, 4) accurate SOC and SOH estimation, 5) cheap hardware cost.

A battery experimental platform is constructed to acquire the experimental data. The UDDS (urban dynamometer driving schedule) current profile is used to verify the algorithm for online parameters identification, SOC and SOH estimation.

As shown in Fig. 1, the proposed method includes three synchronous parts, namely the parameter adaptive model specification of a battery, the estimation of SOC and the estimation of SOH. The paper is organized as follows to explain it. In section 2, the new online parameter estimation algorithm is proposed based on a simple first order RC battery model, then the adaptive battery model is built according to the parameters estimated online. In section 3 and 4, PASMOs for SOC and SOH estimation are built based on the online parameter estimation algorithm proposed in section 2, respectively. In section 5, under the UDDS current profile, experiments are performed on the lithium-ion battery to verify the reliability and robustness of the proposed method. The results indicated that accurate SOC and SOH estimation results can be obtained by the proposed approach.

2. Battery Modeling

In the model specification part, a first order RC equivalent circuit model is adopted as the base. Ohm resistance, polarization resistance, polarization capacity and open circuit voltage are parameters of the model. They are assumed to be dynamic to reflect actual characteristics of a battery.

2.1 Equivalent Circuit of A Battery

As shown in Fig. 2, the first order RC battery model consists of a voltage source (E_0), a resistor (R_1), and a parallel capacitor (C_2) and resistor (R_2).

R_1 represents the battery ohm resistance. C_2 and R_2 are utilized to model the polarization effect with the batteries. E_0 which represents the open circuit voltage of the battery is a nonlinear function of SOC. In general, the E_0-SOC curve of a battery changes slowly over time when battery electrochemistry properties vary due to aging or other factors [17]. The relationship between E_0 and SOC could be decomposed as $E_0 = \alpha_n \times z + \beta_n$ by interpolation, where z represents SOC. The related parameters α_n and β_n are listed in Table 1 through linear interpolation.

According to Kirchhoff voltage law in circuit theory, terminal voltage V_0 shown in Fig. 2 could be written as Eq. (1).

$$V_0 = E_0 + IR_1 + V_2 \quad (1)$$

where V_2 denotes the electrochemical polarization voltage. The derivative of it could be expressed as Eq. (2) according to Kirchhoff current law.

$$\dot{V}_2 = -V_2/(R_2C_2) + I/C_2 \quad (2)$$

The SOC of a battery is the ratio of the remaining capacity to the nominal capacity. Assume the initial SOC and the current SOC to be $z(0)$ and $z(t)$ respectively. The SOC could be written as Eq. (3) through the Ah counting approach.

$$z(t) = z(0) + \Delta z = z(0) + \int_0^t (I(\tau)/C_{\mathrm{n}})d\tau \quad (3)$$

where z denotes SOC, Δz is the variation of battery SOC during time period 0 to t, $I(\tau)$ is the instantaneous battery current, C_{n} is the nominal battery capacity. Thus, the derivative of SOC could be written as Eq. (4).

$$\dot{z} = I/C_{\mathrm{n}} \quad (4)$$

2.2 Online Parameter Estimation

Parameters of a battery model, such as ohm resistance, polarization resistance, polarization capacity and open circuit voltage, vary with operating environment and battery state. However, the variation is slight and slow in a normal operating condition [15]. Thus, E_0 together with R_1, R_2, C_2 are assumed to be slow time-varying parameters. I 、 $\dot{I}$ 、 V_0 are set to be measurable inputs and response of a battery system. The derivative of V_0 in Eq. (1) can be rewritten by substituting Eq. (2) and Eq. (4) into itself.

$$\dot{V}_0 = R_1\dot{I} + [(R_1 + R_2)I]/(R_2C_2) - V_0/(R_2C_2) + E_0/(R_2C_2)$$

$$= [R_1 \quad (R_1 + R_2)/(R_2C_2) \quad 1/(R_2C_2) \quad E_0/(R_2C_2)][\dot{I} \; I \; -V_0 \; 1]^{\mathrm{T}} = [\theta_1 \; \theta_2 \; \theta_3 \; \theta_4][\mu_1 \; \mu_2 \; \mu_3 \; \mu_4]^{\mathrm{T}} = \boldsymbol{\theta}\boldsymbol{\mu}^{\mathrm{T}} \quad (5)$$

where $\boldsymbol{\theta}(E_0, R_1, R_2, C_2)$ is a matrix of the slow time-varying parameters needed to be identified. $\boldsymbol{\mu}$ is the symbol of the matrix consist of the inputs could be measured through sensors.

According to Eq. (5), $\dot{V}_0$ observer is constructed as follow.

$$\dot{\hat{V}}_0 = \hat{\boldsymbol{\theta}}\boldsymbol{\mu}^{\mathrm{T}} + \lambda e_{V_0}$$

$$= [\hat{\theta}_1\ \hat{\theta}_2\ \hat{\theta}_3\ \hat{\theta}_4][\dot{I}\ I\ -V_0\ 1]^{\mathrm{T}} + \lambda e_{V_0} \quad (6)$$

where $e_{V_0} = V_0 - \hat{V}_0$ is battery terminal voltage error.

Define $\boldsymbol{e}_\theta = \boldsymbol{\theta} - \hat{\boldsymbol{\theta}}$. Eq. (7) and Eq. (8) are needed for the convergence of the E_0, R_1, R_2, C_2 observed online.

$$\lim_{t\to\infty} \boldsymbol{e}_\theta = \mathbf{0} \quad (7)$$

$$\lim_{t\to\infty} e_{V_0} = 0 \quad (8)$$

Construct Lyapunov function as Eq. (9). $\boldsymbol{\Lambda}$ is a positive definite matrix, therefore V is positive definite.

$$V = \frac{1}{2}e_{V_0}^2 + \frac{1}{2}e_\theta \boldsymbol{\Lambda} e_\theta^{\mathrm{T}} \quad (9)$$

In order to satisfy the Lyapunov stability criterion, $\dot{V}$ expressed as Eq. (10) should be negative definite.

$$\begin{aligned}\dot{V} &= e_{V_0}\dot{e}_{V_0} + e_\theta \boldsymbol{\Lambda} \dot{e}_\theta^{\mathrm{T}} \\ &= e_{V_0}[\theta\mu^{\mathrm{T}} - (\hat{\theta}\mu^{\mathrm{T}} + \lambda e_{V_0})] + e_\theta \boldsymbol{\Lambda}(\dot{\theta}^{\mathrm{T}} - \dot{\hat{\theta}}^{\mathrm{T}}) \\ &\approx e_\theta(\mu^{\mathrm{T}} e_{V_0} - \boldsymbol{\Lambda}\dot{\hat{\theta}}^{\mathrm{T}}) - \lambda e_{V_0}{}^2\end{aligned} \quad (10)$$

Thus,

$$\begin{bmatrix} \dot{\hat{\theta}}_1 \\ \dot{\hat{\theta}}_2 \\ \dot{\hat{\theta}}_3 \\ \dot{\hat{\theta}}_4 \end{bmatrix} = \begin{bmatrix} \rho_1 \dot{I}(V_0 - \hat{V}_0) \\ \rho_2 I(V_0 - \hat{V}_0) \\ -\rho_3 V_0(V_0 - \hat{V}_0) \\ \rho_4(V_0 - \hat{V}_0) \end{bmatrix} \quad (11)$$

where $\rho_i (\mathrm{i} = 1,2,3,4)$ are the feedback parameters which constitute the positive matrix Λ.

It means the accurate quantitative relationship between the unknown $\boldsymbol{\theta}(E_0, R_1, R_2, C_2)$ and the measurable inputs, response of a battery system is constructed.

Thus, slow time-varying parameters of a battery could be estimated as follows.

$$\hat{R}_1 = \hat{\theta}_1 \quad (12)$$

$$\hat{R}_2 = \hat{\theta}_2 / \hat{\theta}_3 - \hat{\theta}_1 \quad (13)$$

$$\hat{E}_0 = \hat{\theta}_4 / \hat{\theta}_3 \quad (14)$$

$$\hat{C}_2 = [(\hat{R}_1 + \hat{R}_2)I - V_0 + \hat{E}_0] / [(\dot{V}_0 - \dot{I}\hat{R}_1)\hat{R}_2] \quad (15)$$

The parameters estimated online need to be filtered by a moving average filter to reduce the impacts of noise before the next step of operation. It won't affect the estimation accuracy as the parameters vary slowly in a short period of time.

2.3 Parameter Adaptive Battery Model

The continuous state space equation of a static first-order RC battery model can be constructed as shown in Eq. (16) based on Eq. (1), Eq. (2) and Eq. (4).

$$\begin{aligned} \dot{V}_0 &= -V_0/(R_2C_2) + E_0/(R_2C_2) + [I(R_1+R_2)]/(R_2C_2) + \omega_1 \\ \dot{z} &= (V_0 - E_0 - V_2)/(R_1C_n) + \omega_2 \\ \dot{V}_2 &= -V_2/(R_2C_2) + I/C_2 + \omega_3 \end{aligned} \quad (16)$$

where I is the input, V_0 is the response, z and V_2 are the state variables of the model, $\omega_i (i = 1,2,3)$ are noises.

The battery model could be updated by using the parameters estimated online. It means that a dynamical battery model is built as Eq. (17).

$$\begin{aligned} \dot{V}_0 &= -V_0/(\hat{R}_2\hat{C}_2) + \hat{E}_0/(\hat{R}_2\hat{C}_2) + [I(\hat{R}_1+\hat{R}_2)]/(\hat{R}_2\hat{C}_2) + \omega_1 \\ \dot{z} &= (V_0 - \hat{E}_0 - V_2)/(\hat{R}_1C_n) + \omega_2 \\ \dot{V}_2 &= -V_2/(\hat{R}_2\hat{C}_2) + I/\hat{C}_2 + \omega_3 \end{aligned} \quad (17)$$

3. Adaptive Sliding Mode SOC Observer

In the SOC estimation part, the PASMO is proposed based on parameters (ohm resistance, polarization resistance, polarization capacity) identified online. The systematic error led from variation of work environment could be effectively reduced.

As the observation matrix is positive definite, state variables of the battery model Eq. (17) are observable.

Based on Eq. (17), state observer of the battery could be constructed as the style shown in Eq. (18).

$$\begin{aligned}
&\dot{\hat{V}}_0 = -V_0/(\hat{R}_2\hat{C}_2) + \hat{E}_0/(\hat{R}_2\hat{C}_2) + [I(\hat{R}_1+\hat{R}_2)]/(\hat{R}_2\hat{C}_2) + \delta_1 \operatorname{sgn}(e_{V_0}) \\
&\dot{\hat{z}} = (V_0 - \hat{E}_0 - \hat{V}_2)/(\hat{R}_1 C_n) + \delta_2 \operatorname{sgn}(e_Z) \\
&\dot{\hat{V}}_2 = -\hat{V}_2/(\hat{R}_2\hat{C}_2) + I/\hat{C}_2 + \delta_3 \operatorname{sgn}(e_{V_2})
\end{aligned} \tag{18}$$

where $\hat{V}_0$、$\hat{E}_0$、$\hat{z}$、$\hat{V}_2$ are the estimated values of V_0、E_0、z、V_2 respectively. Feedbacks are constructed to guarantee the robustness and eliminate the noise. $\delta_i\,(i=1,2,3)$ are positive feedback coefficients. e_{V_0}, e_Z, e_{V_2} are defined as follows respectively.

$$\begin{aligned}
&e_{V_0} = V_0 - \hat{V}_0 \\
&e_Z = z - \hat{z} \\
&e_{V_2} = V_2 - \hat{V}_2
\end{aligned}$$

Eq. (19), Eq. (20) and Eq. (21) are needed for the convergence of the SOC estimation.

$$\lim_{t\to\infty} e_{V_0} = \mathbf{0} \tag{19}$$

$$\lim_{t\to\infty} e_z = 0 \tag{20}$$

$$\lim_{t\to\infty} e_{V_2} = 0 \tag{21}$$

Among them, V_0 could be accurately measured, however z and V_2 could not be measured through sensors directly. Therefore, the quantitative relationship between e_Z, e_{V_2} and e_{V_0} are important for the effective feedback of the battery model.

Thus, construct the following error equations based on Eq. (17) and Eq. (18) in the first place.

$$\begin{aligned}
&\dot{e}_{V_0} = (E_0 - \hat{E}_0)/(\hat{R}_2\hat{C}_2) + [\omega_1 - \delta_1 \operatorname{sgn}(e_{V_0})] \\
&\dot{e}_z = -(E_0 - \hat{E}_0)/(\hat{R}_1 C_n) - (V_2 - \hat{V}_2)/(\hat{R}_1 C_n) + [\omega_2 - \delta_2 \operatorname{sgn}(e_z)] \\
&\dot{e}_{V_2} = -(V_2 - \hat{V}_2)/(\hat{R}_2\hat{C}_2) + [\omega_3 - \delta_3 \operatorname{sgn}(e_{V_2})]
\end{aligned} \tag{22}$$

Definite Lyapunov function $V_{V_0} = \frac{1}{2}e_{v_0}^2$, to guarantee the convergence of e_{V_0}, $\dot{V}_{V_0} = e_{V_0}\dot{e}_{V_0} = e_{V_0}\{(E_0 - \hat{E}_0)/(\hat{R}_2\hat{C}_2) + [\omega_1 - \delta_1 \operatorname{sgn}(e_{V_0})]\}$ should be negative definite. As $(E_0 - \hat{E}_0)/(\hat{R}_2\hat{C}_2) < (4.2-2.8)/(0.015*730) = 0.128$, δ_1 is assumed to be larger than 0.128. After a period of time of observation, there will be

$$\begin{aligned} & e_{V_0} = 0 \\ & \dot{e}_{V_0} = 0 \\ & \omega_1 \to 0 \end{aligned} \quad (23)$$

Thus, the relationship between e_Z and e_{V_0} could be obtained

$$(z - \hat{z}) = \frac{R_2 C_2 \delta_1 \operatorname{sgn}(e_{V_0})}{\alpha_{\mathrm{n}}} \quad (24)$$

Similarly, definite Lyapunov function $V_Z = \frac{1}{2} e_z^2$, to guarantee the convergence of e_Z, $\dot{V}_Z$ should be negative definite. It means that δ_2 should be larger than w_2. After a period of time of observation, there will be

$$\begin{aligned} & e_z = 0 \\ & \dot{e}_z = 0 \\ & \omega_2 \to 0 \end{aligned} \quad (25)$$

Thus, the relationship between e_{V_2} and e_Z could be obtained,

$$(V_2 - \hat{V}_2) = -R_1 C_{\mathrm{n}} \delta_2 \operatorname{sgn}(z - \hat{z}) = -R_1 C_{\mathrm{n}} \delta_2 \operatorname{sgn}\left(\frac{R_2 C_2 \delta_1 \operatorname{sgn}(e_{V_0})}{\alpha_{\mathrm{n}}}\right) \quad (26)$$

According to the Lyapunov stability criterion, while δ_3 is assumed to be larger than w_3, the convergence of e_{V_2} is guaranteed in observation as the same way.

Based on the quantitative relationship between e_Z, e_{V_2} and e_{V_0} constructed before, the adaptive sliding mode SOC observer could be rewritten as follow.

$$\begin{aligned} & \dot{\hat{V}}_0 = -V_0 / (\hat{R}_2 \hat{C}_2) + \hat{E}_0 / (\hat{R}_2 \hat{C}_2) + [I(\hat{R}_1 + \hat{R}_2)] / (\hat{R}_2 \hat{C}_2) + \delta_1 \operatorname{sgn}(e_{V_0}) \\ & \dot{\hat{z}} = (V_0 - \hat{E}_0 - \hat{V}_2) / (\hat{R}_1 C_{\mathrm{n}}) + \delta_2 \operatorname{sgn}[\hat{R}_2 \hat{C}_2 \operatorname{sgn}(e_{V_0}) / \alpha_{\mathrm{n}}] \\ & \dot{\hat{V}}_2 = -\hat{V}_2 / (\hat{R}_2 \hat{C}_2) + I / \hat{C}_2 + \delta_3 \operatorname{sgn}\{-\hat{R}_1 C_{\mathrm{n}} \operatorname{sgn}[\hat{R}_2 \hat{C}_2 \operatorname{sgn}(e_{V_0}) / \alpha_{\mathrm{n}}]\} \\ & \begin{cases} \delta_1 >> 0 \\ \delta_2 >> 0 \\ \delta_3 >> 0 \end{cases} \qquad \operatorname{sgn}(e_{V_0}) = \begin{cases} +1, e_{V_0} > 0 \\ -1, e_{V_0} < 0 \end{cases} \end{aligned} \quad (27)$$

4. Sliding Mode SOH Observer

As capability fading is the indicator of battery SOH, estimating an accurate actual capacity in variable operating conditions is very important. By tracing the continuous derivate of battery open circuit voltage which is identified online in section 2.2, an ASMO for battery capacity estimation is constructed in this section. The estimated battery capacity will converge to its actual value when the error of battery open circuit voltage converges to zero. The reference open circuit voltage is estimated only based on measurable inputs and outputs, rather than an assumed constant capacity value. Thus, the actual capacity could be obtained by feedback based on a quantitative relationship of the open circuit voltage error.

Based on the open circuit voltage $\hat{E}_0$ identified online before and the definition of SOC, a new state variable E_{Cn} which is assigned as the filtered output of $\hat{E}_0$ could be defined as follow.

$$\dot{E}_{Cn} = \alpha_n I / C_{\mathrm{n}} + \Delta f_{E_{Cn}} \quad (28)$$

where $\Delta f_{E_{Cn}}$ is noise. The observer equation could be expressed as follow.

$$\dot{\hat{E}}_{Cn} = \alpha_n I / \hat{C}_{\mathrm{n}} + h_1 (E_{Cn} - \hat{E}_{Cn}) \quad (29)$$

where $\hat{E}_{Cn}$, $\hat{C}_{\mathrm{n}}$ are the estimated values of E_{Cn} and C_{n}. h_1 is a constant positive-feedback gain. When the E_{Cn} error is defined as $e_{E_{Cn}} = (E_{Cn} - \hat{E}_{Cn})$, the following error equation is obtained.

$$\dot{e}_{E_{Cn}} = (\alpha_n I / C_{\mathrm{n}} - \alpha_n I / \hat{C}_{\mathrm{n}}) + \Delta f_{E_{Cn}} - h_1 (E_{Cn} - \hat{E}_{Cn}) \quad (30)$$

Define the Lyapunov candidate function $V_{E_{Cn}} = \frac{1}{2} e_{E_{Cn}}^2$. To guarantee the convergence of $e_{E_{Cn}}$, $\dot{V}_{E_{Cn}} = e_{E_{Cn}} \dot{e}_{E_{Cn}} = e_{E_{Cn}} [(\alpha_n I / C_{\mathrm{n}} - \alpha_n I / \hat{C}_{\mathrm{n}}) + \Delta f_{E_{Cn}} - h_1 (E_{Cn} - \hat{E}_{Cn})]$ should be negative definite. The nominal C_{n} of the battery tested in the paper is 3Ah (10800 As). As actual C_{n} slowly monotonically decreases with battery aging over time, the estimation error $(I / C_{\mathrm{n}} - I / \hat{C}_{\mathrm{n}})$ must be a very small value. When $h_1 >> \Delta f_{E_{Cn}}$, the signs of $\dot{e}_{E_{Cn}}$ and $e_{E_{Cn}}$ are opposing. The condition for convergence of the error equation is satisfied. As in the previous case, after a period of time, there will be the following results.

$$\begin{aligned} \dot{e}_{E_{Cn}} &= 0 \\ e_{E_{Cn}} &= 0 \\ \Delta f_{E_{Cn}} &\to 0 \end{aligned} \quad (31)$$

According to equation (31), after a period of time there will be the following equation

$$(\alpha_n I/C_n - \alpha_n I/\hat{C}_n) - h_1(E_{Cn} - \hat{E}_{Cn}) = 0 \quad (32)$$

Define $e_{Cn} = C_n - \hat{C}_n$, the relationship between e_{Cn} and $e_{E_{Cn}}$ could be obtained based on equation (32).

$$\begin{aligned} e_{Cn} &= (C_n - \hat{C}_n) = -C_n\hat{C}_n(1/C_n - 1/\hat{C}_n) \\ &= -C_n\hat{C}_n[h_1(E_{Cn} - \hat{E}_{Cn})]/\alpha_n I = -C_n\hat{C}_n(h_1 e_{E_{Cn}})/\alpha_n I \end{aligned} \quad (33)$$

As mentioned before, C_n which represents the actual capacity of a battery decreases slowly over time. Therefore, it could be rewritten in derivation as follow.

$$\dot{C}_n = \Delta f_{C_n} \quad (34)$$

According to the relationship between e_{Cn} and $e_{E_{Cn}}$ constructed previously, define the observer equation for C_n as.

$$\dot{\hat{C}}_n = -h_2 C_n \hat{C}_n [h_1(E_{Cn} - \hat{E}_{Cn})]/\alpha_n sgn(I) \quad (35)$$

Define the Lyapunov function as follow.

$$V_{C_n} = \frac{1}{2}e_{C_n}^2 \quad (36)$$

As the signs of $\dot{e}_{C_n}$ and e_{C_n} are opposing, $\dot{V}_{C_n} = \dot{e}_{C_n} e_{C_n} < 0$. Thus, after a period of time of observation, there will be.

$$\hat{C}_n \to C_n \quad (37)$$

Thus, the observer equations for battery actual capacity are obtained.

$$\begin{aligned} \dot{\hat{E}}_{Cn} &= I/\alpha_n\hat{C}_n + h_1(E_{Cn} - \hat{E}_{Cn}) \\ \dot{\hat{C}}_n &= -h_2 C_n \hat{C}_n [h_1(E_{Cn} - \hat{E}_{Cn})]/\alpha_n sgn(I) \end{aligned} \quad (38)$$

5. Validation of The Proposed Algorithm: Set-up Parameters

A battery experimental platform is established to obtain the experimental data (battery current, terminal voltage) which are needed for the verification of the proposed algorithm. As shown in Fig. 3(a), the experimental platform consists of a monitoring computer, a battery test instrument and a thermostat. The monitoring computer is used to control the experiment and record experimental data. The battery test instrument is used to load a battery according to the EV operating modes, including starting, running and braking. The thermostat is used to set the battery in the certain experimental temperature. To effectively compare the results of the algorithm proposed in this paper with the traditional one, the test temperature is set to be 20°C by the thermostat. A simple flow chart of the platform is shown in Fig. 3(b). NCR 18650 lithium-ion batteries are adopted in the experiment. Each cell has a nominal voltage of 3.62 V and a nominal capacity of 3 Ah. It has an upper voltage limit of 4.2V and a lower cut-off voltage of 2.8V.

The whole experiment includes two main parts, namely the HPPC test and the UDDS cycles test. The HPPC test is used to evaluate the accuracy of the parameters identified online. The RLS (recursive least squares) method is used to identify parameters offline. Then, the parameters identified offline will be used as reference to compare with our online estimated values.

The UDDS cycles test is used to simulate the actual operating and accelerate the decline of the battery. The UDDS current profile is shown in Fig. 4. Based on it, we verify our proposed algorithm of online parameters identification, SOC and SOH estimation. In the test, the battery's terminal voltage and current are measured per 50 millisecond. Negative current represents battery discharge while positive current means battery charge.

To apply the algorithm in implementation, a hardware platform including current censors, voltage sensors and a digital signal processor is needed. As the variation of the actual capacity is small in a short period, it could be updated periodically using a multi-time dimension method to reduce the computation of DSP. At the beginning of the estimation period, the estimated capacity is not stable, so the historical parameter could be used to replace it.

6. Validation of The Proposed Algorithm: Results and Discussion

The proposed method is verified through the UDDS driving cycle. The validation procedure consists of three main parts as below.

6.1 Parameters Estimation Online

Computation cost is critical to online estimation test. To guarantee the effectiveness of online estimation, a good sampling precision and a sufficient sampling frequency are needed. In our test, the sampling frequency is set to be 50 ms. It means we have to solve a five-element differential equation every 50 ms. Then the parameters estimated online will be filtered by a moving average filter to reduce the impacts of noise before the next step of operation. As the parameters vary slowly in a short period of time, the sampling frequency maybe modified in actual operation to reduce the computing cost.

Initial parameters and feedback coefficients needed for parameters estimation online are listed in Table 2.

Comparison between curves of online estimated parameters and the reference ones are shown in Fig. 5. The red points plotted in Fig. 5 are identified offline by applying the RLS method with the actual data of HPPC test. According to piecewise linear interpolation, the reference curves battery parameters are obtained. As shown in Fig. 5, the estimated curves of parameters quickly converge to the reference ones with small fluctuations. It indicates the online parameters estimation algorithm proposed in this paper is useful and accurate. The MAE (mean absolute error) and RMSE (root mean square error) of parameters estimated online are shown in Table 3.

After being filtered, they are used to dynamically update the first order RC model. The terminal voltage based on model and the actual measured one are compared in Fig. 6. MAE and RMSE of parameters estimated online. The curves are almost the same. It indicates that the proposed adaptive battery model could accurately reflect the characteristics of the battery.

6.2 State of Charge Estimation Online

Initial parameters and feedback coefficients which are needed for SOC estimation based on the parameter adaptive battery model proposed previously are listed in Table 4. In order to verify the estimation accuracy of the SOC under unknown initial situation, the initial error of estimated SOC are set to be 20% and 40%, respectively.

The estimated SOC curve based on the method proposed previously, the estimated SOC curve based on the typical static one-order RC equivalent circuit battery model and the actual one are compared in Fig. 7 (a), (c). The results indicate that the estimated SOC curves estimated by the proposed method rise rapidly and converges to the actual quickly. Then the estimated SOC curves tend to be stable with few minor fluctuations. The error of SOC estimation is less than 2% as shown in Fig. 7 (b), (d).

To verify the accuracy of the proposed method, we add a traditional static RC model as comparison. In Fig.7, we can see that the SOC estimated by the proposed method is much closer to the reference SOC. Almost in any points, the estimation error of the proposed method is smaller. It means the proposed method is more suitable and effective than the traditional method by taking advantage of the updated battery model.

As a feedback structure is built for keeping the robustness in SOC estimation, the estimated SOC could converge to its reference value in a period of time no matter what the initial SOC value is. It is obvious that the more initial estimation error there is, the more time it needs to converge. Under normal conditions, the initial SOC error of a battery is from self-discharge. In general, it is much smaller than 20%. So the convergence time should be less than 400 seconds generally.

Additionally, the comparisons of MAE and RMSE based on the proposed method and the typical static one-order RC equivalent circuit battery model under dynamic current condition are shown in Table 5.

6.3 State of Health Estimation Online

To obtain the battery actual capacity in working condition, the current profile used for SOH estimation is designed based on UDDS current profile. It includes two main parts. The former part is UDDS cycles, the latter one is a constant-current discharge process. Between the upper voltage limit of 4.2V and the lower cut-off voltage of 2.8V, the UDDS cycles test is operated on the lithium-ion battery. When the battery terminal voltage reaches the cut-off voltage, the UDDS cycles test ends to protect it from over-discharging. After 10 minutes rest, the constant-current discharge process is taken on the lithium-ion battery. 400 cycles of UDDS are taken on the battery to obtain the actual capacity data of each time for the verification of the proposed SOH estimation method.

Initial parameters and feedback coefficients which are needed for SOH estimation are listed in Table 6.

To verify the accuracy of the actual capacity estimation method proposed previously under unknown initial condition, the initial capacity $\hat{C}_n$ is set to be 4 Ah while the actual capacity is much less than it. The comparison of the estimated capacity curve and the actual one is shown in Fig. 8.

The open circuit voltage identification online needs a period of time to converge to its actual value. As the capacity is estimated by feedback based on a quantitative relationship of the open circuit voltage error, there will be influence on our estimation value in the beginning. However, the convergence time is always less than 500s. The estimated capacity starts to calculate after 500 seconds. In the beginning, the estimated capacity has a larger error for its initial setting. In about 2500 seconds, the estimated capacity converges to the actual one and tends to be stable with few minor fluctuations. The rapid convergence and continuous stability reflect the SOH estimation algorithm proposed in this paper is feasible and effective under variable conditions, though initial capacity is unknown.

To apply the algorithm in implementation, a hardware platform including current censors, voltage sensors and a digital signal processor is needed. As the variation of the actual capacity is small in a short period, it could be updated periodically using a multi-time dimension method to reduce the computation of DSP. At the beginning of the estimation period, the estimated capacity is not stable, so the historical parameter could be used to replace it.

As we all know, temperature is one of the factors which could influent the parameters values of a battery. However, the temperature chosen in our experiment (20°C) cloud be thought as a random value for validation. It means the conclusion, our online estimated values will converge to the actual reference values has an extensive adaptability.

7. Conclusion

A new battery states estimation method has been proposed in this paper. It consists of a new online parameter estimation algorithm, a parameter filtering element, an adaptive battery model, and two PASMOs for SOC and SOH estimation, respectively. The ohm resistance, polarization resistance, polarization capacity, open circuit voltage could be estimated online synchronously. The battery capacity is adopted as the direct indicator of battery SOH. Based on these, the SOC and the SOH (battery capacity) could be obtained through the proposed PASMOs, respectively.

Compared with the previous researches, the SOC systematic error led from various work environments could be effectively reduced. The estimated battery capacity could converge to the actual value, rather than fluctuate around the assumed constant capacity. The validity of the proposed method was verified through the UDDS driving cycle. The results indicated that: 1) parameters estimated online are accurate, 2) the absolute error of SOC is less than 2%, 3) the estimated lithium-ion battery capacity could converge to the actual value in 2500s and the estimated battery capacity error rate was less than 3%.

8. Acknowledgement

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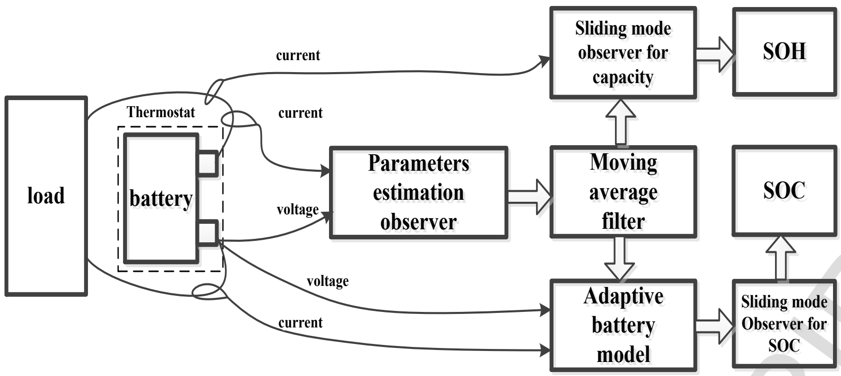


Figure 1 Schematic of the parameter adaptive sliding mode SOC and SOH estimation method

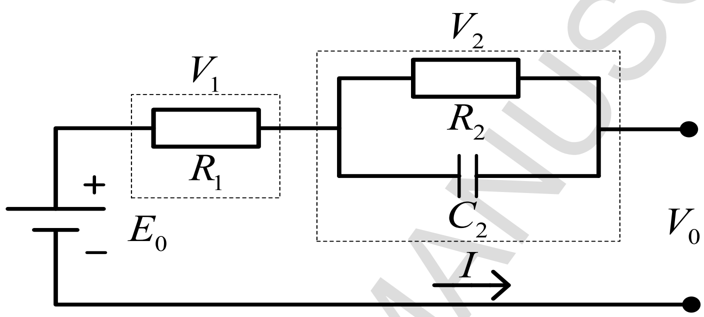


Figure 2 First order RC equivalent circuit battery model

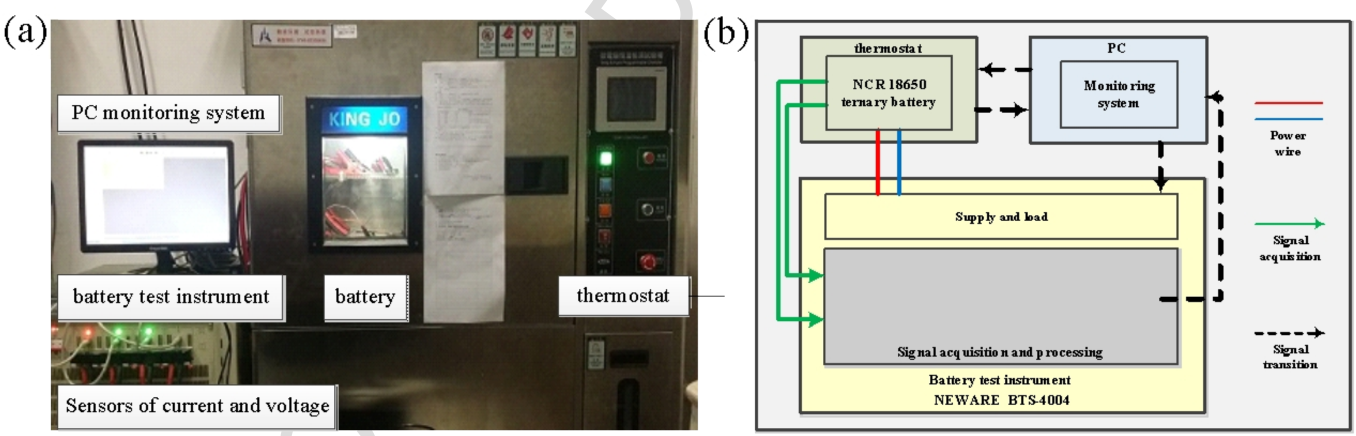


Figure 3 Experimental platform: (a) Experimental instruments; (b) Experimental flow chart.

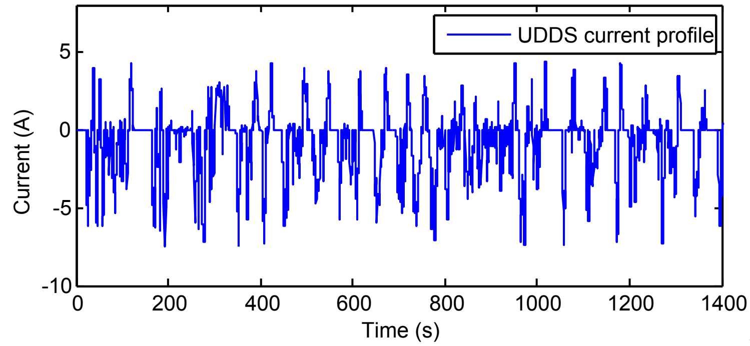


Figure 4 UDDS current profile

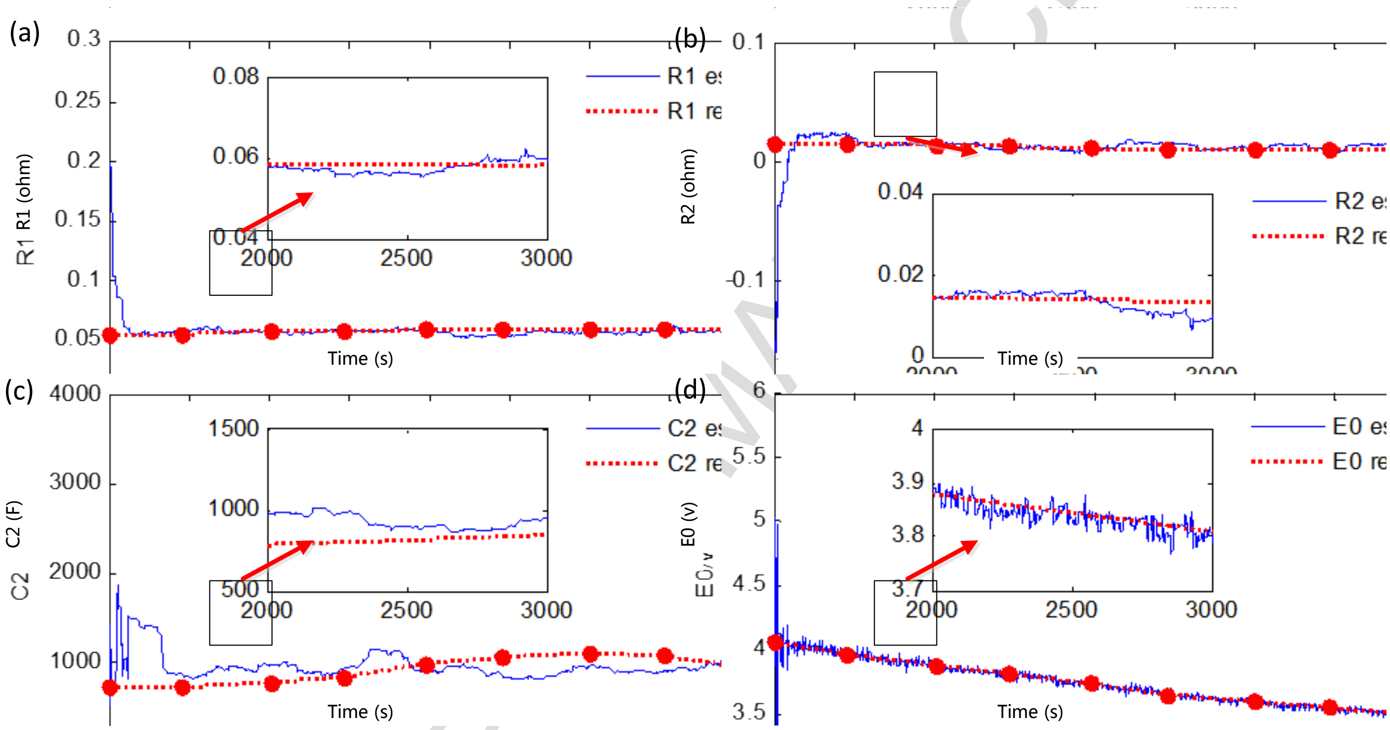


Figure 5 Online parameter estimation: (a) Ohm resistance estimation curve; (b) Polarization resistance estimation curve; (c) Polarization capacitance estimation curve; (d) Open circuit voltage estimation curve

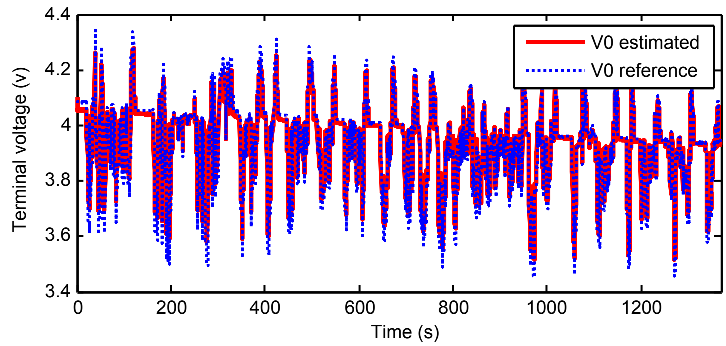
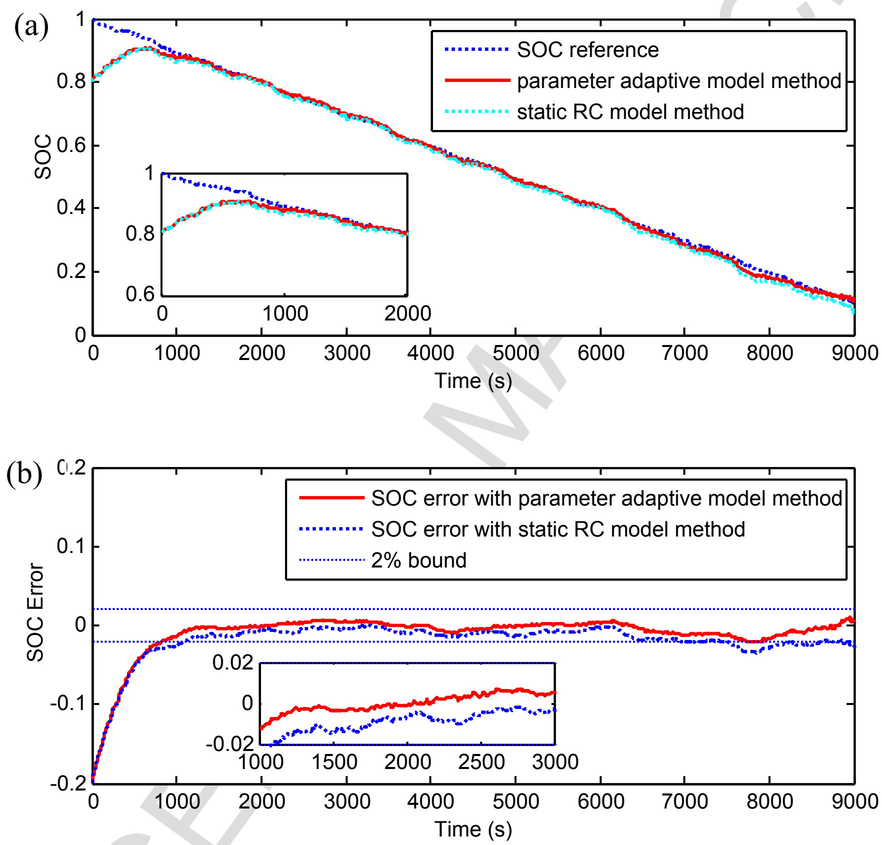


Figure 6 Terminal voltage under UDDS current



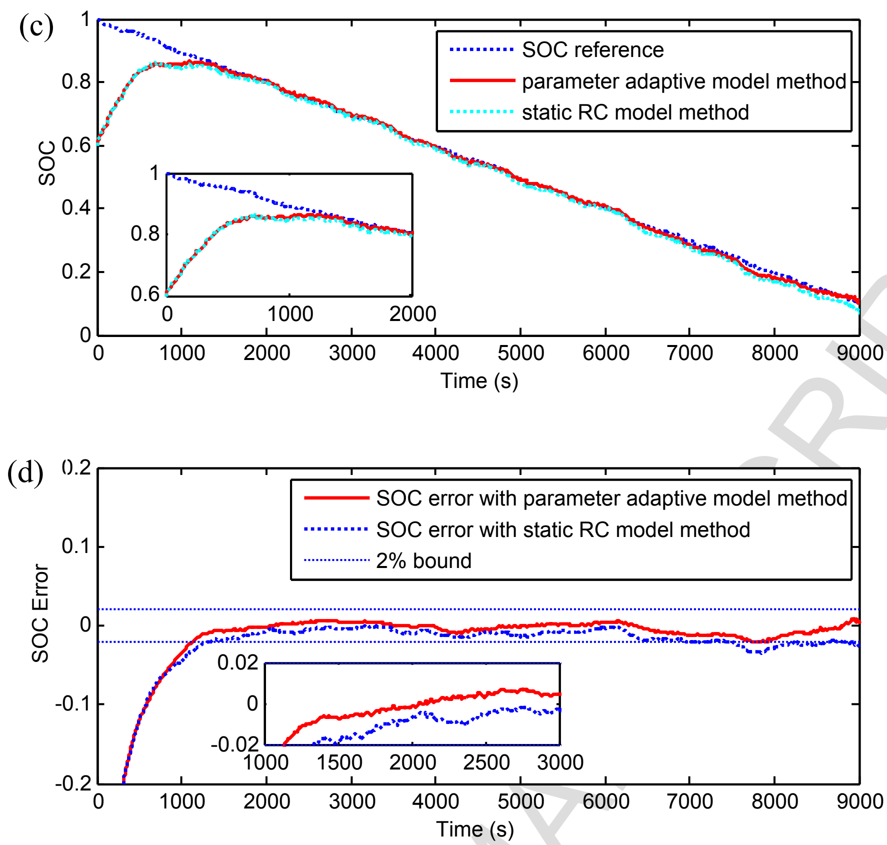


Figure 7 SOC estimation: (a) SOC estimation curve (initial SOC error: 0.2); (b) SOC estimation error curve (initial SOC error: 0.2); (c) SOC estimation curve (initial SOC error: 0.4); (d) SOC estimation error curve (initial SOC error: 0.4).

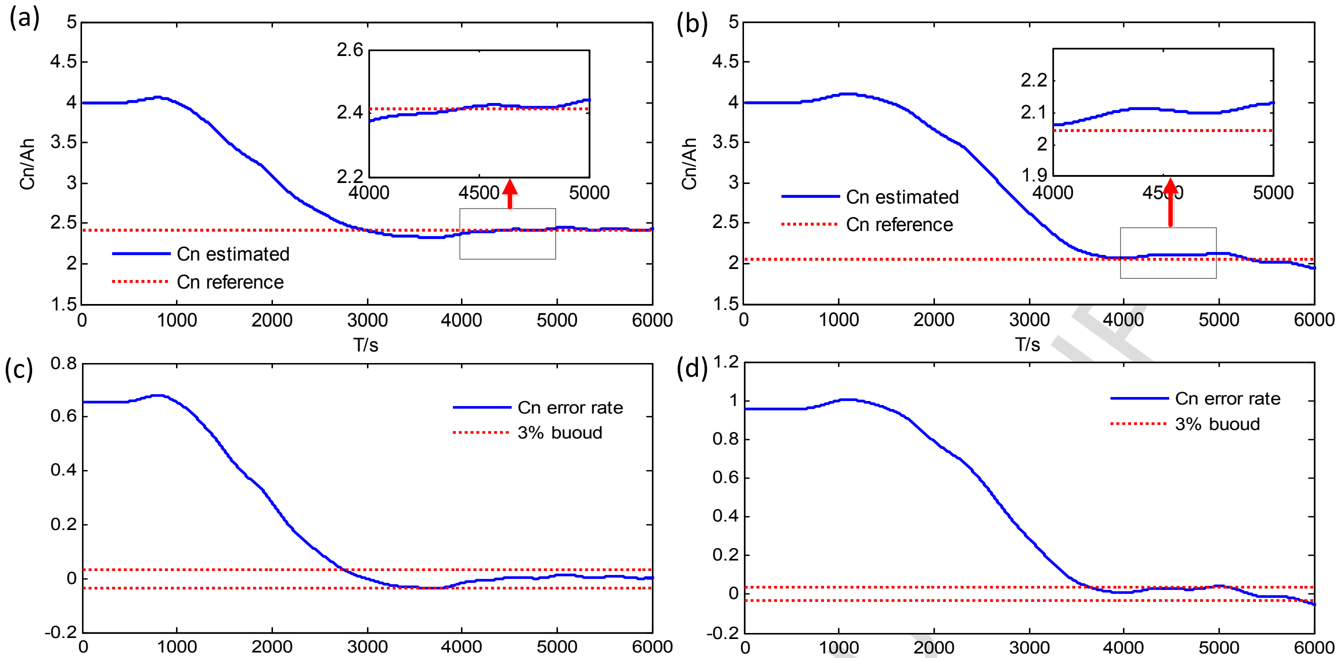


Figure 8 Battery actual capacity estimation: (a) 1th cycle actual capacity(2415mAh); (b) 400th cycle actual capacity (2046mAh); (c) 1th cycle actual capacity error(2415mAh); (d) 400th cycle actual capacity error(2046mAh).

TABLE 1 Relationship between E_0 and SOC

z	0-0.1	0.1-0.2	0.2-0.3	0.3-0.4	0.4-0.5
α_n	1.011	0.663	0.406	0.434	0.608
β_n	3.326	3.351	3.417	3.419	3.354
z	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1
α_n	0.902	0.759	0.642	0.843	0.952
β_n	3.197	3.283	3.365	3.204	3.106

TABLE 2 Initial parameters and coefficients

parameter	value
$\hat{\theta}_{1(0)}$	0.2
$\hat{\theta}_{2(0)}$	0.01
$\hat{\theta}_{3(0)}$	0.2
$\hat{\theta}_{4(0)}$	1
$\hat{V}_{t(0)}$	4
λ	0.2
ρ_1	0.01
ρ_2	0.002
ρ_3	0.02
ρ_4	0.005

Table 3 MAE and RMSE of parameters estimated online

	MAE	RMSE
R1	-0.00024	0.0024
R2	0.0045	0.0065
C2	5.7978	188.765
E0	0.0014	0.0209

TABLE 4 Initial parameters and coefficients

parameter	value
z_0	0.8
V_2	0.0
V_0	4.0
δ_1	0.2
δ_2	0.001
δ_3	0.005

Table 5 Comparisons of MAE and RMSE under dynamic current condition

	Parameter adaptive model (%)	Traditional static model (%)
MAE	-0.0031	-0.0133
RMSE	0.0071	0.0155

TABLE 6 Initial parameters and coefficients

parameter	value
$\hat{E}_{Cn}$	3.9
h_1	0.005
h_2	500