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State-of-Charge and State-of-Health Estimation Algorithms of Lithium-ion Batteries using SMO

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***Abstract*—The state of charge (SoC) and state of health (SoH) monitoring of power lithium-ion batteries is the basis of the battery management system (BMS). The estimation of SoC and SoH is a hot issue in battery management system research today. This paper refers to a third-order electrochemical model based on the average electrode of a lithium battery. Based on this model, the paper establishes a battery SoC and SoH estimation observer based on linear sliding mode and full-order terminal sliding mode algorithms. The paper uses the Luenberger algorithm and terminal sliding mode algorithms to estimate the SoC and SoH of lithium-ion batteries to improve their stability and convergence and uses Lyapunov's theory to verify the convergence of the observer. The accuracy and robustness of SoC and SoH estimations are verified by the dynamic stress test (DST) and federal urban driving conditions (FUDS) test data.**

***Keywords*—Lithium-ion battery; State of charge; State of health; Observers; Sliding mode control.**

I. Introduction

The performance and reliability of new energy vehicles are affected by energy storage systems and energy control system [1]. The energy storage element is the basis of the energy storage system and also an important factor limiting the development of new energy [2]. The key part of the energy storage system is the choice of energy storage components. At present, there are many types of energy storage components, such as lead-acid batteries, nickel-hydrogen batteries, lithium-ion batteries, sodium-sulfur batteries, and fuel cells, etc [3]. Lithium-ion batteries are widely used in energy storage systems due to their small size, high energy density, no pollution, and no memory [4]. Lithium-ion batteries can carry out hundreds of charge and discharge cycles, and the monthly power loss is as low as 55%, while nickel-metal hydride (NIMH) batteries have a monthly power loss of 20% [5].

A car's power system usually contains hundreds of battery cells. A reliable and efficient battery management system(BMS) is needed To coordinate these hundreds of battery cells to work in the best condition [6]. BMS can ensure that the lithium-ion battery usually works and efficiently within a safe voltage and temperature range [7]. The state of charge (SoC) and state of health (SoH) monitoring of power lithium-ion batteries is the foundation of a sound battery management system [8]. As one of the most critical states in the battery, SoC is defined as the ratio of the remaining capacity to the maximum available capacity [9]. It provides the basis for the effective use of battery power by the battery management system and the optimal management of the upper-level energy system [10]. SoH characterizes the health of the battery, facilitates the aging analysis of the car battery, and promptly warns the damaged, aging, and unusable battery, thereby improving the safety and reliability of the battery pack [11]. Since SoC and SoH cannot be measured directly, they need to be estimated indirectly through observable variables, such as voltage, current, and temperature.

There are two main models of lithium-ion batteries: equivalent circuit model (ECM) and electrochemical model (EM) [12]. ECM has the advantages of low computational complexity, simple structure, and a small amount of calculation, but ECM cannot reflect the dynamic process of electrochemical reactions inside the battery. Its parameters have no actual physical meaning and cannot describe the dynamic characteristics of lithium-ion batteries [13]. EM can characterize the internal state of the battery, and its accuracy is improved to a certain extent compared to ECM. Compared with ECM, EM has a broader range of applications when the accuracy is higher, and the computing power is allowed.

The rest of this paper is organized as follows. The second section proposes an electrochemical model based on the average electrode. The third section discusses the comparative analysis of the Luenberger sliding mode observer (SMO) and terminal SMO of the battery SoC and the design of the SoH terminal SMO. The fourth section presents the simulation results and verification.

II. Mathematic Model of Lithium-ion Battery

The simplified average electrode electrochemical model simplifies the solid-phase lithium-ion diffusion process of the positive and negative electrodes into two spherical solid particles and replaces the specific horizontal distribution of the solid-phase lithium-ions in the electrode with the average amount of solid lithium-ions. The model ignores the change of the electrolyte concentration and treats the electrolyte's concentration as a constant value. The average

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electrode electrochemical model can be composed of the ordinary differential equation of lithium-ion concentration, the relationship equation between SoC and lithium-ion concentration, and the port voltage output equation [14].

$$\frac{\partial C_s(x,r,t)}{\partial t} = \frac{1}{r^2}\frac{\partial}{\partial r}\left(D_s r^2 \frac{\partial C_s(x,r,t)}{\partial r}\right)$$

The electrode solid-phase lithium-ion diffusion equation is Ficks second law expressed in spherical coordinates. Discrete the particles in the radial direction and then use the finite difference calculation method to simplify the diffusion equation into a set of ordinary differential equations. Three discrete points are selected for finite difference:

$$\begin{aligned}\dot{c}_{s1} &= -2ac_{s1} + 2ac_{s2}\\ \dot{c}_{s2} &= \frac{1}{2}ac_{s1} - 2ac_{s2} + \frac{3}{2}ac_{s3}\\ \dot{c}_{s3} &= \frac{2}{3}ac_{s2} - \frac{2}{3}ac_{s3} + \frac{4}{3}bI\end{aligned}$$

where $a = D_s/\Delta^2$, D_s is the solid phase lithium-ion diffusion coefficient, Δ is interval length of discrete points, $b = 1/a_s F \Delta A L^-$, A is collecting plate area, L^- is the length of negative electrode, F is faraday constant, I is current. The direction of current is selected to be positive for charging and negative for discharging .

The output port voltage equation of lithium-ion battery can be composed of overvoltage, positive and negative electrode open circuit voltage and Butler-Volmer kinetic equation

$$\begin{aligned}V_t =& \frac{RT}{\alpha_\alpha F} ln \frac{\xi_n + \sqrt{\xi_n^2+1}}{\xi_p + \sqrt{\xi_p^2+1}} + \left[U_p\left(\bar{c}_{se,p}\right) - U_n\left(\bar{c}_{se,n}\right)\right]\\ &-\frac{I}{2A}\left(\frac{\delta_n}{k^{eff}} + 2\frac{\delta_{sep}}{k^{eff}} + \frac{\delta_p}{k^{eff}}\right) - R_f I\end{aligned}$$

where $\xi_n = \bar{j}_n^{Li}/2aj_0$, $\xi_p = \bar{j}_p^{Li}/2aj_0$, R is the universal gas constant, T is single battery temperature, α_a is charge transfer coefficient, $\bar{j}_p^{Li}$, $\bar{j}_n^{Li}$ the average current density of the positive and negative electrodes, a is surface area to volume ratio of electrode active material, j_0 is exchange current density, δ_n, δ_{sep}, δ_p are respectively the thickness of the negative electrode, separator and positive electrode, k^{eff} is effective ion conductivity of electrolyte, $\bar{c}_{se,p}$, $\bar{c}_{se,n}$ are the average solid phase lithium-ion concentration of the positive and negative electrodes, R_f is the internal resistance of the battery, r is the radial size of the electrode particles.

The average electrode electrochemical model is generally used for discharge testing under working conditions, and the charging process is rarely considered. When charging and discharging lithium iron phosphate batteries, the open-circuit voltage of charging and discharging is different under the same surface concentration of lithium-ions. This phenomenon is called hysteresis; the deviation of charge and discharge open circuit voltage is called hysteresis voltage. Therefore, the output voltage equation in the lithium iron phosphate battery electrochemical model should include the expression of hysteresis voltage. The output equation of the average electrode electrochemical model is modified according to the effect of hysteresis voltage as follows:

$$\begin{aligned}V_\mathrm{t} =& \frac{RT}{\alpha_\alpha F}\sin\mathrm{h}^{-1}\left(\frac{I}{A^+}\right) - \frac{RT}{\alpha_\alpha F}\sin\mathrm{h}^{-1}\left(\frac{I}{A^-}\right)\\ &+ U^+\left(k_1 c_{s3} + k_2\right) - U^-\left(c_{s3}\right) + R_f I + V_\mathrm{h}\end{aligned}$$

where $A^+ = 2as^+aL^+i_0^+$, $A^- = 2as^-aL^-i_0^-$, $\sinh(x) = [exp(x) - exp(-x)]/2$, V_h is the average value of the hysteresis voltage.

In the paper, the empirical function of the open-circuit electromotive force of the lithium iron phosphate battery is selected as the analytical expression of the open-circuit electromotive force of the positive and negative electrodes [10]:

$$\begin{aligned}&U^+\left(k_1 c_{s3} + k_2\right) = a_0 + a_1 e^{a_2} + a_3 e^{a_4} + a_5 e^{a_6}\\ &U^-\left(c_{s3}\right) = b_0 + b_1 e^{b_2} + b_3 b_4 + b_5 b_6 + b_7 b_8 + b_9 b_{10}\end{aligned}$$

where,

$$\begin{aligned}&a_0 = 3.4323, a_1 = -0.8428\\ &a_2 = -80.2493\left(1 - \left(k_1 c_{s3} + k_2\right)/c_{s,\max}^+\right)^{1.3198}\\ &a_3 = -3.2474 \times 10^{-6}\\ &a_4 = 20.2645\left(1 - \left(k_1 c_{s3} + k_2\right)/c_{s,\max}^+\right)^{3.8003}\\ &a_5 = 3.2482 \times 10^{-6}\\ &a_6 = 20.2646\left(1 - \left(k_1 c_{s3} + k_2\right)/c_{s,\max}^+\right)^{3.7995}\\ &b_0 = 0.6379, b_1 = 0.5416, b_2 = -305.5309\left(c_{s3}/c_{s,\max}^-\right)\\ &b_3 = 0.004, b_4 = \tan\mathrm{h}\left(-\left(c_{s3}/c_{s,\max}^- - 0.1958\right)/0.1088\right)\\ &b_5 = -0.1978, b_6 = \tan\mathrm{h}\left(\left(c_{s3}/c_{s,\max}^- - 1.057\right)/0.0854\right)\\ &b_7 = -0.6875, b_8 = \tan\mathrm{h}\left(\left(c_{s3}/c_{s,\max}^- + 0.1958\right)/0.0529\right)\\ &b_9 = -0.0175, b_{10} = \tan\mathrm{h}\left(\left(c_{s3}/c_{s,\max}^- - 0.5692\right)/0.0875\right)\end{aligned}$$

The remaining charge (SoC) of a lithium-ion battery is the volume average SoC, which can be obtained from the lithium-ion concentration of all nodes.

$$SoC = \frac{1}{\frac{4}{3}\pi R^3 c^-}\int_0^R 4\pi r^2 c^- s(r)\,dr$$

where R is the radius of lithium-ion.

So far, the average electrode electrochemical model has been established, and the state equation is as follows:

$$\dot{c}_{s1} = -2ac_{s1} + 2ac_{s2} \tag{1}$$

$$\dot{c}_{s2} = \frac{1}{2}ac_{s1} - 2ac_{s2} + \frac{3}{2}ac_{s3} \tag{2}$$

$$\dot{c}_{s3} = \frac{2}{3}ac_{s2} - \frac{2}{3}ac_{s3} + \frac{4}{3}bI \tag{3}$$

$$\begin{aligned}SoC &= \frac{1}{9c_{s,\max}^-}\left(c_{s1} + 4c_{s2} + 9c_{s3}\right)\\ V_{oc} &= U^+\left(k_1 c_{s3} + k_2\right) - U^-\left(c_{s3}\right)\end{aligned}$$

$$\begin{aligned}V_\mathrm{t} =& \frac{RT}{\alpha_\alpha F}\sin\mathrm{h}^{-1}\left(\frac{I}{A^+}\right) - \frac{RT}{\alpha_\alpha F}\sin\mathrm{h}^{-1}\left(\frac{I}{A^-}\right)\\ &+ V_{oc} + R_f I + V_\mathrm{h}\end{aligned}$$

After considering the model error in the actual system and the disturbance problem in the system itself, the construction of an actual battery nonlinear system considering the disturbance is shown below.

$$\left\{\begin{array}{l} \dot{x}=Ax+Bu+f \\ y=h(x,u) \end{array}\right. \tag{4}$$

where x is lithium-ion concentration of each layer of lithium-ion battery, $x = [c_{s1}, c_{s2}, c_{s3}]^T$. u is the input of the system,the charging and discharging current of the battery I,positive symbol indicates that the battery is charging. $y = h(x,u)$ is the output of the system,is the nonlinear relationship between the terminal voltage Vt at both ends of the battery, the state variable x and the system input u, f is the disturbance of the system state variable, $f = [f, 0, 0]^T$, A and B are the state matrix and output matrix of the lithium-ion battery model system, respectively.

$$A=\left[\begin{array}{ccc} -2a & 2a & 0 \\ \frac{1}{2}a & -2a & \frac{3}{2}a \\ 0 & \frac{2}{3}a & -\frac{2}{3}a \end{array}\right] \quad B=\left[\begin{array}{c} 0 \\ 0 \\ \frac{4}{3}b \end{array}\right]$$

III. Estimation Scheme Design

A. Luenberger Sliding-Mode Observers for SoC

The estimated error of the terminal voltage is e_{V_t}, and e_3 is set as the estimated error of the outermost lithium-ion concentration. e_2 is the estimated error of lithium-ion concentration in the middle layer, e_1 is defined as the estimated error of the innermost lithium-ion concentration, then their equation expressions are governed by

$$\begin{aligned} e_{V_t} =&\hat{V}_t - V_t, \quad e_3 = \hat{c}_{s3} - c_{s3}, \\ e_2 =&\hat{c}_{s2} - c_{s2}, \quad e_1 = \hat{c}_{s1} - c_{s1}, \end{aligned} \tag{5}$$

where $\hat{c}_{s1}$ is the estimated value of the lithium-ion concentration in the innermost layer of the lithium-ion battery, and $\hat{c}_{s2}$ is the lithium-ion concentration in the middle layer Estimated value, $\hat{c}_{s3}$ is the estimated value of the outermost lithium-ion concentration.

Based on the state equation established above, the sliding mode observer is designed as follows [15] [16]:

$$\dot{\hat{c}}_{s1} = -2a\hat{c}_{s1} + 2ac_{s2}\dot{e}_1 - L_1 e_{V_t} - L_{v1}\left(e_{V_t}\right) \tag{6}$$

$$\dot{\hat{c}}_{s2} = \frac{1}{2}a\hat{c}_{s1} - 2a\hat{c}_{s2} + \frac{3}{2}a\hat{c}_{s3} - L_2 e_{V_t} - L_{v2}\left(e_{V_t}\right) \tag{7}$$

$$\dot{\hat{c}}_{s3} = \frac{2}{3}a\hat{c}_{s2} - \frac{2}{3}a\hat{c}_{s3} + \frac{4}{3}bI - L_3 e_{V_t} - L_{v3} sign\left(e_{V_t}\right) \tag{8}$$

Theorem 1. When system is (4), the observer is selected as (8), and the feedback gain satisfies (9)(10)(11), the observer error (5) will converge to zero in a finite time.

$$\eta_3 \geq 0, \beta_3 \geq 0, L_{v3} \geq \frac{2}{3}a\left|e_2\right| + \eta_3, 0 \leq L_3 K \leq \frac{2}{3}a - \beta_3 \tag{9}$$

$$\eta_2 \geq 0, L_2 \geq 0, L_{v2} \geq \frac{1}{2}a\left|e_1\right| - L_2\left|e_{V_t}\right| + \eta_2 \geq 0 \tag{10}$$

$$|\Delta f| \leq F, L_1\left|e_{V_t}\right| + L_{v1} + F \geq 0 \tag{11}$$

Proof. According to the definition above,

$$\dot{e}_3 = \frac{2}{3}ae_2 - \frac{2}{3}ae_3 - L_3 e_{V_t} - L_{v3} sign\left(e_{v_t}\right)$$

Construct Lyapunov function $V_3 = \frac{1}{2}e_3^2$:

$$\begin{aligned} \dot{V}_3 &= e_3\dot{e}_3 \\ &= e_3\left(\frac{2}{3}ae_2 - \frac{2}{3}ae_3 - L_3 e_{V_t} - L_{v3}\operatorname{sign}\left(e_{V_t}\right)\right) \\ &= \frac{2}{3}ae_2e_3 - \frac{2}{3}ae_3^2 - L_3 e_{V_t}e_3 - L_{v3}\operatorname{sign}\left(e_3\right)e_3 \\ &\leq \frac{2}{3}a\left|e_2\right|\left|e_3\right| - \frac{2}{3}ae_3^2 + L_3Ke_3^2 - L_{v3}\left|e_3\right| \\ &\leq -\left|e_3\right|\left(L_3 - \frac{2}{3}a\left|e_3\right|\right) - e_3^2\left(\frac{2}{3}a - L_3K\right) \\ &\leq -\left|e_3\right|\eta_3 - e_3^2\beta_3 \\ &\leq 0 \end{aligned}$$

When the parameters meet (9), the system is stable. And $e_3 \to 0$, then

$$\begin{aligned} sign\left(\frac{2}{3}ae_2\right) &= sign\left(L_3 e_{V_t} + L_{v3} sign\left(e_{V_t}\right)\right) \\ &= sign\left(\left(L_3\left|e_{V_t}\right| + L_{v3}\right) sign\left(e_{V_t}\right)\right) \\ &= sign\left(e_{V_t}\right) \end{aligned}$$

The same process can prove for the error system of c_{s2} and c_{s1}, when the parameters satisfy (10) (11), the system is stable.

B. Terminal Sliding-Mode Observers for SoC

According to the state equation established above, the sliding mode observer is designed as follows:

$$\dot{\hat{c}}_{s1} = -2a\hat{c}_{s1} + 2a\hat{c}_{s2} + v_{t1} \tag{12}$$

$$\dot{\hat{c}}_{s2} = \frac{1}{2}a\hat{c}_{s1} - 2a\hat{c}_{s2} + \frac{3}{2}a\hat{c}_{s3} + v_{t2} \tag{13}$$

$$\dot{\hat{c}}_{s3} = \frac{2}{3}a\hat{c}_{s2} - \frac{2}{3}a\hat{c}_{s3} + \frac{4}{3}bI + v_{t3} \tag{14}$$

where, v_{t1}, v_{t2}, v_{t3} is the control variable of the sliding mode observer.

Theorem 2. The system is set as (3), if the observer is selected as (14), and the full-order terminal sliding mode observer control variable c_{t3} satisfies (15), the observer error e_{t3} will converge to zero in a finite time.

$$\left\{\begin{array}{l} v_t = v_{eq} + v_{tn} \\ v_{eq} = -\frac{2}{3}ae_{t3} + \alpha_t e_t^{q_t/p_t} \\ \dot{v}_{tn} = k_t sgns_t \end{array}\right. \tag{15}$$

where, $e_{t3} = c_{s3} - \hat{c}_{s3}$ is the error between the actual value and the estimated value of the outermost lithium-ion concentration, $k_t = 2aF_p + \eta_t$, $\eta_t > 0$, $\alpha_t > 0$ are constants, p_t and q_t are positive odd numbers, satisfying $1 < q_t/p_t < 2$.

Proof. Select sliding surface $s_{t3} = \frac{2}{3}ae_{t2} - c_{t3n}$, then

$$\dot{s}_{t3} = \frac{2}{3}a\dot{e}_{t2} - \dot{c}_{t3n} = \frac{2}{3}a\dot{e}_{t2} - k_t sgns_t$$

Taking the Lyapunov function $V_{t3} = 1/2s_{t3}^2$, the derivative can be obtained:

$$\dot{V}_{t3} = s_{t3}\dot{s}_{t3} \leq 2a\dot{e_{t2}}s_{t3} - k_t\left|s_{t3}\right| \leq -\eta_t\left|s_{t3}\right| \leq 0$$

Meet the sliding mode reach condition.

When reaching the ideal sliding surface $s_{t3} = 0$, there are:

$$e_{oc} = 3v_{tn}/2a$$

The the similar control variable of c_{s2} and c_{s1} can be chosed according to (15), the process can be proved that for the error system of their system are stable.

C. SoH Observer Design

According to SoC calculation formula based on ampere-hour integral :

$$\dot{SoC} = \frac{I}{C_{\mathrm{n}}} = \frac{1}{9c_{s,\max}^{-}}\left(c_{s1} + 4c_{s2} + 9c_{s3}\right) \tag{16}$$

Derivation of SoC can be obtained:

$$\dot{SoC} = \frac{1}{9c_{s,\max}^{-}}\left[\dot{c}_{s1} + 4\dot{c}_{s2} + 9\dot{c}_{s3}\right] \tag{17}$$

Combining $C_n = 3c_{s,\max}^{-}/4b$ and (16), the above equation becomes:

$$\dot{SoC} = \frac{4bI}{3\hat{c}_{s,\max}^{-}}$$

The SoH observer is designed as:

$$\dot{\hat{SoC}} = \frac{4bI}{3\hat{c}_{s,\max}^{-}} + v$$

Definition e_Z is the estimated error of SoC, then $e_Z = \hat{SoC} - SoC$, the error equation of the system can be expressed as:

$$\dot{e}_Z = \frac{4bI}{3}\left(\frac{1}{\hat{c}_{s,\max}^{-}} - \frac{1}{c_{s,\max}^{-}}\right) + v$$

Select the sliding surface:

$$s_z = \dot{e}_z + \alpha e_z^{q/p}$$

where, $\alpha > 0$ is a constant, p and q are positive odd numbers, satisfying $1 < q/p < 2$ [17].

The design of the full-order terminal sliding mode controller is:

$$\begin{cases} v_t = v_{eq} + v_{tn} \\ v_{teq} = -\alpha e_z^{q/p} \\ \dot{v}_{tn} = k_z sgn s_z \end{cases}$$

Select Lyapunov function $V = 1/2s_z^2$:

$$\dot{V} = s_z\left(\frac{4b\dot{I}}{3}A + \frac{4bI}{3}\left(\frac{\dot{c}_{s,\max}^{-} - \dot{\hat{c}}_{s,\max}^{-}}{\hat{c}_{s,\max}^{-}}\right)\right) + s_z\left(k\operatorname{sgn}\left(s_z\right)\right) \tag{18}$$

When the parameter k satisfies (19), $\dot{V} < -\eta|s_z|$, the system is gradually stable.

$$k < -\max\left|\frac{4b\dot{I}}{3}A + \frac{4bI}{3}\left(\frac{\dot{c}_{s,\max}^{-} - \dot{\hat{c}}_{s,\max}^{-}}{\hat{c}_{s,\max}^{-2}}\right)\right| - \eta \tag{19}$$

where, $A = \left(1/\hat{c}_{s,\max}^{-} - 1/c_{s,\max}^{-}\right)$.

Define $e_{c_{s,\max}^{-}}$ to be the estimated error of the maximum lithium-ion concentration of the battery, then

$$e_{c_{s,\max}^{-}} = \hat{c}_{s,\max}^{-} - c_{s,\max}^{-}$$

The proof process of $e_{c_{s,\max}^{-}}$ convergence is the same as that of SoC, so the proof is not repeated here.

Select the Lyapunov function:

$$V = \frac{1}{2}e_{c_{s,\max}^{-}}^{2}$$

Derivation can be obtained from

$$\dot{V} = e_{c_{s,\max}^{-}}\dot{e}_{c_{s,\max}^{-}} = -L|e_{c_{s,\max}^{-}}| \leq 0$$

The system is gradually stable, and the observed value will gradually converge to the true value.

IV. Results and Discussions

In this section, the performance of the proposed SoC and SoH estimation scheme based on sliding mode observer is verified through simulation research.

Dynamic Stress Test (DST) is one kind of test for lithiumion batteries. DST working conditions are easy to test in the laboratory and can effectively reflect power batteries' dynamic charging and discharging characteristics. The data used in this experiment come from [18].The paper verifies the estimated performance of SoC sliding mode observers through a DST test with an initial error of 0.2. The parameters of the model are identified by the recursive gradient descent method [19] [20]. The average electrode electrochemical model parameters obtained by this method are $k_1 = -0.0005$, $k_2 = 21100$, $R_f = 0.2061\Omega$, $i_0^{+} = 3.814A/m^2$, $i_0^{-} = 0.0038A/m^2$.

Figure 3 shows the simulation results of the terminal sliding mode observer and linear sliding mode observer in the case of DST data testing. Figure 4 shows the observation results of the SoH terminal sliding mode observer under the DST data test. It can be seen from these two figures that in the dynamic

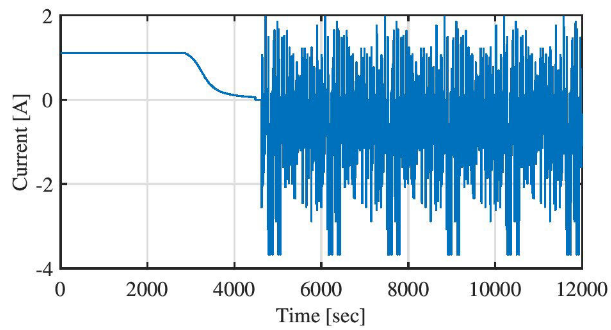

Fig. 1. Measured current of Li-ion cell from FUDS.

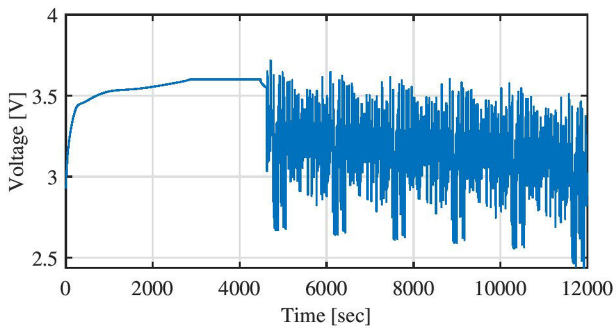

Fig. 2. Measured voltage of Li-ion cell from FUDS.

test, SoC can be estimated in real-time, and its observed value can quickly follow the change of the actual value. The SoC observation value estimation error fluctuates very little, and the ability to resist external interference is relatively strong.

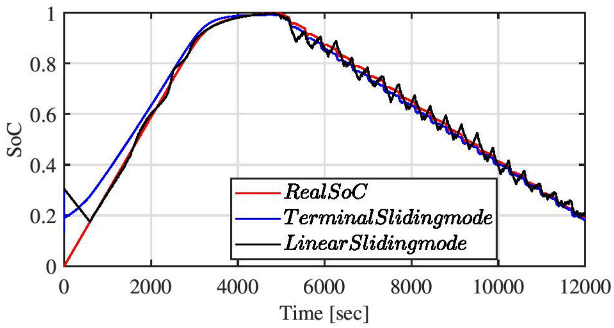

Fig. 3. SOC estimation from DST.

The observation error of SoC and SoH can quickly converge to zero.

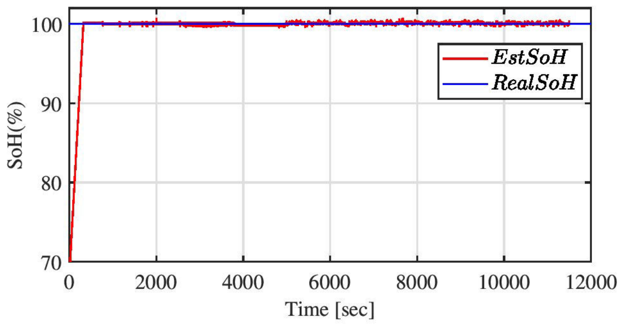

Fig. 4. SOH estimation from DST.

V. Conclusion

The paper has proposed a complete real-time SoC and SoH estimation algorithm for lithium-ion batteries. A thirdorder electrochemical model of a battery based on the average lithium battery electrode is estabilshed. The super-twisting technique is used to design an sliding mode observer to obtain the SoC and SoH. The proposed method has strong robustness compared with linear sliding mode observers. In finally, The experimental results validate the proposed SoC and SoH estimation method.

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