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A Sliding Mode Observer SOC Estimation Method Based on Parameter Adaptive Battery Model

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Abstract

Errors of a battery model will dramatically enlarge as the internal parameters of a battery varying. To reduce the systematic errors, a parameter adaptive battery model is proposed. Based on it, sliding mode algorithm is adopted to estimate the SOC of a battery. The experimental platform is constructed and the UDDS driving cycles is used to verify the method. The results show the error of SOC estimation is less than 2% and it indicates the monitoring algorithm is of great value to power batteries which are generally used in variable environment.

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Keywords: battery model; parameter adaptive battery model; sliding mode observer; SOC estimation

Nomenclature

E_0	Open Circuit Voltage
V_0	Terminal Voltage
V_2	Polarization Voltage
z	SOC
R_1	Ohm Resistance
R_2	Polarization Resistance
C_2	Polarization Capacitor
C_n	Nominal Battery Capacity

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ω_i	Noise
δ_i	Feedback Coefficient
e_{V_0}	The Observable Error of Terminal Voltage
e_Z	The Observable Error of SOC
e_{V_2}	The Observable Error of Polarization Voltage

1. Introduction

Battery management system (BMS) is one of the most important parts of an electric vehicle. As the core of BMS, state of charge (SOC) estimation has an extremely considerable effect on safety, dynamic and economy of the electric vehicles. If an accurate SOC can be obtained, the SOC range can be used of batteries could be extended[1]. Thus, a smaller battery pack will be able to satisfy the demand of electric vehicles. It means the price for building low-carbon cities by improving the market penetration of electric vehicles could be dramatically decreased.

The precision of SOC estimation rely on the accuracy of the battery model[1]. Currently, static battery models are generally adopted in implement, such as Rint、RC[2]、Thevenin[3]、PNGV[4] and nonlinear equivalent circuit model[5]. However, static battery models initialized in laboratory are unable to adapt variable actual using environment[6]. Though many robust SOC observer have been built to reduce the negative impacts, such as sliding mode observer[7], proportional integral observer[8] and extended Kalman filter observer[9], the model systemic error led from the variation of internal parameters is hard to be eliminated.

Thus, keeping the coherence of a battery model and its actual characteristics under actual using environment becomes the key point to ensure the accuracy of SOC estimation. It means dynamic battery models are needed to adapt the change of internal parameters of a battery. Plett proposed a dual extended Kalman filter method[10] and Song proposed a dual sliding mode observer to estimate SOC and state of health (SOH) of a battery[11]. However, these kinds of battery models have obvious drawbacks: 1) ignoring the variation of other parameters except for internal resistance, 2) ignoring the transmission error's impacts on parameter estimation, 3) a complex identification of parameters is needed.

Thus, research on dynamic battery model and related SOC estimation methods are still inadequate. To solve the problems stated above, an adaptive battery model is established and a sliding mode observer for SOC estimation is proposed in this paper. As shown in Figure 1, parameters estimation, model updating and SOC estimation are synchronous. Compared with previous models, advantages are obvious: 1) eliminating systemic error of battery model effectively, 2) online estimation of parameters, 3) no need of accurate initial parameters, 4) transmission errors are avoided by independent parameter observer, 5) simple mathematical operation.

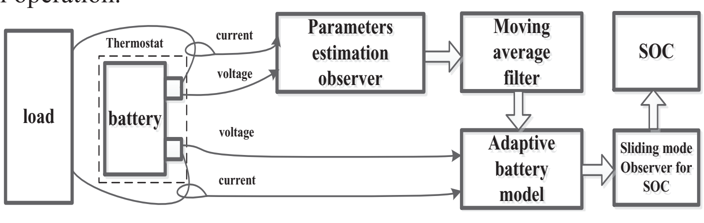


Fig. 1. Parameter adaptive battery model and sliding mode SOC estimation method

2. Theoretical analysis

2.1. Equivalent circuit of a battery

A simple first order RC equivalent circuit battery model is adopted for a further study in this paper. The RC model is shown in Figure 2. It consists of a voltage source (E_0), a resistor (R_1), and a parallel capacitor (C_2) and resistor (R_2).

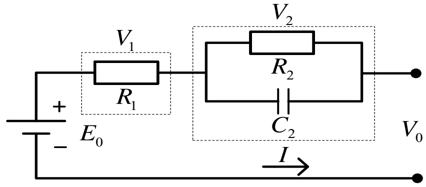


Fig. 2. One order RC equivalent circuit battery model

E_0 is a nonlinear function of SOC[12]. The relationship of E_0 and SOC could be decomposed as $E_0 = \alpha_n \times z + \beta_n$ by linear interpolation. The related parameters are listed in Table 1.

Table 1. Relationship between E0 and SOC

z	0-0.1	0.1-0.2	0.2-0.3	0.3-0.4	0.4-0.5
α_n	0.59	0.46	0.62	0.73	0.79
β_n	3.4	3.413	3.381	3.348	3.324
z	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1
α_n	0.64	0.65	0.76	0.87	0.60
β_n	3.399	3.393	3.316	3.228	3.471

In Figure 2, the relationship between polarization voltage and current can be obtained according to Kirchhoff's law

$$\dot{V}_2 = -V_2/(R_2C_2) + I/C_2 \tag{1}$$

Terminal voltage V_0 could be written as follow

$$V_0 = E_0 + IR_1 + V_2 \tag{2}$$

C_n is assumed to be constant in this paper. SOC can be depicted by derivation

$$\dot{z} = I/C_n \tag{3}$$

2.2. Online estimation of model parameters

As terminal voltage varies slightly in a short period, R_1、 R_2、 C_2 and E_0 are assumed to be slowly varying parameters. The derivative of equation (2) can be rewritten by substituting equation (1) and (4) into itself

$$\begin{aligned}\dot{V}_0 &= R_1\dot{I} + [(R_1+R_2)I]/(R_2C_2) - V_0/(R_2C_2) + E_0/(R_2C_2)\\ &= [R_1 \;\; (R_1+R_2)/(R_2C_2) \;\; 1/(R_2C_2) \;\; E_0/(R_2C_2)][\dot{I} \;\; I \;\; -V_0 \;\; 1]^{\mathrm{T}}\\ &= [\theta_1 \;\; \theta_2 \;\; \theta_3 \;\; \theta_4][\mu_1 \;\; \mu_2 \;\; \mu_3 \;\; \mu_4]^{\mathrm{T}} = \boldsymbol{\theta}\boldsymbol{\mu}^{\mathrm{T}}\end{aligned} \tag{4}$$

where $\boldsymbol{\theta}(E_0, R_1, R_2, C_2) = [\theta_1 \;\; \theta_2 \;\; \theta_3 \;\; \theta_4]$ is a matrix consists of parameters under estimation. Define error $e_{V_0} = V_0 - \hat{V}_0$, then a $\dot{V}_0$ observer is constructed

$$\begin{aligned}\dot{\hat{V}}_0 &= \hat{\boldsymbol{\theta}}\boldsymbol{\mu}^{\mathrm{T}} + \lambda e_{V_0} \\ &= [\hat{\theta}_1\ \hat{\theta}_2\ \hat{\theta}_3\ \hat{\theta}_4][\dot{I}\ I\ -V_0\ 1]^{\mathrm{T}} + \lambda e_{V_0}\end{aligned} \tag{5}$$

If $e_\theta = \boldsymbol{\theta} - \hat{\boldsymbol{\theta}}$, equation (6) and (7) are needed for the convergence of the estimated parameters

$$\lim_{t\to\infty} e_\theta = 0 \tag{6}$$

$$\lim_{t\to\infty} e_{V_0} = 0 \tag{7}$$

Definite Lyapunov function as follow

$$V = \frac{1}{2}e_{V_0}^2 + \frac{1}{2}e_\theta \boldsymbol{\Lambda} e_\theta^{\mathrm{T}} \tag{8}$$

Where $\boldsymbol{\Lambda}$ is a positive definite matrix. Thus

$$\begin{aligned}\dot{V} &= e_{V_0}\dot{e}_{V_0} + e_\theta \boldsymbol{\Lambda}\dot{e}_\theta^{\mathrm{T}} \\ &= e_{V_0}[\theta\mu^{\mathrm{T}} - (\hat{\theta}\mu^{\mathrm{T}} + \lambda e_{V_0})] + e_\theta \boldsymbol{\Lambda}(\dot{\theta}^{\mathrm{T}} - \dot{\hat{\theta}}^{\mathrm{T}}) \\ &\approx e_\theta(\mu^{\mathrm{T}} e_{V_0} - \boldsymbol{\Lambda}\dot{\hat{\theta}}^{\mathrm{T}}) - \lambda e_{V_0}{}^2\end{aligned} \tag{9}$$

In order to satisfy the law of Lyapunov's stability criterion, $\dot{V}$ shoule be negative definite. Thus, a model for estimation of parameters is constructed

$$\begin{bmatrix}\dot{\hat{\theta}}_1 \\ \dot{\hat{\theta}}_2 \\ \dot{\hat{\theta}}_3 \\ \dot{\hat{\theta}}_4\end{bmatrix} = \begin{bmatrix}\rho_1 \dot{I}(V_0 - \hat{V}_0) \\ \rho_2 I(V_0 - \hat{V}_0) \\ -\rho_3 V_0(V_0 - \hat{V}_0) \\ \rho_4(V_0 - \hat{V}_0)\end{bmatrix} \tag{10}$$

$$\hat{R}_1 = \hat{\theta}_1 \tag{11}$$

$$\hat{R}_2 = \hat{\theta}_2 / \hat{\theta}_3 - \hat{\theta}_1 \tag{12}$$

$$\hat{E}_0 = \hat{\theta}_4 / \hat{\theta}_3 \tag{13}$$

$$\hat{C}_2 = [(\hat{R}_1 + \hat{R}_2)I - V_0 + \hat{E}_0] / [(\dot{V}_0 - \dot{I}\hat{R}_1)\hat{R}_2] \tag{14}$$

As battery internal parameters vary slowly in a short period, a moving average filter is built to reduce noise of estimated parameters for the next step of operation.

2.3. Adaptive sliding mode SOC observer

The continuous state space equation of the battery model is established according to the equation (1), (2) ,(4)

$$\begin{aligned}\dot{V}_0 &= -V_0/(R_2C_2) + E_0/(R_2C_2) + [I(R_1+R_2)]/(R_2C_2) + \omega_1 \\ \dot{z} &= (V_0 - E_0 - V_2)/(R_1C_{\mathrm{n}}) + \omega_2 \\ \dot{V}_2 &= -V_2/(R_2C_2) + I/C_2 + \omega_3\end{aligned} \tag{15}$$

And it can be updated dynamically by parameters estimated online

$$
\begin{aligned}
&\dot{V}_0 = -V_0 \big/ (\hat{R}_2 \hat{C}_2) + \hat{E}_0 \big/ (\hat{R}_2 \hat{C}_2) + [I(\hat{R}_1 + \hat{R}_2)] \big/ (\hat{R}_2 \hat{C}_2) + \omega_1 \\
&\dot{z} = (V_0 - \hat{E}_0 - V_2) \big/ (\hat{R}_1 C_n) + \omega_2 \\
&\dot{V}_2 = -V_2 \big/ (\hat{R}_2 \hat{C}_2) + I \big/ \hat{C}_2 + \omega_3
\end{aligned}
\tag{16}
$$

State variables of the battery model are observable, because the observation matrix is positive definite. A state observer can be constructed as follow

$$
\begin{aligned}
&\dot{\hat{V}}_0 = -V_0 \big/ (\hat{R}_2 \hat{C}_2) + \hat{E}_0 \big/ (\hat{R}_2 \hat{C}_2) + [I(\hat{R}_1 + \hat{R}_2)] \big/ (\hat{R}_2 \hat{C}_2) + \delta_1 \operatorname{sgn}(e_{V_0}) \\
&\dot{\hat{z}} = (V_0 - \hat{E}_0 - \hat{V}_2) \big/ (\hat{R}_1 C_n) + \delta_2 \operatorname{sgn}(e_Z) \\
&\dot{\hat{V}}_2 = -\hat{V}_2 \big/ (\hat{R}_2 \hat{C}_2) + I \big/ \hat{C}_2 + \delta_3 \operatorname{sgn}(e_{V_2})
\end{aligned}
\tag{17}
$$

Where e_{V_0} can be easily got through a voltage sensor, however e_{V_0} and e_{V_2} could not be got directly. According to the law of Lyapunov's stability criterion, when formula (19) is satisfied, the relationship between e_Z and e_{V_0} , e_{V_2} and e_{V_0} can be constructed

$$
\begin{aligned}
&\operatorname{sgn}(e_Z) = \operatorname{sgn}[\hat{R}_2 \hat{C}_2 \operatorname{sgn}(e_{V_0}) \big/ \alpha_n] \\
&\operatorname{sgn}(e_{V_2}) = \operatorname{sgn}\{-\hat{R}_1 C_n \operatorname{sgn}[\hat{R}_2 \hat{C}_2 \operatorname{sgn}(e_{V_0}) \big/ \alpha_n]\}
\end{aligned}
\tag{18}
$$

$$
\begin{cases} \delta_1 >> 0 \\ \delta_2 >> 0 \\ \delta_3 >> 0 \end{cases}
\qquad
\operatorname{sgn}(e_{V_0}) = \begin{cases} +1, e_{V_0} > 0 \\ -1, e_{V_0} < 0 \end{cases}
\tag{19}
$$

Then an adaptive sliding mode SOC observer could be described as follow

$$
\begin{aligned}
&\dot{\hat{V}}_0 = -V_0 \big/ (\hat{R}_2 \hat{C}_2) + \hat{E}_0 \big/ (\hat{R}_2 \hat{C}_2) + [I(\hat{R}_1 + \hat{R}_2)] \big/ (\hat{R}_2 \hat{C}_2) + \delta_1 \operatorname{sgn}(e_{V_0}) \\
&\dot{\hat{z}} = (V_0 - \hat{E}_0 - \hat{V}_2) \big/ (\hat{R}_1 C_n) + \delta_2 \operatorname{sgn}[\hat{R}_2 \hat{C}_2 \operatorname{sgn}(e_{V_0}) \big/ \alpha_n] \\
&\dot{\hat{V}}_2 = -\hat{V}_2 \big/ (\hat{R}_2 \hat{C}_2) + I \big/ \hat{C}_2 + \delta_3 \operatorname{sgn}\{-\hat{R}_1 C_n \operatorname{sgn}[\hat{R}_2 \hat{C}_2 \operatorname{sgn}(e_{V_0}) \big/ \alpha_n]\} \\
&\begin{cases} \delta_1 >> 0 \\ \delta_2 >> 0 \\ \delta_3 >> 0 \end{cases}
\qquad
\operatorname{sgn}(e_{V_0}) = \begin{cases} +1, e_{V_0} > 0 \\ -1, e_{V_0} < 0 \end{cases}
\end{aligned}
\tag{20}
$$

3. Experimental verification

NCR18650 lithium-ion battery is adopted in the experiment. It has a rated voltage of 3.7V and a cut off voltage of 2.8V. Urban dynamometer driving schedule (UDDS) current profile shown in Figure 3 is used to verify the accuracy of the algorithm for online parameter identification and SOC estimation of the power battery.

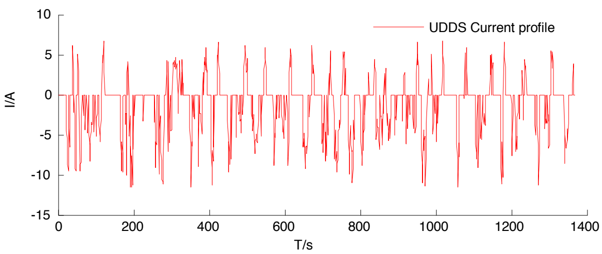
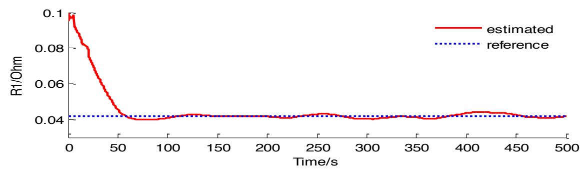


Fig. 3. UDDS current profile

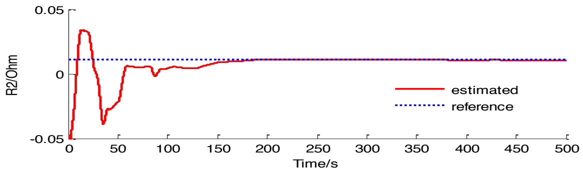
Initialization parameters and feedback coefficients $\hat{\theta}_{1(0)} = 1$ $\hat{\theta}_{2(0)} = 0.01$ $\hat{\theta}_{3(0)} = 0.2$ $\hat{\theta}_{4(0)} = 1$ $\lambda = 0.1$ $\rho_1 = 0.02$ $\rho_2 = 0.005$ $\rho_3 = 0.005$ $\rho_4 = 0.05$.

Comparison between estimated curves of parameters and actual curves filtered by sliding average filter are shown in Figure 4. The reference curve is calculated and interpolated offline through hybrid pulse power characterization (HPPC) test.

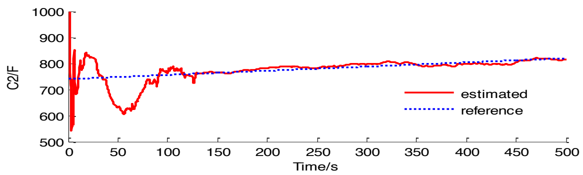
In Figure 4, the estimated curves of parameters quickly converge to the reference curves with small fluctuations. Then they are used to dynamically update the SOC estimation model. The estimated terminal voltage based on parameter adaptive battery model proposed before and the actual one are compared in Figure 5. The curves fit well, which indicates that the adaptive battery model updated online could truly reflect the characteristics of the battery.



(a) Ohm resistance estimation curve



(b) Polarization resistance estimation curve



(c) Polarization capacitance estimation curve

Fig. 4. Online parameter estimation curves

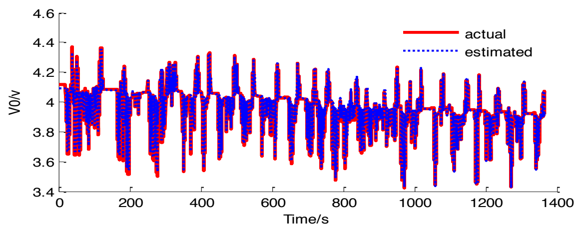
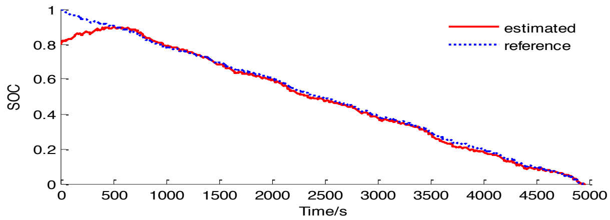


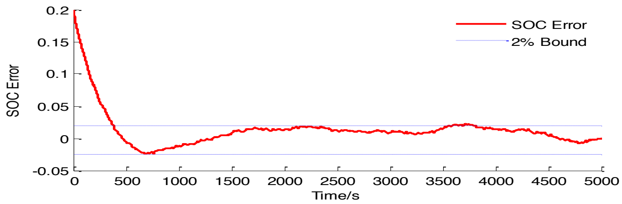
Fig. 5. Terminal voltage under UDDS current

Initialize state variable $z_0 = 0.8$ $V_2 = 0$ $V_0 = 4$, initialize coefficients $\delta_1 = 0.05$ $\delta_2 = 0.001$ $\delta_3 = 0.005$. In order to verify the estimation accuracy of the SOC under unknown initial situation, the initial error of estimated SOC is set to be 20%.

The comparison of the estimated SOC curve and the actual curve are shown in Figure 6.



(a) SOC estimation curve



(b) SOC estimation error curve

Fig. 6. The results of the proposed method

It shows that the estimated SOC curve rises rapidly and converges to the actual SOC curve in 400 seconds. The rapid convergence and small overshoot reflect a great robustness of the algorithm. After 400 seconds the estimated SOC tends to be stable with few minor fluctuations. The error of SOC estimation is less than 2% as shown in Figure 6 (b).

Different initial SOC error has a considerable effect on the convergence time. Under normal conditions, the initial SOC error of a battery is led from self-discharge, which is generally much lower than 20%. So the convergence time should be less than 400 seconds.

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 parameters is small in a short period, the model 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 parameters are not stable, so the historical parameters are used to replace them.

4. Conclusion

In this paper, a complete adaptive battery model is established based on battery parameters identified online to take the variation of battery internal characteristics under variable environment into consideration. Based on it, the sliding mode SOC observer is constructed to eliminate the error of the battery model and reduce the noise of measurement. The battery environmental platform is built and Lithium-ion battery is adopted to verify the effectiveness of the proposed method in estimating battery internal parameters and SOC under the UDDS driving cycles. The experiment results indicates that the online estimated parameters all converged to the true value in 400 seconds and the SOC estimation error is less than 2% .

Acknowledgements

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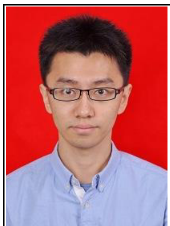
5. Author Artwork



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