Research on SOC Estimation Method of Lithium Battery Based on IAE-AEKF

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Abstract

In order to solve the problem that the noise covariance of extended Kalman filter cannot be adaptive changed in SOC estimation of lithium battery, which leads to large error and slow convergence of lithium battery SOC estimation, the IAE window estimation adaptive extended Kalman filter method is used to estimate lithium battery SOC. The measurement noise error covariance and process noise error covariance of the system were adaptively matched by the windowed estimation method to improve the SOC estimation accuracy of lithium battery. The simulation results show that compared with the extended Kalman filter, the average error of SOC estimation of lithium battery with adaptive extended Kalman filter is increased by 1.82%. Therefore, the adaptive extended Kalman filter can better reflect the actual state of the system and has a wider application prospect.

Keywords

Lithium battery; Moving window estimation; Adaptive extended Kalman filter; SOC estimation.

1. INTRODUCTION

Environmental pollution and energy crisis are two serious problems facing the world in recent years. Electric vehicles are considered to be the main solution to achieve low-carbon travel, solve environmental pollution and alleviate energy crisis [1]. Due to the characteristics of long cycle life, high power durability and high power density, lithium batteries have received extensive attention and research in various industries [2]. Lithium battery SOC estimation has always been the core technology of battery management system (BMS), and accurate SOC estimation can avoid battery overcharge and overdischarge, and improve battery safety[2]. SOC estimation methods mainly include time-based integration method, open-circuit voltage method, data-driven method and model-based method[3][4] . The open circuit voltage method uses the OCV-SOC relationship to find the table and interpolate to obtain the SOC, but in order to obtain a stable OCV, the battery needs to be left standing for more than 2 hours, which limits the online application of the OCV method[5]. The time integration method calculates the remaining capacity by accumulating the incoming or outgoing charge of the battery, which requires high accuracy of SOC initial value and is easy to lead to cumulative errors[6]. The data-driven method[7] requires a large amount of reliable data support and is difficult to generalize. Model-based methods can obtain strong robustness and accuracy under different complex conditions, which has attracted wide attention [8]. Therefore, the model-based method is selected as the SOC estimation method for lithium batteries.

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2. THE BATTERY MODEL IS FITTED TO THE OPEN CIRCUIT VOLTAGE

2.1. Lithium battery model selection

Lithium battery models mainly include electrochemical model, equivalent circuit model, black box model and so on. The equivalent circuit models mainly include Rint model, Devinin model and PNGV model [10]. Among them, Devinin model has low computing cost, can quickly reflect the working state of lithium battery, and can maintain the accuracy of the model for a long time in simulation, so it is widely used in various literature research. An equivalent circuit model of lithium battery, such as the first-order Thevenin model, is selected, which contains an ohm internal resistance R0, a polarization internal resistance Rp and a polarization capacitor Cp, and the polarization internal resistance Rp and the polarization capacitor Cp together constitute an RC network model. The structural model is shown in Figure 1.

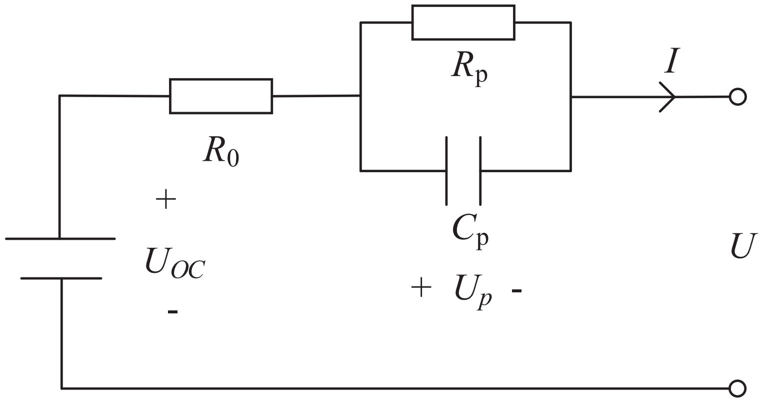

Figure 1. First-order Thevenin equivalent circuit

2.2. Open circuit voltage fitting

The fitting of open circuit voltage OCV and SOC is carried out through the experimental data of lithium battery pulse discharge. Pulse discharge experiment refers to the lithium battery is fully charged, the lithium battery takes a certain interval of time to discharge the way, each discharge interval is long enough to ensure that the electrochemical reaction and polarization reaction inside the lithium battery basically no longer react, at this time the measured lithium battery terminal voltage is open circuit voltage. MATLAB cftool toolbox was used to fit the open circuit voltage and SOC in the 8th order, and the fitting curve was shown in Figure 2.

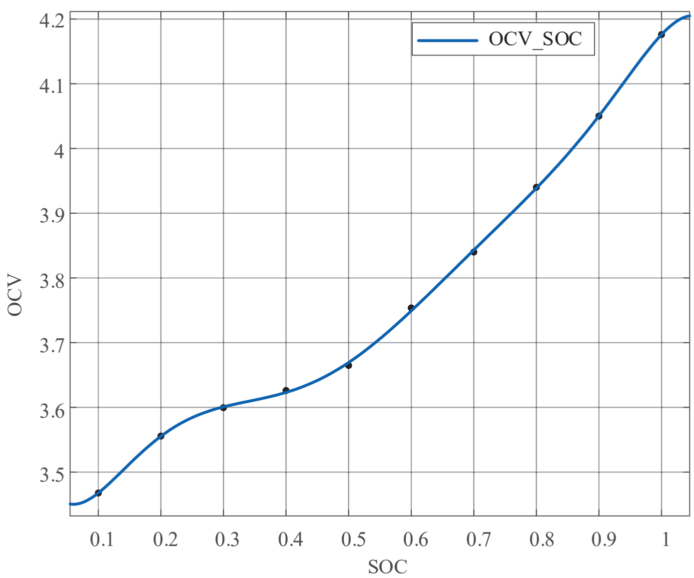

Figure 2. Fitting curve of OCV_SOC relationship

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3. PARAMETER IDENTIFICATION OF LITHIUM BATTERY BY LEAST SQUARE METHOD

3.1. Least square method

The least square method can minimize the whole error by calculating the minimum sum of squares of the deviation of all equations, which is of great significance to the error suppression, so it is widely used in parameter identification. The parameter estimation formula of least square method is shown in equation(1).

$$\theta = (\phi^{\mathrm{T}}\phi)^{-1}\phi^{\mathrm{T}}Y \tag{1}$$

Where, θ is the parameter to be estimated, ϕ is the data vector, and Y is the actual measured value.

As the number of observations increases, more and more observations will be generated, and when the data vector is relatively large, the amount of computation will become particularly large. Therefore, the least square method is not suitable for online parameter identification of lithium-ion batteries. In order to solve the problem that LS has a large amount of computation, it can be applied to recursive least square method. In the process of system parameters, as the number of observations increases, the k-1 estimate results can be modified based on the k-1 estimate and according to the new round of observation data z(k), so as to obtain the current estimate. Namely.

$$\theta_k = \theta_{k-1} + \Delta\theta \tag{2}$$

Where, θ_k is the estimated value, θ_{k-1} is the previous estimated value, and $\Delta\theta$ is the revised value. Therefore, recursive least square method can be summarized as

$$P_k = (\mathrm{I} - \frac{P_{k-1}\varphi_k\varphi^{\mathrm{T}}}{1+\varphi_k^{\mathrm{T}}P_{k-1}\varphi_k})P_{k-1} \tag{3}$$

$$K_k = \frac{P_{k-1}\varphi_k}{1+\varphi_k^{\mathrm{T}}P_{k-1}\varphi_k} \tag{4}$$

$$\theta_k = \theta_{k-1} + K_k(y_k - \varphi_k\theta_{k-1}) \tag{5}$$

3.2. Parameter identification

According to the working principle of the least square method, the MATLAB program was written to identify the parameters of the lithium battery, and the identification results were shown in Figure 3.

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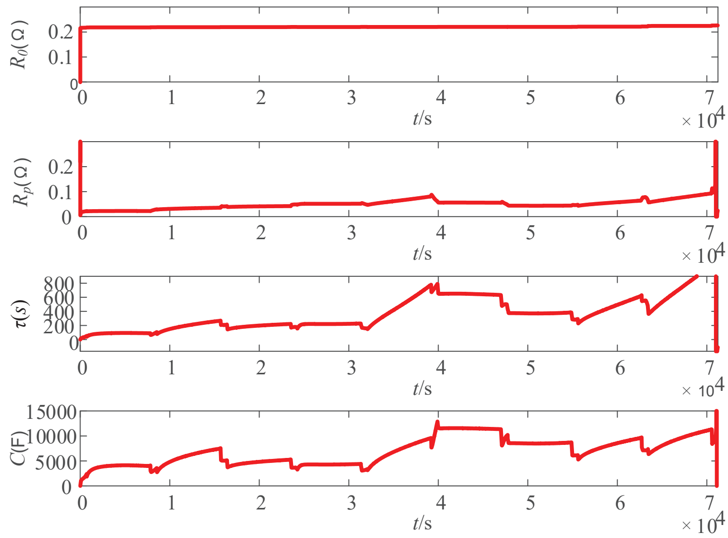

Figure 3. Parameter identification results of lithium battery

4. IAE-AEKF LITHIUM BATTERY SOC ESTIMATION

4.1. Extended Kalman filter

Extended Kalman filter (EKF) algorithm is a process of nonlinearization of classical Kalman filter, which is obtained by expanding Kalman filter algorithm by first order Taylor` formula and removing higher order terms of second order and above. The nonlinear state space model is shown in equation(6).

$$\begin{cases} x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \\ y_k = g(x_k, u_k) + v_k \end{cases} \tag{6}$$

In the formula, x_k is the state variable, y_k is the observation variable, u_k is the input variable of the system, w_{k-1} and v_k are the process noise and observation noise.

By performing a first-order Taylor expansion of formula(6), we obtain

$$\begin{cases} f(x_k, u_k) \approx f(\hat{x}_k, u_k) + \dfrac{\partial f(x_k, u_k)}{\partial x_k}|_{x_k = \hat{x}_k} (x_k - \hat{x}_k) \\ g(x_k, u_k) \approx g(\hat{x}_k, u_k) + \dfrac{\partial g(x_k, u_k)}{\partial x_k}|_{x_k = \hat{x}_k} (x_k - \hat{x}_k) \end{cases} \tag{7}$$

In the formula, define $A_k = \dfrac{\partial f(x_k, u_k)}{\partial x_k}|_{x_k = \hat{x}_k}$, $C_k = \dfrac{\partial g(x_k, u_k)}{\partial x_k}|_{x_k = \hat{x}_k}$ .Thus can be obtained

$$\begin{cases} x_{k+1} \approx A_k x_k + [f(\hat{x}_k, u_k) - A_k \hat{x}_k] + w_k \\ y_k \approx C_k x_k + [g(\hat{x}_k, u_k) - C_k \hat{x}_k] + v_k \end{cases} \tag{8}$$

According to the principle of classical Kalman filtering, the recursive process of extended Kalman filtering is shown in the following table.

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Table 1. EKF recurrence process

procedure	formula
State prediction	$\hat{x}_{k\|k-1} = f(\hat{x}_{k-1}, u_{k-1})$
Covariance prediction	$P_{k\|k-1}C_k^{\mathrm{T}}(C_k P_{k\|k-1} C_k^{\mathrm{T}} + R)^{-1}$
Gain calculation	$K_k = P_{k\|k-1}C_k^{\mathrm{T}}(C_k P_{k\|k-1} C_k^{\mathrm{T}} + R)^{-1}$
Status update	$\hat{x}_k = \hat{x}_{k\|k-1} + K_k[y_k - g(\hat{x}_{k\|k-1}, u_k)]$
Covariance updating	$P_k = (I - K_k C_k) P_{k\|k-1}$

4.2. Adaptive error covariance

In the process of SOC estimation for lithium batteries, according to the dimensions of variables in the state-space equation, the estimation process is mainly affected by the state process error and measurement error, and the size of the error has a great impact on the final estimation results. If the error parameters are determined or adjusted closely by artificial experience, the estimation results are not accurate enough and the process is complicated. Therefore, the estimation method of adaptive covariance matching is particularly necessary. The moving window estimation method uses the sample mean of the first N epoch to estimate the observation vector error covariance matrix and model error covariance matrix of the current epoch.

According to the window estimation method, the new interest estimate of the current epoch is

$$\hat{H}_{ek} = \begin{cases} \dfrac{k-1}{k}\hat{H}_{ek-1} + \dfrac{1}{k}e_k e_k^{\mathrm{T}} & k \le M \\ \dfrac{1}{M}\displaystyle\sum_{i=k-M+1}^{k} e_i e_i^{\mathrm{T}} & k > M \end{cases} \tag{9}$$

$$\hat{R}_k = H_{ek} - C_k P_{k|k-1} C_k^{\mathrm{T}} \tag{10}$$

$$\hat{Q}_k = K_k H_{ek} K_k^{\mathrm{T}} \tag{11}$$

4.3. AEKF algorithm flow

Adaptive extended Kalman filter is derived by adding noise covariance matrix on the basis of Kalman filter. The flow of lithium battery SOC estimation algorithm based on adaptive extended Kalman filter is shown in the following figure.

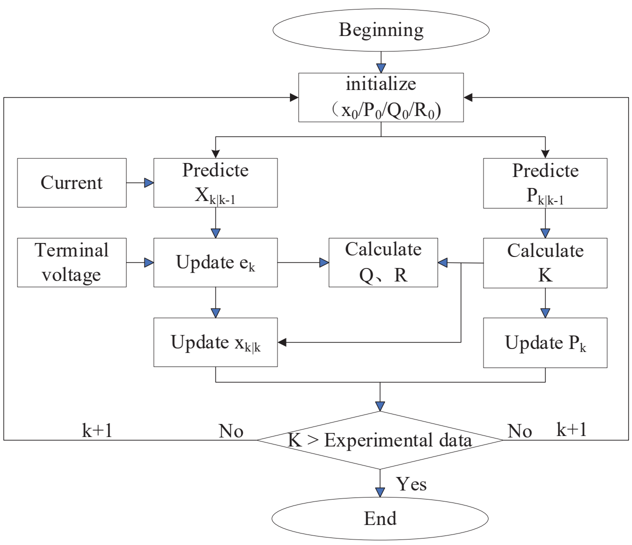

Figure 4. SOC estimation process based on AEKF

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5. SIMULATION

DST conditions were selected for simulation verification, and the simulation results were shown in Figure 5.

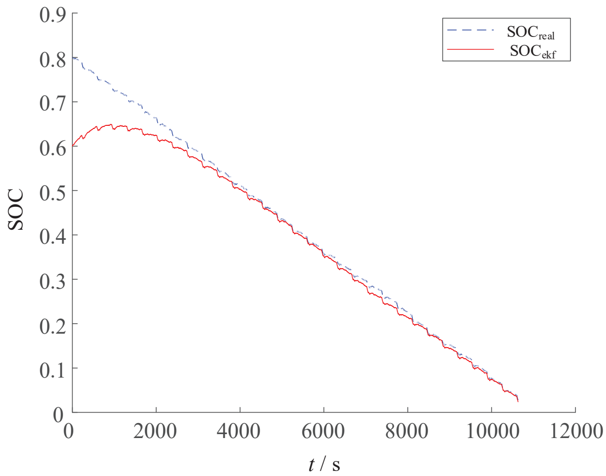

Figure5-a. EKF algorithm

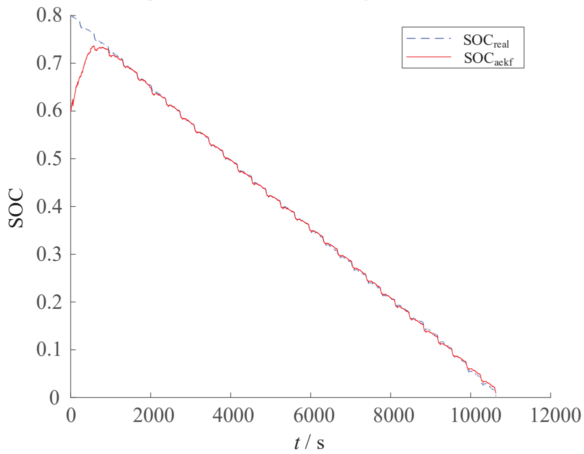

Figure 5-b. AEKF algorithm

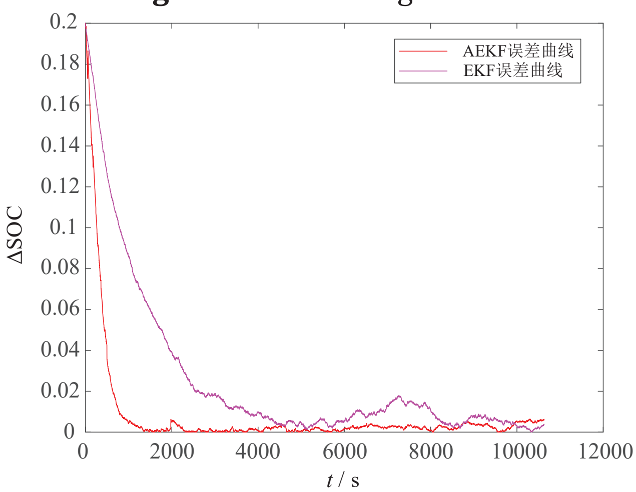

Figure 6. Comparison of error curves

Table 2.MAE values

algorithm	MAE
EKF	0.0077
AEKF	0.0259

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In Figure 5, the ordinate is SOC value, and the abscissa is the discharge time of lithium battery. As can be seen from FIG. 5, compared with the extended Kalman filtering method, the adaptive extended Kalman filtering method converges to the truth value faster and has stronger ability to track the truth value. In Figure 6, the ordinate is SOC error value, and the abscissa is lithium battery discharge time. As can be seen from Figure 6, the overall error of the adaptive extended Kalman filtering method is smaller than the extended Kalman rate.

6. CONCLUSION

According to the simulation results, to solve the problem that the error covariance and measurement error covariance of the extended Kalman filter model are fixed values and the SOC estimation accuracy of lithium battery is not high, the error covariance adaptive matching of the moving window estimation method is introduced, so that the error covariance can change according to the changes of the system, and the SOC estimation accuracy of lithium battery is improved.

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