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# AEKF-based Method of SOC Estimation for Batteries under the Active Short-time External Short Circuit

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## Abstract

State of charge (SOC) estimation is a key function of battery management system. This study examines the possibility of estimating the battery SOC under a certain short time External short circuit (ESC) process. Active short time ESC is sometimes useful in special applications that may not cause serious outcomes. The following contents are introduced in this papery. Firstly, ESC of cell experiment is designed under different SOC and temperatures. Then, genetic algorithm (GA) is used to identify model parameter, and SOC is estimated based adaptive extended Kalman filter (AEKF). It is illustrated that the presented SOC estimation can be well used in active ESC process with error less than 0.2%.

**Keywords:** external short circuit, genetic algorithm, AEKF, state estimation, battery management

## 1. Introduction

Till now, electric vehicles (EVs) have been attracted a lot of attentions due to its clean driving matter and low cost [1]. Lithium-ion batteries are key component in EVs. SOC estimation is a key function of battery management system. However, the current SOC estimation studies [2-5] are mostly directed against the normal condition. In this study, a special application of ESC in battery low temperature heating is considered. In short time ESC[6], the battery can be heated in very high speed, however, it may cause interference on the normal SOC information. Therefore, we examine the possibility of using SOC estimation in the certain short-time ESC and try to obtain an accurate SOC estimation for the later use. The remainder of this paper is organized as follow: the external short circuit is briefly introduced in Section 2; the model parameter identification is given in Section 3; the estimation of SOC and the result analysis are presented in Section 4 while the conclusions are summarized in Section 5.

## 2. External short circuit of cell

Figure 1 shows the experimental platform of ESC, which is composed of the upper computer, a Motohawk controller, relay module to trigger the short circuit, a CAN bus, a temperature control box, a safety box, several sensors, etc. The upper computer is linked with the controller through a CAN bus to operate relay module and its break time. Here we conduct a short time (less than 20s) short circuit of the battery to produce a useful heating.

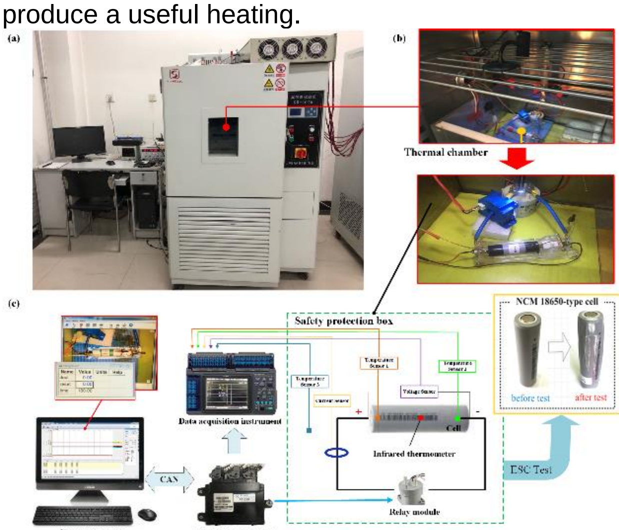



**Figure 1** The experimental platform of ESC

## 3. Model parameter identification

### 3.1 ESC battery model

First-order RC model is utilized to describe the ESC process of lithium battery, as shown in Figure 2. The voltage of RC item is calculated as:

$$U_{p,k+1} = U_{p,k} e^{\frac{-\Delta t}{\tau}} + R_p (1 - e^{\frac{-\Delta t}{\tau}}) I_{L,k} \qquad (1)$$

where $U_p$ is the voltage of RC network, $R_p$ is the polarization resistance, $\tau$ is the time constant, $I_{L,k}$ is charge current in ESC process.

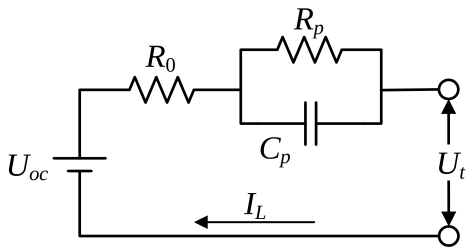



**Figure 2** The first-order RC model

To distinguish state of charge under normal and fault condition, $\gamma_{ESC}$ is introduced to instead the discharge status.

$$\gamma_{\mathrm{ESC,k+1}} = \gamma_{\mathrm{ESC,k}} - \frac{\xi \cdot I_{L,k}\Delta t}{Q_{ESC}} \tag{2}$$

Thus, the terminal voltage $U_t$ of battery is given by:

$$U_{t,k} = U_{oc}(\gamma_{\mathrm{ESC,k}}) - I_{L,k}R_0 - U_{p,k} \tag{3}$$

The open circuit voltage (OCV) $U_{oc}$ is treat as a polynomial function of the $\gamma_{ESC}$,

$$U_{oc}(\gamma_{\mathrm{ESC,k}}) = \sum_{n=0}^{6} \xi_i \gamma_{\mathrm{ESC},k}^{n},\ i = 1,2,....6 \tag{4}$$

### 3.2 Optimization of the battery model

The optimization is to get the optimal parameters, making the model fit the test data. The cost function is root mean square error (RMSE) between the test data and model prediction, described by:

$$J\left(\hat{\boldsymbol{\theta}}\right) = \min\left\{\sqrt{\frac{1}{n}\sum_{k=1}^{n}(U_t(k) - \hat{U}_t(k,\hat{\boldsymbol{\theta}}))^2}\right\} \tag{5}$$

Where $U_t$ and $U_t$ are terminal voltage from test data and model simulation respectively, n is the length of measure data during ESC process, $\theta$ is vector matrix of parameters that require to be determined, and there are eleven parameters based on ESC battery model: $\theta=[R_p,\tau]$, and optimal value can minimize cost function *J* to fit the test data.

Considering the nonlinearity of optimization problems, so the GA method is selected.

## 4. Releasable capacity Estimation of ESC

### 4.1 Adaptive extended Kalman filter (AEKF)

For the nonlinearity of releasable capacity estimation problem, Taylor formula is used to linearize the state space equation of system. The state space equation of nonlinear discrete system is generally written as follows:

$$\begin{cases} x_{k+1} = f(x_k,u_k) + \omega_k \\ y_{k+1} = h(x_k,u_k) + \upsilon_k \end{cases} \quad \begin{cases} \omega_k \sim (0,\, Q_k) \\ \upsilon_k \sim (0,\, R_k) \end{cases} \tag{6}$$

where $x_k$ is state variable at the time k, $u_k$ is the input variable, $\omega_k$ and $\upsilon_k$ are independent and represents process and measured noise at time k respectively. F and h are expanded at each moment with Taylor formula. The state transition matrix and observation matrix of nonlinear systems are given:

$$\hat{\boldsymbol{A}}_k = \left.\frac{\partial f(x_k,u_k)}{\partial \boldsymbol{x}_k}\right|_{x_k=\hat{x}_k^+},\ \hat{\boldsymbol{C}}_k = \left.\frac{\partial h(x_k,u_k)}{\partial \boldsymbol{x}_k}\right|_{x_k=\hat{x}_k^+} \tag{7}$$

A widely used discretized state space equation can be demonstrated to describe battery state as follows:

$$\begin{cases} \begin{bmatrix} \gamma_{k+1} \\ U_{p,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau}} \end{bmatrix} \begin{bmatrix} \gamma_k \\ U_{p,k} \end{bmatrix} + \begin{bmatrix} \eta\Delta t / Q_{ESC} \\ R_p(1-e^{-\frac{\Delta t}{\tau}}) \end{bmatrix} I_{L,k} + \omega_k \\ U_{L,k} = U_{oc}(\gamma_{\mathrm{ESC}}) - U_{p,k} - R_0 I_{L,k} + \upsilon_k \end{cases} \tag{8}$$

Where $\gamma$ represents SOC under ESC condition, $\eta$ is the Coulombic efficiency, $Q_{ESC}$ is the capacity of charge under continuous ESC test.

At above equation, the state variable, output variable, transfer matrix and observation matrix is expressed as:

$$\boldsymbol{x}_k = \begin{bmatrix} \gamma \\ U_{p,k} \end{bmatrix},\ y_k = U_{L,k},\ \hat{\boldsymbol{A}}_k = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau}} \end{bmatrix},\ \hat{\boldsymbol{C}}_k = \begin{bmatrix} 1 \\ \left.\frac{\partial U_{oc}}{\partial \gamma}\right|_{\gamma=\gamma^-} \end{bmatrix} \tag{9}$$

The process of SOC estimation using the AEKF algorithm is as follow [7]:

**Step 1:** Initialize. For k=0, set the initial value and state error covariance

$$\hat{\boldsymbol{x}}_0^+ = E[\boldsymbol{x}_0],\ \boldsymbol{P}_0^+ = E\left\lfloor (x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T \right\rfloor$$

Specific parameter setting is given as follow:

$P_0=[0.01,0;0,0.01]$; $R_0=10^{-4}$; $Q_0=[10^{-4},0;0,10^{-4}]$;

**Step 2:** Time update. For sustained time process, the state at the k-1 time is calculated to that at the k time, and the time update equation of the AEKF algorithm is as follows.

State pre-estimation:

$$x_{k+1} = f(x_k,u_k) + \omega_k \tag{10}$$

Error covariance time update:

$$\boldsymbol{P}_k^- = \boldsymbol{A}_{k-1}\boldsymbol{P}_{k-1}^+\boldsymbol{A}_{k-1}^T + \boldsymbol{Q}_k \tag{11}$$

Error innovation:

$$e_k = y_k - h(x_k^-,u_k) \tag{12}$$

**Step 3:** Measure update.

Kalman gain matrix:

$$\boldsymbol{K}_k = \boldsymbol{P}_k^-\boldsymbol{C}_k^T(\boldsymbol{C}_k\boldsymbol{P}_k^-\boldsymbol{C}_{k-1}^T + R_k)^{-1} \tag{13}$$

Adaptive noise covariance matching:

$$\begin{cases} H_k = \dfrac{1}{M}\displaystyle\sum_{i=k-M+1}^{k} e_i e_i^T \\ \boldsymbol{Q}_k = \boldsymbol{K}_k H_k \boldsymbol{K}_k^T,\ R_k = H_k - \boldsymbol{C}_k\boldsymbol{P}_k^-\hat{\boldsymbol{C}}_k^T \end{cases} \tag{14}$$

State estimate measurement update:

$$\hat{x}_k^+ = \hat{x}_k^- + \boldsymbol{K}_k e_k \tag{15}$$

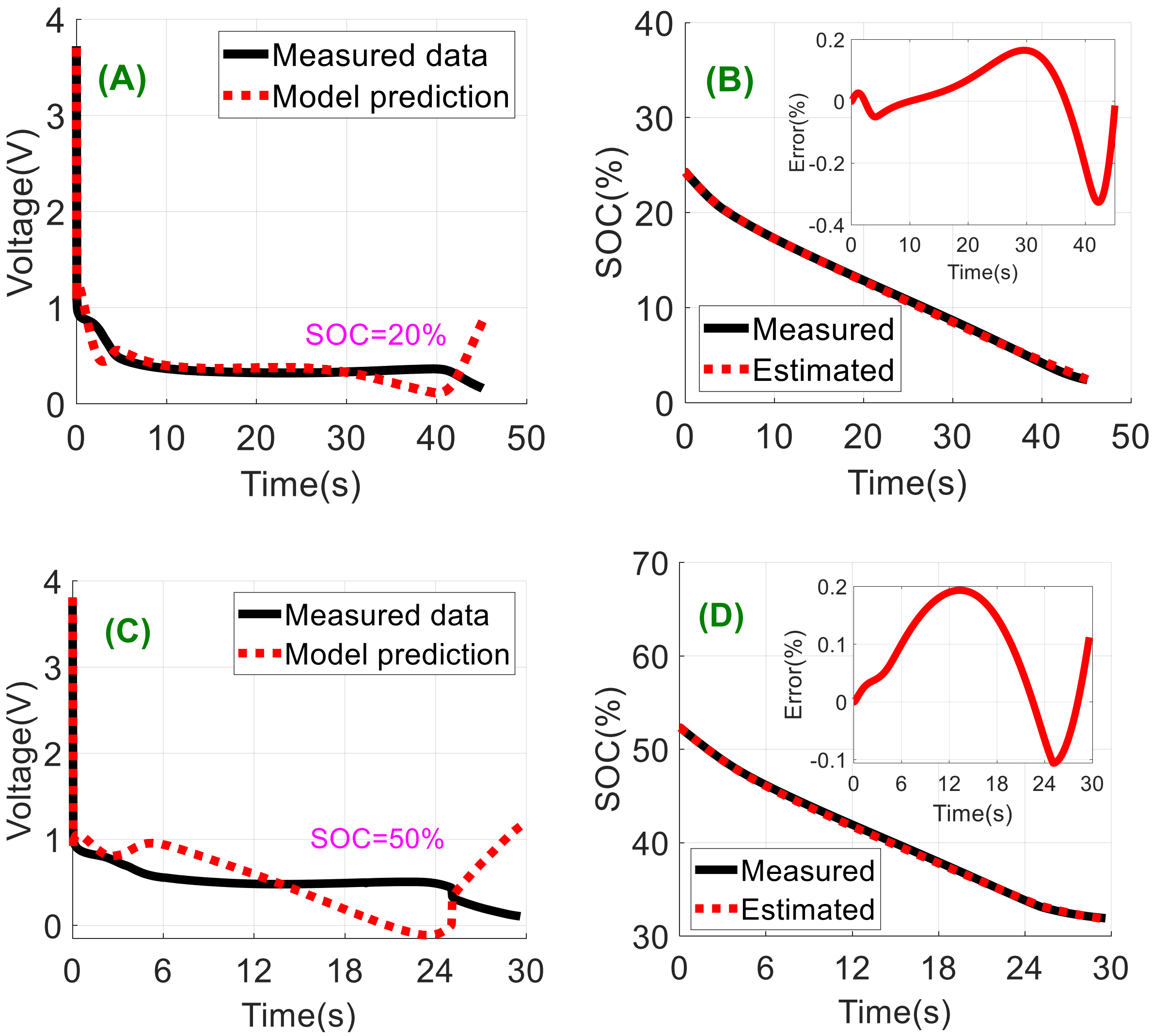
Error covariance measurement update:

$$\boldsymbol{P}_k^+ = (\boldsymbol{I} - \boldsymbol{K}_k \hat{\boldsymbol{C}}_k)\boldsymbol{P}_k^- \tag{16}$$

**Step 4:** Time scale update. The state and covariance matrix are estimated from $k^+$ to $(k+1)^-$, and the state estimation at k+1 is prepared.

## 5. Result and analysis

Model parameters based on GA are determined are shown in Figure 3(A)(C)(E). and releasable capacity under different SOC based on AEKF are estimated and shown in Figure 3(B)(D)(F), There are three sub images of estimation errors under SOC=20%, 50% and 80% of external short circuit. From the global effectiveness and error analysis, combined method based on GA and AEKF has a good effectiveness and estimation error can be controlled within 0.5%. The results indicate that for the certain short time ESC period, the SOC estimation can be implemented to obtain a useful information.



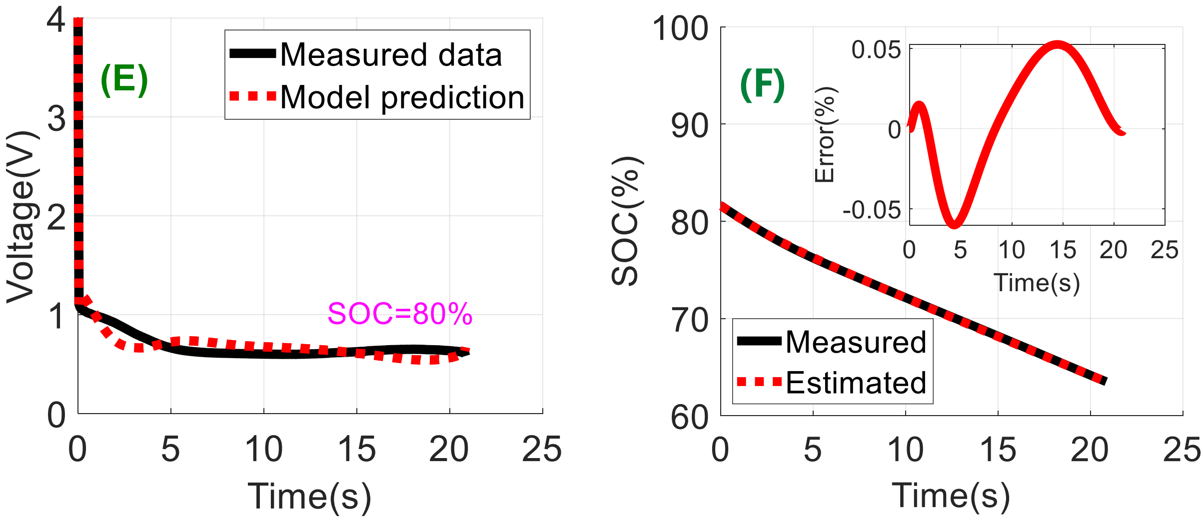



**Figure 3** Model prediction of ESC and Releasable capacity estimation results under different SOC. (A) and (B) SOC=20%; (C) and (D) SOC=50%; (E) and (F) SOC=80%;

## 6. Conclusion

In this paper, the estimation method of SOC under active ESC process is examined. The GA is used to identify the battery model parameters based on the ESC experimental data of 18650 lithium-ion battery, and then the model parameters are used for RCE based on the AEKF method. The results demonstrate that presented method based on GA and AEKF can accurately estimate the SOC under certain conditions. This study would be useful in active ESC applications like ESC-based low temperature heating.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