Online Parameters and State of Charge Co-estimation of Lithium-Ion Battery in Varying Temperature Using Joint Extended Kalman Filter

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Abstract. This paper compares the mode based lithium-ion battery state of charge (SOC) estimations using offline and online parameters under varying temperature. An innovative offline identification method based on genetic algorithm (GA) is used for offline identification of battery model parameters. The common extended Kalman filter (EKF) and the joint extended Kalman filter (JEKF) are implemented as the algorithms to implement SOC estimation with offline and online parameters. The SOC estimations by JEFK using online parameters and by EKF using offline parameters from mismatched temperature are compared. The results are as follows. When battery temperature is inaccurate, the inaccurate temperature can result in inaccurate offline parameters parameters, which will further increase the SOC estimation errors by EKF using offline parameters. In contrast, SOC estimation accuracy by JEFK are still accurate when no temperature information is provided, because the parameters are online updated by JEFK.

Keywords. Lithium-ion battery; state of charge; varying temperature; joint extended Kalman filter.

1. Introduction

Lithium-ion battery packs are widely used as energy storage unit. The lithium-ion battery pack requires a battery management system (BMS) to observe the states of batteries. One of the main functions of BMS is to accurately estimate the state of charge (SOC) of batteries.

Plenty of mode based algorithms are used in battery SOC estimation, such as Kalman filter [1, 2], Luenberger observer [3], and H-infinity filter [4], et al. In these mode based estimation algorithms, a battery model is essential. Besides using offline identified model, there are also a variety of online parameter algorithms integrated in battery SOC estimation, such as recursive least squares (RLS) based methods [5-7], dual estimation methods [8, 9] and joint estimation methods [8, 10].

Most of the studies about battery SOC estimation are implemented and verified under constant temperature. However, in practice application, the batteries may work under varying temperatures due to the external environment change. The SOC estimation accuracy deteriorates under varying temperatures are still need to be researched.

In this paper, the mode based SOC estimations under varying temperatures by using offline and online parameters are compared. Firstly, 2 DST tests are conducted to test the battery response under constant temperature and varying temperature. Secondly, a novel offline model identification method
based on GA is proposed to identify the battery model with time-varying parameters. The identification results show that the battery parameters are greatly affected by temperature. Thirdly, the EKF with mismatched offline parameters are used to estimate SOC and the JEKF algorithm is used to co-estimate SOC and parameters. Lastly, the performance of these two methods is compared.

This paper is organized as follows. The details of DST tests are presented in Section 2. The procedures and results of the offline model identification are presented in Section 3. The estimation algorithm is presented in Section 4. The estimation results are presented and discussed in Section 5. Finally, this study is summarized in the conclusion in Section 6.

2. Experiment Test

2.1. Experiment Setup
In this study, an 18650 nickel-cobalt-aluminium lithium-ion battery is used as experiment sample. The capacity of the battery is 2.9 Ah. The discharging and charging cut-off voltage of this battery are 2.5 V and 4.2 V respectively. The experiments are executed on a battery test system named Neware BTS-4008 (current range -6 ~ 6 A, voltage range 0 ~ 5 V). The sampling frequency of the experiment data is set to 1 Hz. The battery temperature is controlled by a programmable temperature chamber.

2.2. DST Tests Under Various Temperatures
In order to evaluate the parameter variation characteristics of the battery at different temperatures, the battery is loaded by the dynamic stress test (DST) under constant and varying temperatures. The current profile of the whole DST test under constant temperature (25 °C) is shown in figure 1a. Figure 1b shows the current profile of one DST cycle. The battery is fully charged before the DST test. The battery voltages and temperatures in the DST tests under constant temperature at 25 °C and varying temperature are shown in figures 2a and 2b. As seen in figure 2, the magnitude of voltage drops increase with the decrease of temperatures, because the battery resistances increase with the decrease of temperature.

Figure 1. (a) Current profiles of DST at 25 °C; (b) Current of one DST cycle.

Figure 2. (a) Voltage profiles of DST at 25 °C; (b) Voltage of DST at varying temperature.
3. Offline Model Identification by GA

3.1. Equivalent Circuit Model of Lithium-Ion Battery

Equivalent circuit models (ECM) are commonly implement to model lithium-ion batteries. The ECM, named 1RC model, is used in this study. The schematic diagram of the 1RC model is shown in figure 3. The 1RC model is consists of one voltage source, one ohmic resistance and one parallel connected RC network. The voltage across the parallel connected RC network is $U_{1k}$. The battery terminal voltage and current are $V_t$ and $I_t$ respectively.

![Figure 3. Schematic diagram of 1RC model.](image)

The discrete state space function of the 1RC model is shown in the following formula.

\[
\begin{align*}
x_k &= A_{x,k} x_{k-1} + B_{x,k} I_{L,k-1} \\
V_t &= F(x_k, I_{L,k}) = V_{ocv}(SOC_k, T_s) + R_{0,k} I_{L,k} + U_{1,k}
\end{align*}
\]

where, $x_k = \begin{bmatrix} U_{1,k} \\ SOC_k \end{bmatrix}$, $A_{x,k} = \begin{bmatrix} \phi_{1,k} & 0 \\ 0 & 1 \end{bmatrix}$, $B_{x,k} = \begin{bmatrix} R_{1,k-1} (1 - \phi_{1,k-1}) \\ T_s / 3600 Q_s \end{bmatrix}$, $\phi_{1,k-1} = \exp \left( -\frac{T_s}{R_{1,k-1} C_{1,k-1}} \right)$, $Q_s$ and $T_s$ are battery capacity and data sampling time interval respectively.

3.2. Offline Model Identification Methods

In this study, an innovative offline parameter identification method based on genetic algorithm (GA) is used to identify the 1RC model parameters. In order to represent the time-varying property of the parameters, each of the 1RC model parameters is presented by the cubic interpolation of 21 control points. The control points are uniformly distribute in the whole DST cycles. The ohmic resistance and the parameters in the parallel connected RC network are identified in two different steps.

In the first step, the ohmic resistance control points vector, $R_{0a} = \begin{bmatrix} R_{0a1}, R_{0a2}, \ldots, R_{0a21} \end{bmatrix}$, is identified by GA. The optimization objective of GA is to minimize the root mean square error between the $R_{0i}$ interpolated by control points vector $R_{0a}$ and the $R_{0i}$ calculated by $R_{0i} = \Delta V / \Delta I$ at current change edge in the DST test.

In the second step, the two control points vectors represented the $R_{1}$ and $\phi_{1}$ in the parallel connected RC network are identified by GA. The optimization objective of GA is to minimize the root mean square error between the experiment battery terminal voltage and the simulative battery terminal voltage calculated by the 1RC model. The ohmic resistance identified in the first step is used in calculating the simulative battery terminal voltage.

3.3. Parameter Identification Results

The temperature and offline identified parameters of batteries in two different DST tests are plotted in figure 4. As seen, all parameters change with temperature and SOC. Battery resistances obviously
increase when temperature decreases. Resistances in parallel connected RC networks go up dramatically at the low SOC section.

![Figure 4](image)

**Figure 4.** Offline identified battery parameters in DST: (a) battery temperatures, (b) ohmic resistances, (c)-(d) parameters of parallel connected RC network.

### 4. Estimation Algorithm

In this study, extended Kalman filter (EKF) [8] is used as the algorithm to implement SOC estimation using offline parameters, and the procedure of EKF is summarized in table 1.

| Procedure of extended Kalman filter (EKF) [8]. |
|-----------------------------------------------|
| **State space model** |
| $x_k = A_{k-1}x_{k-1} + B_{k-1}I_{L,k-1} + w_k$ |
| $V_k = F(x_k, I_{L,k}) + v_k$ |
| where $w_k$ and $v_k$ are independent, zero mean, Gaussian noise, |
| Cov($w_k, w_j$) = $\Sigma_w \delta_{kj}$, Cov($v_k, v_j$) = $\Sigma_v \delta_{kj}$ |
| **Definition** |
| $C_k = \frac{\partial F(x_k, I_{L,k})}{\partial x_k}$ |
| $\Sigma_{x,0} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T]$, $x_0^+ = E[x_0]$ |
| **Initialization** |
| For $k=0$, set |
| $\Sigma_{x,0} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T]$, $x_0^+ = E[x_0]$ |
| **For $k=1,2,3,4,\ldots$, iterative calculation** |
| $\hat{x}_k = A_{k-1}\hat{x}_{k-1} + B_{k-1}I_{L,k-1}$ |
| $\Sigma_{x,k} = A_{k-1}\Sigma_{x,k-1}A_{k-1}^T + \Sigma_w$ |
| $K_k = \Sigma_{x,k}C_k^T(C_k\Sigma_{x,k}C_k^T + \Sigma_v)^{-1}$ |
| $\hat{x}_k^+ = \hat{x}_k + K_k[V_k - F(\hat{x}_k^-, I_{L,k})]$ |
| $\Sigma_{x,k}^+ = (I - K_kC_k)\Sigma_{x,k}$ |

EKF can be augmented to joint extended Kalman filter (JEKF) [8, 10] to implement online parameter identification. JEFK is used as the SOC and parameter co-estimation algorithm in this
paper. JEKF concurrently estimate state and parameters by augmenting the model parameters into the system state. Treating parameter vector, $\theta_k$, as the augmented system state, the state space model can be represented by

$$
\begin{align*}
\dot{x}_k^a &= A_k^a x_{k-1}^a + B_k^a I_{L,k-1} + w_k^a \\
V_t &= F(\hat{x}_k^a, I_{L,k}) + v_k
\end{align*}
$$

(9)

with $x_k^a = \begin{bmatrix} x_k \\ \theta_k \end{bmatrix}$, $A_k^a = \begin{bmatrix} A_k & 0 \\ 0 & I \end{bmatrix}$, $B_k^a = \begin{bmatrix} B_k \\ 0 \end{bmatrix}$, and $w_k^a = \begin{bmatrix} w_k^x \\ w_k^\theta \end{bmatrix}$.

where $w_k^x$ and $v_k$ are Gaussian noise, $\text{Cov}(w_k^x, w_j^x) = \Sigma_{k,j}^{\delta_k}$, $\text{Cov}(v_k, v_j) = \Sigma_{k,j}$, $w_k^\theta$ is a small fictitious noise of parameters that allows the filter to change its estimation of parameters. For $1RC$ model, $\theta_k = [R_{0,k}, R_{1,k}, \phi_{k,k}]$.

5. Comparing of Estimation Results

The SOC estimation errors by EKF using offline parameters and by JEKF of the DST in varying temperature are shown in figure 5a. As the current sensor of the battery test system is precise, the SOC calculated by ampere-hour integral method is regarded as reference SOC in this research. In the SOC estimation by EKF, the model parameters identified from DST in 25 °C is used as model parameters to simulate the model parameters mismatch.

As seen in figure 4, the temperature has great influence on battery parameters. There is a great reduction in model accuracy, if the battery parameters do not update with temperature. The inaccurate model will further deteriorate the SOC estimation precision by the mode based methods [6]. So, as seen in figure 5a, because of the model inaccuracy caused by temperature mismatch, the SOC estimation error using offline parameters reaches to 5.4%. In contrast, the maximal SOC estimation error by JEKF do not exceed 1.0%, this is because the parameter is estimated by the JEKF. The offline parameters of the battery in varying temperature identified by GA and the parameters estimated by JEKF are shown in figures 5b-5d. As seen in figures 5 b-5d, the parameters estimated by JEKF can track the offline identified values properly. So the model parameter mismatching caused by temperature mismatching in varying temperature is dispelled. Therefore, the SOC estimation accuracy by JEKF is much better than that by EKF with mismatched temperature in varying temperature.

Figure 5. (a) SOC estimation errors by EKF and JEKF, (b)-(d) parameters identified by JEKF and GA.
6. Conclusion

In this paper, the mode based SOC estimations under varying temperatures by using offline and online parameters are compared. The parameters of battery identified by the proposed offline identification method based on genetic algorithm show that the parameters of lithium-ion battery change dramatically with temperature changes. When temperature is mismatched, the SOC estimation accuracy by EKF using offline parameters are greatly deteriorated. The JEKF can co-estimate SOC and parameters of the battery with reasonable accurate under varying temperatures. The advantage of using online identified model is that the battery temperature is not necessary in estimation, inaccurate battery temperature has no effect on the estimation by JEKF.

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