Abstract
The accuracy of common battery state estimation method is usually influenced by the temperature input. The capacities at different temperatures were found to be similar when the starting temperature and the final temperature only have subtle differences by carrying out a series of capacity experiments. Based on the finding, the original DEKF algorithm is improved by using the curved surface of OCV-SOC-CAP instead of the one of OCV-SOC-Temperature to estimate battery state without temperature input. Moreover, piecewise debugging parameters of Q and R is used to estimate battery state when the SOC is at high level and low level respectively. Large amounts of data at different temperatures and at different lifecycles are used to verify the accuracy and find the scope of the method. Results show that the error of estimated SOC is lower than 3% when the temperature is between 45℃ and -10℃ and the SOH is between 80% and 100%. Finally, the HIL experiments also verify the effectiveness of the method.

Keywords: battery state estimation, dual extended kalman filter, piecewise debugging parameters, without temperature input, hardware in loop.

1. Introduction
As one of the power sources and energy storage devices, lithium-ion batteries are widely used on electric vehicles in recent years, considering its high power density, energy density, low maintenance requirement, low self-discharge, no memory effect and the mature manufacturing technologies [1].
the one of OCV-SOC-Temperature to estimate battery state without temperature input [11]. Moreover, piecewise debugging parameters of Q and R is used to estimate battery state when the SOC is at high level and low level respectively.

2. Co-estimation of parameters and SOC

2.1 Battery model and OCV curved surface

Thevenin model is one of the typical equivalent circuit models, which consists of a RC group, another resistor and voltage sources. The battery model is established to represent the dynamic response characteristics of power battery. Compared with EIS model and electrochemical model, the equivalent circuit model shows sufficient precision and simplicity. As is shown in Figure 1, the schematic diagram represents the electrical behavior of Eq. (1):

\[
U_{oc,k+1} = e^{-\frac{-\Delta t_k}{C_{p,k} R_{p,k}}} U_{p,k} + \left(1 - e^{-\frac{-\Delta t_k}{C_{p,k} R_{p,k}}} \right) R_{p,k} i_{L,k}
\]

\[
U_{t,k} = \begin{cases} 
U_{oc,k} - U_{p,k} - i_{L,k} R_{d,k} + i_{L,k} & i_{L,k} \geq 0 \\
U_{oc,k} - U_{p,k} - i_{L,k} R_{d,k} - i_{L,k} & i_{L,k} < 0 
\end{cases}
\]

Where \( U_{OC,k} \) means the battery OCV, \( U_{t,k} \) is the terminal voltage, \( i_{L,k} \) is the battery current, \( R_{p,k}, C_{p,k}, R_{d,k} \) are the polarization resistance, polarization capacitance, charge ohmic resistance and discharge ohmic resistance, respectively, \( U_{p,k} \) is the polarization voltage, \( \Delta t_k \) is the sample intervals.

The OCV has a relationship with the SOC which can be described as a 12 order polynomial. And each coefficient in the 12 order polynomial has a relationship with the capacity which can be described as a 3 order polynomial.

However, all the coefficients are independent of temperature. The functions can be defined as Eq. (2):

\[
U_\infty (z) = \sum_{i=0}^{12} c_i z^i, \quad c_i = \sum_{j=0}^{3} c_{aj} z^j
\]

Where \( z \) is the SOC and \( C_a \) is the capacity. \( c_i (i = 0, 1, \ldots, 12) \) is the polynomial coefficients to fit the OCVs and SOCs. \( c_{aj} (j = 0, 1, 2, 3) \) is the polynomial coefficients to fit the \( c_i \) and \( C_a \).

2.2 DEKF method

Considering the influence of measurement and system noise, the DEKF algorithm which consists of a state filter and a parameter filter is chosen to realize the online real-time estimation of a battery’s parameters and states. Assume that the state-space model of battery states is expressed as Eq. (3) and the state-space model of battery parameters is expressed as Eq. (4).

According to the model built above, some vectors and functions are defined as Eq. (5).

\[
\chi_{k+1} = F(\chi_k, \theta_k, \mathbf{u}_k) + \mathbf{w}_k, \quad \omega_k \sim (0, Q^k)
\]

\[
Y_k = G(\chi_k, \theta_k, \mathbf{u}_k) + \mathbf{v}_k, \quad \nu_k \sim (0, R^k)
\]

\[
\chi_k = \left[ U_{p,k}, z_k \right]^T
\]

\[
\theta_k = \left[ R_{0,k}, R_{p,k}, C_{p,k}, C_{a,k} \right]
\]

\[
\mathbf{u}_k = i_{L,k}
\]

\[
Y_k = U_{t,k}
\]

\[
F = A_k \chi_k + B_k \mathbf{u}_k
\]

\[
A_k = \text{diag} \left( e^{\frac{-\Delta t_k}{C_{p,k} R_{p,k}}}, 1 \right)
\]

\[
B_k = \left[ \left(1 - e^{\frac{-\Delta t_k}{C_{p,k} R_{p,k}}} \right) R_{0,k} \frac{\Delta t_k}{\eta C_{a,k}} \right]^T
\]

\[
G = \sum_{i=0}^{12} \left( \sum_{j=0}^{3} c_{aj} z^j \right) \left( \Delta t_k \right) - U_{p,k} - i_{L,k} R_{p,k}
\]

Where, \( \chi_k \) is state vector, \( \mathbf{u}_k \) is system excitation, \( \theta_k \) is parameter vector, \( \mathbf{Y}_k \) are the measurement vectors and \( \omega_k \), \( \nu_k \) are assumed to be independent Gaussian white noise of covariance matrices \( Q^k \), \( R^k \), \( Q^0 \), \( R^0 \), respectively.

After the state-space model is established, the improved DEKF algorithm can be summarized as shown in Table 1.
Table 1 General process of DEKF algorithm

<table>
<thead>
<tr>
<th>Step</th>
<th>Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td><strong>Initialization.</strong> For $k=1$, set $\hat{x}_k$, $\tilde{x}_k$, $u_k$, $P^{0}<em>k$, $P^{k+}$, $P^{\tilde{k}</em>+}$, $P^{\tilde{k}-}$ set $Q^{u}_k$, $R^{u}_k$, $Q^{z+}_k$, $R^{z+}<em>k$ set $Q^{\tilde{z}</em>+}<em>k$, $R^{\tilde{z}</em>+}<em>k$, $Q^{\tilde{z}</em>-}<em>k$, $R^{\tilde{z}</em>-}_k$</td>
</tr>
<tr>
<td>2</td>
<td><strong>Time update of parameter filter.</strong> For $k=1,2,\cdots$ calculate Parameter time update: $$\hat{\theta}<em>k = \hat{\theta}</em>{k-1}$$ Parameter error covariance time update: $$P^{\hat{\theta}_k}<em>k = P^{\hat{\theta}</em>{k-1}}<em>k + Q^{\hat{\theta}<em>k}, \quad Q^{\hat{\theta}<em>k} = \begin{cases} Q^{u}</em>{k-1}, &amp; z_k \geq z</em>{\text{limit}} \ Q^{\tilde{z}</em>+}<em>k, &amp; z_k &lt; z</em>{\text{limit}} \end{cases}$$ (6)</td>
</tr>
<tr>
<td>3</td>
<td><strong>Time update of state filter.</strong> For $k=1,2,\cdots$ calculate State coefficient matrix update: $$A_k = f_A(\hat{\theta}<em>k, \Delta t_k)$$ $$B</em>{k-1} = f_B(\hat{\theta}<em>k, \Delta t_k)$$ State time update: $$\tilde{x}<em>k = A_k \tilde{x}</em>{k-1} + B_k u</em>{k-1}$$ State error covariance time update: $$P^{\tilde{x}<em>k}<em>k = A_k P^{\tilde{x}</em>{k-1}}<em>k A^T_k + Q^{\tilde{x}}$$ $$Q^{\tilde{x}} = \begin{cases} Q^{u}</em>{k-1}, &amp; z_k \geq z</em>{\text{limit}} \ Q^{\tilde{z}_+}<em>k, &amp; z_k &lt; z</em>{\text{limit}} \end{cases}$$ (7)</td>
</tr>
<tr>
<td>4</td>
<td><strong>Measurement update of state filter.</strong> For $k=1,2,\cdots$ calculate State coefficient matrix update: $$C^\chi_k = \frac{\partial G}{\partial \chi} \biggr</td>
</tr>
</tbody>
</table>

3. **Experiments and verifications**

3.1 **Cell working condition tests**

In order to verify the accuracy and find the scope of the method, 6 selected cells were tested in 2 kinds of working conditions including UDDS and NEDC. Each of wording conditions were carried out at different temperatures including -10°C, 0°C, 25°C and 45°C. During 6 months tests, all the tests mentioned above were carried out at different lifecycles. Results are shown in the following figures. Figure 2 shows the error of SOC of all the tests with time. Figure 3 shows the maximum error of SOC of all the tests. Figure 4 shows the maximum error of voltage of all the tests.

**Figure 2 SOC error of all cells' tests with time.**
3.2 Pack working condition tests

In order to verify the accuracy and find the scope of the method, a pack with 3 batteries in parallel and 144 batteries in series was tested in 4 kinds of working conditions including NEDC, UDDS, US06 and WLTC. Working conditions were carried out at different temperatures including 0℃, 6℃, 25℃ and 40℃. Results are shown in Table 2. Figure 5 shows the error of SOC of all the tests with time. Figure 6 shows the maximum error of SOC of all the tests. Figure 7 shows the maximum error of voltage of all the tests.

Table 2 Results of pack working condition tests

<table>
<thead>
<tr>
<th>Working Condition</th>
<th>Temperature</th>
<th>Error of SOC</th>
<th>Error of Voltage</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEDC</td>
<td>0℃</td>
<td>2.0037</td>
<td>245.68</td>
</tr>
<tr>
<td>UDDS</td>
<td>0℃</td>
<td>2.0013</td>
<td>108.78</td>
</tr>
<tr>
<td>US06</td>
<td>0℃</td>
<td>1.9875</td>
<td>189.94</td>
</tr>
<tr>
<td>WLTC</td>
<td>0℃</td>
<td>2.0011</td>
<td>17.62</td>
</tr>
</tbody>
</table>

Figure 3 Maximum SOC error of all cells’ tests.

Figure 4 Maximum voltage error of all cells’ tests.

Figure 5 SOC error of all pack’s tests with time.

Figure 6 Maximum SOC error of all pack’s tests.
is 50Ah. And the upper and lower cut-off voltage are 4.25V and 2.8V respectively. During the 6 months tests, the capacity test, the low current test of OCV and the accelerated aging test are applied many times at different temperature to identify the coefficients in Eq. (2) until the capacity is less than 40Ah. A curved surface of OCV is shown in Figure. 10.

![Curved surface of OCV.](image)

3.3 Test bench

The test bench is established to carry out the experiments in which the MPC5644 is the main chip and the ARBIN is the charge and discharge test equipment as is shown in Figure. 8. And monitoring system is established by LabVIEW as is shown in Figure. 9.

![Test bench.](image)

![Monitoring system.](image)

The experimental data were acquired on the LiNiMnCoO2 (NMC) lithium-ion cells. Each cell has a nominal output voltage of 3.68V and the normal capacity is 50Ah. And the upper and lower cut-off voltage are 4.25V and 2.8V respectively. During the 6 months tests, the capacity test, the low current test of OCV and the accelerated aging test are applied many times at different temperature to identify the coefficients in Eq. (2) until the capacity is less than 40Ah. A curved surface of OCV is shown in Figure. 10.

![Curved surface of OCV.](image)

During these time, the mixed operation condition test loading profile is applied to verify the performance of DEKF based parameter and SOC estimation method at different temperature. Considering the difficulty to obtain accurately initial SOC value in real conditions, we assume that the initial guess value of SOC is the 70% of the reference SOC. Moreover, we define the converge time of the estimation as the first time that the estimated SOC approach the 3% error bound compared with the reference SOC. Figure. 11(a)-Figure. 11(d) are the current, voltage, temperature and sample interval of the original data, respectively. During the all experiments, the anti-temperature interference ability of the algorithm is tested.

![Mixed operation condition test.](image)

Figure. 12(a) is the comparative profiles between the simulated SOC and reference SOC which is obtained via Ampere-hour counting method. Results show that the simulated SOC can be fast convergent in 60 seconds and stable keeping error below 3% in different current rate, temperature and cycle times. Figure. 12(b) is the comparative profiles between the simulated $U_{i,k}$ and reference $U_{i,k}$ which is measured via sensor. Figure.

![Mixed operation condition test.](image)
12(c)–Figure. 12(f) are the simulated $R_{C_k}$, $C_{P_k}$, $R_{0_k}$ and $C_0$ respectively.

Figure 12 Simulated results in diffident current rate, temperature and cycle times.

4. Conclusion

Large amounts of results show that the improved DEKF based parameter and SOC estimation method have high robustness and can reduce the influence of measurement and system noise and can be fast convergent in 60 seconds and stable to keep error low in different current rate, temperature and cycle times in the all cycle life of the LiNiMnCoO2 (NMC) lithium-ion cells, with the help of the novel OCV curve acquisition method and piecewise debugging parameters of Q and R. The error of estimated SOC is lower than 3% when the temperature is between 45°C and -10°C and the SOH is between 80% and 100%. Finally, the HIL experiments also verify the effectiveness of the method.

Acknowledgement

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Reference


