State of Charge estimation of lithium ion battery based on extended Kalman filtering algorithm

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Abstract: Accurate estimation of state-of-charge (SOC) for lithium ion battery is crucial for real-time diagnosis and prognosis in green energy vehicles. In this paper, a state space model of the battery based on Thevenin model is adopted. The strategy of estimating state of charge (SOC) based on extended Kalman filter is presented, as well as to combine with ampere-hour counting (AH) and open circuit voltage (OCV) methods. The comparison between simulation and experiments indicates that the model’s performance matches well with that of lithium ion battery. The algorithm of extended Kalman filter keeps a good accuracy precision and less dependent on its initial value in full range of SOC, which is proved to be suitable for online SOC estimation.

1 Introduction
The lithium-ion batteries (LIB) are widely used in consuming electronics, green energy vehicles and storage devices nowadays, due to its characteristics of high energy density, long lifetime, fast charge/discharge ability, memoryless and eco-friendly [4]. Especially, with the extensively marketization of hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and electric vehicle (EVs), safety and stability are becoming critical components in battery management system (BMS) for real-time diagnosis and prognosis. The precise estimation of SOC is prerequisite for batteries balancing, charge/discharge management, as well as the assessment of state of power (SOP), state of healthy (SOH) and state of functions (SOF) [7]. Thus, SOC estimation is thought to be one of the most important parts of BMS [3].

The absolute precise estimation of SOC becomes great challenge due to the nature that battery is a complicated electrochemistry and thermal-dynamics system, as well as unexpected work situations. For SOC estimation, building the battery model is a high priority. General battery models could be considered by chemistry and physics mechanism, circuit equivalent and data-driven methods. From the practical consideration, the model based on circuit equivalent is general in use.

Most SOC estimation methods in use, such as AH method, OCV, battery-model based methods, particle filter method, Kalman filter and neural network model method etc. [1], as well as their hybridization, have advantages and also drawbacks. AH method could be used for all kinds of batteries, however it can produce the accumulating error and makes the estimate value increasingly deviating from true values. OCV method is easy and has high accuracy, but it doesn’t fit for the dynamic estimation. Artificial intelligence (AI) method is really fast and convenient, but it needs a great amount of original training data and resource consumption. Kalman filter method (KF), as a branch of AI, which is to make the optimal estimation of the minimum variance of the state of the dynamical system and suit for both linear and nonlinear system. The idea of KF is to remove noise from data system by pre-
dicting new state and its uncertainties, and then calibrating the predicted values with new measurements.

In this paper, SOC estimation adopt Thevenin model, employ extended Kalman filter (EKF) algorithm, as well as to combine with AH and OCV method [5, 8]. The experiment aims to build the battery model and extract the battery parameters are given firstly [2]. EKF algorithm is described in detail. Finally, the comparison between simulation and experiments results are discussed.

2 Experiments

The test bench is composed by a battery test system (Neware CT-4001, Shenzhen, China), programmable incubator (HDS-3120, Wuhan, China) and host computer. LiCoO$_2$ with nominal voltage of 3.7V and nominal capacity of 2.5Ah per cell is used for the testing and SOC estimation. The battery electromotive force (EMF), which is also called OCV, has a monotonous relationship with SOC [6]. By tracing the relationship between OCV and SOC, a baseline for real-time SOC estimation is built.

The OCV-SOC is obtained by the following steps: (a) Put the battery into the incubator, set the constant 25℃, left for 24h; (b) Fully charged the battery and set aside for 6h; (c) Discharge the battery with 0.5C for 300s, if the terminal voltage lowers than the discharge cut-off voltage, proceed to step e, otherwise go to step d; (d) Hold for 1h, then return to step c; (e) Discharge the battery with 0.01C for 300s, if the terminal voltage lowers than the discharge cut-off voltage, proceed to step g, otherwise go to step f; (f) Hold for 600s, then return to step e; (g) Finish. The result is shown in Fig 1.

![Fig 1](image)

(a) The voltage and current profile. (b) The relationship between SOC and OCV. The black square is the measurement, and red dotted line is fitted by polynomial function.

In more practical, the internal SOC is associated with the external voltage, current, temperature and other quantities. Considering the intricate work conditions and complicate electrochemistry system of the battery system, an accurate model of external characteristics should be established. Finding the numerical relationship between SOC and various directly measurable physical quantities is highly priority. The Thevenin RC battery model is employed in this paper, as shown in Fig 2.
Fig 2. Thevenin RC battery model.

E(t) is the EMF, $R_1$ is the ohmic resistance of the battery, the parallel circuit which is made of $R_2$ and $C$ is used to fit the battery polarization effect caused by dynamic characteristics. $U_c(t)$ is the terminal voltage of the capacitance $C$. $V(t)$ is the battery terminal voltage, $I(t)$ is the current.

Combining the Thevenin battery model with AH method, the following mathematic model are built:

$$V(t) = E(t) - R_1 I(t) - U_c(t)$$  \hspace{1cm} (1)

$$I(t) = \frac{U_c(t)}{R_2} + C \frac{dU_c(t)}{dt}$$  \hspace{1cm} (2)

$$E(t) = F(Soc(t))$$  \hspace{1cm} (3)

$$Soc(t) = Soc(t_0) - \frac{1}{Q_0} \int_{t_0}^{t} I(t) dt$$  \hspace{1cm} (4)

Here, Eq. (1) and Eq. (2) are the KVL and KCL relations of the circuit, respectively. Eq. (3) is the function relationship of between $E(t)$ and $Soc(t)$. Eq. (4) is AH method expression, and $Q_0$ is the battery rated capacity. Discrete the Eq. (1), (2), (3), (4), the space model is obtained:

$$\begin{bmatrix}
Soc_{(k+1)} \\
U_{c_{(k+1)}}
\end{bmatrix} = \begin{bmatrix}
1 & 0 & -\Delta t \\
0 & e^{-\frac{\Delta t}{R_2C}} & U_{c_{(k)}}
\end{bmatrix} \begin{bmatrix}
Soc_{(k)} \\
U_{c_{(k)}}
\end{bmatrix} + \begin{bmatrix}
\Delta t \\
R_2 \left( 1 - e^{-\frac{\Delta t}{R_2C}} \right)
\end{bmatrix} I_{(k)} + \begin{bmatrix}
W_{1_{(k)}} \\
W_{2_{(k)}}
\end{bmatrix}$$  \hspace{1cm} (5)

$$V_{(k)} = F(Soc_{(k)}) - U_{c_{(k)}} - R_1 I_{(k)} + V_{(k)}$$  \hspace{1cm} (6)

Here $W_{(k)}$ is unmeasured random input with the system state variable. $V_{(k)}$ is the battery terminal voltage measured noise.

The battery model parameters are obtained by pulse discharge method. Fig 3. shows a typical voltage pulse waveform in discharge process with SOC going down from 95% to 90%. Due to nature of capacitor transient effect, the capacitor $C$ in Fig 2. does not change abruptly at the moment when the battery is switched to the discharge state. At this point, the increase of $V(t)$ is equal to the voltage drop across $R_1$, $R_1=V_{(k)}/I(t)$. Along with the time goes, the capacity $C$ and resistor $R_2$ constitute the discharge circuit. After about 1h, $C$ is almost finished the discharge. The increase in $V(t)$ thus is equal to the
voltage drop across $R_2$. $R_2 = V_2/I(t)$. In the whole discharge progress of the capacity C, the voltage $U_c(t) = V_2 e^{-\tau/t}$. When $t = 3\tau$, the terminal voltage of C drops 95.02% of the initial state. The capacity could be calculated: $C = t/(3R_2 U_c = 0.0498V_2)$. The Thevenin model parameters are obtained as listed in Table 1.

![Voltage pulse waveform, the SOC is from 95%-90%](image)

Table 1. Fitted parameters of $R_1$, $R_2$ and $C$ at different SOC.

| SOC (%) | 94.98 | 79.93 | 59.87 | 39.80 | 19.73 | 4.68 |
|---------|-------|-------|-------|-------|-------|------|
| $R_1/m\Omega$ | 20.87 | 22.61 | 23.34 | 21.74 | 22.54 | 21.67 |
| $R_2/m\Omega$ | 47.75 | 39.08 | 47.35 | 41.15 | 34.08 | 64.69 |
| $C/F$ | 8642.2 | 16496.1 | 11510 | 14005.7 | 13624 | 13788.8 |

### 3 Extended Kalman Filter Algorithm

By discretization the time space state model, the state equation and measurement equation are obtained:

\[ x_{k+1} = A_x x_k + B_x u_k + w_k \]
\[ y_k = C_k x_k + D_k u_k + v_k \]

Here $x_{(k)}$ is the state variable, $I_{(k)}$ is the input variable, and $y_{(k)}$ equals to $V(k)$ which is the battery terminal voltage. The process noise and measured noise are described by $W_{(k)}$ and $V_{(k)}$. Model parameters $A_{(k)}$, $B_{(k)}$, $C_{(k)}$ are expressed in the following equations:

\[ A_{(k)} = \begin{bmatrix} 1 & 0 \[\Delta t] \[\Delta t] \\
0 & e^{-\Delta t} \end{bmatrix}, \quad B_{(k)} = \begin{bmatrix} -\frac{\Delta t}{Q_0} \\
R_0 (1 - e^{-\Delta t}) \end{bmatrix}, \]

\[ C_{(k)} = \begin{bmatrix} \frac{\partial F(Soc_{(k)})}{\partial Soc_{(k)}} - 1 \end{bmatrix} \left| x_{(k)} = x_{(k|-1)} \right\}
\]

\[ D_{(k)} = R_1; \]

The EKF algorithm follows the general steps listed as below:

\[ \hat{x}_{(k|-1)} = A_{(k)} \hat{x}_{(k-1)} + B_{(k)} I_{(k-1)} \]

\[ \hat{x}_{(k)} = x_{(k|-1)} + K_{(k)} (y_{(k)} - C_{(k)} \hat{x}_{(k|-1)}) \]

\[ K_{(k)} = P_{(k)} C_{(k)}^T (C_{(k)} P_{(k)} C_{(k)}^T + R)^{-1} \]

\[ P_{(k)} = (I - K_{(k)} C_{(k)}) P_{(k|-1)} \]

\[ \hat{x}_{(k+1|-1)} = A_{(k)} \hat{x}_{(k)} + B_{(k)} I_{(k)} \]

\[ y_{(k+1)} = C_{(k)} \hat{x}_{(k+1|-1)} + v_{(k+1)} \]

\[ R_{(k)} = R_{(k-1)} + R \]

Fig 3. The voltage pulse waveform, the SOC is from 95%-90%.
\[ P_{(k|k-1)} = A_{(k-1)}^T P_{(k-1)} A_{(k-1)} + Q \]  
\[ \hat{x}(k) = \hat{x}(k|k-1) + K(k) (V(k) - \hat{V}(k)) \]  
\[ K(k) = P_{(k|k-1)} C(k) (C(k)^T P_{(k|k-1)} C(k) + R)^{-1} \]  
\[ P(k) = \left[ I - K(k) C(k) \right] P_{(k|k-1)} \]  

Among the parameters, Q and R are involved in the recursive operation of each step. W(k) and V(k) are included in the estimate value X(k|k-1) and measured value V(k), without further explicitly participation in the computation.

4 Results and Discussions

To verify the stability and robustness of AH-EKF method, self-defined dynamic current and pulse current tests were performed. The current profile are shown as Fig 4. (a) and Fig 5. (a) respectively. Fig 4. (b) and Fig 5. (b) show the experimental measured values and estimated voltage from battery model, which indicate the general shape of the model output and that of the true experimental value are almost the same under two different current profiles. Fig 4. (c) and Fig 5. (c) present the estimation result based on AH method and AH-EKF method. The terminal SOCs are calculated by the OCV, which were measured after six hour rest. The absolute errors comparison of AH and EKF are listed in Table 2. The errors from EKF are relatively lower than AH, which indicates the noise suppression works properly and SOC calibration takes effect.
In addition, the initial SOC value is also important value for validating the algorithm convergence and robustness. Here is a verification to set the initial SOC value to 80%, while its true status is full charged, as shown in Fig 5. (c).

| SOC (%) | SOC (%) | AH (%) | EKF (%) | Absolute error |
|---------|---------|--------|---------|----------------|
| Initial | Final   |        |         | AH | EKF |
| 47.3    | 24.7    | 27.277 | 26.48   | 2.577 | 1.7828 |
| 100     | 3.475   | 1.9172 | 3.6495  | 1.5578 | 0.1745 |

Table 2. Comparison of AH method and EKF under dynamic current condition.
Fig 5. (a) Pulse dynamic current profile in one cycle. (b) Measured and estimate voltage. (c) SOC obtained by coulombic count methods and EKF.

5 Conclusion
With the development of energy storage technology and popularization of Evs, the application of BMS technology becomes significant from the safety and stability considerations. The precise SOC estimation is a critical index in BMS. In this paper, Thevenin model was used to describe the battery electrochemistry performance. EKF algorithm was studied for SOC estimation. The results show EKF algorithm has a good accuracy with less than 2% estimation errors. The initial SOC value fluctuation tests indicate that the algorithm has a good convergence and robustness. However, precise of SOC depends both on the accuracy of electrical model and EKF algorithm, as well as its model parameters. In more practical, the model parameters of $R_1$, $R_2$, $C$ change with the battery aging and temperature. The dynamic parameters online identification and implementation is necessary and need for further studies.
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