An Estimation Algorithm of Extended Kalman Filter based on improved Thevenin Model for the management of Lithium Battery System

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Abstract. We proposed a new estimation algorithm of extended Kalman filter (EKF) based on improved Thevenin model; Experiments were carried out to verify the validity with seven 4Ah lithium cobalt acid batteries in series. The experimental results showed that when using the algorithm, the estimation error of SOC is in the scope of error allowed, and the requirement of online SOC estimation can be satisfied.

1. Introduction
State Of Charge (SOC) is an important parameter to characterize the state of residual battery power. Accurately estimating SOC can effectively avoid battery overcharge or overdischarge and prolong the service life of the battery. SOC estimation is an essential function of the battery management system and also the key to reliable operation of cells [1].

There are several battery SOC estimation methods. They are shown below:

1) Current integration: SOC is estimated based on the integration of input and output energy of the battery. Because the battery pack will be recharged and discharged repeatedly. Therefore, the estimation error will also be integrated and increased[2].

2) Open-circuit voltage (OCV) measurement: OCV is the battery terminal voltage when the current of the battery is zero. The relationship between OCV and SOC is simple. Therefore, if we know the battery OCV, we can easily estimate SOC. However, when the battery pack contains surplus electricity, the battery current is not zero. Therefore, it is difficult to measure OCV directly[3].

3) Equivalent Circuit: This method uses the equivalent circuit of battery to estimate SOC. Therefore, it is necessary to determine the constant of equivalent circuit accurately. Using the equivalent circuit, OCV can be calculated by measuring the battery current and terminal voltage. Therefore, this is a possible way of operating the system. Because the noise in practical application polluted the data of voltage and current measured by sensors, the traditional estimation methods of SOC, such as time integral method and open-circuit voltage method, are not ideal for reducing noise, so there are some shortcomings such as more error and difficulty in real-time estimation of SOC of batteries. Kalman filtering algorithm [4] is a powerful tool to deal with noise. Because Classical Kalman is only suitable for the narrow field while Lithium battery SOC is a non-linear system, we use an extended Kalman algorithm to estimate the SOC of the battery.

In the above analysis, Thevenin model is chosen in this paper. The model has simple structure, less parameters involved, and its accuracy can meet the requirements of Engineering application. On this
basis, considering the influence of polarization on voltage and SOC itself, the non-linear state equation is established, and then the SOC is estimated.

2. Theoretical analysis

2.1 Thevenin Equivalent Model
The electro chemical model is generally suitable for the development and improvement of lithium batteries, but not for the research of the battery management system. Artificial Neural Network (ANN) model needs a lot of experimental data, which is too dependent on the historical data of batteries and is also not suitable for this study[5]. Typical circuit models include Rint model, Thevenin model[[5], PNGV model[6], Masimo Ceraolo model and so on. The comparison analysis shows that the Thevenin model can represent not only the sudden change of battery terminal voltage, but also the gradual shift in battery terminal voltage, and the calculation amount is appropriate. So this paper uses the Thevenin model.

We show the battery Thevenin model in Figure 1. In this model, the lithium battery is equivalent to a model consisting of electromotive force $E$, ohmic resistance $R_1$, polarization resistance $R_2$, polarization capacitance $C_0$, battery current $I$ and terminal voltage $U_{OCV}$. The model have the electrical relations as follows:

$$\begin{align*}
E(t) &= U_{OCV} + R_1 i(t) + u_c(t) \\
i(t) &= \frac{u_c(t)}{R_2} + C_0 \frac{du_c}{dt} \quad (1)
\end{align*}$$

As shown in formula (1). The first and second parts of equation (1) are the relationship between KVL and KCL of the Thevenin model.

2.2 Model identification
Hybrid Pulse Power Characteristic (HPPC) is usually used to identify the parameters in the model[7]. We carried out the 7-order polynomial fitting of e-soc data. The experimental steps of lithium iron phosphate at room temperature are as follows:

1) When the battery is fully charged, it is placed for 1 h, and the time required to discharge the battery with 1C current is recorded. The experiment was repeated three times to calculate the real capacity of the battery and take its average value.

2) After the battery is fully charged, the battery is set aside for 40 minutes, discharged for 10 seconds at 1c current, and rested for 40 seconds, then charged for 10 seconds with 1c current, and then rested for 1 hour.

3) The SOC value decreases by 10% with discharge of 1C current. Repeat step (2). When the value of the SOC equals to 10%, the experiment ends.

Voltage curve as shown in Figure 2:
Figure 2. Voltage curve

It can be seen from the figure that the transient voltage between UA and UB is caused by internal resistance $R_1$. The voltage change of UB is due to the charging of polarization capacitor $C_0$ in RC network and the slow drop of voltage. The change of UD is due to the discharge of $C_0$ and the slow rise of voltage.

The parameters can be calculated according to the above analysis, the abrupt voltage change in the BC section caused by the ohmic internal resistance $R_1$ of the battery, $R_1 = U_{AB}/I$. The variation of voltage in the CD segment shows polarization resistance $R_2$, $R_2 = U_{CD}/I$. For the first order RC circuit in the model, the time constant $\tau = R_1 \times C$ is a constant, $\tau = t_1 - t_2$. Polarization capacitance $C = \tau / U_{CD}$.

2.3 Research on Extended Kalman Filtering Algorithms

There are many methods for estimating SOC of lithium batteries. The typical methods are the current integration method, open-circuit voltage method, discharge experiment method, neural network method, Kalman filter method [8] and so on.

The open-circuit voltage method uses the open-circuit voltage $U$ of the battery to estimate the SOC of the cell. The function relation of $U$-SOC can be expressed. We determine the SOC of the battery by measuring the open-circuit voltage of the battery and the $U_{OCV}$-SOC relationship. However, it is difficult to obtain accurate open-circuit voltage under the working condition of lithium batteries, so the error of this method is more. We estimated the current integration method according to the definition of SOC. The description of SOC is shown in Formula (2):

$$SOC(t) = SOC(t_0) - 1/Q_i \int_{t_0}^{t} i(t) dt$$

(2)

The classical Kalman filtering algorithm is suitable for linear systems, while the lithium battery SOC system is non-linear. Extended Kalman filtering algorithm is an improvement of the traditional Kalman algorithm. It is an algorithm that expands the non-linear space equation by Taylor series and obtains the approximate linear space equation by discarding the second order and above terms. Then the Kalman filtering algorithm is applied to the linear space equation to estimate the current space state. It is suitable for discrete nonlinear systems.

The space of discrete nonlinear systems can be expressed as:

$$\begin{align*}
\dot{x}(k+1) &= G(x_k, k)X(k) + h(x_k, k)j_k + \omega_k \\
y(k) &= C(x_k, k)x(k) + \nu_k
\end{align*}$$

(3)

The first part of the formula (3) represents the equation of state, and the second part describes the observation equation.

$K$ stands for discrete time, $x_{k+1}$ is an n-dimensional state vector, $y_k$ is an m-dimensional observation vector, and $\omega_k$, $\nu_k$ stand for mutual independent white Gaussian noise, (WGN).

In formula (3):
\[ G(x_k, k) = \begin{pmatrix} 1 & 0 \\ 0 & e^{-\frac{t}{\tau}} \end{pmatrix}, \quad h(x_k, k) = \begin{pmatrix} -\frac{t}{Q_0} \\ R_2(1-e^{-\frac{t}{\tau}}) \end{pmatrix} \]

Linearize the Taylor series of equation, and then we get the results:

\[ \hat{G}(x_k, k) = \begin{pmatrix} 1 & 0 \\ 0 & e^{-\frac{t}{\tau}} \end{pmatrix}, \quad \hat{h}(x_k, k) = \begin{pmatrix} -\frac{t}{Q_0} \\ R_2(1-e^{-\frac{t}{\tau}}) \end{pmatrix}, \quad \hat{C}(x_k, k) = \left( \frac{\partial U_{OV}}{\partial SOC}, -1 \right) \]

Firstly, the state \( \hat{x}_k \) and the mean square error \( \hat{h}(x_k, k) \) of k-time are used to estimate the state and the mean square error of the current time, and the prior state \( \hat{x}_{k+1} \) and the previous mean square error \( \hat{h}(x_k, k) \) are obtained. Then we calculate the current Kalman gain \( K_{k+1} \). Finally, the state \( \hat{x}_{k+1} \) of the current moment is obtained by correcting the prior state with \( K_{k+1} \), and the mean square error \( \hat{h}(x_k, k) \) of the current moment is obtained by correcting the prior mean square error.

2.3 Extended Kalman Filtering Process

After collecting the voltage and current parameters of the battery, it begins to enter the algorithm cycle.

1) Initialize the estimated parameters and take the estimated values of the previous time as the initial values of this time;
2) Predicted values of state and covariance are obtained from the square of state;
3) Update the parameters and find out the relevant intermediate parameters;
4) Update the state and correct the predicted state by weighting coefficient;
5) Update System State Value and Covariance Matrix.

3. Experimental verification

In this paper, the commonly used lithium cobalt oxide battery was used for experimental verification.

The rated capacitance of the cell is 4Ah, and rated voltage is 3.7V working voltage range is 3.7~4.15V. We simulated the working state under actual working conditions. This paper adopts the lithium battery in a series of 7 for experimental verification.

3.1 The relationship between E-SOC curve

We left the cell under different SOC for 40 minutes, and measured the open circuit voltage, while the open circuit voltage is equal to the lithium battery E. Then we carried out the 7-order polynomial fitting of e-soc data. The obtained \( U_{OCV} \)-SOC curve is shown in Figure 3, and the relationship of E-SOC is shown in equation (4):

\[ U_{OCV} = 112.234 \times SOC^7 - 330.45 \times SOC^6 + 423.46 \times SOC^5 - 321.21 \times SOC^4 + 130.54 \times SOC^3 - 32.64 \times SOC^2 + 5.432 \times SOC + 4.633 \]  

(4)
Figure 3. The UOCV-SOC curve of lithium cobalt oxide battery

Figure 3 shows that when SOC is 0-10% and 90%-100%, the UOCV changes obviously, and the relationship between them is non-linear, while when SOC is 10%-90%, the relationship between UOCV and SOC is linear.

3.3 EKF estimation of SOC experiments for lithium batteries

We verified the EKF SOC algorithm by using the battery pack with a constant current of 0.5c, combined with equations (1), (2), (3) and (4). The results are shown in Figure 4.

Figure 4. EKF estimates the SOC of lithium cobalt oxide batteries

In Figure 4, the black curve is the real SOC, and the red curve is the extended Kalman estimated SOC curve.

Figure 5. EKF estimation error curve of SOC

The error analysis results are shown in Figure 5. The black curve in Figure 5 is the difference between the extended Kalman estimation of SOC and the actual value. It is found that the error of SOC estimation is less than 3%, which is within the allowable range.

Conclusion

Aiming at the SOC online estimation problem of the lithium battery pack, we conduct the Thevenin model equivalence for the lithium battery pack and propose an estimation method based on the extended Kalman filter algorithm. A series of 7 4Ah lithium cobalt battery pack was used to simulate the lithium battery pack for experimental verification. The results show that the estimation error is less than 3%, and within the allowable range, it can meet the requirement of online estimation of SOC of
the lithium battery.

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