The Analysis of Modeling of Dual Kalman Filter In Lithium Battery SOC Estimates

Yun-gan Wang¹,²,a, Zhong-feng Wang², Kun-ya Guo³, Xiao-tian Wang¹,², Li-gang Li², Zhe-zhu Huang³

¹University of Chinese Academy of Sciences, China
²ShenYang Institute of Automation, Chinese Academy of Sciences Shen-Yang, China
³Shenyang PowerSupply Company Liaoning State Grid

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Abstract. Dual Kalman filter (DEKF) algorithm is analysed on this paper to online estimate the state of charge of lithium battery. After introducing the estimation methods international used currently, we choose an appropriate equivalent circuit model of lithium battery and identify the parameters by least square method. By building the Kalman filter state space equation of lithium battery SOCand battery internal resistance R0, we form a dual Kalman filter algorithm that can estimate battery SOC with higher precision. And then, the workflow of this algorithm is given, which demonstrates the feasibility of online state estimate and ease of programming.

Introduction

In this paper, we build a lithium battery model which is used in the estimation of the SOC. In order to make battery life longer, we need maximizing battery performance, improving the safety, and preventing battery overcharge and over-discharge. Currently, lead-acid battery is widely used, but which has some of inherent shortcomings [1]. For example, safety performance is difficult to meet the requirements, short life and poor discharge characteristics and so on. So we have adopted a lithium-ion battery pack which has 232V of rated voltage.

Establishing a battery model usually bases on the complex physical and chemical reactions of internal battery [2-3]. The SOC represents a ratio between the remaining electric and rated capacity under the same conditions, which plays an important role in the detection of health and performance of lithium-ion battery pack [4]. Generally, there are two kinds of methods in SOC estimation of the battery. One way is direct method and the other way is indirect method [5]. The direct method is based on the physical properties of battery. Such as detect the density of acid. It is generally not used for online management in the battery pack. The indirect method is based on detection the measurement parameter of battery-related characterization. Such as open-circuit voltage method, discharge test method, neural networks and Kalman filtering method and so on. The open circuit voltage method needs to stand long enough to ensure that the open circuit voltage has reached a stable state before SOC estimation. The discharge test method also needs to interrupt the work which cannot be estimated online. The neural network algorithm requires a lot of training data. The Kalman SOC estimation filtering algorithm is an effective method. But this method has a strong dependence on the accuracy of the model, and it is sensitive for the parameters of the battery.

Equivalent circuit model

There are some models are being used at home and abroad now. Such as Rint model, Thevenin model, PNGV model and GNL model and so on. The Thevenin equivalent circuit model is used in this paper. It has better dynamic adaptability then the Rint model and PNGV model. It can be more accurately simulate the dynamic characteristics of the lithium-ion battery. It is a simple and practical model which is shown in Figure 1.
Fig.1 The Equivalent Circuit of Thevenin

Fig.2 Battery Voltage Curves Under Current Pulse

Wherein, the R0 represents battery resistance, Rp and Cp describe battery polarization effect. According to Kirchhoff’s voltage law and Kirchhoff’s current law, we can obtain the circuit equations:

\[
\begin{align*}
U_L(t) &= U_{OC}(SOC, T) - U_p(t) - i(t) \cdot R_0(SOC, T, I) \\
i(t) &= \frac{U_p(t)}{R_p} + C_p \cdot \frac{d(U_p(t))}{dt}
\end{align*}
\]

(1)

The i(t) is a first-order non-linear equations. We assume the battery discharge current is positive and charging current is negative. Defining the model initial polarization voltage is Up(0). The I represents constant current, The time constant is \( \tau = R_p C_p \). Solving the above equation:

\[
\begin{align*}
U_p(t) &= U_p(0) \cdot e^{-\frac{t}{\tau}} + I \cdot R_p \cdot \left(1 - e^{-\frac{t}{\tau}}\right) \\
U_L(t) &= U_{OC}(SOC, T) - I \cdot R_0(SOC, T, I) - \left[U_p(0) \cdot e^{-\frac{t}{\tau}} + I \cdot R_p \cdot \left(1 - e^{-\frac{t}{\tau}}\right)\right]
\end{align*}
\]

(2)

In order to identify the initial parameters of battery model, this paper makes a pulse power characteristic test. The experimental result is shown in Figure 2. At the current load moment, the voltage fluctuation is primarily caused by internal resistance. According to Ohm’s law, \( R_0 = \frac{dU_1}{I} \). The slowly varying voltage dU2 is mainly caused by Rp and Cp. According to the variation of dU2, We make Up(0) and \( \tau \) as time constants, and use formula (2) and the least squares fitting method. We can get the initial values of Up(0), Rp and Cp.

**The SOC estimation of lithium-ion battery pack**

According to the definition of SOC, we can have the SOC calculation expression as follows:

\[
SOC = SOC_0 - \frac{\int \eta i(t) dt}{c}
\]

(3)

The SOC0 is the initial value of the SOC. The \( \eta \) represents the efficiency of charging and discharging (charging \( \eta = 1 \); discharge \( \eta < 1 \)). The C is the rated capacity of the battery. The i(t) is the current electric (charging, i(t) < 0; discharge, i(t) > 0).

In order to using the Kalman filter, the formula (3) is discredited. We assume the sampling time is \( \Delta t \), the above equation can be written as:

\[
SOC_k = SOC_{k-1} - \frac{\eta \Delta t}{c} i_{k-1}
\]

(4)

The SOC estimation method is the optimal estimation method which is based on Ah counting method. This paper introduces Kalman filter and makes SOC as a state space variables. Thus, we can estimates the correct SOC.

The Kalman filter gain matrix K weight plays an important role in SOC correction. The K weight is large when the initial SOC0 error is large or the accumulated error is large. The K weight is small and SOC correction function is also weak when the error is small. This way overcomes the inherent problems of Ah counting method, and effectively cut down the noise.

The Kalman filtering algorithm is fit for estimation of linear time-varying model. The non-linear model needs the extended Kalman filter algorithm. The performance mainly depends on the accuracy of the state space mode. According to the battery circuit equations and SOC model definition, we can draw a discrete space battery model state equation and output equation.
\[
\begin{bmatrix}
\frac{SO_{C,k+1}}{U_{k+1}} \\
\frac{U_{k+1}}{R_{p,0}}
\end{bmatrix} = \begin{bmatrix}
1 & 0 \\
0 & e^{-\frac{(\Delta t)}{\tau}}
\end{bmatrix} \begin{bmatrix}
SO_{C,k} \\
U_{k+1}R_{p,0}
\end{bmatrix} + \begin{bmatrix}
\frac{-\eta_{i} \Delta t}{c} \\
R_{p}(1-e^{-\frac{\Delta t}{\tau}})
\end{bmatrix} i_{k} + w_{k}
\]

(5)

Wherein, the \(w_{k}\) represents the process noise, which is caused by the system sensor error. The \(v_{k}\) represents system noise which is caused by the system modeling and system parameters. Its covariance is \(Q_{k} = E[w_{k}w_{k}^{T}]\) and \(R_{k} = E[v_{k}v_{k}^{T}]\).

\[
\begin{align*}
 x_{k} &= \begin{bmatrix} SO_{C,k} & U_{k}^{R_{p}C_{p}} \end{bmatrix}^{T} \\
 A_{k} &= \frac{\partial f}{\partial x}_{|x=x(k|k)} = \begin{bmatrix} 1 & 0 \\
0 & e^{-\frac{\Delta t}{\tau}} \end{bmatrix} \\
 B_{k} &= \begin{bmatrix}
\frac{-\eta_{i} \Delta t}{c} \\
R_{p}(1-e^{-\frac{\Delta t}{\tau}})
\end{bmatrix} \\n C_{k} &= \frac{\partial h}{\partial x}_{|x=x(k|k-1)} = \begin{bmatrix} \frac{dU_{ack}(SO_{C,k-1},T)}{dSO_{C,k-1}} & -1 \end{bmatrix}
\end{align*}
\]

Definition:

\[
\begin{align*}
 x(0|0) &= E(x_{0}) \\
 P_{x}(0|0) &= E[(x_{0} - x(0|0))(x_{0} - x(0|0))^{T}]
\end{align*}
\]

(7)

The Kalman filter recursive calculation:

Update time:

\[
\begin{align*}
 x(k|k-1) &= A_{k}x(k-1|k-1) + B_{k}i_{k-1} \\
 P_{x}(k|k-1) &= A_{k}P_{x}(k-1|k-1)A_{k}^{T} + Q_{k-1}
\end{align*}
\]

(8)

(9)

Observations update:

\[
k_{g}(k) = \frac{P_{x}(k|k-1)C_{k}^{T}}{C_{k}P_{x}(k|k-1)C_{k}^{T} + R_{k}}
\]

(10)

\[
x(k|k) = x(k|k-1) + k_{g}(k) * (y(k) - h(x(k|k-1),u_{k}))
\]

(11)

\[
P_{x}(k|k) = (I - k_{g}(k)C_{k})P_{x}(k|k-1)
\]

(12)

Using the contents of previous section, we can estimate the SOC of lithium-ion batteries. But it cannot reflect the dynamic changes of the battery model. This paper introduces dual extended Kalman filter (DEKF) algorithm, which can estimate both battery status and parameters online, and describes the dynamic characteristics of the battery well. The algorithm has a better adaptability, and improves the SOC estimation accuracy. The main idea of DEKF is to use models to estimate the system state and use system state to estimate the model parameters alternately. We use two separate Kalman filter to estimate the system state and parameters respectively.

The \(R_{0}\) is the battery resistance which is a parameter vector. It is slowly changing. We can obtain the following system of equations and discrete output state space observation equation:

\[
\begin{align*}
 R_{0}(k+1) &= R_{0}(k) + r_{k} \\
 U_{lk} &= U_{ack}(SO_{C},T) - i_{k}R_{0}(k) - U_{k}^{R_{p}C_{p}} + n_{k}
\end{align*}
\]

(13)

Wherein, the \(r_{k}\) and \(n_{k}\) represent error. The covariance is \(M_{k} = E[y_{k}y_{k}^{T}]\) and \(N_{k} = E[n_{k}n_{k}^{T}]\).

According to Kalman filtering algorithm, we can get:

\[
\begin{align*}
 x_{r,k} &= R_{0}(k), \quad A_{r,k} = 1 \\
 C_{r,k} &= \frac{\partial h}{\partial r}_{|r=R_{0}(k|k-1)} = -i_{k}
\end{align*}
\]

Adding initialization value, and combining with formula (7), we can get:

\[
\begin{align*}
 R_{0}(0|0) &= E(R_{0}) \\
 P_{r}(0|0) &= E[(R_{0} - R_{0}(0|0))(R_{0} - R_{0}(0|0))^{T}]
\end{align*}
\]

(15)

According to the above analysis, we can get the flowchart of the dual Kalman filter which is shown in Figure 3.
Conclusion

We use Thevenin battery model as a research foundation to estimate the lithium-ion battery SOC. Using dual Kalman filter algorithm online estimate the battery resistance $R_0$ in order to improved Thevenin model accuracy. Using this algorithm and the improved model to online estimate SOC. It solves the problems that initial value of the SOC estimation and error accumulation.

Fig.3 The algorithm flowchart of DEKF

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