SOC Estimation of Modular Lithium Battery Pack Based on Adaptive Kalman Filter Algorithm

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Abstract. Lithium battery state of charge (SOC) is a core parameter in battery management systems. In order to suppress the influence of noise characteristics on the accuracy of SOC estimation, this paper proposes an adaptive kalman filter (AKF) algorithm with variable noise variance based on the battery equivalent circuit model. In order to improve the accuracy of SOC estimation, the algorithm estimates the noise variance online and applies the noise variance estimation to kalman filter iteration process. Aiming at the modular structure of the battery pack, a segmentation variable weighting coefficient algorithm is proposed to estimate the SOC value of the entire battery pack. Based on the simulation platform of matlab, this paper carries out experimental verification and analysis. The results demonstrate the effectiveness and superiority of the algorithm.

1. Introduction

The SOC (state of charge) is an important indicator reflecting the state of remaining battery capacity. Accurate SOC estimation is particularly important. However, the SOC is an indirect measurement parameter, and its value can be estimated indirectly by correlation algorithm. The lithium battery SOC estimation algorithm, which combines the kalman filter algorithm with the ampere-time method and the equivalent circuit model, is applied more and more widely. However, the accuracy of SOC estimation depends on the battery model and the initial value of the parameters. During long-term operation, the lithium battery will change with the influence of temperature, discharge rate, number of charge cycles and other factors. The model parameters of the lithium battery are no longer kept constant. As a result, the SOC estimation algorithm designed according to the initial battery model cannot obtain a satisfactory estimation result. In order to solve the problem, the literature [1-3] proposes the method of online model parameter identification and updating. By modifying the model parameters in real time online, the influence of the change of working conditions on the SOC estimation is reduced, and the estimation accuracy is improved. However, in the battery SOC value identification process, the battery voltage, current and other parameters often contain various measurement noise. When using kalman filter, if the model noise variance set value is significantly different from the noise characteristics under the current operating conditions, the accuracy of the SOC estimation will be seriously reduced, even diverging [1]. Therefore, in order to improve the SOC estimation value in consideration of the changes of the battery operating conditions, it is necessary to study an SOC estimation method that can effectively suppress the influence of noise. In the literature [4], an adaptive kalman filter algorithm is proposed to suppress the estimation accuracy of the model noise parameter values. However, the setting of the noise variance R and Q is basically based on
experience, and the calculation is complicated. In the literature [5-6], an adaptive kalman filter (AKF) algorithm based on innovation can effectively solve the problem of inaccurate state estimation caused by measurement noise time-varying. The AKF algorithm has not yet been applied to battery SOC estimation. This paper will introduce the SOC estimation of lithium battery based on AKF algorithm to improve the accuracy of SOC estimation, which is used to solve the SOC estimation under the condition of measurement noise and state noise characteristics. At present, there are many topologies for high-power battery packs, and applications for building high-power battery packs based on modularity are also widely used [7-9]. The so-called modular battery pack refers to a battery pack that is connected to a larger power by serially connecting a plurality of low-power battery modules. The SOC value of the entire battery pack is calculated based on the estimated value of the battery module SOC. According to the author literature search, there is no relevant research result. In response to this problem, the paper proposes a modular battery pack SOC estimation method with segmented variable weighting coefficients.

2. Material and Methods

2.1. Lithium battery model and kalman filter algorithm

The electrochemical composite model is shown in Equation 4:\(^{[10-11]}\):

\[ y_k = \frac{K_0 - R}{K_1 + \ln(x_k)} (x_k - x_k) + K_2 K_3 K_4 K_5 K_6 K_7 K_8 K_9 K_{10} (1 - x_k) \] (1)

Where \( y_k \) represents the battery terminal voltage, \( i_k \) represents the instantaneous current, \( R \) represents the internal resistance of the battery, \( x_k \) represents the battery SOC, \( K_0 - K_4 \) represents the model matching coefficient. Based on the composite model in equation (1) and the ampere time measurement method, considering the state noise and observation noise caused by factors such as changes in operating conditions, the state equation of the battery is obtained, as shown in equation (2), the observation equation as shown in equation (3):

\[ x_{k+1} = x_k - \left( \frac{\eta \Delta t}{C_n} \right) x_k + w_k \] (2)

\[ y_k = K_0 - R_i - K_i / x_k - K_2 x_k + K_3 \ln(x_k) + K_4 \ln(1 - x_k) + v_k \] (3)

Where \( C_n \) represents battery rated capacity, \( \eta \) represents Coulomb efficiency, \( \Delta t \) represents sampling time, \( w_k \) represents process excitation noise, and \( v_k \) represents observation noise. Based on equations (2) and (3), the extended kalman filter algorithm can be used to estimate the SOC of the lithium-ion battery. The detailed estimation steps and results can be referred to the literature [6] and the literature [7]. Normally, the statistical properties of state noise and observed noise are assumed to be zero mean, and the noise is reduced to Gaussian white noise \( E(w_k w_k^T) = Q_k \), \( E(v_k v_k^T) = R_k \), where \( Q_k \) represents the system state noise covariance matrix, \( R_k \) represents the system observed noise covariance matrix, and \( E(.) \) represents the expectation function. Extended kalman filtering preserves low-order linear equations by taylor series expansion and high-order truncation of nonlinear functions. For the (2) and (3) battery composite models, taylor series expansion and high-order truncation are performed on the nonlinear system. The results are as follows:

\[ x_{k+1} = x_{a,k+1} + A_k (x_k - x_{a,k}) + w_k \] (4)

\[ y_k = y_{a,k} + H_k (x_k - x_{a,k}) + v_k \] (5)

Where \( x_k \) represents the true value of the system state variable at time \( k \), \( y_k \) represents the true value of the system output; \( x_{a,k} \) represents the observed value of the system state variable, and \( y_{a,k} \) represents the observed value of the system output variable at time \( k \); \( w_k \) represents \( k \) State noise at
the moment, \( v_k \) represents the measurement noise at time \( k \); \( A_k \) represents the statistical coefficient of the dynamic characteristics of the Jacobian matrix of the state equation, and \( H_k \) represents the statistical coefficient of the dynamic characteristics of the observation equation.

\[
A_k = \left. \frac{\partial f(x_k, u_k)}{\partial x_k} \right|_{x_k = x_{k-1}} \\
H_k = \left. \frac{\partial h(x_k, u_k)}{\partial x_k} \right|_{x_k = x_{k-1}}
\]

After linearization of equations (2) and (3), the battery state observation composite model is:

\[
x_{k+1} = x_k - \left( \frac{\eta A}{C_n} \right) i_k + w_k
\]

This shows that, \( A_k = \left. \frac{\partial f(x_k, u_k)}{\partial x_k} \right|_{x_k = x_{k-1}} = 1 \cdot B_k = -\frac{\eta A}{C_n}, \ u_k = i_k \)

The observation equation is:

\[
y_k = K_0 - R_i - K_1 / x_k - K_2 x_k + K_3 \ln(x_k) + K_4 \ln(1 - x_k) + v_k
\]

This shows that, \( H_k = \left. \frac{\partial h(x_k, u_k)}{\partial x_k} \right|_{x_k = x_{k-1}} = K_1 / x_k^2 - K_2 + K_1 / x_k - K_3 / (1 - x_k) \), \( D_k = -R, \ u_k = i_k \)

The kalman steps are mainly:
(1) Set initial values \( x_0 \) and \( P_0 \)

(2) Based on the initial value and the equation (8), the system state variable is updated from \( k \) to \( k+1 \), and the solution expression is:

\[
x_{k+1} = x_k - \left( \frac{\eta A}{C_n} \right) i_k
\]

(3) Based on \( P_0 \) and \( Q \), the mean squared estimated error covariance is updated from \( k \) to \( k+1 \) according to equation (11):

\[
P_{k+1} = A_k P_k A_k^T + Q_k
\]

(4) Find the kalman gain according to equation (12)

\[
K_k = P_{k+1} H_k H_k^T + R_k^{-1}
\]

(5) According to the observation equation, the system output variable is updated from \( k \) time to \( k+1 \) time based on equation (10):

\[
y_{k+1} = K_0 - R_i_{k+1} - K_1 / x_k - K_2 x_{k+1} + K_3 \ln(x_{k+1}) + K_4 \ln(1 - x_{k+1})
\]

(6) Calculate the state optimal estimate according to equation (14):

\[
x_{k+1} = x_k + K(y_{k+1} - y_k)
\]

(7) Mean estimation error optimal estimation

\[
P_{k+1} = P_{k+1} - K P_{k+1} K^T
\]

(8) Iterative judgment

If the set number of steps is reached, the loop ends and the algorithm is terminated; otherwise, \( k = k+1 \), the turn time update phase, and the iteration loop continues.

2.2. Kalman Filter SOC Estimation Algorithm with Variable Noise Variance

In the conventional kalman filter algorithm, the covariance \( Q \) and \( R \) in the state and observation equations are fixed values. In the case of actual variable conditions, \( Q \) and \( R \) are not updated in real time. Therefore, it is difficult to obtain an accurate SOC estimation value. In order to reduce the influence of noise characteristics change under variable operating conditions on the accuracy of SOC estimation based on kalman filter algorithm, it is necessary to update the covariance \( Q \) and \( R \) of noise in real time according to the change of working conditions. By detecting the working condition, the
noise variance is self-corrected with the actual working condition \[1\]. According to the research results in \[1\], the state equation dynamic noise \(Q\) can be corrected online in real time using equation (16).

\[
Q_k = \left(\frac{31}{210C}A_k\right)^2 \tag{16}
\]

Where \(A_k\) is the ampere-hour value obtained by integrating the ampere-hours of each step. From equation (16), it is known that during each iteration, the equation noise variance is related to the total battery capacity and the ampere-hour integral value. Therefore, the \(Q\) value will be updated online, in line with the actual situation of each step.

Since the actual covariance of the measured noise cannot be directly measured, it is very difficult to estimate indirectly. Therefore, it is more difficult to practice by obtaining the covariance of the actual measured noise and performing online modification. According to equation (12), it can be seen that the measurement noise covariance \(R\) affects the estimation accuracy of the SOC value by the kalman algorithm through the gain matrix \(K\) \[5\]. Therefore, the correction of the measurement noise covariance value can be realized by adjusting the value of \(K\).

According to formula (14), the definition of the new interest calculation formula is:

\[
e_{k+1} = y_{k+1} - y_{k+jk} \tag{17}
\]

Based on (9), the new interest can be expanded into (18)

\[
e_{k+1} = H_{k+1}x_{k+1} + D_{k+1}u_{k+1} + v_{k+1} - H_{k+1}x_{k+jk} - D_{k+1}u_{k+1} = H_{k+1}(x_{k+1} - x_{k+jk}) + v_{k+1} \tag{18}
\]

Where \(x_{k+1} - x_{k+jk}\) is the estimation error of the state quantity. As can be seen from equation (18), the innovation contains measurement noise information. When the measurement noise changes, the innovation also changes. The variance for calculating the innovation based on equation (18) is:

\[
P_{e_{k+1}} = H_{k+1}P_{k+jk}H_{k+1}^T + R_{k+1} \tag{19}
\]

It can be seen that equation (19) contains the measured noise variance value \(R\), which is the same as the equation (12). According to the literature [5], the recursive formula of the formula (19) is:

\[
C_{i+1} = C_i + \frac{1}{k-M+1}[e_{k+1}^2 - C_i] \tag{20}
\]

According to the literature [5] and [14], it can be seen that the formula (20) is the optimal estimate of the formula (19). Therefore, the kalman gain of equation (12) can be changed to

\[
K_{k+1} = P_{k+jk}H_{k+1}^T(C_{k+1})^{-1} \tag{21}
\]

The gain value \(K\) calculated by equation (21) varies with the measurement noise variance \(R\). The influence of the measured noise variance is updated. A real-time estimation of the actual variance of the noise can be achieved using equations (19) and (20), as shown in equation (22).

\[
R_{k+1} = C_{k+1} - H_{k+1}P_{k+1}H_{k+1}^T \tag{22}
\]

When the SOC estimation is performed on the entire battery pack, it is obtained by the SOC value of each module. When \(SOC_{\text{min}} \leq 0.6SOC_{\text{max}}\)

\[
SOC = SOC_{\text{min}} \tag{23}
\]

\(SOC_{\text{min}}\) are the minimum SOC value and the maximum SOC value in each battery module. When \(SOC_{\text{min}} > 0.6SOC_{\text{max}}\), the SOC value of the battery pack is calculated according to equation (24).

\[
SOC = \sum \lambda_i SOC_i \tag{24}
\]

Where \(SOC_i\) is the SOC estimation value of each battery module, and \(\lambda_i\) is the weighting coefficient of the \(i\) module.
\[ \hat{X}_{k+1|j} = \frac{P_{k+1|j}}{\sum_{m=1}^{N} P_{k+1|m}} \] (25)

Figure 1 is a schematic flow chart of the SOC estimation method.

| Set initial value | Equation (10) state variable update | Equation (16) state variance Q calculation |
|-------------------|------------------------------------|------------------------------------------|
| Equation (11) Error Covariance P Update | Equation (21) gain K calculation | Equation (20) calculation |
| Equation (14) SOC optimal value | Equation (23) or (24) battery pack SOC calculation |
| Equation(15) P-value optimal estimation |

Figure 1. Modular battery pack SOC estimation flow chart

3. RESULTS
In order to evaluate the effect and advantages of the variable noise adaptive kalman filter SOC estimation algorithm, the battery data of the INR 18650-20R of the Maryland University CALCE is used. In order to simulate the change of the noise characteristics in the state equation and the measurement equation during the operation of the battery, the zero-mean gaussian white noise of the variance variation is superimposed in the battery data. In order to verify the validity and superiority of the proposed algorithm for SOC estimation, the extended kalman algorithm (EKF) with fixed noise variance is used to estimate the SOC and adapt to the paper under the same noise environment and initial conditions. The algorithm AKF is compared. figure 2 shows a comparison of SOC estimation results. It can be seen from figure 2 that the adaptive kalman filter algorithm mentioned in the paper is more accurate for SOC estimation than the EKF algorithm with fixed noise variance, and the error relative to the actual SOC value is smaller.

Figure 2. Module battery SOC estimation results

4. Conclusions
In this paper, an adaptive kalman filter algorithm that can estimate the updated noise variance in real time is adopted for the problem that the SOC estimation result of lithium battery based on kalman
filter algorithm is not accurate. The algorithm can estimate the noise variance of the state direction and the observation method on-line in real time, and introduce the noise variance estimation value into the iterative calculation process of the kalman filter algorithm. It can effectively suppress the influence of the noise characteristic change on the calculation result and realize an accurate SOC estimation value. Simulation experiments show that the adaptive kalman filter algorithm can effectively track the change of actual noise in the case of changing noise characteristics. The SOC estimation value is more accurate than the standard extended kalman filter algorithm. Considering the modular topology of high-power battery packs, based on the SOC estimation of battery modules, a whole battery pack SOC estimation algorithm with segmented variable weighting coefficients is proposed, which provides a SOC estimation method for modular lithium battery packs.

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References
[1] Tianyi Zh, Xiyuan P, Yu P and Datong L 2016 Chinese Journal of Scientific Instrument 37 1441.
[2] Kexin W and Qiaoyan CH 2012 Proceedings of the CSEE 32 19.
[3] Yu X, Chenguang L and Jiaqi L. 2016 Journal of Ordnance Equipment Engineering 37 147.
[4] Yi L, Guojun T and Xiaoqun H 2017 TRANSACTIONS OF CHINA ELECTROTECHNICAL SOCIETY 32 108.
[5] Tong W and Ru G 2012 Optics and Precision Engineering 20 2308.
[6] Hong wei B, Zhi hua J, Jun pu W and Wei feng T 2006 Journal of Shang Hai Jiao Tong University 40 1000.
[7] Yuanyuan L, Wei H, Zhifu ZH, Yi ZH and Chong CH 2018 High Voltage Engineering 44 169.
[8] Lixia K, Chenlu M and Yongzhong L. 2019 CIESC Journal 70 599.
[9] Li-yong T, Dongyu ZH, Xin liang B and Xiaole L 2016 Chinese Journal of Power Sources 40 1874.
[10] Youqun Zh, Xiaofeng Zh and Yingjie L 2015 China Mechanical Engineering 26 394.
[11] Zewang CH, Liwen Y, Xiaobing ZH and Youren W 2019 Acta Metroligica Sinica 40 40.
[12] Fangdan Zh, Yijin Xia, Jiuchun J, Bingxiang S and Jonghun K 2016 Applied Energy 183 513.
[13] Yinjiao X, Wei H, Michael Pecht and Kwok Leung Tsui 2014 Applied Energy 113 106.
[14] Wei H, Nicholas Williard, Chaochao Ch and Michael Pecht 2014 International Journal of Electrical Power & Energy Systems 62 783.