A Novel Adaptive Multi-time Scale Joint Online Estimation Method for SOC and SOH of Lithium-ion Batteries

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Abstract. The state of charge (SOC) and state of health (SOH) are essential indicators for estimating the performance of lithium-ion batteries. In most of the existing methods to estimate SOC and SOH through step-by-step calculation may bring obstacles to real-time prediction of battery performance. To adapt the complex and dynamic situation of the batteries and estimate SOC and SOH in an accurate and fast manner, a novel multi-time scale joint online estimation method is proposed. In order to quickly identify the battery model and estimate the battery state, SOC and SOH are evaluated on a multi time scale framework based on extended Kalman filter (EKF). To improve the accuracy of the equivalent circuit model (ECM), a variable forgetting factor recursive least square (VFFRLS) method is introduced to identify the internal parameters in the battery model. A fuzzy variable time scale EKF (FVEKF) is proposed to estimate SOC and SOH online, where the fuzzy inference engine change the time scale to increase the convergence speed especially in complex stress conditions. Database from the University of Maryland is adopted to testify the effectiveness and efficiency of the algorithm. The results demonstrate that the method has better estimation accuracy and efficiency comparing to traditional joint estimation method, and meet the requirements of real-time estimation.

Keywords: Lithium-ion battery; State of health; State of charge; Variable forgetting factor; Variable time scale; Online estimation.

1. Introduction
With the wide application of lithium-ion battery in electric vehicle, battery management system (BMS) has become an important part of electric vehicle control system, which is used to monitor the state of battery and provide guidance information for users. State of charge (SOC) is considered to be a key factor reflecting the aging state of BMS. In addition, battery capacity attenuation is also one of the main limiting factors for vehicle application. If the lithium-ion battery whose capacity decays to the end of life (EOL) is not replaced in time, the stable operation of the system will be affected, and even serious consequences such as explosion may be caused. Therefore, in addition to detecting battery SOC, BMS must also accurately estimate battery health state (SOH).

SOC and SOH cannot be measured directly by sensors. Open circuit voltage method, Coulomb counting method, adaptive filtering method and machine learning method are four commonly used SOC estimation methods. Each method has its own advantages. In fact, the most commonly used method is Kalman filter and its variants.

Compared with SOC, SOH estimation is more complicated. To estimate SOH, three major indicators are provided, which are: charge and discharge behavior, capacity and internal resistance [2]. (i) The
charge and discharge behavior usually requires a large number of battery charges and discharge cycle tests and expensive experimental equipment, which is usually used in laboratory research. (ii) Capacity is most commonly used to predict SOH through data-driven algorithms (such as neural network, support vector machine, etc.). But the huge calculation recourses are needed for a data-driven algorithm which is not suitable for online estimation. (iii) The internal resistance of the battery can be directly obtained from the equivalent circuit model without complicated calculation. The internal resistance has a close correlation with the battery life, which degrades the accuracy of estimation. Most researchers only pay attention to the internal parameters and SOC of the battery, but ignore the problem that the SOC estimation accuracy is getting lower and lower with the aging of the battery. Therefore, Plett [3] first proposed a dual extended Kalman filter to simultaneously estimate the SOC of lithium-ion battery and the SOH based on the definition of capacity and resistance. Shahriari used EKF and neural network to estimate SOC, and then used fuzzy logic and least square method to estimate SOH.[4]

According to the slow variation characteristics of SOH and the fast variation characteristics of SOC, researchers propose a multi time scale framework. In reference [5], SOH is regarded as lithium-ion battery parameters. A multiscale DEKF framework was developed to reduce the computational complexity of the estimation by computing battery parameters at a slow time scale and computing SOC at a fast time scale. Zou et al [6] improved Plett's work by estimating SOH and SOC offline, real-time, respectively, on different time scales.

However, all of the above methods have a disadvantage that their time scales are determined offline. In practice, the current response is often complex, because the fixed time scale determined off-line can not track the current dynamic response, it will reduce the accuracy of estimation. Because there is a correlation between SOH estimation and SOC and battery parameters, it is necessary to conduct an overall study on these methods. The equivalent circuit model used in this study is second-order RC. Meanwhile, in order to improve the accuracy of the model, variable forgetting factor least squares (VFFRLS) is proposed to identify the model parameters, and a fuzzy variable time scale extended Kalman filter (EVEKF) with EKF is proposed for SOC estimation and SOH estimation. In addition, combined with variable forgetting factor least squares and fuzzy variable time scale extended Kalman filter (VFFRLS-FVEKF), the model parameters and SOC are estimated at the micro-scale, and the SOH is estimated at the macro scale, so as to realize the joint online estimation of parameters, SOH and SOC. The fuzzy engine is used to update the time scale, optimize the convergence ability of the algorithm under complex stress conditions, and improve the prediction accuracy and efficiency.

The structure of this article is as follows. The second section introduces the framework of equivalent circuit model and adaptive joint estimation method. The third section introduces a variable time scale joint estimator based on fuzzy control system (VFFRLS-FVEKF) to estimate the internal parameters, SOC and SOH in real time. The fourth section uses the University of Maryland database to verify the superiority of the proposed method through experiments. Various joint estimation algorithms are compared and analyzed in terms of algorithm accuracy and computational complexity. In the end, draw conclusions in Section 5.

2. Adaptive Joint Estimation Framework
In this section, the novel adaptive joint online estimation framework for SOC and SOH of batteries will be introduced in detail, and the ohmic internal resistance will be used as an indicator of SOH.

2.1. Definition of SOH
To accurately and quickly track battery life, due to the strong correlation between battery internal resistance and SOH, this paper uses battery internal resistance as an indicator of battery SOH, which is expressed by (1).

\[
SOH = \frac{R_{EOL} - R_{SOH}}{R_{EOL} - R_{BOC}} \times 100\%
\]
Where $R_{EOL}$ is the ohmic resistance of the accumulator when 80% SOH is defined based on
capacity. When the actual maximum capacity is reduced to 80% of the nominal, the battery is
considered to be end of life (EOL). $R_{BOL}$ is the ohmic resistance of the accumulator at the beginning
of life (BOL). $R_{NOW}$ is the current ohm resistance of the accumulator. The SOH range defined in this
paper is 0% to 100%. When the SOH is 0%, it means that the battery needs to be replaced. According
to typical automotive EOL standards, set $R_{EOL} = 2 \times R_{BOL}$ (in this paper $R_{BOL} = 0.04 \Omega$).

2.2. Equivalent Circuit Model

Compared with the first-order model, the second-order model is usually used for lithium-ion batteries,
which is more in line with the accuracy requirements of the estimation algorithm. As shown in the Fig.
1, where $i$ is the load current, $u$ is the terminal voltage, $R_0$ is the internal resistance, $R_1$, $C_1$ and $R_2$, $C_2$
represent the battery cell diffusion process and charge transfer process, $u_1$ and $u_2$ represent $R_1$, $C_1$
and $R_2$, $C_2$ branch voltage, voltage source $U_{oc}$ is used to describe the open circuit voltage (OCV) directly
related to SOC.

![Second-order RC model](image)

Figure 1. Second-order RC model.

According to Kirchhoff's law of voltage and current, the electrical characteristic equation of the
second-order RC model is expressed by (2).

$$
u(k) = U_{oc}[SOC(k)] - u_1 - u_2 - i(k) \cdot R_0$$

$$\dot{u}_1 = -\frac{u_1}{c_1 R_1} + \frac{i}{c_1}$$

$$\dot{u}_2 = -\frac{u_2}{c_2 R_2} + \frac{i}{c_2}$$

(2)

Where $U_{oc}[SOC(k)]$ represents the open circuit voltage obtained based on the OCV-SOC curve fitting.

2.3. SOC/SOH Online Estimation Framework

We present a multi-time scales framework in Fig. 2. First, the battery model is determined by the
adaptive forgetting factor recursive least square (AFFRLS) method. The forgetting factor is adaptively
adjusted according to the recognition result to speed up the convergence speed and improving the
accuracy of the model. To balanced variation characteristics between battery SOC and SOH, parameter
identification and state estimation are performed on two separate time scales, respectively. Model
parameter identification and battery SOC estimation are performed on the micro-scale, and battery
SOH estimation is performed on the macroscale.
There are two common methods for separating time scales. The first method usually determines the time scale offline. The algorithm is simple to execute, but it ignores the fast dynamics of the battery when the real car is running, so it cannot reflect the true battery state. The second method changes the time scale according to the change of the battery state, so as to track the dynamic response of the battery. However, the real car does not always maintain a high power state. This method does not respond well to the battery state under slow dynamics.

In order to reduce the influence of offline data on battery state estimation under complex stress conditions, this paper proposes a variable time scale estimator based on fuzzy inference engine. According to the fuzzy inference engine, the parameters of the state estimation process are coupled with the time scale, and the time scale is dynamically adjusted according to the intermediate results of the estimation process, so as to speed up the convergence speed of the algorithm under abnormal initial values, and improve the efficiency and accuracy of the algorithm.

3. Joint Estimation Method

3.1. Fuzzy Time Scale Estimator

In order to change the time scale more reasonably, a fuzzy system is introduced. The fuzzy system consists of four main components: fuzzizer, fuzzy rule base, fuzzy inference engine and defuzzizer. The fuzzy system converts the accurate input quantity into the fuzzy quantity, the fuzzy inference engine combines the fuzzy rules to map the fuzzy input into the fuzzy output, and finally the defuzzizer obtains the accurate output.

The parameters $\frac{dSOC}{dt}$, SOC and $\frac{dR0}{dt}$ are input, and the time step $L$ is the output; when $\frac{dSOC}{dt}$, SOC and $\frac{dR0}{dt}$ are blurred, the membership function is shown in Fig. 3.
Figure 3. Fuzzy membership functions.

The fuzzy control rule table is as follows:

| dSOC/dt  | dR/dt                  |
|----------|------------------------|
| negative | small, null, positive  |
| SOC=empty| small, middle, large   |
| positive | small, null, small     |
| SOC=full | null, small, small     |

### 3.2. Variable Forgetting Factor Recursive Least Squares

The mathematical model derived from the battery equivalent circuit can be identified online by the least square method through (3) - (5).

\[
\begin{align*}
    u(k) &= \theta_1 E(k - 1) + \theta_2 E(k - 2) + \theta_3 i(k) \\
    &\quad + \theta_4 i(k - 1) + \theta_5 i(k - 2) \\
    E(k) &= U_{ov}(k) - u(k) \\
    R_0 &= \frac{\theta_3 - \theta_4 + \theta_5}{1 + \theta_1 - \theta_2} \\
    \tau_1 &+ \tau_2 = \frac{\tau^2(1 + \theta_1 - \theta_2)}{4(1 - \theta_1 - \theta_2)} \\
    \tau_1 + \tau_2 &= \frac{\tau_1(1 + \theta_2)}{1 - \theta_1 - \theta_2} \\
    R_0 + R_1 + R_2 &= \frac{\theta_3 + \theta_4 + \theta_5}{1 - \theta_1 - \theta_2} \\
    R_0 \tau_1 + R_1 \tau_2 + R_2 \tau_1 &= \frac{\tau_1(\theta_3 - \theta_5)}{1 - \theta_1 - \theta_2}
\end{align*}
\]

Where T is the sampling time. In FFRLS the forgetting factor is fixed, it is difficult to fit the dynamic process of online parameter identification. when the parameter error is large, the forgetting factor strengthens the later data, resulting in the failure to converge as quickly as possible to reduce the error; when the parameter error is small, due to convergence Insufficient speed causes the parameter error to increase. If the forgetting factor is close to 1, FFRLS has high stability, but the convergence speed is...
slow, and the actual value cannot be quickly tracked. Therefore, the forgetting factor needs to be adaptively changed according to the estimation error, so as to achieve a faster convergence speed and a smaller recognition error under the rapid change of battery parameters. The specific method of changing the forgetting factor is explained in the next section.

3.3. Joint Estimation of Internal Parameters, SOH and SOC

According to the second-order RC equivalent circuit model, the discrete state space equation is established by (6) and (7) to estimation of battery SOC and SOH.

\[
\begin{bmatrix}
SOC(k) \\
\mathbf{u}_1(k) \\
\mathbf{u}_2(k)
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 \\
0 & e^{-\frac{\tau}{R_1C_1}} & 0 \\
0 & 0 & e^{-\frac{\tau}{R_2C_2}}
\end{bmatrix}
\begin{bmatrix}
SOC(k-1) \\
\mathbf{u}_1(k-1) \\
\mathbf{u}_2(k-1)
\end{bmatrix} +
\begin{bmatrix}
\frac{-\eta T}{Q_N} \\
R_1(1-e^{-\frac{\tau}{R_1C_1}}) \\
R_2(1-e^{-\frac{\tau}{R_2C_2}})
\end{bmatrix}
\times
i(k-1) + w(k-1) \tag{6}
\]

\[
R_0(k) = R_0(k-1) + v(k-1) \tag{7}
\]

Where \( Q_N \) is the current capacity of the battery, and the maximum capacity of the battery changes as the battery ages; \( \eta \) is the charge and discharge efficiency of battery; \( w(k-1) \) and \( v(k-1) \) are the observation errors of SOC and \( R_0 \), respectively.

The output observation model is expressed by (8).

\[
y(k) = u_{oc}[SOC(k)] - u_1(k) - u_2(k) - i(k) \cdot R_0(k) \tag{8}
\]

In this paper, the estimation of SOH and SOC is completely carried out on two different time scales. According to the error of SOC estimation, the forgetting factor is adjusted in real time to maximize the recognition accuracy of the model. Simultaneously, considering the interference of complex stress on accuracy, a time scale estimator based on fuzzy control is designed for the time scale.

4. Results

4.1. Experimental Data

The experimental data used in this study comes from the Life Cycle Laboratory of the University of Maryland. In order to evaluate the estimation results of the joint estimation algorithm, some complex dynamic current curves are used: dynamic stress test (DST), federal city driving schedule (FUDS) and US06 highway driving schedule. In terms of current change and discharge rate, these tests are more complicated than HPPT. Similar to the HPPT test, the current sequence of DST, FUDS and US06 is also transmitted from the speed curve of industry standard cars. The curve shown in Figure 4 is the current and voltage under fuds cycle. The ocv-soc curve of the battery obtained by off-line fitting is shown in Figure 5, and other parameters are obtained by on-line identification.
4.2. SOC/SOH Estimation Results for DST Test

In this section, the test condition is DST test. The initial SOC is 80\%, the initial R0 is 0.03, the sampling time is 1s, and the sampling time of MEKF parameter filter is 30s. As shown in Figure 6, it is the estimation results of SOC and SOH.

![Figure 4](image1.png)

**Figure 4.** Measure voltage and current under FUDS test.

![Figure 5](image2.png)

**Figure 5.** OCV-SOC fitting curve.
Figure 6. The experimental results of SOC and SOH estimation and their errors under DST test: (a) is the voltage profiles tested by DST; (b) is the corresponding SOC estimation; (c) is the corresponding SOC estimation error; (d) is the corresponding current profiles; (e) is the corresponding SOH estimation; (f) is the corresponding SOH estimation error.

In Fig. 6, the SOC estimation accuracy of EKF is not as good as that of the proposed method, which shows that taking model parameters into account can improve the accuracy. In addition, Fig. 6 also shows that the variable time scale estimation method can improve the SOH estimation accuracy under dynamic conditions. The comparison results between the three methods are shown in Table 2. From Table 2, obviously, the algorithm proposed in this paper has higher efficiency than the other two methods.

Table 2. Comparison of SOC and SOH estimation results under DST test.

| Algorithm        | AFFRLS-DEKF | FFRLS-MEKF | VFFRLS-FVEKF |
|------------------|-------------|------------|--------------|
| RMSE of SOC      | 0.0141      | 0.00125    | 0.0089       |
| RMSE of SOH      | 0.0115      | 0.0165     | 0.0095       |
| Time(s)          | 1.68        | 1.29       | 1.02         |

4.3. SOC/SOH Estimation Results for Fuds Test

In this section, the test conditions are fuds test. The initial SOC is 100%, the initial R0 is 0.04, the sampling time is 1s, and the parameter filter sampling time of MEKF is 60s. The SOC & SOH estimation results are plotted in Figure 7.
Figure 7. The experimental results of SOC & SOH estimation and their errors under FUDS test: (g) is the voltage profiles tested by FUDS; (j) is the corresponding current profiles; (h) is the corresponding SOC estimation; (i) is the corresponding SOC estimation error; (k) is the corresponding SOH estimation; (l) is the corresponding SOH estimation error.

Figure 7 shows that the proposed method obtains better results than the traditional multi time scale estimation method and DEKF when the initial SOC value is incorrect. The joint estimation method is robust to the initial values of SOC and SOH. Table 3 shows the comparison results of the three.

**Table 3.** Comparison of SOC and SOH estimation results under FUDS test.

| Algorithm   | AFFRLS-DEKF  | FFRLS-MEKF  | VFFRLS-FVEKF |
|-------------|--------------|-------------|--------------|
| RMSE of SOC | 0.0171       | 0.0195      | 0.0128       |
| RMSE of SOH | 0.0104       | 0.0126      | 0.0079       |
| Time(s)     | 1.78         | 1.30        | 1.09         |

4.4. SOC/SOH Estimation Results for us06 Test

In this section, the test condition is us06 test. The initial value of SOC is 80%, the initial R0 is 0.05, the sampling time is 1s, and the sampling time of MEKF parameter filter is 100s. The SOC & SOH estimation results are plotted in Figure 8.
Figure 8. The results of SOC & SOH estimation and their errors under US06 text: (m) is the voltage profiles tested by US06; (p) is the corresponding current profiles; (n) is the corresponding SOC estimation; (o) is the corresponding SOC estimation error; (q) is the corresponding SOH estimation; (r) is the corresponding SOH estimation error.

When the initial value is near the true value, it can be seen from Fig. 8 and table 4 that the proposed method can improve the estimation accuracy of SOC and SOH in complex stress environment.

Table 4. Comparison of SOC and SOH estimation results under US06 test.

| Algorithm     | AFFRLS-DEKF | FFRLS-MEKF | VFFRLS-FVEKF |
|---------------|-------------|------------|--------------|
| RMSE of SOC   | 0.0188      | 0.0152     | 0.0087       |
| RMSE of SOH   | 0.0121      | 0.0115     | 0.0086       |
| Time(s)       | 1.70        | 1.20       | 1.05         |

In summary, the algorithm in this paper not only improves the calculation accuracy, but also improves the calculation efficiency of the algorithm. It is very important to reduce the calculation burden of the hardware and better operate the online estimation of battery status.

5. Conclusion

To adapt the complex and dynamic situation of the batteries and estimate SOC and SOH in an accurate and fast manner, a multi-time scale joint estimation method (VFFRLS-FVEKF) is proposed and which estimates the model parameters and SOC at the macro scale, and then estimates SOH at the micro scale. A parameter adjustment method of forgetting factor recursive least square method for estimating multiple parameters is proposed to improve the accuracy of the equivalent circuit model. To increase the convergence speed especially in complex stress conditions, a fuzzy inference engine is used to change the time scale.

In order to verify the proposed multi-time scale joint estimation method, three calculation cases (DST, fuds and us06 text) are executed. The results show that (1) the introduction of fuzzy inference engine and multi-scale parameter adaptive identification method greatly improves the accuracy of SOC and SOH stability estimation on the basis of improving the calculation efficiency, and its RMSE is less...
than 0.015. In conclusion, VFFRLS-FVEKF is suitable for accurate and robust SOC and SOH estimation in practical applications.

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