Battery State Estimation based on Dual Extended Kalman Filtering with Fixed Step

Weihong Zang¹, Facheng Wang¹, Zhonghua Li¹ and Wei Zhou²
¹ China north vehicle research institute, Beijing, 100072, China
² Military representative bureau of army in Beijing, Beijing,100050, China
*Corresponding author’s e-mail: fchwang@noveri.com.cn

Abstract. With the rapid popularization of new energy vehicles, users pursue reliable mileage as well as stable and efficient power battery charging and discharging performance, which puts forward higher requirements for on-board battery management system (BMS). Realizing online update of battery model parameters and accurate estimation of charged state has also become one of the key technical problems in the field of new energy vehicles at present. In this paper, based on the second-order resistor-capacitor (RC) equivalent circuit model, multiple parameters in the voltage relaxation stage were obtained through the curve relationship between open circuit voltage and state of charge, and the fast time-varying parameters were converted into parameters of different step sizes. An estimation model of state of charge based on fixed step Kalman Filtering algorithm was built by Simulink to realize online estimation of battery parameters and state of charge estimation. In this paper, a kind of ternary lithium battery was selected to establish data sets and test, which verified good robustness and high accuracy of the model.

1. Introduction
Environmental deterioration and energy crisis have promoted the wide application of electric vehicles, the key technologies of which are constantly achieving breakthroughs and innovations. State of charge (SOC) represents the internal storage capacity of a battery and is one of the most important state quantities of the battery [1]. For drivers, it is similar to the fuel gauge of traditional vehicles. Its value affects the power distribution strategy and safety strategy of the battery and protects the battery from danger (such as excessive discharge, overcharge, etc.), which is therefore an important parameter for the BMS to control the whole vehicle system and power battery [2]. Accurate estimation results of SOC can effectively prolong the battery service life and reflect the reliable range, which is of great significance for energy optimization management and health life management of electric vehicles [3].

The impedance of the battery and the actual maximum available capacity can be used to indicate the aging state of the battery. The increase of ohmic internal resistance during the service of lithium battery is limited. With the thickening of SEI film and the deposition of irreversible substances on the surface of active electrode substances, the charge transfer impedance and diffusion impedance increase continuously. The impedance of these two parts can qualitatively evaluate the aging of the battery. The reality is that the requirements for equipment and test environment in a wide range of frequency sweep test are too high, which is generally replaced by 1 kHz. Essentially, the test results are mainly ohmic resistance, which cannot well reflect the aging degree of the battery [4]. At the same time, the internal electrochemical reaction in the process of battery charge and discharge is very complex, which is a typical nonlinear system. Therefore, the capacity of the battery cannot be measured directly by sensor.
Researchers from various countries and research institutes have conducted extensive and in-depth research on the methods to improve the accuracy of SOC estimation. The commonly used battery SOC estimation methods are mainly divided into three categories: traditional open-loop estimation algorithm, black-box model-based method, and lumped parameter battery model\(^6\).

The traditional open-loop estimation methods include open-circuit voltage method, Ampere-hour integration method, etc. The open-loop estimation method is simple, direct, easy to understand and measure. However, due to the open-loop test, there is a lack of correction and feedback to the results. Therefore, the estimation accuracy is difficult to guarantee. The open-circuit voltage method obtains the relationship between the open-circuit voltage and SOC by standing the battery for a long time, and estimate the SOC by interpolation of the current open-circuit voltage of the battery, which has great limitations in practical driving applications\(^7\). The Ampere-hour integration method refers to the integration of charge and discharge current of the battery over time to obtain the SOC at the current time\(^9\). Due to the limited accuracy of the current sensor, the changes of environmental factors such as external noise and temperature, and the large errors in the initial SOC, the two will produce large cumulative errors during long-term operation. Therefore, Ampere-hour integration method cannot be used to estimate SOC directly\(^10\).

In the era of big data, machine learning algorithms have achieved rapid development and have been well applied in many fields. The black-box model-based method has become a popular option for many researchers, such as artificial neural network (ANN)\(^11\), support vector machine (SVM)\(^12\), fuzzy control\(^13\), etc. It greatly simplifies the mathematical structure of the problem and has natural good adaptability for establishing the complex nonlinear relationship between external battery characterization parameters and SOC estimation. However, the black box model has high requirements for the quality and quantity of battery data sets, otherwise it cannot achieve good prediction effect. Therefore, it is only applicable to the battery SOC estimation of the same vehicle model or the same batch of batteries at present. The generalization and robustness of data set are poor. The black box model has high requirements for real time data, memory space, and computing speed. It is usually used to analyze and process battery charge and discharge current data when vehicle enterprises or battery factories establish a big data platform and connect to tens of thousands of new energy vehicles. The high cost further limits its application in a single vehicle.

Battery charge and discharge are actually internal electrochemical reaction processes which is affected by temperature, charge and discharge ratio, self-discharge reaction and other factors. The battery model is a mathematical model established according to the specific relationship between the internal state variables and the external characteristics of the battery, which is obviously ignored by machine learning algorithms.

The lumped parameter battery model includes electrochemical model, fractional order model, and equivalent circuit model\(^14\). The equivalent circuit uses commonly used components such as capacitance and resistance to build a battery model to describe the working characteristics of the battery. The multi-stage RC equivalent circuit includes the simulation of the charge transfer impedance and the diffusion impedance in the process of battery charge and discharge, which can better reflect the dynamic and static characteristics of the battery and obtain the state space equation of the battery through the equivalent circuit model. In addition, because Kalman filtering (EKF) is the most widely used filtering technology in nonlinear systems, it is widely used to solve the current state of the battery to realize the estimation of SOC\(^15\).

The prediction-correction closed-loop algorithm based on lumped parameter battery model has good robustness and fast convergence ability. In view of this, scholars have carried out in-depth research from two aspects: one is to quickly obtain an algorithm that can identify the internal resistance and capacitance parameters of the battery\(^21\); the other is to track the battery terminal voltage with high precision and set up a battery model structure that highly simulates the dynamic characteristics of charge and discharge of power battery\(^23\).

In terms of battery model parameter identification, it is divided into off-line and on-line parameter identification. The off-line parameter identification or the training data of the black box model are
established by previous measurements. The charge-discharge curve of battery is often fitted by the least square method (LS), so as to obtain the corresponding relationship between the influencing factors (such as different temperatures and open circuit voltages, etc.) and SOC, and establish a table. Through “look-up table” method, SOC can be estimated. This algorithm can only achieve high accuracy under simulation conditions. It ignores the changes of parameters under different operating conditions and therefore lacks accurate estimation of SOC. In addition, the process of establishing the table requires a lot of manpower and material resources, which is limited to the actual complex working conditions. As a result, the algorithm of on-line parameter identification based on the time-varying characteristics of battery internal parameters has become the mainstream. Recursive least squares (RLS) and its derivative algorithms [25], such as recursive least squares with genetic factors (FFRLS), have been widely developed and applied due to their low computational complexity and their ability to obtain optimal analytical solutions. They have high accuracy in complex battery models with obvious nonlinear characteristics.

The authors of reference 26 combined RLS and EKF to realize online parameter identification and SOC estimation [26], and achieved high accuracy. Since EKF is formed by the first-order truncation change of KF Taylor expansion to linearize the nonlinear system and then realize state prediction and correction, it is easy to produce large errors for systems with obvious nonlinear characteristics. Therefore, the method of Gaussian regression combined with unscented Kalman (UKF) was used in reference [27]. The accuracy of SOC estimation was significantly improved using Sigma point sampling, but the influence of time-varying parameters on the estimation results was not considered. Parameters and capacity are important battery parameters, which affect each other and need to be estimated simultaneously. Plett [28] uses dual EKF to achieve joint estimation of battery capacity and SOC. However, all the above SOC estimates are carried out on the same time scale.

In fact, the voltage response of the battery under the action of current includes fast response link and slow change link, which is reflected in which the dynamic characteristics of the battery are distributed in a wide frequency range, and the changes caused by the charge transfer process and double-layer effect and diffusion effect are different in time scale. If the identification step size is too small, it is easy to lead to data saturation for the link with large time constant, which will greatly affect the accuracy of parameter identification, and may even lead to oscillation or divergence of results. Considering that the system parameters change slowly with time while the system state changes rapidly with time, using the same calculation time scale to calculate the battery parameters and state is not the best choice and will greatly increase the calculation burden of BMS. Therefore, the method based on time scale separation, that is, using long time step to calculate battery parameters and short time step to calculate battery state will reduce the calculation cost of BMS.

At the same time, it can be seen from the experimental data that the equivalent circuit model does not mean that the more RC loops the battery has, the higher the SOC estimation accuracy will be. In order to balance the relationship between the structural complexity of the model and the accuracy requirements of practical engineering applications, the second-order RC equivalent circuit model was selected in this paper.

Ternary lithium battery has become the mainstream power battery of new energy vehicle batteries in the market because of its small volume, high energy density, good low temperature performance, and long cycle life. Therefore, this paper chooses a ternary lithium battery battery to verify the second-order equivalent circuit model.

In conclusion, based on the second-order RC equivalent circuit model, the internal parameter values of the battery were preliminarily determined by LS method, and the online identification and SOC estimation of the parameters were realized by EKF with different fixed step sizes. Finally, a 70 Ah ternary power monomer lithium battery on the market were selected to establish a data set to test and verify the accuracy of the model.
2. Battery modeling

![Second-order RC equivalent circuit](image)

The second-order RC equivalent circuit was built by using the physical component model in Simscape. As shown in the Figure 1, the circuit is composed of resistance, capacitance, ideal voltage source and other circuit components that can be observed directly through the oscilloscope to describe the internal dynamic characteristics of the battery. The ideal voltage source $U_{oc}$ represents the thermodynamic equilibrium electromotive force of the battery, the value of which is obtained by the interpolation method of the SOC-open circuit voltage (OCV) calibration curve. The resistance represents the internal electrode material, electrolyte, diaphragm resistance, and wire contact resistance of the battery\cite{32}. $R_0$ is ohmic internal resistance; RC network is composed of a resistor and a capacitor in parallel; $R_1$ and $C_1$ represent the charge transfer effect of the battery; $R_2$ and $C_2$ represent the dynamic process of concentration diffusion effect. $U_t$ is the voltage of battery load terminal; $I_t$ is the input/output current of the battery, which is positive when the battery is discharged.

According to Kirchhoff theorem, the circuit equation of the model was obtained, shown as equation (1) and equation (2), where $\phi(0)$ is the initial OCV value of the battery and $\phi$ is solved by Ampere-hour integration method.

$$
\begin{align*}
\dot{U}_1 &= -\frac{1}{R_1 C_1} U_1 + \frac{1}{C_1} I \\
\dot{U}_2 &= -\frac{1}{R_2 C_2} U_2 + \frac{1}{C_2} I \\
\phi &= \frac{1}{q} I
\end{align*}
$$

$$
U_t = OCV + U_1 + U_2 + IR_0
$$

3. Offline parameter estimation

The principle of parameter identification is based on the physical dynamic changes in the charging and discharging process of the battery. In order to obtain the accurate initial value of model parameters, the discharge experiment at equal SOC interval was carried out at room temperature. In order to achieve electrochemical equilibrium state, the battery was allowed to stand for an hour after discharging 5% SOC at a constant current. The process from the moment when the current changes from a certain value to zero to the moment when the battery reaches equilibrium is called voltage relaxation stage, namely, the d-e stage. The circuit equations corresponding to the zero state response of the second-order equivalent circuit a-b-c and the zero input response of c-d-e were listed in the figure below, from which the resistance and capacitance of the RC circuit can be obtained.
At the moment of current loading and unloading, because the capacitor in the RC circuit has the function of blocking direct current and passing alternating current, the RC circuit is short-circuited, and the voltage at both ends of the RC circuit does not change instantly. Therefore, ohmic resistance $R_0$ is the cause of instantaneous increase and decrease of terminal voltage. The ohm internal resistance value can be identified by loading/unloading the two sections of data. The equation is as follows

$$R_0 = \frac{|v_2-v_1|}{2I_t}$$

(3)

The identification of polarization internal resistance and polarization capacitance is utilized to obtain the zero state response equation (4)–(5) and zero input response equation (6)–(7).

$$U_1(t) = U_1(t_c)e^{\frac{t-t_c}{\tau_1}}$$

(4)

$$U_2(t) = U_2(t_c)e^{\frac{t-t_c}{\tau_2}}$$

(5)

$$U_1(t) = I_tR_1(1 - e^{\frac{t-t_c}{\tau_1}})$$

(6)

$$U_2(t) = I_tR_2(1 - e^{\frac{t-t_c}{\tau_2}})$$

(7)

$$\tau_1 = R_1 \times C_1$$

(8)

$$\tau_2 = R_2 \times C_2$$

(9)

Table 1 shows the offline parameter identification results, which can be used as the initial values for the following online parameter identification.

| Parameter identification results | $R_0$ | $R_1$ | $R_2$ | $C_1$ | $C_2$ |
|---------------------------------|------|------|------|------|------|
| $R_0$                           | 0.575 mΩ | 0.447 mΩ | 0.573 mΩ | 101.310 kF | 1889.820 kF |

### 4. Online parameter and SOC estimation

Kalman filtering algorithm (KF) is a filter proposed in the 1960s. Amid the state estimation, the state is treated as a signal, and the useful components in the estimation results are retained by statistical characteristics, while the noise is removed. For the filtering problem of nonlinear system, the common processing method is to transform it into an approximate linear filtering problem by using linearization technique, and the most widely used method is EKF method. EKF is built on the basis of linear KF. The core idea is that for general nonlinear systems, firstly, the nonlinear functions $F(x_k, \theta_k, I_k)$ and $G(x_k, \theta_k, I_k)$ are expanded into Taylor series around the filtering value $x_k$ and the first-order truncation is performed (ignoring the second-order and above terms) to obtain an approximate linearization model. Then KF is applied to complete the filtering and estimation of the target.

In order to build a dual Kalman filter, the first-order differential equation of the battery, equation(10)-(12) needs to be discretized. The state space equation of the battery model is shown in the equation(13).

$$x_k = [U_{1,k}, U_{2,k}, SOC_k]^T$$

$$OCV(SOC_k) = K_{0,k} + K_{1,k}SOC_k + \ldots + K_{m,k}SOC_k^m$$

(10)

(11)
inside the battery. The dual Kalman filtering algorithm. The process estimation equation is shown in the equation.

battery state and parameters. The algorithm uses two extended Kalman filtering for state update and directly measured by the sensor, and a large number of battery parameters, it needs to adjust a long time at the beginning of the algorithm test, the initial state is usually set to \([0, 0, 0.9]\).

namely, two RC circuits and an ideal voltage source. Therefore, it is a three-dimensional system. The three state quantities of the system are defined as equation(10). Since the charged battery is lefting for external current excitation, the terminal voltage to the state and the derivative value of the terminal voltage to all the parameters in variable. Both the model parameters are regarded as fixed values. According to the actual physical law, the model parameters will not fluctuate and change frequently. Only when the time exceeds a certain period or the battery SOC increases or decreases to a certain extent, the electrochemical reaction leads to the thickening of SEI film and the reduction of lithium ions, will the model parameters change. Therefore, it is stipulated that the model parameters will be updated and corrected according to the real-time SOC once the time scale exceeds 60 s.

Principle of EKF Algorithm

\[ x_{k+1} = F(x_k, \theta_k, I_k) = \begin{bmatrix} (1 - \frac{\Delta t}{R_1 C_1}) & 0 & 0 \\ 0 & (1 - \frac{\Delta t}{R_2 C_2}) & 0 \\ 0 & 0 & 1 \end{bmatrix} x_k + \begin{bmatrix} \Delta t \frac{\Delta t}{R_1 C_1} \\ \Delta t \frac{\Delta t}{R_2 C_2} \\ \Delta t \end{bmatrix} I_k + w_k \]  

\[ \theta_{k+1} = \theta_k + w_k^\theta \]

\[ U_k = G(x_k, \theta_k, I_k) = OCV(SOC_k) + U_{1,k} + U_{2,k} + I_k R_0 + v_k \]

\[ x_{k+1} = F(x_k, \theta_k, I_k) + w_k \]

\[ y_{k+1} = G(x_k, \theta_k, I_k) + v_k \]

\[ \theta_k = [R_{0,k}, R_{1,k}, C_{1,k}, R_{2,k}, C_{2,k}, Q_{k}]^T \]  

\[ \theta_{k+1} = \theta_k + w_k^\theta \]

\[ U_k = G(x_k, \theta_k, I_k) = OCV(SOC_k) + U_{1,k} + U_{2,k} + I_k R_0 + v_k \]

\[ x_k \] is the system state value. The visible second-order RC model has three energy storage links, namely, two RC circuits and an ideal voltage source. Therefore, it is a three-dimensional system. The three state quantities of the system are defined as equation(10). Since the charged battery is lefting for a long time at the beginning of the algorithm test, the initial state is usually set to \([0, 0, 0.9]\). \( I_k \) is the external current excitation, \( w_k \) is the system error, \( y \) is the system observation value, which can be directly measured by the sensor, and \( v_k \) is the measurement error. \( F(x_k, \theta_k, I_k) \) and \( G(x_k, \theta_k, I_k) \) can be obtained from the state space equation and output observation equation of the system.

\( k \) is used to represent the value of each variable in step \( k \). \( \Delta t \) is the sampling time, representing the time constant from \( k \) to \( k+1 \). \( x \) represents the state of the battery, and \( \theta \) represents all parameters inside the battery. \( x \) and \( \theta \) as upper and lower indices indicate that the symbol is the value of the state and parameter. For example, \( w_k^x \) and \( w_k^\theta \) represent the independent process noise of the battery model system and parameters in step \( k \), respectively, and their covariance matrices are \( Q^x \) and \( Q^\theta \), respectively, representing the model error. \( v_k \) is the measurement noise in step \( k \), and its covariance matrix is \( R_k \). They are used to represent the measurement error. Because this method needs to estimate a large number of battery parameters, it needs to adjust \( Q^x \), \( Q^\theta \) and \( R_k \) many times to achieve the optimal performance of the algorithm. Dual extended Kalman filtering algorithm is used to estimate battery state and parameters. The algorithm uses two extended Kalman filtering for state update and parameter update respectively. The process estimation equation is shown in the equation.

The parameter values identified by the least square method are substituted as the initial values of the dual Kalman filtering algorithm. \( \hat{x}_0 \) is the initial state of the battery, and \( P_{\theta_0} \) and \( P_{x_0} \) indicate the initial matrix of the system parameter covariance matrix of parameter filtering and state filtering, respectively. \( k \) represents Kalman gain. The superscript “\(^{\text{\#}}\)” indicates the estimated value of the variable. Both \( F(\hat{x}_k, \theta_k, I_k) \) and \( G(\hat{x}_k, \theta_k, I_k) \) function are related to the battery parameter value. In order to obtain the linear equation, the following equation is used to solve the derivative value of the terminal voltage to the state and the derivative value of the terminal voltage to all the parameters in the battery.

As a fast time-varying parameter, SOC is required to be predicted and updated every second and the model parameters are regarded as fixed values. According to the actual physical law, the model parameters will not fluctuate and change frequently. Only when the time exceeds a certain period or the battery SOC increases or decreases to a certain extent, the electrochemical reaction leads to the thickening of SEI film and the reduction of lithium ions, will the model parameters change. Therefore, it is stipulated that the model parameters will be updated and corrected according to the real-time SOC once the time scale exceeds 60 s.

The realization of SOC estimation and parameter online identification by dual Kalman filtering algorithm with fixed step can be divided into the following steps:

(1) Initialization: determine model parameters, state matrix, system covariance, measurement covariance, etc
(2) Parameter filter: calculate the parameter prediction value and parameter error covariance in the parameter filter, and realize the prediction and update of model parameters.

(3) Parameter correction: substitute the updated parameters into the subsequent state filter to solve the parameter value after SOC correction. After 60 s, the parameter filter updates the parameters again.

(4) State filter: calculate the state prediction value and covariance prediction value in the state filter.

(5) SOC correction: calculate the SOC prediction value in the state filter based on the corrected parameters. Update SOC every 1 s.

5. Model verification

5.1 Battery Test

Table 2 is the battery specification used in this paper.

| Battery | Capacity | Type  | Nominal voltage | Max voltage | Min voltage |
|---------|----------|-------|-----------------|-------------|-------------|
| 70Ah    | NCM      | 3.6V  | 4.2V            | 2.8V        |

The test is valid if the capacity error of the battery is less than 2% for three charge and discharge tests. Then OCV-SOC calibration test was performed on the battery. After discharging, the battery needs to stand for a period of time to reach a thermodynamic equilibrium state. Therefore, after the battery is charged and discharged, it needs to stand for a long time to collect the battery open-circuit voltage and draw the OCV-SOC curve.

The test methods and steps are as follows: (1) The batteries are fully charged at a constant current and a constant voltage. After standing for 2 hours, the voltage value at both ends of the battery is regarded as the OCV value when SOC = 100%. (2) The batteries were discharged for 5% SOC at a constant current of 1 C. After standing for 1 hour, the voltage value at both ends of the battery is regarded as the OCV value under the SOC at the moment. (3) Step (2) was repeated continuously until the voltage drops to the lower limit, which means the discharge is over. After standing for 1 hour, the voltage at both ends of the battery is regarded as the OCV value when SOC = 0%.

The curvefitting toolbox under Matlab was used for polynomial fitting of OCV-SOC. It was found that the best fitting effect could be achieved by polynomial of degree 8. The figure below is the OCV-SOC calibration curve, and equation (10) is the OCV-SOC polynomial fitting curve equation.

\[
OCV(SOC) = 3.2 + 5.35SOC - 58.65SOC^2 + 368.25SOC^3 + 1272.35SOC^4 + 2494.9SOC^5 + 962.5SOC^6 + 1606.6SOC^7 - 382.25SOC^8
\]

Figure 3 OCV-SOC fitting curve
5.2 Verify the Parameter Identification Model

Figure 4 Terminal voltage of parameter identification model

Figure 5 Errors of terminal voltage

Figure 4, Figure 5 show the terminal voltage of the battery from full power to constant current discharge to SOC = 0 by using the least square method. It can be seen from the simulation results that the parameter identification of the battery model using the least square method can achieve high accuracy, and the terminal voltage follow-up error is within 20 mV, which can provide a reliable initial value of identification parameters for the next battery SOC estimation, and accelerate the convergence speed of online identification of battery parameters and the accuracy of initial SOC estimation.

5.3 Verify the Accuracy SOC Estimation Model

After the battery was fully charged at a constant current and a constant voltage and stood for 3 hours, the DST and FUDS working conditions were tested respectively. It is used to simulate the charging and discharging of urban street batteries and test the robustness of SOC estimation of the model. The comparison of SOC estimation results, terminal voltage follow-up, and SOC estimation error during the test process are shown in the Figures below.
6. Discussion
In this paper, a 70 Ah ternary battery was selected to carry out DST and FUDS test at room temperature. The test results in figure 6 and figure 7 show that during 100%-20% SOC under DST working condition, the terminal voltage following error is within 0.1 V, and the SOC estimation error is always within 3%, which can meet the accuracy requirements of users in daily driving. Under the FUDS condition, the terminal voltage following error is always within the range of 50 mV when the SOC is 100% - 20%, but the error rapidly increases when SOC reduced to 20%, which is probably caused by the change of the internal electrochemical performance of the battery at that stage. In the actual use of vehicles, in order to prolong the service life of the battery, drivers often choose to charge their vehicles before the SOC drops to 20%. The SOC estimation error fluctuates within the range of 2% and is less than 4%. Therefore, the estimation accuracy based on the DEKF method before the first 80% SOC can well meet the requirements of daily estimation accuracy of vehicle power state.
7. Conclusion
1. The off-line identification of battery model parameters by LS method can provide reliable initial parameters for on-line parameter estimation and SOC estimation.
2. In the case of more complex working conditions, DEKF can still maintain high terminal voltage following accuracy. The 70Ah ternary battery is selected to verify the robustness of fix-step long operation of parameter identification and SOC estimation.
3. Updating the parameters of the battery model once after a long time fixed step can greatly reduce the amount of calculation, lower the operation cost of SOC and parameter parallel estimation, and provide a reliable reference for later physical verification.

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