New Energy Vehicle Battery SOC Evaluation Method based on Robust Extended Kalman Filterd

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Abstract. In actual charging/discharging scenarios of new energy vehicles, low temperature, natural disasters, extreme weather, electromagnetic radiation and other factors will cause strong noise interference in SOC evaluation. Aiming at the problem of SOC evaluation accuracy in extreme environments, a power battery SOC evaluation method based on robust Kalman filter is proposed. The experimental results prove that the method is suitable for the accurate assessment of SOC in the charging/discharging process of the power battery of new energy vehicles under the interference of complex and harsh environment noise, and it has good robustness.

1. Introduction

With the gradual exhaustion of fossil energy and the deteriorating environment, the development of new energy vehicles has brought dawn to solve energy and environmental problems. It has been highly valued by the academic community and has become an important energy development strategy for all countries in the world. However, the power battery is the core component of new energy vehicles, and its safety status and safety management have become the key technical bottleneck restricting the development of new energy vehicles[1]. Among them, the state of charge (State of Charge, SOC) is an important battery state evaluation indicator, which is defined as the ratio of the remaining power of the battery at a certain moment to the actual charge capacity of the battery, as shown in equation (1).

\[ SOC = \frac{Q}{Q_n} \times 100\% \]  

Accurate estimation of SOC is the key to ensuring efficient and safe operation of batteries and improving battery efficiency and safety performance of new energy vehicles. The current SOC estimation methods mainly include ampere-hour integration method, open circuit voltage method, neural network method, Kalman filter method, etc.[2] Among them, the Kalman filter method is an optimized autoregressive data processing algorithm based on the white box model. It has good applicability for any type of power battery SOC evaluation and has been used in many applications. Literature[3] proposed a battery SOC estimation method based on improved extended Kalman filter, which has high accuracy and convergence. Literature[4] proposes an improved adaptive strong tracking Kalman filter, which effectively solves the statistical uncertainty of system noise.

However, the above studies are based on the ideal laboratory environment, and the noise is uniformly modeled as Gaussian white noise or with minimal noise interference. In the actual charging process of new energy vehicles, due to various factors such as harsh environment, natural disasters, low
temperature, electromagnetic interference, etc., measurement data such as voltage and current are often extremely inaccurate or there is strong noise interference, resulting in large deviations in SOC estimation. Therefore, this paper proposes a new energy vehicle battery SOC evaluation method based on Robust Extended Kalman Filter(REKF) for extreme malicious working conditions, which improves the accuracy of SOC evaluation under various types of working conditions.

This paper constructs the second-order power battery equivalent circuit model in Section 2. In Section 3, the battery SOC evaluation method based on REKF is discussed in detail. In Section 4, the method in this paper is verified experimentally, and compared with the traditional EKF algorithm, and the conclusion is given in Section 5.

2. Equivalent model of power battery
The complex electrochemical reactions inside the power battery make it have strong nonlinearity and strong coupling. The SOC, SOH and other states cannot be directly measured. It needs to be estimated based on the measurable current and voltage. The accurate battery model is the accurate estimation of battery SOC and SOH. Foundation, so the establishment of an accurate battery model is very important. Common power battery equivalent circuit models include Rint model, Thevenin model, PNGV model, Massimo Ceraolo model[5]. In order to reflect the actual dynamic characteristics of the battery and improve the accuracy of the model, this paper selects the second-order Thevenin model as the equivalent model of the power battery, as shown in Figure 1. The second-order model is not much different from the terminal voltage response of the high-order RC network, and is very close to the terminal voltage response of the actual battery, while reducing the amount of calculation. In the figure, Uoc is the open circuit voltage; R0 is the internal resistance of the battery; R1 and R2 are the polarization resistances; C1 and C2 are the equivalent capacitances; U1 and U2 are the polarization voltages.

\[ U_{o} = U_{oc} - iR_0 - U_1 - U_2 \]
\[ \dot{U}_1 = -\frac{1}{R_1C_1}U_1 + \frac{1}{C_1}i \]
\[ \dot{U}_2 = -\frac{1}{R_2C_2}U_2 + \frac{1}{C_2}i \] (2)

Analyze the second-order equivalent circuit model, and obtain the relationship between the terminal voltage and current of the battery according to Thevenin's theorem. As shown in equation (2), the HPPC test method can be used to identify the battery equivalent circuit model parameters to obtain the above R0, R1, R2, C1, C2 parameter values.

3. REKF algorithm

3.1. Bad data detection based on different working conditions
In the actual charging process of new energy vehicles, affected by many factors such as low temperature, natural disasters, extreme weather, electromagnetic radiation, etc., the measurement of the voltage and current of the power battery collected by the charging gun often has strong noise interference, and even causes SOC. Evaluate bad data for failure. Traditional SOC evaluation methods ignore the monitoring and identification of bad data, which makes the overall method less robust.
Based on the 3σ criterion[6], in the detection and identification of bad data, it is generally considered that the measurement error is greater than ±3σ as bad data. Therefore, the threshold for bad data detection in battery detection is set to ±3σ. In order to avoid the phenomenon of “residual flooding” or “residual pollution”, considering the strong randomness and uncertainty of interference noise under different working conditions, a method for pre-filtering to adjust the threshold according to the change trend of the measurement is proposed. The specific description is as follows. First set an initial threshold δ₀ for pre-filtering, and then run the battery detection estimation program, and calculate the difference between the estimated value \( Z_k \) at time \( k \) and the measured value to obtain \( \Delta Z_k \), and the ratio of the estimated value to the estimated value is:

\[
\beta_k = \frac{\Delta Z_k}{Z_k}
\]

Then update the threshold \( \delta_k \):

\[
\delta_k = \delta_{k-1} + \frac{\delta_{k-1} \beta_{k-1}}{m}, \quad \delta_{k-1} < \beta_{k-1}
\]

\[
\delta_k = \delta_{k-1} - \frac{\delta_{k-1} \beta_{k-1}}{m}, \quad \delta_{k-1} > \beta_{k-1}
\]

Where: \( m \) is a constant with a value range of [4, 10]. According to the threshold \( \delta_k \) calculated by equation (4), bad data is detected. \( \Delta V_k \) is the absolute value of the difference between the measured value \( m_k \) and \( m_{k-1} \), namely

\[
\Delta V_k = |m_k - m_{k-1}|
\]

If \( \Delta V_k > \delta_{hm_{k-1}} \), the measurement \( m_k \) is considered to be bad data, then the measurement value is discarded, and then the estimated value is used instead of the measurement value.

3.2. Extended Kalman filter

Power battery is a typical nonlinear system. The extended Kalman filter method can effectively solve the shortcomings of traditional Kalman filter method that can only be applied to linear equations. It is very suitable for power battery SOC estimation. Its improvement idea is the nonlinear equation of the system. The equation is linearized by the Taylor expansion formula in mathematics, and then the recursive process of the KF algorithm is used to estimate the state variables of the nonlinear system. Suppose the state space equation of the nonlinear system is

\[
\begin{align*}
X_{k+1} &= f(X_k, U_k) + \Gamma_k W_k \\
Y_k &= h(X_k, U_k) + V_k
\end{align*}
\]

The linearized linear system is obtained by Taylor series expansion, and its state space equation is

\[
\begin{align*}
\hat{X}_{k+1} &= f(\hat{X}_k, U_k) + A_k [X_k - \hat{X}_k] + \Gamma_k W_k \\
Y_k &= h(\hat{X}_k, U_k) + C_k [X_k - \hat{X}_k] + V_k
\end{align*}
\]

In the formula, \( A_k \) and \( C_k \) are the parameter matrix of the system.

\[
A_k = \left. \frac{\partial f(X_k, U_k)}{\partial X_k} \right|_{X_k = \hat{X}_k}, \quad C_k = \left. \frac{\partial h(X_k, U_k)}{\partial X_k} \right|_{X_k = \hat{X}_k}
\]

After linearization, the system can be calculated by traditional Kalman filter algorithm, including time update and measurement update. The specific calculation steps are as follows:

1. Initialization: set the initial value \( X_0, P_0, Q_0, R_0 \) of the observer;
2. Time update (a priori estimate):

According to the second-order equivalent circuit model established in Chapter 2, the battery SOC value and the terminal voltages U1 and U2 of the two capacitors in the model are set as the three state variables of the entire system. The excitation is the input of the current, and the battery’s The terminal voltage is the observed value. In (13) and (14), \( w_k \) and \( v_k \) are two types of uncorrelated Gaussian white
noise in the system; \( \eta \) is the efficiency; \( T \) is the sampling period of the system; \( \tau_1 \) and \( \tau_2 \) are the two RCs in the equivalent model. The time constant of the parallel module, its value is \( \tau_1=RC_1, \tau_2=RC_2 \); \( I(k) \) is the output current at this moment (suppose the output \( I \) is positive when discharging, and the output \( I \) is negative when charging).

1. Time update of system state estimation:
\[
\hat{X}_{k+1|k} = f\left(\hat{X}_{k|k},U_k\right) + \Gamma_k W_k
\]
(8)

2. Time update of error covariance:
\[
\hat{P}_{k+1|k} = A_k \hat{P}_{k|k} A_k^T + \Gamma_k Q_k \Gamma_k^T
\]
(9)

3. Measurement update (posterior estimation):
1. Calculation of Kalman gain matrix:
\[
K_{k+1} = \hat{P}_{k+1|k} C_k^T \left( C_k \hat{P}_{k+1|k} C_k^T + R \right)^{-1}
\]
(10)

2. Measurement update of system status:
\[
\hat{X}_{k+1|k+1} = \hat{X}_{k+1|k} + K_{k+1} \left( Y_{k+1} - h\left(\hat{X}_{k+1|k},U_k\right)\right)
\]
(11)

3. Update the measurement of error covariance:
\[
\hat{P}_{k+1|k+1} = \left( I - K_{k+1}C_k \right) \hat{P}_{k+1|k}
\]
(12)

3.3. SOC evaluation method based on REKF

Combined with the second order of the power battery, the extended Kalman filter algorithm is adopted for linearization, and the state equation and observation equation of the system need to be established, as shown in Equations (13) and (14).

\[
\begin{bmatrix}
SOC(K+1) \\
U_1(K+1) \\
U_2(K+1)
\end{bmatrix}
= \begin{bmatrix}
1 & 0 & 0 \\
0 & e^{-\frac{T}{\tau_1}} & 0 \\
0 & 0 & e^{-\frac{T}{\tau_2}}
\end{bmatrix}
\begin{bmatrix}
SOC(K) \\
U_1(K) \\
U_2(K)
\end{bmatrix}
+ \begin{bmatrix}
\eta T \\
0 \\
0
\end{bmatrix}
\begin{bmatrix}
\frac{\eta T}{Q_1} \\
R_1 \left(1-e^{-\frac{T}{\tau_1}}\right) \\
R_2 \left(1-e^{-\frac{T}{\tau_2}}\right)
\end{bmatrix} I(k) + w_k
\]
(13)

\[
U_i(k+1) = U_{i,oc}(k+1) - U_i(k + 1) - U_{2i}(k+1) - R_i I_i(k+1) + v_{i+1}
\]
(14)

According to the second-order equivalent circuit model established in Chapter 2, the battery SOC value and the terminal voltages \( U_1 \) and \( U_2 \) of the two capacitors in the model are set as the three state variables of the entire system. The excitation is the input of the current, and the battery’s The terminal voltage is the observed value. In (13) and (14), \( w_k \) and \( v_k \) are two types of uncorrelated Gaussian white noise in the system; \( \eta \) is the efficiency; \( T \) is the sampling period of the system; \( \tau_1 \) and \( \tau_2 \) are the two RCs in the equivalent model. The time constant of the parallel module, its value is \( \tau_1=RC_1, \tau_2=RC_2 \); \( I(k) \) is the output current at this moment (suppose the output \( I \) is positive when discharging, and the output \( I \) is negative when charging.

By constructing the power battery state equation and combining the bad data detection links based on different working conditions, a REKF-based SOC evaluation method is proposed to accurately estimate the SOC of the lithium-ion battery at each moment.

4. Experimental simulation analysis

In this paper, ternary lithium battery was used for experimental tests to verify the effectiveness of the proposed method. First, HPPC experiment was conducted to obtain the second-order model parameters of electric battery, and Matlab fitting toolbox was used to fit the test data. The specific process will not be described in detail, and the voltage working curve of the battery was obtained, as shown in Figure 2. It is obvious that the error between the second-order RC equivalent model and the real value is very small, indicating that the model can accurately fit the experimental battery.
This paper focuses on analyzing the SOC evaluation method based on REKF. Simulate the comprehensive harsh environment such as low temperature and electromagnetic interference, conduct constant current charging and constant current discharge experiments, and compare the algorithm in this paper with the EKF and ASTUK algorithms. Under constant current charging, the SOC evaluation results of each algorithm and the error of the true SOC value are shown in Figure 3 (a) and (b), respectively.

It can be seen from Figure 4 that in the case of constant current charging, the SOC evaluation value change trend corresponding to the three algorithms is the same as the true value, but the SOC evaluation value of the EKF algorithm and the ASTUK algorithm is far from the true value, and the EKF algorithm estimates the largest The error is 0.0908, the maximum error estimated by the ASTUK algorithm is 0.0456, and the maximum error estimated by the algorithm in this paper is 0.008. Compared with the EKF and ASTUKF methods, the REFK method has better robustness, smaller errors, and higher accuracy of estimating SOC. Under constant current discharge, the SOC evaluation results of each algorithm and the error of the true SOC value are shown in Figure 5 (a) and (b), respectively. It can be
seen from Figure 5 that in the case of constant current discharge, the average error of the EKF algorithm is 0.0034, the average error estimated by the ASTUK algorithm is 0.0030, and the average error estimated by the REKF algorithm is 0.0008. Therefore, the REKF proposed in this paper is more suitable for discharge estimation under severe conditions.

5. Experimental simulation analysis

To solve the problem of inaccurate SOC assessment in harsh environment, this paper proposes a new energy vehicle power battery SOC assessment method based on REKF, and carries out experimental tests. The following conclusions are obtained:

1) According to the historical statistical characteristics of samples, the self-applicable bad data detection and identification method is used to deal with false measurement data, which effectively solves the problems of strong noise interference in the process of SOC evaluation.

2) Because REKF algorithm has the advantage of linearization of nonlinear system, it can calculate current SOC index more accurately.

3) In terms of SOC evaluation, the algorithm in this paper is more suitable for complex and harsh environment, which is of great significance to the safety improvement of new energy vehicles.

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