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Estimation of Lithium Battery State of Charge by Fusion Algorithm of Forgetting Factor Multi-innovation Least Squares and Extended Kalman Filter

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Lithium-ion power batteries have been widely used in electric vehicles, micro-electromechanical systems (MEMS), and integrated circuits owing to their high energy and long life. The state of charge (SoC) of the power batteries is an important parameter of electric vehicles, which directly affects the safety control and range of electric vehicles. In this paper, we propose a method of accurately estimating the lithium battery SoC in the presence of sensor bias and varying environmental temperature by the fusion algorithm based on the forgetting factor multi-innovation least squares (FF-MILS) and extended Kalman filter (EKF). To establish an accurate ternary lithium battery model and monitor the SoC of the battery online, a second-order RC equivalent circuit model was used to fit the relationship between the open-circuit voltage (OCV) and the SoC through experimental data. The online FF-MILS algorithm was used to identify the model parameters of lithium batteries, which were introduced into the fading factor EKF algorithm. To alleviate the decline in accuracy caused by the sensor deviation, the sensor deviation was set in the fading factor EKF state-space model by using a sensor deviation cooperative estimation method. In a MATLAB/Simulink simulation, the proposed fusion algorithm quickly converged to the initial error, and the maximum error was less than 2% in the stable state, thus verifying the estimation accuracy of the proposed fusion algorithm and its robustness to sensor deviation and changes in ambient temperature.

1. Introduction

In recent years, environmental pollution and the development of sustainable energy have attracted increasing attention, and the development of new energy has become a worldwide focus of attention. Owing to their reliable power supply, high energy density, stable voltage, and long cycle life, lithium batteries are widely used as energy storage devices that gained widespread interest in the fields of manufacturing, microgrids, diesel power supply, renewable

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energy power station self-construction, renewable energy power station transactions, and peak load regulation.(1) In addition, a lithium battery is the core component of hybrid electric and electric vehicles as the indirect or direct power supply of the system, and ensuring its safe and reliable operation is crucial to the safety of the system. The battery management system (BMS), the link between batteries and users, is characterized by accurate monitoring, efficient evaluation, and accurate management.(2,3) The BMS collects real-time operating data of the battery system and evaluates its state, which mainly includes the state of charge (SoC), the power boundary, the health state, and the fault state. The SoC of lithium batteries is one of the important parameters in the BMS. An accurate estimation of the SoC of lithium batteries can effectively prevent the battery overcharge and overdischarge, which has guiding significance for safe production.

However, owing to the inherent characteristics of lithium batteries, there are still some disadvantages in actual scenarios.(4) First, it is difficult to achieve the expected lifetime for a battery group. Second, the workload for operation and maintenance is large. Third, the real-time monitoring technology is backward. Therefore, it is of great significance to establish a reasonable battery equivalent model and achieve the accurate estimation of battery SoC to monitor battery performance. In recent years, many studies have been conducted on estimation methods for SoC, mainly including the open-circuit voltage (OCV) method,(5) ampere-hour integral method,(6) particle filtering method,(7) neural network method,(8) Kalman filtering method,(9) and fusion algorithm.(10) However, a lithium battery is a strongly nonlinear system, the working environment is complex and variable, and the parameters in the equivalent model are invariant; thus, it is difficult to accurately estimate SoC using the existing algorithms.

In this study, the forgetting factor multi-innovation least squares (FF-MILS) and extended Kalman filter (EKF)-based fusion algorithm is proposed. To satisfy the high precision of the input model required for the EKF algorithm, we use the FF-MILS algorithm to identify the parameters of the model and improve its accuracy. Then, the fading factor is added to the EKF algorithm to improve the stability and tracking ability of the system in a complex working environment. Finally, to verify the feasibility of the fusion algorithm, we establish a second-order RC circuit equivalent model, and hybrid pulse power characterization (HPPC) was used for experimental analysis to verify the maximum error, robustness, and estimation accuracy of the fusion algorithm.

2. Related Works

SoC cannot be directly observed and can only be obtained by collecting relevant battery parameters, building a model, and using an estimation algorithm. In the estimation of the SoC of lithium batteries, there are two main processes: parameter identification and parameter estimation. In parameter identification, the recursive least squares (RLS) algorithm is one of the commonly used online identification methods.(11) This algorithm can identify parameters online and is simple and accurate, but the problem of data saturation may occur. To improve the SoC estimation accuracy of lithium batteries in complex working environments, Deng *et al.* used the limited memory recursive least squares (LM-RLS) algorithm to estimate SoC for ternary lithium batteries. The good performance of the improved algorithm in estimating SoC for lithium batteries was verified.(12) The forgetting factor recursive least squares (FFRLS) algorithm introduced the forgetting factor in the iteration process, and Chioua *et al.* improved the utilization of new data by reducing the impact of old data, thus effectively solving the problem of data saturation.(13) However, this approach required the system input to be stationary and ergodic, making it difficult to apply in practice. Moreover, the setting of initial values strongly affected the dynamic responsiveness, which makes it unable to accurately track time-varying parameters. On the basis of FFRLS, FF-MILS was introduced as the parameter identification algorithm of the selected model. Baldi *et al.* extended the scalar novelty to the vector or matrix novelty, strengthened the use of the parameter novelty, added the forgetting factor, accelerated the convergence of the error of the algorithm, and improved the identification accuracy of battery parameters.(14)

To solve the problem of parameter estimation, a series of improved SoC estimation methods have been proposed. Odry *et al.* proposed the EKF algorithm and adopted the fuzzy reasoning system of the Mamdani model to adjust the measurement noise variance in real time, which effectively improved the convergence speed of the traditional adaptive EKF algorithm.(15) An estimation method based on the EKF and support vector machine utilized the regression prediction ability to compensate and optimize the estimation results of the EKF algorithm and correct its errors, thus greatly improving the estimation accuracy of SoC.(16) On the basis of the intelligent adaptive Kalman filter of lithium battery SoC estimation, Sun *et al.* proposed a new rate sequence estimation covariance matrix and improved the accuracy of the SoC estimation algorithm, so that the robustness of the algorithm to the initial measurement noise covariance matrix is enhanced.(17) To obtain accurate SoC estimation results in nonlinear systems such as linear-ion batteries, Shateri *et al.* modeled the batteries accurately and optimized the system to adapt to the complex working environment.(18)

The use of a single method has its defects, and the combined use of the above methods can improve the accuracy of SoC estimation. To determine the real-time performance of the battery model achieving accurate SoC estimation, the discrete state-space equation of the second-order RC circuit is derived in this paper, and the OCV–SoC relationship was obtained through experiments. The online parameter estimation of the lithium battery was performed by combining FF-MILS, which was used to identify the model parameters online, with EKF. The feasibility of the proposed fusion algorithm was verified by experiments and simulations under various working conditions.

3. Equivalent Mathematical Model of Lithium Battery

SoC is defined as $SOC = SOC_0 - \frac{1}{C_N}\int_{t_0}^{t} \eta \cdot I(t)dt$.(19) The equivalent circuit model of a lithium battery is different from the electrochemical model.(20) It is established by deducing the ordinary differential equation from the circuit principle, which is more convenient for calculation and has accuracy that also meets the requirements. As the name implies, this equivalent circuit model is used to simulate the dynamic characteristics of the battery and is composed of electrical components such as resistors and capacitors. Currently, the RC, Thevenin, and PNGV models are widely used in the equivalent circuit model.[21] The equivalent circuit model is widely used because it can be applied to all types of batteries, and the state-space equation can be derived from the equivalent circuit. Moreover, many methods can be used in the experimental analysis. Therefore, considering the above advantages, we adopt a second-order RC equivalent circuit model to simulate the dynamic characteristics of a lithium ion phosphate battery to achieve the separation and equivalence of electrochemical polarization and concentration polarization phenomena, and accurately simulate the nonlinear characteristics of the battery system. The second-order RC equivalent circuit model is shown in Fig. 1. The parameter identification process of the second-order RC model is simple. Compared with the first-order or third-order RC equivalent circuit model, the state-space equation is easier to establish, and the dynamic response of the battery can be more effectively improved.

In Fig. 1, U_{oc} is the OCV, R_0 is the internal resistance of the battery, R_1 and R_2 are polarization resistances, C_1 and C_2 are polarization capacitances, R_1C_1 represents the process of rapid circuit voltage change, R_2C_2 represents the process of slow circuit voltage change, and $U_L(t)$ is the terminal voltage of the battery. Taking the discharge direction as positive, the Kirchhoff voltage law equation for the circuit is

$$\begin{aligned} &U_L(t) = U_{oc} - I(t)R_0 - U_1(t) - U_2(t), \\ &\frac{dU_1(t)}{dt} = \frac{I(t)}{C_1} - \frac{U_1(t)}{R_1 \cdot C_1}, \\ &\frac{dU_2(t)}{dt} = \frac{I(t)}{C_2} - \frac{U_2(t)}{R_2 \cdot C_2}, \end{aligned} \tag{1}$$

where $U_1(t)$ and $U_2(t)$ are the terminal voltages of the two RC circuits. The OCV U_{oc} can be expressed as a function of the battery SoC. The state variable $x_k = \left[SOC_k, U_{1,k}, U_{1,k}\right]$ is selected to discretize the equivalent circuit, and the model state-space expression can be obtained as

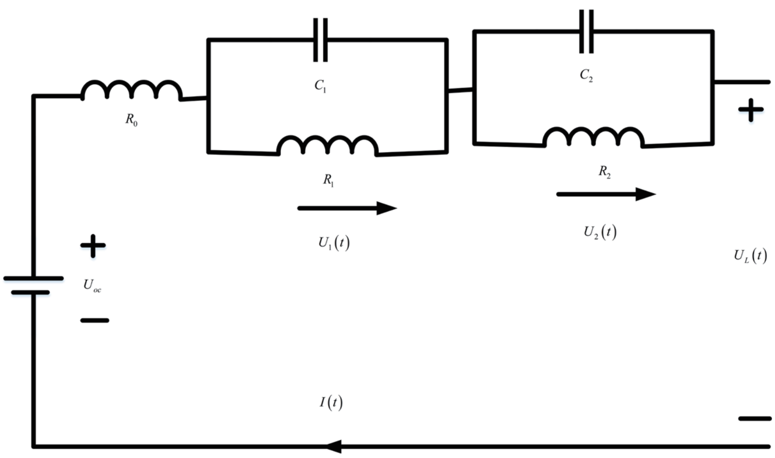


Fig. 1. Second-order RC equivalent model of lithium battery.

$$x_{k+1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{\Delta t}{\tau_1}} & 0 \\ 0 & 0 & e^{\frac{\Delta t}{\tau 2}} \end{bmatrix} \cdot x_k + \begin{bmatrix} -\frac{\eta \Delta t}{Q_N} \\ R_1\left(1-e^{\frac{\Delta t}{\tau_1}}\right) \\ R_2\left(1-e^{\frac{\Delta t}{\tau_2}}\right) \end{bmatrix} + w_k, \tag{2}$$

$$U_L(kt) = f\left[SOC(kt)\right] - U_1(kt) - U_2(kt) - R_0 \cdot I(kt) + v_k. \tag{3}$$

Equations (2) and (3) are the state and observation equations of the system, respectively. Δt is the sampling time, τ is the time constant, $\tau_1 = R_1C_1$, $\tau_2 = R_2C_2$, and subscripts k and $k + 1$ are the current state and the next state, respectively. w_k is the observation error, v_k is the measurement error, Q_n is the rated capacity of the battery, and η is the Coulomb efficiency.

4. Fusion-oriented SoC Estimation Method

4.1 Parameter identification based on FF-MILS

The RLS identification algorithm constantly revises the estimation results by considering the error between the observed values obtained by continuous sampling and the values estimated by iterative recursion until the optimal estimation results appear. The specific steps for the parameter identification of the second-order RC equivalent model are as follows.

$$E_{oc}(s) - U_L(s) = I(s)\left(R_0 + \frac{R_1}{1+sR_1C_1} + \frac{R_2}{1+sR_2C_2}\right). \tag{4}$$

Taking the voltage difference $E_{oc}(s) - U_L(s)$ as the input and $I(s)$ as the output, the transfer function of the system is

$$G(s) = \frac{R_0\tau_1\tau_2 s^2 + \left(R_0\tau_1 + R_0\tau_2 + R_1\tau_2 + R_2\tau_1\right)s + \left(R_0 + R_1 + R_2\right)}{\tau_1\tau_2 s^2 + \left(\tau_1 + \tau_2\right)s + 1}. \tag{5}$$

By discretizing Eq. (5), the bilinear transformation $s = \frac{2}{T}\left(\frac{1-z^{-1}}{1+z^{-1}}\right)$ is obtained.

$$G(z^{-1}) = \frac{a_3 + a_4 z^{-1} + a_5 z^{-2}}{1 - a_1 z^{-1} - a_2 z^{-2}} \tag{6}$$

Here, a_1, a_2, a_3, a_4, and a_5 are undetermined coefficients. Equation (6) can be converted into the following differential equation:

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + a_3 I(k) + a_4 I(k-1) + a_5 I(k-2). \tag{7}$$

Assuming a data vector of $\varphi(k) = \begin{bmatrix} y(k-1) & y(k-1) & I(k) & I(k-1) & I(k-2) \end{bmatrix}$ and a parameter vector of $\theta(k) = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \end{bmatrix}$, both $\theta(k)$ and $\varphi(k)$ are extended to N dimensions, and the zero mean noise $e(k)$ is added. The difference between the current output observation value and the optimal prediction output observation value at the previous iteration is called the innovation, and the innovation vector can be expressed as

$$e(k) = y(k) - \varphi^T(k-1)\hat{\theta}(k-1), \tag{8}$$

where $\varphi^T(k-1)\hat{\theta}(k-1)$ is the predicted value $y(k)$ based on the historical data at time $k - 1$, $y(k)$ is the actual observed value, and $\hat{\theta}(k-1)$ is the optimal parameter at time $k - 1$. According to the principle of the RLS algorithm,[22] the following formula for the recursive operation can be obtained:

$$\begin{cases} \hat{\theta}(k) = \theta(k-1) + \mathrm{A}(k)\left[y(k) - \varphi^T(k-1)\theta(k-1) \right], \\ A(k) = \dfrac{B(k-1)\varphi(k-1)}{1 + \varphi^T(k-1)B(k-1)\varphi(k-1)}, \\ B(k) = \left[E - A(k)\varphi^T(k-1) \right] B(k-1), \end{cases} \tag{9}$$

where E is the identity matrix of the same type and $B(k)$ is the covariance matrix at time k. The product of the innovation and its correction gain term $A(k)$ added to the optimal estimation $\hat{\theta}(k-1)$ at time $k - 1$ is the optimal estimation parameter $\hat{\theta}(k)$ at time k.

$$B(k-1) - B(k) = A(k)\varphi^T(k-1) = B(k-1)\frac{\varphi(k-1)\varphi^T(k-1)}{1 + \varphi(k-1)\varphi^T(k-1)B(k-1)} \tag{10}$$

As the number of samples increases, $B(k)$ will gradually approach 0. It can be seen from Eq. (9) that the gain matrix $A(k)$ will also approach 0, which will lead to the failure of the new sampling value to improve the optimal estimation result, and thus the problem of data saturation appears. The forgetting factor (λ = 0.99) is introduced into the RLS method, and the data saturation phenomenon is alleviated to realize the online parameter identification. The specific recursive formula is

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + \mathrm{A}(k)\left[y(k) - \varphi^T(k-1)\theta(k-1) \right], \\ A(k) = \dfrac{B(k-1)\varphi(k-1)}{\lambda + \varphi^T(k-1)B(k-1)\varphi(k-1)}, \\ B(k) = \dfrac{1}{\lambda}\left[E - A(k)\varphi^T(k-1) \right] B(k-1). \end{cases} \tag{11}$$

When the lithium batteries are sampled, a set of battery voltage and current data is obtained, and there will be a large error in the setting of the initial parameters, which will lead to the initial identification of the battery parameters that cannot be well tracked. Even in the case of a small number of samples, the final identification results have an error larger than that of a mass of samples. The FF-MILS obtains the innovation vector and finally achieves rapid convergence to the error. The scalar $e(k)$ can be expanded to a vector $E(p, k)$ of degree p as follows.

$$E(p,k) = \begin{bmatrix} y(k) - \varphi^T(k)\hat{\theta}(k-1) \\ y(k-1) - \varphi^T(k-1)\hat{\theta}(k-1) \\ \vdots \\ y(k-p+1) - \varphi^T(k-p+1)\hat{\theta}(k-1) \end{bmatrix} = Y(p,k) - \Psi^T(p,k)\hat{\theta}(k-1) \tag{12}$$

At this point, the extended output vector and the stacked data matrix are respectively

$$\begin{cases} Y(p,k) = \left[y(k) \quad y(k-1) \quad \cdots \quad y(k-p+1) \right], \\ \Psi(p,k) = \left[\varphi(k) \quad \varphi(k-1) \quad \cdots \quad \varphi(k-p+1) \right]. \end{cases} \tag{13}$$

The result is the following recursive formula:

$$\begin{gathered} \hat{\theta}(k) = \hat{\theta}(k-1) + A(k) \cdot E(p,k), \\ A(k) = \frac{B(k-1)\Psi(p,k)}{\lambda \cdot E_{p\times p} + \Psi^T(p,k)B(k-1)\Psi(p,k)}, \\ B(k) = \frac{1}{\lambda}\left[E_{5\times 5} - A(k)\Psi^T(p,k) \right] B(k-1). \end{gathered} \tag{14}$$

The optimal parameter vector $\hat{\theta}$ can be calculated from Eq. (14) and substituted into the discrete system transfer function [Eq. (6)]. The model parameter transfer $G(s)$ can be obtained from the equivalent corresponding coefficients of Eqs. (5) and (6).

$$\begin{cases} \tau_1 + \tau_2 = \dfrac{1+a_2}{1-a_1-a_2} \cdot T \\ \tau_1 \tau_2 = \dfrac{1+a_1-a_2}{1-a_1-a_2} \cdot \dfrac{T^2}{4} \\ R_0 + R_1 + R_2 = \dfrac{a_3+a_4+a_5}{1-a_1-a_2} \\ R_0\tau_1 + R_0\tau_2 + R_1\tau_2 + R_2\tau_1 = \dfrac{a_3-a_5}{1-a_1-a_2} \cdot T \\ R_0\tau_1\tau_2 = \dfrac{a_3-a_4+a_5}{1-a_1-a_2} \cdot \dfrac{T^2}{4} \end{cases} \tag{15}$$

Here, T defines the sampling period, and each parameter of the second-order equivalent circuit model is obtained, providing accurate data for the following SoC estimation. The OCV–SoC relationship is imported into the identification process, and dynamic parameters of the model are identified by current parameters and initial SoC. The detailed steps are shown in Fig. 2.

4.2 Parameter estimation of fading factor EKF algorithm

Owing to the complex and changeable working environment of lithium batteries, the equivalent model parameters are greatly affected by the environment, which reduces the accuracy of SoC estimation. In addition, when the system mutates, the SoC estimated from the

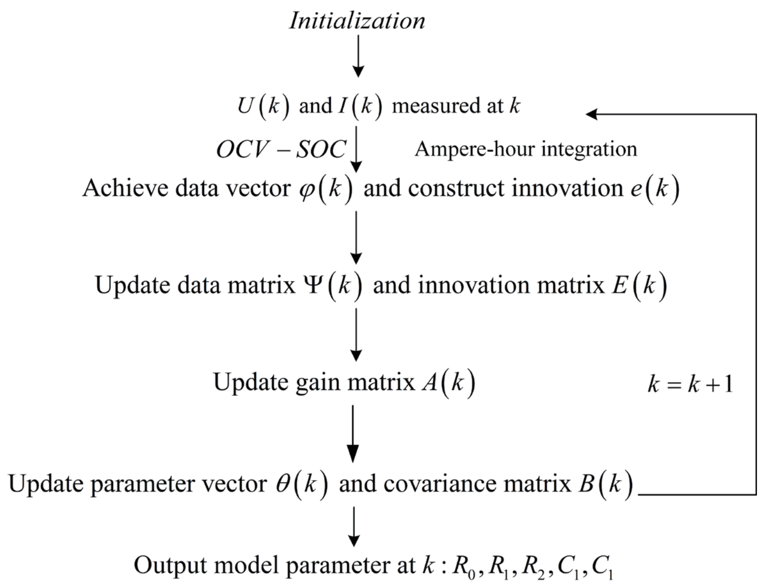


Fig. 2. FF-MILS identification process.

EKF algorithm has a large error. To improve the stability and tracking effect of the algorithm, the suboptimal fading factor γ_k is introduced into the EKF algorithm in combination with the theory of a strong tracking filter.[23] The factor γ_k is used to adjust the prediction covariance matrix in real time and adjust the Kalman gain to gradually eliminate the past data and reduce the error of SoC estimation caused by the effects of the environmental factors. The covariance matrix of the state prediction error after introducing the fading factor is

$$P_{k|k-1} = \gamma_k A_{k-1} P_{k-1} A_{k-1}^T + Q_k, \tag{16}$$

where A is the state transition matrix and Q_k is the variance matrix of the process noise. In the EKF algorithm, when the estimation accuracy is high, the innovation sequence shows a weak autocorrelation that is much smaller than the state value. Therefore, the selection of the fading factor γ can take the weak autocorrelation of the innovation sequence as a basis for the judgment. Consider the expression $s(k)$ shown in Eq. (17). After a series of derivations, when S approaches zero infinitely, the estimation result of the EKF is the optimal value.

$$\begin{cases} s(k) = P_{k|k-1} C_k^T - K_k G_k \\ G_k = C_1 P_1 C_1^T + R_1, & k = 0 \\ G_k = G_1 + Z_2 Z_2^T, & k = 1 \\ G_k = \dfrac{k-2}{k-1}\left[G_{k-1} + \dfrac{Z_k Z_k^T}{k-2} \right], & k \geq 2 \end{cases} \tag{17}$$

Here, G_k is the mean square error matrix and $s(k)$ is set to zero. Equation (17) is substituted into Eq. (16), and the custom matrices M and N are introduced. The calculation formula of the fading factor and the expressions for M and N can be obtained as shown in Eq. (18).

$$\begin{gathered} \gamma_k = \max\left(1, \frac{tr(N_k)}{tr(M_k)}\right) \\ N_k = G_k - R_k - C_k Q_k {C_k}^T \\ M_k = C_k A_{k-1} P_{k-1} A_{k-1}^T {C_k}^T \end{gathered} \tag{18}$$

Here, γ_k represents the fading factor, and the specific steps of the EKF algorithm can be obtained. First, the initial value is set, and γ_k is calculated through the error covariance matrix. Second, the error covariance matrix is updated using γ_k. Third, the Kalman gain is updated using the error covariance matrix. Fourth, the state is estimated posteriori using the gain and innovation. Fifth, the error covariance matrix is updated. The calculation is expressed as

$$\begin{cases} x_{k|k-1} = A_{k-1}x_{k-1} + B_{k-1}I_{k-1} \\ P_{k|k-1} = \gamma_k A_{k-1}P_{k-1}A_{k-1}^T + Q_k \\ K_k = P_{k|k-1}C_k^T\left(C_k P_{k|k-1}C_k^T + R_k\right)^{-1} \\ \hat{x}_{k|k} = x_{k|k-1} + K_k\left[Y_k - y_k\right] \\ \hat{P}_{k|k} = \left(E - K_k C_k\right)P_k \end{cases}, \tag{19}$$

where B is the control matrix, C is the observation matrix, $Y_k - y_k$ is the innovation at the current moment, R_k is the variance matrix of the measurement noise, and E is the identity matrix. The SoC estimation process based on the FF-MILS and fading factor EKF algorithms is shown in Fig. 3.

5. Results and Discussion

As the research object, we took a lithium battery with a rated capacity of 70 Ah and an actual capacity of 68.47 Ah. We built the experimental platform to obtain relevant experimental data through the bTS200-100-104 battery testing equipment and temperature control box provided by Shenzhen Yakeyuan Technology Co., Ltd.

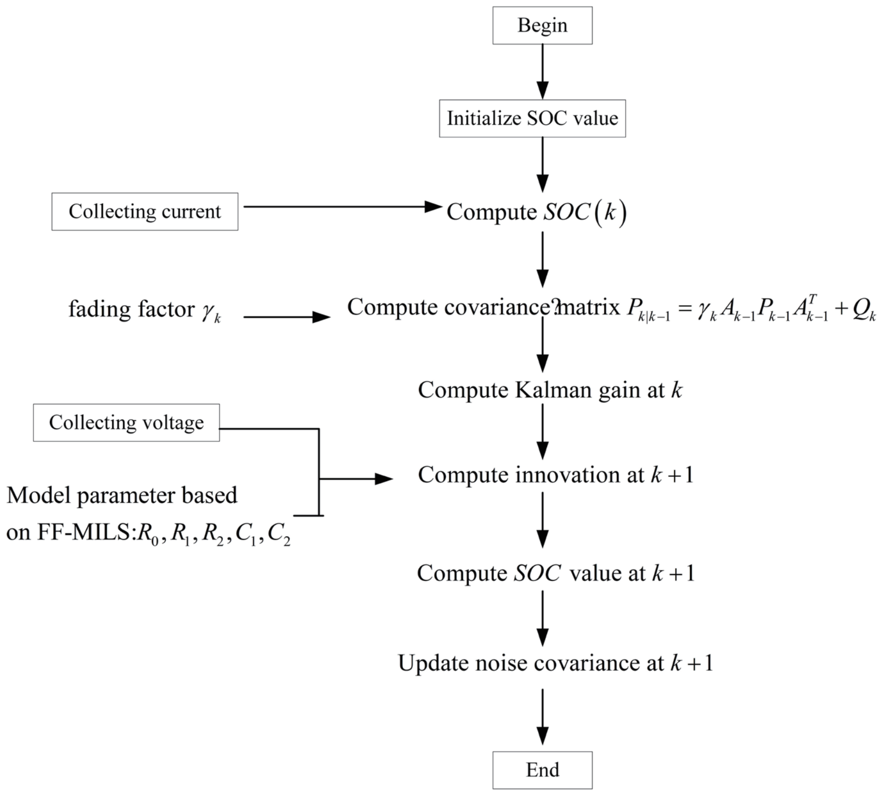


Fig. 3. Flow chart of SoC estimation.

5.1 Verification of SoC parameter identification accuracy

To verify the feasibility and accuracy of the proposed FF-MILS- and EKF-based online SoC estimation algorithm for lithium-ion batteries, we used the HPPC operating condition data at room temperature for the online parameter identification of the model. The accuracy of parameter identification was evaluated by considering the error between the experimental voltage and the simulated voltage, and the effectiveness of the FF-MILS- and EKF-based fusion algorithm was verified.

The HPPC experiment tests the acceleration, average speed, deceleration, idle speed, and other states in the process of vehicle driving. The above conditions were separated and then combined to carry out the cycle discharge of the lithium battery. Figure 4(a) shows the current data curve under working conditions. Figure 4(b) shows the actual voltage data of a lithium battery with a capacity of 30 Ah when SoC tends to be 0 after 21 cycles in the HPPC experiment.

To compare the terminal voltage estimation results of different algorithms for the second-order RC equivalent circuit model, FF-MILS and LM-RLS were separately used for the online identification of the model parameters after experimental data collection to verify the effectiveness of the improved algorithm.[12] The parameter identification results are shown in Fig. 5, which shows a comparison between the online estimated terminal voltage by FF-MILS and LM-RLS and the actual terminal voltage in an HPPC working cycle. The forgetting factor of the algorithm is 0.99.

As can be seen from Fig. 6, when the initial SoC is set to 1, the convergence of both algorithms is relatively fast. After convergence, the maximum error of the LM-RLS algorithm is 0.2 V in the working cycle of HPPC and the maximum error of the FF-MILS algorithm is 0.04 V, which shows its significantly improved accuracy. In the final HPPC working cycle, the lithium battery is sensitive to the terminal voltage change, the stability is poor, the forgetting factor is large, and there is a large fluctuation. It has been shown that the FF-MILS algorithm realizes

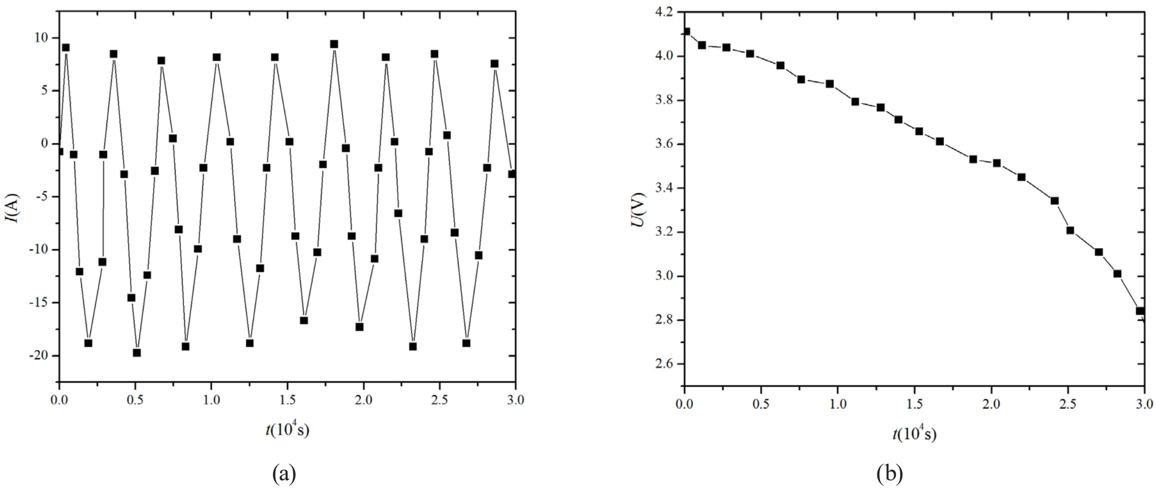


Fig. 4. (a) Current and (b) voltage curves under HPPC working condition.

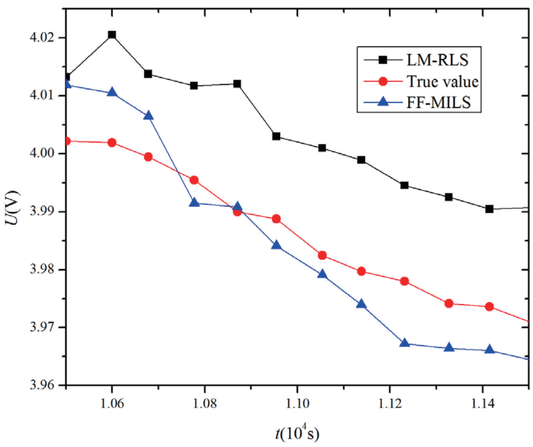


Fig. 5. (Color online) Comparison of estimated and actual terminal voltages.

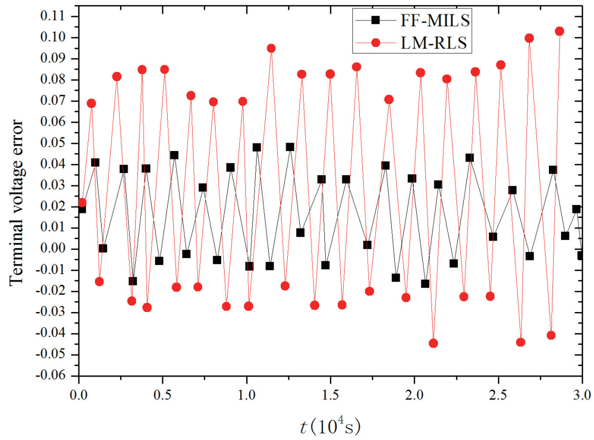
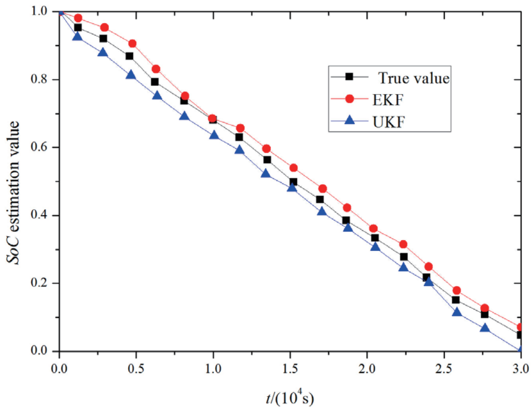
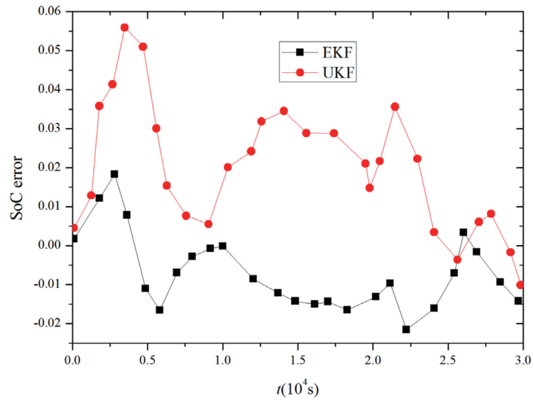


Fig. 6. (Color online) Comparison of terminal voltage errors.



(a)



(b)

Fig. 7. (Color online) (a) Estimated SoC values and (b) errors under constant discharge condition.

closed-loop correction through the innovation feedback, and its overall error curve fluctuation is less than that of the LM-RLS algorithm, which verifies the robustness of the FF-MILS algorithm.

5.2 Verification of SoC parameter estimation accuracy

In the next experiment, the FF-MILS algorithm was used for parameter identification, and the ideal SoC value was obtained by ampere-hour integration. SoC was estimated under a constant discharge condition and the above HPPC condition. The SoC values obtained by the unscented Kalman filter (UKF) and EKF algorithms were compared with the actual value to verify the feasibility of the fusion algorithm.(16) Figure 7(a) shows a comparison of the estimated SoC values for the two algorithms under the pulse discharge condition and Fig. 7(b) shows a comparison of the SoC errors for the two algorithms under this condition. It can be seen in Fig. 7(b) that the SoC value obtained from the EKF algorithm is closer to the actual value, and the SoC error can be tracked more quickly. Moreover, the error of the EKF algorithm is smaller than that of the UKF algorithm. Under the constant discharge condition, the maximum error of the EKF algorithm is less than 2%, compared with more than 8% for the UKF algorithm. Therefore, the EKF algorithm has higher stability and accuracy.

6. Conclusions

The precise estimation of the lithium battery SoC is the key and a difficult task in a BMS, where the parameter identification accuracy of the equivalent model and changes in environmental factors will affect the estimation accuracy. In this paper, taking the second-order RC circuit model of lithium-ion batteries as an example, the parameters of the model are identified by FF-MILS. The identified parameters are also estimated using the EKF algorithm to achieve the optimal estimation, and the fusion algorithm is used to estimate the SoC of lithium-ion batteries online under the HPPC condition. In terms of model parameter identification, the FF-MILS algorithm has a higher accuracy than the traditional LM-RLS algorithm. Then, the EKF algorithm is used to estimate the lithium battery SoC, and its real-time performance, accuracy, and robustness are higher than those of the UKF algorithm and can meet actual engineering requirements. Limitations of this study are that we focused on SoC estimation at normal temperatures, and that the fusion FF-MILS and EKF algorithm requires too many execution steps. In the future, the impact of temperature on battery SoC estimation will be focused on, and the system will be simplified to a fractional-order model to improve its performance.

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