



SOC and SOH Joint Estimation of the Power Batteries **Based on Fuzzy Unscented Kalman Filtering Algorithm**

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Abstract: In order to improve the convergence time and stabilization accuracy of the real-time state estimation of the power batteries for electric vehicles, a fuzzy unscented Kalman filtering algorithm (F-UKF) of a new type is proposed in this paper, with an improved second-order resistor-capacitor (RC) equivalent circuit model established and an online parameter identification used by Bayes. Ohmic resistance is treated as a battery state of health (SOH) characteristic parameter, F-UKF algorithms are used for the joint estimation of battery state of charge (SOC) and SOH. The experimental data obtained from the ITS5300-based battery test platform are adopted for the simulation verification under discharge conditions with constant-current pulses and urban dynamometer driving schedule (UDDS) conditions in the MATLAB environment. The experimental results show that the F-UKF algorithm is insensitive to the initial value of the SOC under discharge conditions with constant-current pulses, and the SOC and SOH estimation accuracy under UDDS conditions reaches 1.76% and 1.61%, respectively, with the corresponding convergence time of 120 and 140 s, which proves the superiority of the joint estimation algorithm.

Keywords: power batteries; improved second-order RC equivalent circuit; fuzzy unscented Kalman filtering algorithm; joint estimation

1. Introduction

The power batteries serving as the power supply for electric vehicles (EVs) have direct effects on the overall performance of EVs, and the battery overcharge may cause overheating or even an explosion, while the battery over-discharge may result in accelerated aging and permanently reduced capacity [1]. Concerning the issues of safety usage, the state estimation of batteries available for safety precautions can facilitate the elimination of safety hazards, which means the state of charge (SOC) and state of health (SOH) joint estimation is of great significance for the research on power batteries [2].

Lots of scholars have proposed many SOC estimation methods, such as the open circuit voltage method [3,4], the Coulomb counting method [5], the neural network method [6] and the Kalman filtering algorithm [7]. Among them, the open circuit voltage method was to first establish a corresponding function of the open circuit voltage and the SOC and then obtain the SOC by measuring the open circuit voltage after the battery was stationary [8]; the Coulomb integral method, which discretizes the current flowing through the battery and sums it up, and obtains the SOC value by simple division [9]; the neural network method optimizes the relevant parameters of the SOC estimation algorithm and solves complex abstract problems through autonomous learning [7]; a series of Kalman filtering algorithms based on the extended Kalman filtering algorithm optimize autoregressive data processing, which can make the optimal estimation in the minimum variance sense for the state of the dynamic system [10,11].



The estimation methods in the SOH are mainly divided into two categories: One is to start with the characteristic parameters of the battery, and the other is to analyze the aging characteristics and electrochemical reaction characteristics of the battery [12]. The former mainly uses the direct measurement method, obtaining the current SOH by obtaining aging characteristic parameters such as capacity and ohmic internal resistance [8,13]. There are also methods such as neural networks [14] and fuzzy logic [15], which can directly estimate the SOH of the battery through data training without an a priori model. The latter uses an electrochemical model method [12] that models the internal physical and chemical reactions during the charging process and designs an estimator for SOH estimation. There is also a method based on an equivalent circuit model [16] that establishes a circuit that reflects internal variables for SOH estimation.

All of the above algorithms are only a single estimate for the SOC or the SOH, ignoring the close relationship between the SOC and the SOH. The SOC estimate is affected by battery aging—as the battery ages, inaccurate SOC estimates can affect the SOH correction. Therefore, a joint estimate of the SOC and the SOH is necessary. The literature proposes an online SOH estimation method for the lithium battery using the constant-voltage (CV) charge current, as proposed in reference document [17], which can ensure the estimation error of less than 2.5%. However, it is difficult to accurately estimate the true state of the lithium battery by merely estimating the value of the SOH. Another SOC and SOH joint estimation method applicable to the cycle life of lithium-ion batteries for EVs, as proposed in reference document [18], involves an SOC and SOH identification using offline state estimators with different time scales; this requires substantial data to ensure asymptotic convergence without the real-time update.

Reference document [19] analyzed the error sources from the four angles of measurement, model, algorithm and state parameters for the SOC estimation. Finally, the author put forward new concerns in the practical application of SOC estimation. A multi-time-scale observer of the SOC and the SOH for a lithium-ion battery with coupled fast and slow dynamics was proposed in the reference document [16]. The authors used a deterministic transformation of the extended Kalman filter. The paper made an effective estimation of the SOC and the SOH by strictly characterizing the stability of estimation error. Three model-based filtering algorithms [20] were used to estimate the SOC, and the tracking accuracy, calculation time, robustness, etc., were analyzed and compared. Experimental results showed the advantages of three algorithms; the unscented Kalman filtering (UKF) algorithm has a good stability and the Particle filter (PF) algorithm, in the early stage has extreme rapidity. This article gave a combination of the two algorithms to improve the accuracy of the research direction.

In this paper, full consideration was given to the estimation error caused by the change in ohmic resistance during the service of power batteries, and the constant ohmic resistance was replaced by that of gentle variations resistance so as to propose a joint estimation algorithm of the power battery SOC and SOH based on a fuzzy control trace-free Kalman filter. This algorithm uses two complete fuzzy unscented Kalman filtering (F-UKF) algorithms to estimate the SOC and ohmic resistance of the battery at the same time. First of all, the use of a fuzzy controller can effectively reduce the impact of observation noise under complex conditions and to further improve the accuracy of battery SOC estimation. Secondly, the fuzzy controller is used to make a real-time correction of the variance matrix of the observed noise so as to finally realize the estimation of the battery ohmic internal resistance; experiments show that the joint estimation algorithm is not affected by the initial value of SOC, and it still has good convergence speed and tracking accuracy under complex conditions.

The rest of this paper is organized as follows: Section 2 introduces the model of lithium battery, open circuit voltage, SOC calibration experiment, and parameter identification. Section 3 reviews the implementation method of traceless Kalman filtering, fully considers the intrinsic coupling relationship between the SOC and the SOH, puts forward the fuzzy and traceless Kalman filter algorithm on the basis of traceless Kalman filtering, and uses two F-UKF algorithms to estimate the SOC and ohmic internal resistance at the same time. Section 4 discusses the relevant experimental process and conclusions, and Section 5 summarizes the full text.

2. Model for the Lithium Battery

2.1. Setup of Equivalent Circuit Model for the Lithium Battery

An accurate battery model can effectively describe the external features and characteristics of internal electrochemical reactions, which is of great significance for the SOC and SOH evaluation of power batteries [21]. In this paper, the SOC is defined as the ratio between remaining battery capacity and nominal battery capacity under the same environmental conditions and specified discharge rate [22]:

$$SOC = \frac{Q_{res}}{Q_N} \times 100\%$$
(1)

In which Q_{res} is the remaining battery capacity after the discharge of partial electric quantity and Q_N is the nominal battery capacity.

Through the comparative analysis of differences between old and new batteries, the researchers found that the ohmic resistance and actual maximum battery capacity have more significant changes due to the SOH variations, and SOH is defined as follows from the perspective of ohmic resistance [23]:

$$SOH_R = \frac{R_0(end) - R_0(t)}{R_0(end) - R_0(0)} \times 100\%$$
(2)

In which SOH_R is the battery SOH, which defined based on the ohmic resistance R_0 ; $R_0(end)$ is the ohmic resistance when the actual maximum battery capacity drops to 80% of the nominal battery capacity; $R_0(t)$ is the ohmic resistance of the battery at t; and $R_0(0)$ is the ohmic resistance upon the battery delivery from the factory.

The proposed improved second-order Resistor-capacitor (RC) equivalent circuit model based on the equivalent circuit model [24,25] is shown in Figure 1. The high capacitance C_p and current-controlled current source (CCCS) on the left side characterize the battery capacity, SOC and running time. The second-order RC circuit on the right side simulates the internal polarization characteristics of the battery, R1 and C_1 describe the concentration polarization characteristics of the battery, while R_2 and C_2 describe the electrochemical polarization characteristics of the battery. The voltage-controlled voltage source (VCVS) simulates the nonlinear relationship between the open-circuit voltage and U_{soc} , which links the circuit parts on both sides.



Figure 1. Improved second-order resistor-capacitor (RC) equivalent circuit model.

Based on the improved second-order RC equivalent circuit model for the lithium battery, select $x = [\text{SOC } U_1 U_2]^T$ as the state variable to obtain the following continuous state space equation:

$$\begin{array}{c} \dot{SOC} \\ \dot{U}_1 \\ \dot{U}_2 \end{array} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -\frac{1}{R_1 C_1} & 0 \\ 0 & 0 & -\frac{1}{R_2 C_2} \end{bmatrix} \cdot \begin{bmatrix} SOC \\ U_1 \\ U_2 \end{bmatrix} + \begin{bmatrix} -\frac{\eta}{Q_N} \\ -\frac{1}{C_1} \\ -\frac{1}{C_2} \end{bmatrix} \cdot i$$
(3)

In Equation (3), Q_N is the nominal battery capacity and η is the charge–discharge efficiency of the battery. The discretized state equation and observation equation are as follows:

$$\begin{cases} x(k+1) = A \cdot x(k) + B \cdot i(k) \\ U_L(k) = U_{oc}(SOC) - U_1(k) - U_2(k) - R_0 \cdot i(k) \end{cases}$$
(4)

In which *T* is the sampling period of the system, with *A* and *B* expressed as follows:

$$A = \begin{bmatrix} 1 & 0 & 0\\ 0 & \exp(-\frac{T}{R_1C_1}) & 0\\ 0 & 0 & \exp(-\frac{T}{R_2C_2}) \end{bmatrix}, B = \begin{bmatrix} -\frac{\eta \cdot T}{Q_N} \\ R_1(1 - \exp(-\frac{T}{R_1C_1})) \\ R_2(1 - \exp(-\frac{T}{R_2C_2})) \end{bmatrix}$$
(5)

2.2. Open-Circuit Voltage and SOC Setting Experiments

The procedures of open-circuit voltage and SOC setting experiments for the lithium battery at a normal temperature (25 °C) based on the ITS5300 battery test platform (ITECH ELECTRONIC CO., LTD., Nanjing, China) are as follows: Charge the battery until the full-load capacity is reached before the 3-hour standing and record the open-circuit voltage of the battery, discharge the battery for 6 minutes at a discharge rate of 1 C (40 A), and repeat the above steps until the cutoff voltage is reached. The fitting of open-circuit voltage curve corresponding to the SOC variations of lithium battery was completed via the MATLAB software (2017a, The MathWorks, Inc, Natick, MA, USA), which showed that the fitting curve had the minimum root-mean-square error when the polynomial order was 5. The fitting curve is shown in Figure 2, and the function expression is as follows.

$$U_{oc}(SOC) = 3.2821 \cdot SOC^5 - 10.3004 \cdot SOC^4 + 13.0068 \cdot SOC^3 - 7.9724 \cdot SOC^2 + 2.4054 \cdot SOC + 2.9752$$
(6)





2.3. Parameter Identification of the Lithium Battery Model

In accordance with the improved second-order RC equivalent circuit model, the Bayesian identification algorithm based on the least-square equation was adopted for the identification of resistance and capacitance parameters of the equivalent circuit model. Taking the parameters to be estimated as random variables, the Bayesian identification algorithm achieved the optimal estimation indirectly through the observation on other related parameters [26,27].

Kirchhoff's law should be adopted to obtain the following Laplace's equation of the improved second-order RC equivalent circuit model:

$$U_{oc}(s) - U_L(s) = i(s) \cdot \left(\frac{R_1}{R_1 C_1 s + 1} + \frac{R_2}{R_2 C_2 s + 1} + R_0\right)$$
(7)

The equation obtained using the bilinear transformation method is as follows:

$$d(k) = -k_1 d(k-1) - k_2 d(k-2) + k_3 i(k) + k_4 i(k-1) + k_5 i(k-2)$$
(8)

In which i(k) is the system input, $d(k) = U_{OC}(k) - U_L(k)$, and the final derivation of the Bayesian identification algorithm is as follows.

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + K(k) \cdot \left[z(k) - H^{T}(k)\hat{\theta}(k-1) \right] \\ K(k) = P_{\theta}(k-1)H^{T}(k) \cdot \left[H^{T}(k)P_{\theta}(k-1)H(k) + \frac{1}{\sigma_{r}^{2}} \right]^{-1} \\ P_{\theta}(k) = \left[I - K(k)H^{T}(k) \right] \cdot P_{\theta}(k-1) \end{cases}$$
(9)

The initial value of $\theta(0)$ is 0, and the initial value of covariance matrix $P_{\theta}(0)$ is *a*·*I*, among which *a* is a small positive number and *I* is a 5-order unit matrix. Use the recursion Formula (9) of the Bayesian identification algorithm to estimate the model parameters and then calculate the resistance and capacitance values of the model via Equation (8). In practical applications, it is necessary to consider the amount of calculation and the length of time for parameter identification. The joint estimation algorithm designed in this paper has a large amount of computation. Therefore, the mean value of the online identification result was selected as the parameter identification result. The results are shown in Table 1.

Table 1. Online identification result based on the Bayesian identification algorithm.

Model Parameter	Maximum Value	Minimum Value	Average Value
Ohmic internal resistance R_0 (m Ω)	1.704	0.923	1.278
Concentration polarization internal resistance R_1 (m Ω)	0.0603	0.1189	0.0927
Concentration polarization capacitor C_1 (KF)	6.017	3.021	3.821
Electrochemical polarization internal resistance R_2 (m Ω)	0.248	0.176	0.219
Electrochemical polarization capacitance C_2 (KF)	3.281	2.683	2.746

3. SOC and SOH Joint Estimation Based on F-UKF

3.1. Unscented Kalman Filtering Algorithm

The unscented Kalman filtering algorithm adopts the linear Kalman filter framework instead of the traditional linearization for nonlinear functions, with the nonlinear transfer of mean value and covariance completed via unscented transformation in the one-step prediction equation [7,28]. The unscented Kalman filtering algorithm is applicable to the nonlinear dynamic systems described with the following state-space equation:

$$\begin{cases} x(k+1) = f[x(k), u(k)] + e(k) \\ y(k) = g[x(k), u(k)] + v(k) \end{cases}$$
(10)

In which *f* is the function of nonlinear state equation and *g* is the function of nonlinear observation equation. Assume that e(k) has the covariance matrix *Q* and v(k) has the covariance matrix *R*; thus, the essential operation steps of the unscented Kalman filtering algorithm for a random variable *X* at the different time *K* are shown in Figure 3.



Figure 3. Essential operation steps of the unscented Kalman filtering algorithm.

3.2. Fuzzy Unscented Kalman Filtering Algorithm

The application of the unscented Kalman filtering algorithm should have been based on the already known statistical characteristics of process noises and observation noises; however, the insufficient estimation accuracy caused by the difficulty in noise determination during the use of power batteries required the introduction of adaptive filtering technique for algorithm optimization [29,30]. With reference to the unscented Kalman filtering algorithm, the covariance matching technique based on the fuzzy inference system was adopted in this section to effectively improve the accuracy of real-time observation noise estimation.

Assume that the statistical characteristics of process noises are already known, implement the recursive correction of observation noise variance based on the calculation of real-time ratio between the theoretical and actual covariances of observation errors.

Calculate the theoretical covariance N(k) and actual covariance M(k) of observation errors first, among which i = k - n + 1.

$$N(k) = \sum_{i=0}^{2n} \omega_c^i \cdot \varepsilon_y(k|k-1) \cdot \varepsilon_y^T(k|k-1) + V(k)$$
(11)

$$M(k) = \frac{1}{n} \sum_{i}^{k} [y(i) - y(i|i-1)] \cdot [y(i) - y(i|i-1)]^{T}$$
(12)

The input value G(k) of the fuzzy controller is a ratio between the theoretical and actual covariances of observation errors, while its output value $\alpha(k)$ is the adjustment factor of observation noise variance. Take the adjusted observation noise variance $\hat{V}(k)$ into the unscented Kalman filtering algorithm to calculate the new observation-error covariance matrix $\hat{P}_y(k|k-1)$ and then update the Kalman filter gain and state-error covariance matrix with the updated $\hat{P}_y(k|k-1)$.

$$G(k) = \frac{M(k)}{N(k)} \tag{13}$$

$$\hat{V}(k) = \alpha(k) \cdot V(k) \tag{14}$$

As a kind of uncertainty reasoning method, the fuzzy controller is composed of three parts. First, initiate the fuzzy processing in accordance with the input membership function shown in Figure 4 for the input value G(k) of the fuzzy controller to obtain the corresponding fuzzy index.



Figure 4. Input membership function.

Second, concerning the fuzzy controller with a single input/output, the correspondent fuzzy rules are relatively simple. The greater observation noise will result in the greater actual covariance M(k) and G(k), while the change in theoretical covariance N(k) is subject to the variation of observation noise variance V(k). In order to keep the variation consistency between N(k) and M(k), adjust $\alpha(k)$ to enlarge V(k) when the observation noise becomes greater, so that the decreased G(k) will approach 1. The decreased observation noise will result in the decreased actual covariance M(k) and G(k). Therefore, $\alpha(k)$ should be adjusted accordingly to decrease V(k) so that the enlarged G(k) will approach 1. The fuzzy rules established in accordance with the above derivation process is shown in Table 2.

Table 2.	Fuzzy	rules.
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Input fuzziness	Input Small (IS)	Input Middle (IM)	Input Big (IB)
Output fuzziness	Output Small (OS)	Output Middle (OM)	Output Big (OB)

Finally, initiate the anti-fuzzy processing in accordance with the output membership function shown in Figure 5 for the output fuzziness to obtain the output value $\alpha(k)$ of the fuzzy controller.



Figure 5. Output membership function.

The diagram of working principle using the fuzzy controller for the adjustment of observation noise variance matrix is shown in Figure 6.



Figure 6. Structure diagram of the fuzzy controller.

3.3. Design and Implementation of the SOC and SOH Joint Estimation Algorithm

The following state-space equation can be used to express the improved second-order RC equivalent circuit model:

$$\begin{cases} x(k+1) = A_x(k) \cdot x(k) + B_x(k) \cdot i(k) + e_x(k) \\ y(k) = U_{oc}(SOC(k)) - U_1(k) - U_2(k) - R_0 \cdot i(k) + v_x(k) \end{cases}$$
(15)

In which x(k) is the state variable; y(k) is the predicted terminal voltage of the battery; $e_x(k)$ is the process noise, with the mean value of zero and variance $E_x(k)$; $v_x(k)$ is the observation noise, with the mean value of zero and variance $V_x(k)$; and $V_x(k)$ are irrelevant.

The gradual increase of ohmic resistance in a non-linear way is unnoticeable within a short period, which means the ohmic resistance of the battery at two adjacent moments can be taken as the constant value. Therefore, the state equation and observation equation for the estimation of ohmic resistance can be expressed as follows:

$$\begin{cases} R_0(k+1) = R_0(k) + e_R(k) \\ y(k) = U_{oc}(SOC(k)) - U_1(k) - U_2(k) - R_0(k) \cdot i(k) + v_R(k) \end{cases}$$
(16)

In which $R_0(k)$ is the state variable; y(k) is the predicted terminal voltage of the battery; $e_R(k)$ is the process noise, with the mean value of zero and variance $E_R(k)$; $V_R(k)$ is the observation noise, with the mean value of zero and variance $V_R(k)$; and $E_R(k)$ are irrelevant.

The optimal estimated value of the battery SOC was adopted in the joint estimation algorithm for the one-step-ahead prediction of ohmic resistance; meanwhile, the optimal estimated value of ohmic resistance was also available for the one-step-ahead prediction of the battery SOC, and the above mutual application facilitated the acquisition of the estimated battery SOC and ohmic resistance closer to the actual values.

The flowchart of the SOC and SOH joint estimation algorithm based on F-UKF is shown in Figure 7.



Figure 7. Flowchart of the joint estimation algorithm.

- (1) Parameter initialization. First, initialize the corresponding parameters of the F-UKF algorithm for the battery SOC estimation; then, initialize the corresponding parameters of the F-UKF algorithm for the ohmic resistance estimation, and the ohmic resistance should be close to the actual value to ensure the fast convergence of the battery SOC.
- (2) Obtain the terminal voltage $U_L(k)$ and working current i(k) of the battery at the time k through the voltage-current acquisition module.
- (3) Obtain the estimated value of the battery SOC at the time *k* through the recursion formula using the F-UKF algorithm based on the above terminal voltage and working current at the time *k*.
- (4) Obtain the estimated value of ohmic resistance at the time *k* through the recursion formula using the F-UKF algorithm based on the estimated value of battery SOC and working current at the time *k*.
- (5) Take the value of SOC(k) obtained from step (3) into the nonlinear functions of open-circuit voltage and the battery SOC to obtain the open-circuit voltage $U_{OC}(k)$ at the time k; repeat the steps (2), (3), (4) and (5) for the real-time estimation of the battery SOC and ohmic resistance.

4. Experimental Verification and Result Analysis

The ITS5300-based battery test platform available to verify the proposed SOC and SOH joint estimation algorithm is shown in Figure 8. The nominal capacity of a single lithium iron phosphate battery is 40 Ah, and the corresponding performance parameters are shown in Table 3. In order to measure the terminal voltage and working current of the battery, the software of IT9320 battery

test system (ITECH ELECTRONIC CO., LTD, Nanjing, China) was used to simulate the discharge conditions with constant-current pulses and the urban dynamometer driving schedule (UDDS) driving cycles, and the MATLAB software was adopted for the simulation verification and analysis of the joint estimation algorithm proposed in this paper.



Figure 8. Battery test platform.

Nominal Capacity (Ah)	40		
Battery voltage (V)	Charge cutoff voltage Discharge cutoff voltage	3.6 2.0	
Cycle life (times)	80% DOD 70% DOD	≥2000 ≥3000	
Standard charge–discharge current (A)	0.3C		
Maximum charge current (A)	3C		
Maximum discharge current (A)	4C		
Operating temperature (°C)	-25-55		

Table 3. Parameters of the lithium iron phosphate battery.

4.1. Sensitivity Verification of the F-UKF Algorithm against Initial Values

Concerning the estimation of the battery SOC and ohmic resistance using the F-UKF algorithm, it was difficult to obtain the accurate initial values of battery SOC, but the values of ohmic resistance were relatively stable without violent fluctuations. The lithium iron phosphate battery was charged until the battery SOC reached 85% of the initial state before the experiment. Under the discharge conditions with constant-current pulses, the different initial values of the battery SOC were set to verify the F-UKF sensitivity against initial values. In the MATLAB software, the respective initial values of the SOC were set to 40%/0% and 85% for the F-UKF algorithm and the ampere-hour integration

method, with the sampling period and discharge rate set to 1 s and 0.5 C (20 A) for the 500-second simulation experiment.

The simulations under discharge conditions with constant-current pulses shown in Figures 9 and 10 indicate that the different initial values of battery SOC converged to the vicinity of reference value after a period of filtering iteration. Though the greater deviation of SOC initial values resulted in a longer convergence time, the stabilized values could follow the reference value well, and the estimation error was extremely small. Therefore, the F-UKF algorithm proposed in this paper is insensitive to the initial values.



Figure 9. State of charge (SOC) estimation curve based on the fuzzy unscented Kalman filtering algorithm (F-UKF) under discharge conditions with constant-current pulses.



Figure 10. SOC estimation error curve based on F-UKF under discharge conditions with constant-current pulses.

4.2. Joint Simulation Verification of UDDS Driving Cycles

The lithium iron phosphate battery was charged until the battery SOC reached 85% of the initial state before the experiment.

The software of IT9320 battery test system was used to compile the pulse current driving cycles before the acquisition of terminal voltage and working current from UDDS driving cycles. In the MATLAB software, the initial values of SOC were set to 80% for the F-UKF and joint estimation algorithms and 85% for the ampere-hour integration method, respectively. The initial value of ohmic resistance was set to 1.50 m Ω for the joint estimation algorithm, which was greater than the reference value of 1.278 m Ω .

The simulations of UDDS driving cycles shown in Figure 11 indicate that the convergence time of SOC from the initial 80% to the vicinity of reference value based on the F-UKF algorithm was about 170

s, while the UKF algorithm was about 185 s. The SOC estimation error of the F-UKF algorithm after convergence could be controlled within 2.82%, while the estimation error of the UKF algorithm was about 2.93%. Since the noise of UKF was random white noise, the F-UKF algorithm that introduces adaptive technology was to adjust the noise instead of eliminating the noise. It can be seen that the convergence performance of the F-UKF algorithm was not only better than the UKF algorithm, but the estimation accuracy was also relatively improved in complex conditions.



Figure 11. (a) SOC estimation curve of urban dynamometer driving schedule (UDDS) driving cycles based on the F-UKF and UKF algorithms. (b) SOC estimation error curve of UDDS driving cycles based on the F-UKF and UKF algorithms.

The simulations of UDDS driving cycles shown in Figure 12a indicate that the convergence time of SOC from the initial 80% to the vicinity of reference value based on the F-UKF algorithm was about 170 s, while the corresponding convergence time with an increased rising velocity based on the joint estimation algorithm was about 120 s. Therefore, the convergence performance of the joint estimation algorithm was better than that of the F-UKF algorithm under complex conditions. Figure 12b shows that the respective SOC estimation errors of the F-UKF algorithm and the joint estimation algorithm after convergence were less than 2.82% and 1.76%. Therefore, the tracking performance of the joint estimation.



Figure 12. (a) SOC estimation curve of UDDS driving cycles based on the F-UKF and joint estimation algorithms. (b) SOC estimation error curve of UDDS driving cycles based on the F-UKF and joint estimation algorithms.

The simulations of UDDS driving cycles shown in Figures 13 and 14 indicate that the convergence time of ohmic resistance from 1.50 m Ω to the vicinity of reference value (1.278 m Ω) based on the joint estimation algorithm was about 140 s, and the corresponding battery SOH was about 89.87% of the reference value after stabilization. Figure 15 shows that the maximum SOH estimation error based on the joint estimation algorithm was 1.61%, and the SOH estimation error was less than 1.20% over time.



Figure 13. Ohmic resistance estimation curve of UDDS driving cycles based on the joint estimation algorithm.



Figure 14. State of health (SOH) estimation curve of UDDS driving cycles based on the joint estimation algorithm.



Figure 15. SOH estimation error curve of UDDS driving cycles based on the joint estimation algorithm.

5. Conclusions

In order to implement the real-time state estimation of power batteries for EVs, taking account observation noises and gradually changed ohmic resistance, an improved second-order RC equivalent circuit model was established in this paper for the SOC and SOH joint estimation using the fuzzy unscented Kalman filtering algorithm (F-UKF). The experimental data obtained from a test bench was adopted for the simulation to verify the convergence and stability of the F-UKF algorithm and to achieve the required design effects. The experimental data were obtained by the ITS5300 battery test platform, and the proposed joint estimation algorithm considered the influence of ohmic internal resistance change and noise error.

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