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Adaptive State-of-Charge Estimation Method for an Aeronautical Lithium-ion Battery Pack Based on a Reduced Particle-unscented Kalman Filter

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Abstract

A reduced particle-unscented Kalman filter estimation method, along with a splice-equivalent circuit model, is proposed for the state-of-charge estimation of an aeronautical lithium-ion battery pack. The linearization treatment is not required in this method and only a few sigma data points are used, which reduce the computational requirement of state-of-charge estimation. This method also improves the estimation covariance properties by introducing the equilibrium parameter state of balance for the aeronautical lithium-ion battery pack. In addition, the estimation performance is validated by the experimental results. The proposed state-of-charge estimation method exhibits a root-mean-square error value of 1.42% and a mean error value of 4.96%. This method is insensitive to the parameter variation of the splice-equivalent circuit model, and thus, it plays an important role in the popularization and application of the aeronautical lithium-ion battery pack.

Key words: Lithium-ion battery pack, Reduced particle-unscented Kalman filter, Splice-equivalent circuit model, State of balance, State-of-charge estimation

I. Introduction

Several state-of-charge (SOC) estimation methods have been presented in the literature over the last few years. Among which, the ampere hour (Ah)-based method is the most popular due to its simplicity and low computational cost [1]. However, the Ah-based method depends only on the integration of the current flow in and out of a lithium-ion battery. Consequently, its accuracy depends on the current-detecting sensor and its performance is disturbed by the initial error and the accumulated detection error. The cumulative current detection error can be estimated with an accuracy that can reach as high as 25.00% [2]. A novel sliding-mode observer is reported for the SOC estimation of lithium-ion batteries used in electric vehicles [3]. Furthermore, the robust adaptive sliding-mode observers were presented by using the neural network method for the SOC estimation of lithium-ion batteries in electric vehicles [4], [5]. An online SOC estimation method and an open-circuit voltage (OCV) hysteresis model for lithium-ion batteries, which were conducted by utilizing an invariant embedding method [6]. A robust recursive impedance estimation method is defined for automotive lithium-ion batteries [7]. The aging properties of lithium-ion batteries were also studied at different temperatures and depths of discharge [8], [9]. The investigation of SOC distributions were reported for $LiCoO_2$ composite positive electrodes in all-solid-state lithium-ion batteries via Raman imaging [10], [11]. a novel multi-model probability battery SOC estimation approach was proposed for electric vehicles that used the H-infinity algorithm [12]. A few novel modeling methods are proposed to realize the SOC estimation of lithium-ion

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batteries [13]-[18]. The battery capacity fading characteristics were also studied by using the force-based incremental capacity analysis [19], [20]. The equivalent circuit model (ECM) was studied for the lithium-ion battery steady-state predicting by the dynamic I–V characteristics [21], together with the modeling and experimental evaluation of parallel-connected lithium-ion battery cells for the electric vehicle battery systems [22], [23]. reported the changes in balancing between the anode and the cathode due to fatigue in commercial lithium-ion cells [24], [25]. The path dependence of lithium-ion battery cell aging under storage conditions were investigated [26]. The systematic SOC estimation frameworks were built for the multi-cell battery pack in electric vehicles by using the bias correction technique [27]-[30]. Afterword, the online dynamic equalization adjustment method was also studied for high-power lithium-ion battery packs based on the SOB estimation [31].

However, the methods reported in the literature present a series of drawbacks for unscented Kalman filters (UKFs), such as high computational cost, large number of sigma points, and state decomposition.

To overcome these shortcomings, an improved UKF associated with a sphere, called reduced particle-UKF (RP-UKF), is proposed for the first time for SOC estimation in this study. Compared with the first-order extended Kalman filter EKF, this new methodology exhibits the advantage of higher error order. Moreover, it does not require linearization for the nonlinear model as part of the linear SOC estimation unit. Compared with conventional UKF, the proposed method does not necessitate the decomposition of the state covariance and needs less sigma points, thereby reducing computational cost.

The main points of this study are described as follows. Section II presents the equivalent circuit model (ECM) for lithium-ion batteries and its parameter identification results. Meanwhile, a pioneering SOC estimation method based on the RP-UKF algorithm is proposed and realized. Section III describes the experimental results and evaluates the proposed RP-UKF method. Finally, the conclusions of the study and final remarks are provided in Section IV.

II. Mathematical Analysis

Different ECMs have been proposed in the literature to describe lithium-ion battery operation. An ECM uses electrical components, such as resistors and capacitors, to achieve dynamic battery operation modeling. The aforementioned process describes a simple methodology that can accurately obtain the dynamic response of a battery and this methodology is suitable for control and simulation purposes. Inconsistencies among cells in a lithium-ion battery pack are unavoidable due to the manufactured differences of battery cells and aging influences. The changes in connected battery cells significantly impact pack capacity, durability, and safety,

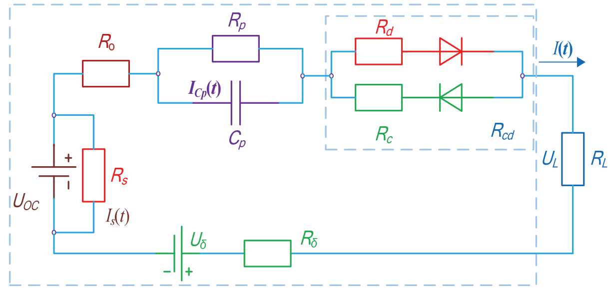

Fig. 1. Equivalent circuit model, i.e., S-ECM.

which is important for the attached battery management system (BMS) equipment. To reduce variation in connected lithium-ion battery cells, the performance of SOC-based and voltage-based algorithms are compared according to different experimental schemes. The RP-UKF algorithm is proposed to improve estimation accuracy and reduce computational cost. The splice-ECM (S-ECM) of an aeronautical lithium-ion battery pack is described and shown in Fig. 1.

Fig. 1 illustrates a series of parameters, such as U_{OC}, which represents the OCV value of the lithium-ion battery pack; R_s denotes a large resistance, which characterizes the self-discharge effect of the lithium-ion battery pack; and R_o indicates ohmic resistance, which describes a transient voltage drop between the positive and negative poles during the discharging and charging process of the lithium-ion battery pack. A one-order resistor–capacitor network is used in S-ECM to model the relaxation effect of the lithium-ion battery pack during the discharging and charging process, which models transient response. R_p represents the polarization resistance of the lithium-ion battery pack, whereas C_p illustrates its polarization capacitance. The generation and elimination of the polarization process for the internal reaction of the lithium-ion battery pack can be illustrated by using this parallel circuit of R_p and C_p. Parameter R_d is the discharging resistance during the discharging maintenance process; it indicates the internal resistance difference in the discharging process. R_c is the charging resistance during the charging maintenance process. Thus, the internal resistance difference can be characterized when the lithium-ion battery is charged. U_L represents the battery terminal voltage between the positive and negative poles when the lithium-ion battery is connected to the external circuit and is undergoing the discharging and charging process. I is the current flowing in or out of the lithium-ion battery when the battery is connected to the outside circuit.

A. Construction of S-ECM

The SOC value of an aeronautical lithium-ion battery pack is denoted as SOC and its calculation process can be expressed in discrete time, as shown in Equation 1.

$$SOC(t) = SOC(0) - \int_0^t \frac{\eta_I \eta_T I(\tau)}{Q_n} d\tau - \int_0^t \frac{I_s(\tau)}{Q_n} d\tau, \tag{1}$$

where parameter $SOC(t)$ represents the SOC value at t time point, and parameter $SOC(0)$ represents the initial SOC value. Parameter η_I represents coulombic efficiency under different current I values, and parameter η_T represents the influence of temperature on coulombic efficiency. Parameter Q_n is the discharging capacity of the aeronautical lithium-ion battery pack. $I_s(t)$ is the self-discharge current, which characterizes the self-discharge effect by using the resistance R_s of the lithium-ion battery pack. The current calculating expression is as follows:

$$I_s(t) = U_{OC}(t)/R_s . \tag{2}$$

The basic equation framework for the estimation process is established for subsequent SOC estimation research by using the state-space model in the charging and discharging process and combining it with the identification process of the model parameters. Then, the design of the model parameter identification system is implemented based on determining the state-space equation. The equivalent model and state-space equation of the battery pack can be first constructed and then combined with the demand of the SOC estimation process. The parameter identification model and the state equation can be constructed such that the closed circuit voltage, single cell voltage, current, and temperature can be used in the experimental tests. Data acquisition and processing are discrete time forms in the actual calculation process; thus, the state equation is described as shown in Equation 3.

$$SOC(k|k-1) = SOC(k-1) - \frac{\eta_I \eta_T I(k) T_s}{Q_n} - \frac{I_s(k) * T_s}{Q_n}, \tag{3}$$

where parameter k describes the time point of SOC estimation for the aeronautical lithium-ion battery pack. Parameter $U_L(k)$ is the closed circuit voltage of the battery pack at k time point. Parameter R_o is the ohmic resistance of the aeronautical lithium-ion battery pack. Parameter $I(k)$ is the output current of the aeronautical lithium-ion battery pack, and parameter T_s is the detection time interval of the battery parameters.

The state space of S-ECM is constructed, and the mathematical description method of the lithium-ion battery equivalent model is studied. Experimental data analysis is conducted according to the working state characterization requirements of the aeronautical lithium-ion battery pack to obtain the coefficient characterization of the estimation parameters. Then, the observation equation representation of the equivalent model and the state-space description can be comprehended, thereby providing the foundation for battery SOC estimation. The observation equation is obtained as follows according to Kirchhoff's law of voltage:

$$(R_o + R_\delta) * (I(t) + I_e(t)) + U_p + I(t) R_{cd} = (U_{OC} - U_\delta) - U_L(t), \tag{4}$$

where the equivalent parameter U_{oc} of the ideal voltage source is used to illustrate the OCV of the battery pack. Simultaneously, the resistance parameter R_o is used to characterize ohmic resistance. Parameters R_p and C_p are used to describe polarization resistance and polarization capacitance. The parallel circuit reflects the generation and elimination process of battery polarization. Parameter U_L is the closed circuit voltage of the aeronautical lithium-ion battery pack after the circuit is connected to the outside circuit. Parameter R_d is the discharge resistance, which describes the resistance difference in the discharging process of the lithium-ion battery pack. Parameter R_c is the charging resistance, which is used to characterize the resistance difference in the charging process of the lithium-ion battery pack. To simplify the description process of the state-space equation, parameter $R_{cd}(t)$ is used to describe the different internal resistances of R_c and R_d when charging and discharging. When the aeronautical lithium-ion battery pack is discharging, the value of parameter $R_{cd}(t)$ is set to $R_{cd}(t)=R_d$. When it is charging, the value of parameter $R_{cd}(t)$ is set to $R_{cd}(t)=R_c$.

In consideration of S-ECM circuit structure analysis, an accurate state-space description can be achieved by using the circuit analysis method. Parameter U_{OC} is the OCV, and its relationship with the closed circuit voltage is $U_{OC}=U_L$ when the aeronautical lithium-ion battery pack is in the open circuit state. To realize the acquisition objective of the observation equation, this equation is analyzed and transformed, along with the analysis of the ECM. Then, the transformation expression of the state-space equation can be obtained as shown in Equation 5.

$$U_L(t) = (U_{OC} - U_\delta) - (R_o + R_\delta) * I(t) - U_p - I(t) R_{cd} \tag{5}$$

From Fig. 1, parameter $\tau=R_pC_p$ is the time constant for the RC parallel circuit in the battery S-ECM. Parameter R_p is the polarization resistance, and its iterative formula is as follows:

$$U_p(k) = I(k) R_p \left(1 - e^{-T_s/R_p C_p}\right), \tag{6}$$

where parameter $U_p(k)$ is the voltage value at both ends of the polarization resistor when the time point is k. Parameter $I(k)$ is the current value at k time point, and parameter T_s is the sampling interval constant. Parameter R_p is the polarization resistance, and parameter C_p is the polarization capacitor. The expression for $U_p(k)$ calculation can be inserted into Equation 5, and discrete treatment can also be conducted. The final expression of the observation equation can be obtained as follows:

$$U_L(k) = (U_{OC} - U_\delta) - (R_o + R_\delta) * I(k) - I(k) R_p \left(1 - e^{-T_s/R_p C_p}\right) - I(k) R_{cd} . \tag{7}$$

The realization process of the mathematical description is not required to introduce a complex mathematical model, which provides high feasibility for the rapid error analysis of the identification results. The observation equation describes the state variation of the output voltage signal for the aeronautical lithium-ion battery pack. Through the OCV-based identification process, the identification result is closely related to the output voltage value of the aeronautical

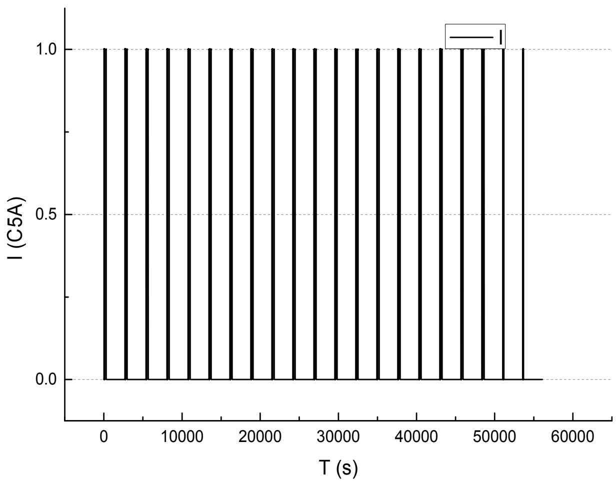

Fig. 2. Cycling intermittent discharge process.

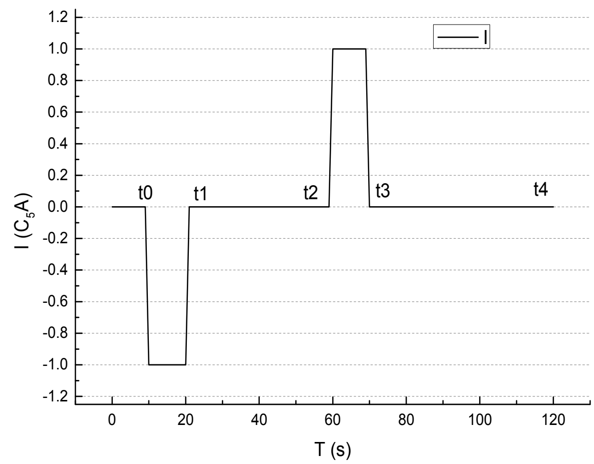

Fig. 3. Current pulses during the intermittent discharge.

lithium-ion battery pack. To obtain an accurate identification target, the S-ECM parameters of the aeronautical lithium-ion battery pack are analyzed and identified using the output voltage of the battery pack and the influences of working current and temperature. In combination with the state and observation equations, the state-space equation for SOC estimation can be constructed as shown in Equation 8:

$$\begin{cases} SOC(k|k-1) = SOC(k-1) - \dfrac{\eta_I \eta_T I(k) T_s}{Q_n} - \dfrac{I_s(k) * T_s}{Q_n} \\ U_L(k) = (U_{OC} - U_\delta) - (R_o + R_\delta) * I(k) - I(k) R_p \left(1 - e^{-T_s/R_p C_p}\right) - I(k) R_{cd} \end{cases} . \quad (8)$$

To identify the ECM parameters of the aeronautical lithium-ion battery pack, various discharging and charging pulse combination experiments were conducted on the battery pack at different SOC levels, and the corresponding output voltage responses were detected in real time. To obtain the changing regularity of the required output voltage responses, the aeronautical lithium-ion battery pack was fully charged by applying the constant current–constant voltage (CC–CV) charging maintenance process. Then, the battery pack was discharged at 9.0 A (0.2 C_5A) cycling intermittent discharge process for 30 min with 30 min rest intervals. The discharging processes are shown in Fig. 2, in which injection hybrid pulse power characterization (HPPC) tests are performed. The HPPC tests are conducted at the end time point of the rest intervals.

As shown in Fig. 2, the interval discharge is 40 min and an HPPC test is conducted at the end of the shelved 40 min. The preceding analysis indicates that the HPPC tests are embedded into the intermittent discharging process, which is conducted at the shelving end time points shown in the chart. In addition, the 5 s current pulse at the last duration with an intermittent hold is set at the end of the shelving time. To address the parameter identification problem of S-ECM and the state-space equation of the aeronautical lithium-ion battery pack, the HPPC constant current pulse charging and discharging experiment is conducted at room temperature based on the mixed pulse power characteristic test method of 1.0 C_5A.

The parameters of the model and their correlation with other parameters are obtained during the pulse charging and discharging process and combined with the working principle analysis of the battery pack. In the experimental analysis, the effects of different SOC values of charge/discharge vary. The dynamic characteristics of the aeronautical lithium-ion battery pack are obtained and used in the identification process of various parameters in the equivalent model. Assume that parameter U_{OC} remains stable and constant over this short-duration process. The corresponding terminal voltage responses of the aeronautical lithium-ion battery pack are recorded with respect to each current pulse. This cycling current pulse is repeated at every declining 10% SOC interval until the aeronautical lithium-ion battery pack is fully discharged. The designed HPPC experimental process is shown in Fig. 3.

Then, the terminal voltage responses of the aeronautical lithium-ion battery pack to the injected current pulses at different SOC levels are used to comprehend its parameter identification. Different sets of transfer functions in the frequency domain, along with their approximate parameters, are identified by conducting the preceding calculation process. The process is performed with respect to the measurement of terminal voltage values at different SOC levels of the aeronautical lithium-ion battery pack. The variation of the model parameters with respect to SOC is insignificant; thus, the identified average parameters are used in the construction of the SOC estimation model. The experimental results show that this state-space model of the aeronautical lithium-ion battery pack, which uses the identified model parameters, can accurately estimate the SOC value and track the terminal voltage of the battery pack. When the charging and discharging pulses are applied to track the output voltage of the aeronautical lithium-ion battery, the mean estimation error is 10 mV and the maximum error is 50 mV.

B. State of Balance Influence on Pack SOC Estimation

To characterize the differences of the connected aeronautical lithium-ion battery cells, SOB is introduced into the SOC estimation process. This parameter describes the balanced state of the aeronautical lithium-ion battery pack among individual serial and parallel connected cells in the battery pack. Consequently, this method mainly comprises differences in capacity, voltage, inner resistance, and other characteristic parameters at the present time point. To investigate and characterize the influence of SOB on SOC estimation, rated capacity attenuation and HPPC test experiment are performed on the aeronautical lithium-ion battery pack.

The accurate calculation of the SOC value is essential for the RP-UKF-based SOC estimation proposed in this study. To estimate the SOC value of the aeronautical lithium-ion battery pack, the basic cumulative calculation process uses the Ah counting treatment. This approach is based on current measurement and integration treatment with time interval. The performance of the Ah counting process is highly dependent on the initial SOC value and the measurement accuracy of current, which is merely an open-loop calculation process. This situation can easily lead to accumulated calculation errors due to the uncertain disturbances for practical applications and the lack of necessary corrective resolutions.

To overcome these risks, the adaptive RP-UKF-based SOC estimation correction treatment is used with the S-ECM for the aeronautical lithium-ion battery pack. As a commonly used system-state estimation technique, the KF-based SOC estimation process exhibits high accuracy in terms of prediction and high reliability.

The preceding cases provide valuable contributions to SOC estimation that considers the inconsistent characteristic of connected cells in the lithium-ion battery pack. However, the constructive SOC value is necessary to decide whether an adjustment treatment should be conducted or to determine the time to start a highly reliable associated BMS equipment of the aeronautical lithium-ion battery pack. This approach is the most direct and effective method to detect the voltage parameters of each battery cell in the aeronautical lithium-ion battery pack and to evaluate the overall balanced state. Relative to the means of detection capacity and internal resistance, the voltage detection circuit exhibits the advantages of real-time and fast operation and easy implementation. In addition, it presents a considerable advantage in realizing online balance evaluation. The single cell voltage parameter U_c is used to evaluate the balanced state of the aeronautical lithium-ion battery pack, during which the expectation values of all single cell voltages are first calculated using Equation 9.

$$E\left(U_c\right)=\overline{U_c}=\frac{1}{n}\sum_{i=1}^{n}U_{ci}\,, \tag{9}$$

where parameter U_{ci} represents the i-th cell voltage, and parameter n indicates the number of the internally connected battery cells in the battery pack. The result is $E(U_c)$, which indicates the expected voltage value of all the internally connected battery cells, i.e., the average value. The standard deviation parameter δ is an important index for evaluating the difference. Thus, the balance status evaluation research of the batteries can be conducted by using the standard deviation measurement method based on the probability distribution. The objective of this approach is to obtain the quantized balance evaluation index and apply it to the SOC state estimation process. To identify the target after quantifying the equilibrium state evaluation, the inconsistent equilibrium degree parameter SOB is set, and probability and statistics theories are applied to define the discrete degree. To simplify the calculation process, the square value of the standard deviation parameter δ is used in the calculation process; that is, the variance parameter δ^2 and its mathematical description are shown in Equation 10.

$$\delta^2=\frac{1}{n}\sum_{i=1}^{n}\left(U_{ci}-E\left(U_c\right)\right) \tag{10}$$

The change in variance describes the working voltage distribution of single battery cells. The coefficient of variation is used to measure the voltage measurement variation introduced by the obtained parameters, through which the equilibrium state of different voltage differences are described in the calculation process. Parameter θ obtained from the square root calculation will increase the complexity of the calculation process; thus, parameter ε obtained from the square value of the variation coefficient θ is used to evaluate SOB. The calculation process is shown in Equation 11.

$$SOB=\varepsilon=\theta^2=\frac{1}{n}\sum_{i=1}^{n}\left(\frac{U_{ci}-E\left(U_c\right)}{E\left(U_c\right)}\right)^2 \tag{11}$$

Parameter ε is used to describe the voltage inconsistency extent of single batteries, whereas parameter θ is used to describe the voltage coefficient variation of battery cells. Parameter U_{ci} represents the i-th battery cell voltage. To realize the dynamic evaluation target of the equilibrium state of the battery pack, the equilibrium state of battery cells can be achieved through the real-time sampling and calculation analysis of each cell voltage during the charging and discharging process. During calculation, the difference between battery cells is described, which is then used to characterize the correlation between the internally interconnected cells and the entire lithium-ion battery pack. To realize the equivalent electromotive force and resistance parameter of the equivalent model under the influence of the equilibrium state, the variations in voltage and internal resistance are used under the influence of the equilibrium state to characterize the state of balance level. The expression is shown as follows:

$$SOB=\varepsilon=\theta^2=\frac{1}{n}\sum_{i=1}^{n}\left(\frac{U_{ci}-E\left(U_c\right)}{E\left(U_c\right)}\right)^2. \tag{12}$$

The balanced state correction link among the battery cells is realized according to the calculation process, thereby ensuring the safety of the aeronautical lithium-ion battery power supply system. Afterward, the RP-UKF-based SOC estimation for the aeronautical lithium-ion battery pack is proposed in this study. Then, the state-space SOC estimation process based on RP-unscented transform (UT) and RP-UKF is used for the comprehensive estimation of the SOC value of the entire aeronautical lithium-ion battery pack.

C. RP-UKF Algorithm

To achieve improved stability and accuracy of SOC estimation for the lithium-ion battery pack, the UKF algorithm is introduced into the estimation process. This algorithm does not require the Jacobian matrix calculation of the state equation and the observation equation for a nonlinear lithium-ion battery power supply system. Moreover, the UKF algorithm does not necessitate the nonlinear function linearization calculation used in traditional approaches for the recursion calculation of a lithium-ion battery pack, which also uses the KF framework in the SOC estimation process. In the one-step prediction equation calculation process of the SOC estimation for the power of a lithium-ion battery, the UT treatment is used to address the nonlinear transformation of the mean and covariance value of SOC estimation.

Simultaneously, considering reliability and real-time embedded implementation, UT is optimized and called simplified particle-UT (SP–UT). The SOC value obtained via linear Kalman estimation is selected as one of the particles by means of streamlining particles. Then, particles are selected on each side of the symmetric value as the remaining two particles for iterative calculation. The UKF algorithm is an approximation of the nonlinear function, in which the SOC posterior probability density of the lithium-ion battery pack is approximated using the data sample series given in the dataset. Unlike the nonlinear function approximation treatment, this algorithm does not require deriving of the Jacobian matrix calculation concept. The SOC estimation process based on the UKF algorithm does not disregard higher-order terms used in the linearization equation treatment.

Consequently, the statistical characteristics of the nonlinear SOC distribution can exhibit the advantage of high calculation accuracy. The UKF-based SOC estimation method effectively overcomes the drawbacks of low SOC estimation accuracy and poor output voltage traction stability in the EKF-based SOC estimation process. The UKF-based SOC estimation process uses the selection process for a series of weighted sigma data points to estimate the mean and covariance of SOC data samples for the lithium-ion battery pack. In the subsequent sections, the RP-UT transform treatment and the improved RP-UKF algorithm realization mechanism is presented for the SOC estimation of the aeronautical lithium-ion battery pack. The closed circuit voltage variable

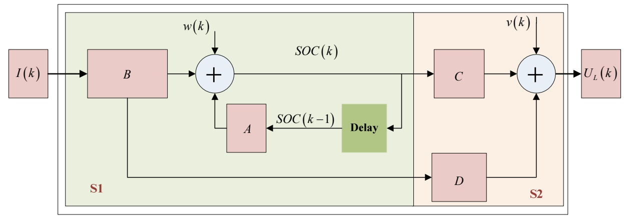

Fig. 4. Kalman-based SOC estimation system program.

$U_L(k)$ is designed and used to represent system output, whereas the variable $I(k)$ is used as the input of the system. The concrete implementation of the estimation process based on the Kalman estimation framework is executed according to the description of the state-space equation. The model structure of this framework is shown in Fig. 4.

The meaning of the parameters in the diagram is described as follows. Parameter $I(k)$ represents the input current signal of the system, whereas parameter $U_L(k)$ denotes the output closed circuit voltage signal of the system. Furthermore, parameter $SOC(k)$ indicates the system state value at k time moment, and parameter $SOC(k-1)$ is similar to the system state value of the $k-1$ moment. Parameters $w(k)$ and $v(k)$ are the estimation process noise and observation noise, respectively. Parameters A, B, C, and D are the coefficient matrices of the state equation and observation equation. In the SOC estimation process for the aeronautical lithium-ion battery pack based on the proposed RP-UKF method, the state covariance matrix $P(k)$ of SOC is recursively updated and propagated by decomposing it into the square root matrix parameter $S(k)$ for the sigma point mapping treatment at each time step. The relationship in this process can be described by using the function $P(k)= S(k)S(k)^T$. Then, the square root matrix parameter $P(k)$ is reconstructed from all the propagated sigma data points for SOC state updating. By contrast, the improved RP-UKF method used for the SOC estimation of the aeronautical lithium-ion battery pack directly calculates and updates the square root matrix parameter $S(k)$ without the need to decompose and reconstruct the state covariance matrix $P(k)$. This treatment process avoids the need to refactor the state covariance matrix $P(k)$ at each time step. Consequently, the positive semi-definiteness of the state covariance matrix $P(k)$ can be effectively guaranteed.

The proposed RP-UKF method uses the three-linear-algebra technique for covariance updating and propagation. At different k time point moments, this nonlinear SOC estimation system for the aeronautical lithium-ion battery pack consists of the random state variable $SOC(k)$ with Gaussian white noise $w(k)$ and the observation variable $U_L(k)$ with Gaussian white noise $v(k)$. These variables can be described using the following equations:

$$\begin{cases} SOC(k) = f\{SOC(k\text{-}1), I(k)\} + w(k) \\ U_L(k) = g\{SOC(k), I(k)\} + v(k) \end{cases}, \tag{13}$$

where equation $f(*)$ is the nonlinear state equation function that describes the SOC characterization of the aeronautical lithium-ion battery pack, and $g(*)$ is the nonlinear observation equation function that describes the output voltage characteristic of the aeronautical lithium-ion battery pack. The covariance of the noise matrix parameter $w(k)$ and the covariance of the noise matrix $v(k)$ are described using the symbols Q and R, respectively. The RP-UKF calculation process in the SOC estimation of the aeronautical lithium-ion battery pack for a random variance noise influence at different time points k can be described as follows.

First, a set of sampling points, called the sigma data point set, and its corresponding weight coefficient can be obtained according to RP-UT transformation, as shown in the following equation:

$$SOC^{(i)}(k\text{-}1)=\left[SOC(k\text{-}1) \quad SOC(k\text{-}1)+\sqrt{(n+\lambda)P(k\text{-}1)} \quad SOC(k\text{-}1)-\sqrt{(n+\lambda)P(k\text{-}1)}\right]. \quad (14)$$

Second, the one-step prediction of the sigma data point set with a length of $2n+1$ can be calculated. The calculation process can be described as shown in Equation 15.

$$SOC^{(i)}(k\,|\,k\text{-}1)=f\left[k,SOC^{(i)}(k\text{-}1)\right], i=1,2,\cdots,2n+1 \quad (15)$$

Third, the one-step prediction and its covariance matrix of the state-space variance parameters can be calculated for the nonlinear SOC estimation system. This prediction can be mainly obtained from the weighted sum of the sigma dataset prediction value according to the equations of the UT treatment process. This procedure differs from the traditional KF-based SOC estimation algorithm, in which the SOC state is substituted into the last time point for the state-space function and only one calculation is required to obtain SOC state value prediction. The proposed RP-UKF algorithm, which is used for the SOC estimation of the aeronautical lithium-ion battery pack, requires a set of sigma points to realize the prediction process and to calculate the mean value with weight coefficients. This procedure can be achieved via the one-step prediction of system-state variance. The calculation process of the SOC state estimation and system state variance is described in Equation 16.

$$SOC(k\,|\,k\text{-}1)=\sum_{i=0}^{2n}\omega^{(i)}SOC^{(i)}(k\,|\,k\text{-}1) \quad (16)$$

Then, one-step prediction of the SOC state variance is obtained, and the calculation process of the system state variance sis described in Equation 17.

Fourth, the new sigma dataset for SOC estimation can be produced using the UT treatment process based on the one-step prediction value. The calculation process is described in Equation 18.

Fifth, the sigma dataset obtained through the last step can be substituted into the observation function of the aeronautical lithium-ion battery pack power supply system. The prediction observation variable matrix can be obtained as shown in Equation 19.

$$U_L^{(i)}(k\,|\,k-1)=h\left[SOC^{(i)}(k\,|\,k-1)\right], i=1,2,\cdots,2n+1 \quad (19)$$

Sixth, the system output voltage prediction mean value and its autocorrelation matrix, along with the cross-variance matrix for the SOC estimation, can be obtained by the weighted summation of the observation prediction value of the sigma dataset. The calculation process can be described as follows.

(1) The mean value of the forecast is shown in Equation 20.

$$\overline{U}_L(k\,|\,k\text{-}1)=\sum_{i=0}^{2n}\omega^{(i)}U_L^{(i)}(k\,|\,k\text{-}1) \quad (20)$$

(2) The autocorrelation matrix is shown in Equation 21.

$$P_{U_L(k)U_L(k)}=\sum_{i=0}^{2n}\omega^{(i)}\left[U_L^{(i)}(k\,|\,k\text{-}1)-\overline{U}_L(k\,|\,k\text{-}1)\right]\left[U_L^{(i)}(k\,|\,k\text{-}1)-\overline{U}_L(k\,|\,k\text{-}1)\right]^T+R \quad (21)$$

(3) The cross-correlation matrix is shown in Equation 22.

$$P_{SOC(k)U_L(k)}=\sum_{i=0}^{2n}\omega^{(i)}\left[U_L^{(i)}(k\,|\,k\text{-}1)-\overline{U}_L(k\,|\,k\text{-}1)\right]\left[U_L^{(i)}(k\,|\,k\text{-}1)-\overline{U}_L(k\,|\,k\text{-}1)\right]^T \quad (22)$$

Seventh, the Kalman gain matrix for the SOC estimation and output voltage traction can be calculated using the following equation:

$$K(k)=P_{SOC(k)U_L(k)}P_{U_L(k)U_L(k)}^{-1}. \quad (23)$$

Finally, the system state update and error covariance update of the nonlinear SOC estimation system can be calculated according to the following equations.

(1) The status updates can be obtained using Equation 24.

$$SOC(k)=SOC(k\,|\,k\text{-}1)+K(k)\left[U_L(k)-U_L(k\,|\,k\text{-}1)\right] \quad (24)$$

(2) The update of the error covariance can be obtained using Equation 25.

$$P(k)=P(k\,|\,k\text{-}1)-K(k)P_{U_L(k)U_L(k)}K^T(k) \quad (25)$$

The proposed RP-UKF algorithm used for the SOC estimation of the aeronautical lithium-ion battery pack does not require the Taylor series expansion. However, it needs the first n-order approximation at the SOC state estimation point when dealing with the nonlinear SOC estimation process. The RP-UT treatment around the SOC estimation data point is used, and it aims to match the mean and covariance values of the sigma data point set with the original statistical characteristics of the SOC value. The nonlinear mapping treatment can be conducted using the sigma dataset to directly

$$P(k\,|\,k\text{-}1)=\sum_{i=0}^{2n}\omega^{(i)}\left[SOC(k\,|\,k\text{-}1)-SOC^{(i)}(k\,|\,k\text{-}1)\right]*\left[SOC(k\,|\,k\text{-}1)-SOC^{(i)}(k\,|\,k\text{-}1)\right]^T+Q \quad (17)$$

$$SOC^{(i)}(k\,|\,k-1)=\left[SOC(k\,|\,k-1) \quad SOC(k\,|\,k-1)+\sqrt{(n+\lambda)P(k\,|\,k-1)} \quad SOC(k\,|\,k-1)\text{-}\sqrt{(n+\lambda)P(k\,|\,k-1)}\right] \quad (18)$$

obtain the state probability density function of SOC estimation, which is a statistical approximating result of the nonlinear SOC estimation system of the aeronautical lithium-ion battery pack.

D. Construction of the RP-UKF-based SOC Estimation Model

The proposed RP-UKF-based SOC estimation method uses the basic KF treatment process in the estimation model. The RP-UT treatment process is investigated in the first part of the SOC estimation. To avoid the predicted offset due to high-order term loss, the unscented transform treatment is used in the SOC estimation process of the aeronautical lithium-ion battery pack. The equilibrium state parameter SOB is used in the last part of the SOC estimation to characterize the effect of packing work between the serial- and parallel-connected lithium-ion battery cells and to obtain the comprehensive SOC value of the entire aeronautical lithium-ion battery pack. The proposed SOC estimation method not only obtains the dynamic characterization of the working process of the aeronautical lithium-ion battery pack, but also estimates the SOC value of the individual lithium-ion battery and characterizes the discharging and charging difference. Furthermore, the equilibrium state parameter SOB is used in the amendment process, thereby obtaining the comprehensive SOC value of the aeronautical lithium-ion battery pack. The realization of the RP-UKF-based SOC estimation exhibits many advantages, such as saving time and high calculation efficiency. The overall construction of the SOC estimation model in the SIMULINK platform is shown in Fig. 5.

The figure illustrates the modular structure design of the overall construction via the modeling treatment of the parameter matrix, the prediction process, and the correction process. For the calculation process, the process state and observation data are monitored and analyzed effectively by using the observation oscilloscope and outputting the state values to the cache space. The physical meanings of the identifiers are described as follows. Parameter *Current* is the working current, which conforms to the Gauss distribution. Parameter *Temp* indicates the working temperature. The mean value and the variance value are set as 35 and 1, respectively. The working temperature is set at approximately 35 °C considering the heating phenomenon of the aeronautical lithium-ion battery pack during the discharging and charging process and the good heat radiation condition. The module *Para* represents the input parameter matrix sub-module, in which the parameter values are set according to S-ECM and the parameter identification results. These values are obtained by using the polynomial curve fitting method in the known OCV–SOC relationship curve.

A cascade of battery cells is used in the aeronautical lithium-ion battery pack to meet the high energy and voltage requirements of the energy supply system. Differences occur in the dynamic and aging characteristics between the connected battery cells due to the lack of material and production technology. Moreover, the differences in working condition, temperature, and internal resistance will affect the SOC value of the aeronautical lithium-ion battery pack. The computation of all the aforementioned parameters for all the connected battery cells in the lithium-ion battery pack will result in huge amount of calculations; thus, a battery pack SOC estimation model with an adaptive capability is designed. The differences in voltage, capacity, and resistance between the battery cells indicate a negative impact on the available energy. These differences occur in the cascade of single batteries, including capacity, voltage, resistance, and other characteristics. SOB is introduced into the estimation process for the difference in the aeronautical lithium-ion battery pack characterization of cascaded battery cells, which is used to describe the equilibrium state of the battery pack. The influence sub-module of the equilibrium state between the battery cells in the group work process is designed and integrated into the entire estimation process as shown in Fig. 6.

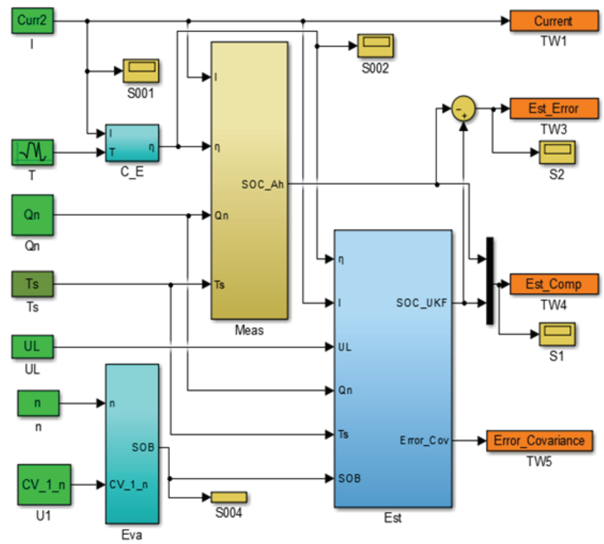

Fig. 5. Overall structure of the SOC estimation model.

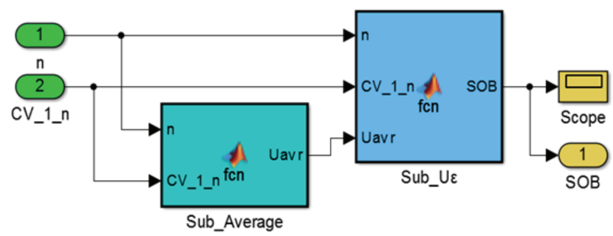

Fig. 6. SOB correction sub-model.

In Fig. 6, the expression of Eva can be calculated according to the functions obtained in the joint strikes, and two functions, i.e., Sub_Average and Sub_Uε, are used in the recursion calculation process to calculate cell voltage mean

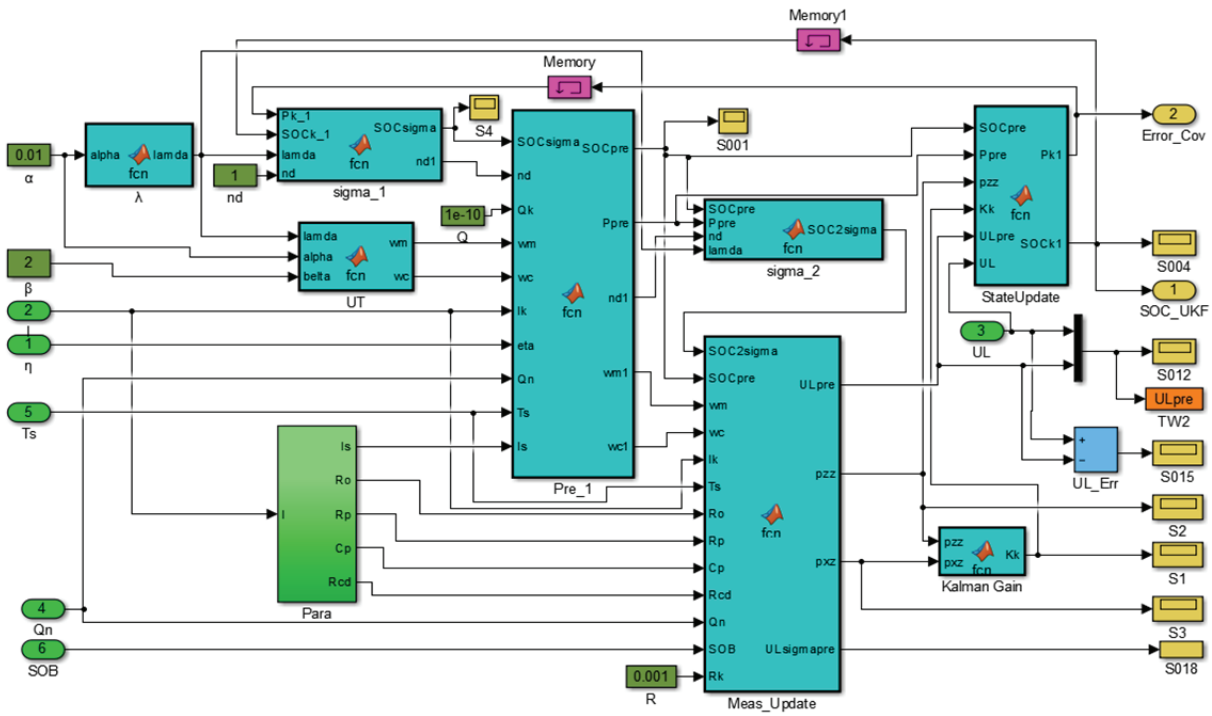

Fig. 7. Modular design of the prediction and correction processes.

and singular function value. The calculated values are used in the equilibrium state evaluation as the value of SOB. This value is used in the revision SOC estimation process. Parameter Q_n indicates the rated capacity of the aeronautical lithium-ion battery pack, and the experimental sample with 45 Ah rated capacity is selected. The module *Coulombic_ Efficiency* represents the coulombic efficiency correction sub-module. The input parameters are the real-time working current parameter *Current* and the working temperature parameter *Temp*. The output parameter of this sub-module is the coulombic efficiency η. The prediction and correction of the SOC estimation process of the aeronautical lithium-ion battery pack are calculated by programming the iterative calculation method. The SOC estimation and error covariance calculation process of Error_Cov is designed by combining the modified fusion measurement equation and the parameters η, I, Q_n, U_{oc}, and R_o. The input signal I represents the working current, and the symbol η signifies efficiency. Parameter Q_n is the rated capacity, and T_s represents the sampling time interval. The state parameter SOC can be predicted via the state equation, which is used to modify the SOC state at k time point moment. The modular design of the prediction and correction processes is shown in Fig. 7.

The descriptions of the labels on each part of Fig. 7 are described as follows. The input signal I represents the working current, and the symbol η denotes coulombic efficiency. Parameter Q_n is the rated capacity, and parameter T_s is the sampling time interval. Simultaneously, the real-time monitoring of the state value is conducted, in which the state parameter $SOC(k)$ and coefficient parameters U_{oc}, R_o, and R_p for the observation equation are used as input and combined with the superimposed observation noise to obtain the closed circuit voltage $U_L(k)$ via the observation equations in the state-space equation. The measured output signal of the closed circuit voltage can be obtained and the values are compared with the calculated value. During the iterative calculation process, Fig. 7 shows that two sigma processes are performed on the SOC estimation result. In each cycle, the first sigma process is the sigma treatment on the corrected SOC value, and the second sigma process is the sigma treatment on the predicted SOC value for the correction calculation of the closed circuit voltage U_L.

Iterative SOC calculation and correction can be conducted by using the Kalman gain. The model *KF_Est* is the KF-based SOC estimation process sub-module, in which the parameters η and *Current* are set as the input parameters, thereby realizing SOC estimation and the calculation of the error covariance parameter *Error_Cov*. The module *Measurement* is the amendment process fusion of the observation equation, in which the parameters η, *Current*, and *Qn* are set as the input parameters, thereby realizing SOC estimation and the calculation of the error covariance parameter *Error_Cov*. The output variables of the nonlinear SOC estimation system are described as follows. Parameter *Current* is the simulation working condition current added with Gaussian white noise, and *Est_Error* is the SOC estimation error. *Est_Compare* is the observation contrast curve between the SOC estimation value and the real-time actual SOC value. *Error_Covariance* is used as the variation curve of the SOC estimation error covariance.

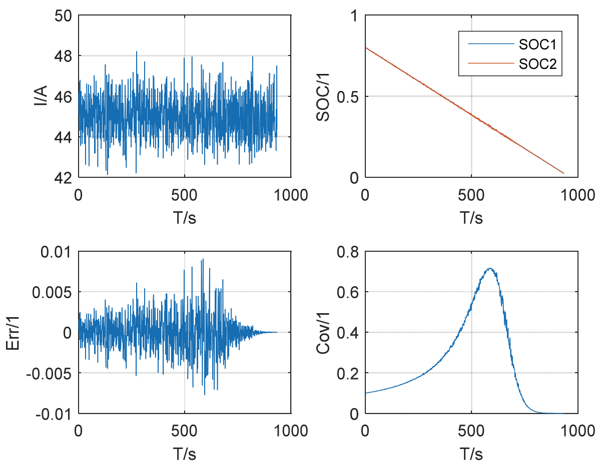

Fig. 8. Output voltage track effect.

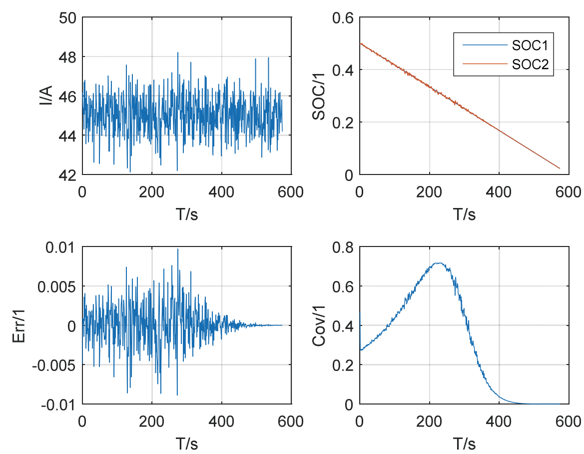

Fig. 9. SOC estimation effect with known initial value.

III. Experimental Results and Discussion

A. Estimation Effect of High Initial SOC Value

To verify the usability of the algorithm, the aeronautical lithium-ion battery pack is used in the experiment. With 1.0 C_5A as the discharge current and 0.2 C_5A as the charge current, the estimation effect under different initial values is analyzed. The experimental results show that the proposed method can obtain the SOC value of the aeronautical lithium-ion battery pack with high accuracy, and the estimated accuracy is 98%. This result indicates that this method can effectively estimate the working state of the aeronautical lithium-ion battery pack. To further validate the SOC estimation and output voltage traction effect of the proposed RP-UKF method with unknown initial SOC state, the output voltage values for the aeronautical lithium-ion battery pack in the entire SOC estimation process are recorded and expressed as shown in Fig. 8.

In the figure, SOC1 denotes the experimental result obtained by the method of integration on time, whereas SOC2 indicates the estimation result using the proposed RP-UKF estimation method. Subfigure 1 depicts the simulated operating current. Subfigure 2 shows the SOC estimation in real time. Subfigure 3 is the estimated error value, and Subfigure 4 represents the calculated error covariance value. The SOC estimation and output voltage traction effect shown in Fig. 8 indicate that the proposed RP-UKF estimation method can rapidly converge to the true SOC value across the entire discharging process. Furthermore, the estimation error is less than 1.83% and the covariance is less than 0.80. A similar study was conducted by using three models to comprehend the SOC estimation of lithium-ion batteries, in which the estimation method achieves similar results [27]. By comparison, the estimation accuracy is higher in the experimental results, thereby showing that the proposed RP-UKF method exhibits better SOC estimation effect. The experimental results show that the initial estimation error minimally affects convergence for SOC estimation using the proposed RP-UKF method.

B. Estimation Effect with Low SOC Initial Value

The initial SOC value of the aeronautical lithium-ion battery pack is determined in this experiment, which is realized via CC–CV full charge and CC discharge in the discharging and charging process before the SOC estimation effect experiment is conducted. The corresponding SOC estimation effect for the aeronautical lithium-ion battery pack with known initial SOC value is shown in Fig. 9.

SOC1 denotes the experimental result obtained by the method of integration on time, whereas SOC2 indicates the estimation result of the proposed RP-UKF estimation method. On the basis of the analysis of the experimental results, the lower the initial SOC value, the smaller the absolute error, and the more effective is the estimation. The proposed method is verified using the experimental data of the battery pack, and its adaptability is analyzed by comparing the experimental data with real-life data. The proposed method can obtain the SOC value of the lithium-ion battery pack and exhibits the advantage of high accuracy. In this case, the SOC estimation method achieves high estimation accuracy. The SOC estimation value in the discharging process converges to the true SOC value within 10 s, and the estimated error is less than 2.00%. Although the estimation curve continues to show fluctuation points, the error is minimal and exerts insignificant influence. The actual estimation results will be corrected in the estimation correction link; thus, the initial fluctuation can be disregarded. A comparison with the experimental results reported in the referenced paper [15] shows that the estimation results are consistent with the experimental results, and the correction capability of the proposed SOC estimation model is further verified through this process.

C. Robust Characteristics of S-ECM Parameters

As usage time increases, the S-ECM parameters varies

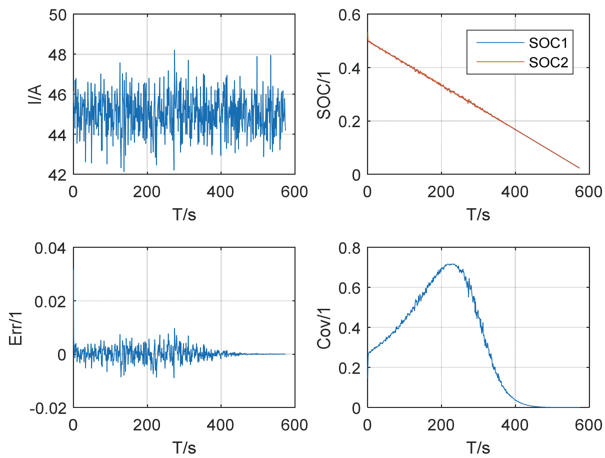

Fig. 10. SOC estimation when the model parameter changes.

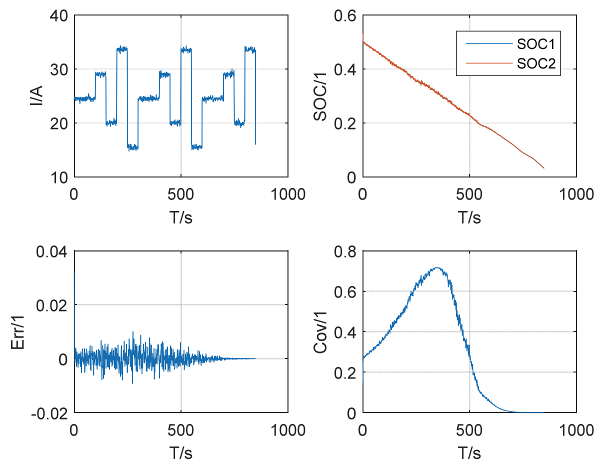

Fig. 11. SOC estimation with S-ECM parameter changes.

with an increase in discharging and charging cycling number, which affects the SOC estimation accuracy of the aeronautical lithium-ion battery pack. The diversification can reach as high as 60% of the initial S-ECM parameters. Different S-ECM parameters are used in the experiments, which aim to obtain the robustness of the proposed RP-UKF method with respect to S-ECM in the SOC estimation process. Different S-ECM parameters are used in the RP-UKF algorithm to estimate the SOC value of the aeronautical lithium-ion battery pack. When the initial SOC value of the observation process is 0.35 and the initial value of the estimation process is 0.50, the estimation effects of the model parameter changes are shown in Fig. 10.

SOC1 denotes the experimental result obtained using the method of integration on time, whereas SOC2 indicates the estimation result by the proposed RP-UKF estimation method. The experimental results in Fig. 10 show that the SOC estimation error based on RP-UKF is extremely low when the model parameter changes and the maximum absolute error is 1.00% after tracking for 6.00 s. Therefore, the proposed RP-UKF algorithm exhibits good robustness to S-ECM parameters with varying time when it is applied to the SOC estimation process. The estimated model demonstrates good tracking effect and good adaptability for the SOC estimation of the aeronautical lithium-ion battery pack.

D. *Experimental Analysis of Complex Conditions*

The complex rate discharge simulation working condition experiment is designed and conducted by considering the complexity of the actual working condition. This experiment is used to further verify the applicability of the proposed RP-UKF method under a complex working condition. The complex working condition of the current change situation is used, in which the pulse discharging characteristic analysis experiments of different currents are realized. This condition can be used to accurately analyze and describe the working characteristics of the aeronautical lithium-ion battery pack, thereby characterizing its working characteristics.

The experiment is realized by using the variable current simulation of different discharge current multiplexes (0.35, 0.45, 0.55, 0.65, and 0.75 C_5A). Through the simulation of complex combination conditions under different current rates, the SOC estimation performance test is achieved under complex current varying conditions, and the convergence of the estimation process to complex current changes can be further verified. The SOC estimation results can be obtained in the complex simulation experimental analysis of the aeronautical lithium-ion battery pack as shown in Fig. 11.

SOC1 denotes the experimental result obtained using the method of integration on time, whereas SOC2 indicates the estimation result by the proposed RP-UKF estimation method. The experimental results show that the difference for the first 300 s is smaller after rapidly following the SOC reference curve, in which the error is less than 1.00%. The error slightly increases during the 300 s to 400 s interval, the value of which is 2.00%. The error is smaller from 400 s to the discharge completion interval, the values of which are all within 0.50%. During the experiment, the change in the estimated value exhibits a downward trend with fluctuation due to the evident change in the working condition. The RP-UKF-based SOC estimation model can accurately track the reference curve of the state change and conform to the general change trend.

IV. CONCLUSIONS

An S-ECM is built in this study for characteristic dynamic equivalent simulation, and a novel SOC estimation method, called RP-UKF, is proposed for an aeronautical lithium-ion battery pack. The presented RP-UKF method exhibits Jacobian-free advantages and requires fewer sigma data points than the regular UKF algorithm. The SP-UT treatment in the SOC estimation process with the RP-UKF algorithm improves SOC covariance properties. The experimental results show that the proposed RP-UKF method performs efficiently with known or unknown initial SOC values, and its robustness is verified by changing the S-ECM parameters. The SOC estimation performance of the proposed method is validated with the experimental results, which indicates that the RP-UKF method exhibits low absolute mean error, absolute maximum error, and root-mean-square error values. In addition, the method is applied to the SOC estimation of the aeronautical lithium-ion battery pack. It will play an important role in the popularization and application of such battery packs.

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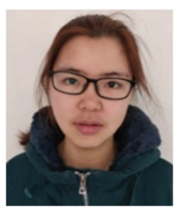

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