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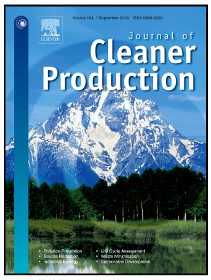

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Open circuit voltage and state of charge relationship functional optimization for the working state monitoring of the aerial lithium-ion battery pack

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Abstract –The aerial lithium-ion battery pack works differently from the usual battery packs, the working characteristic of which is intermittent supplement charge and instantaneous large current discharge. An adaptive state of charge estimation method combined with the output voltage tracking strategy is proposed by using the reduced particle - unscented Kalman filter, which is based on the reaction mechanism and experimental characteristic analysis. The improved splice equivalent circuit model is constructed together with its state-space description, in which the operating characteristics can be obtained. The relationship function between the open circuit voltage and the state of charge is analyzed and especially optimized. The feasibility and accuracy characteristics are tested by using the aerial lithium-ion battery pack experimental samples with seven series-connected battery cells. Experimental results show that the state of charge estimation error is less than 2.00%. The proposed method achieves the state of charge estimation accurately for the aerial lithium-ion battery pack, which provides a core avenue for its high-power supply security.

Keywords: lithium-ion battery pack; open circuit voltage; working state monitoring; state of charge estimation; unscented Kalman filter

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1. Introduction

The lithium-ion battery packs are used for the warplanes and no-man-machines in United States instead of the nickel cadmium battery packs such as military A10, MQ-9 and AH64, which are also supplied by the Eagle-Picher company as described (X. S. Hu, Zou, Zhang, & Li, 2017). The cargo and military aircrafts also use the lithium-ion battery packs gradually. However, due to the electro-chemical reaction, material aging and undesirable operation environment, in which the SOC (State Of Charge) value is essential to be estimated accurately.

A large number of solutions have been proposed by researchers, which have been gradually applied the SOC estimation process of lithium-ion batteries. An SOC estimation study was conducted based on the OCV (Open Circuit Voltage) method (Dang et al., 2016). The online SOC estimation was realized using the lagging OCV model (Dong, Wei, Zhang, & Chen, 2016). An overview can be conducted for the SOC estimation methods of the lithium-ion batteries (Farmann & Sauer, 2016). The dual Kalman algorithm was also used to achieve the high-precision SOC estimation of lithium-ion batteries (Y. J. Wang, Zhang, & Chen, 2016). The OCV-based EKF (Extended Kalman Filter) correction function can be used together with the time-hazard integral method, proposing a KF (Kalman Filter) correction algorithm to reduce the estimation error within 6.0% (Feng, Weng, Ouyang, & Sun, 2016). An adaptive square root UKF (Unscented Kalman Filter) approach was proposed for SOC estimation of lithium-ion batteries (Liu, Cui, & Zhang, 2017). The adaptive SOC estimation was conducted using a split battery model for electric vehicle applications. An SOC estimator was constructed using a first-order RC (Resistance and Capacitance) battery model and achieved an working state estimation error of 5.00% (Gao, Zhang, & Wen, 2015).

The Bayesian technology was also used in the working state monitoring of the lithium-ion batteries. The Bayesian technology is used to implement the SOC estimation framework (Sun, Xiong, & He, 2016). An exploratory research on the SOC estimation was conducted using the sparse Bayesian learning method, improving the robustness working characteristic of the SOC estimation (C. Hu, Jain, Schmidt, Strief, & Sullivan, 2015). The accurate and versatile simulation methods of transient voltage profile were studied for the lithium-ion secondary battery by employing internal ECM (Equivalent Circuit Model) (Tanaka et al., 2015). A radial basis function neural network was used to construct a robust adaptive sliding mode observer (X. P. Chen et al., 2016). The SOC modeling of lithium-ion batteries realized by using dual exponential functions (Kuo et al., 2016). A mixed SOC estimation algorithm was proposed with high accuracy in various driving patterns of EVs (Electric Vehicles) (Lim, Ahn, Kim, & Lee, 2016). The charge and discharge voltage and temperature pattern recognition method was studied using the double EKF, improving the SOC estimation effect to adapt different temperature working conditions (Kim et al., 2015).

The KF-based algorithms were implied in the SOC estimation process. The SOC estimation of lithium-ion batteries was realized by using the dual filters of KF and UKF (Sepasi, Ghorbani, & Liaw, 2014). The electrochemical model parameter identification of a lithium-ion battery was conducted using particle swarm optimization method (Rahman, Anwar, & Izadian, 2016). The state-space modeling and observer design was realized for lithium-ion batteries using Takagi-Sugeno fuzzy system (Samadi & Saif, 2017). A SOC estimation method was developed using the adaptive UKF and support vector machine (SVM) (Meng, Luo, & Gao, 2016). The life cycle assessment was studied for lithium-air battery cells (Zackrisson, Fransson, Hildenbrand, Lampic, & O'Dwyer, 2016). The adaptive EKF and wavelet transform matrix were used to realize the SOC estimation of lithium-ion batteries (Zhang, Cheng, Lu, & Gu, 2017). A hybrid SOC estimation algorithm was proposed (Alfi, Charkhgard, & Zarif, 2014). The spatiotemporal modeling of internal states distribution was conducted for the lithium-ion batteries (M. L. Wang & Li, 2016). A two-scale particle filter-based energy state prediction algorithm was proposed for the lithium-ion batteries (Xiong, Zhang, He, Zhou, & Pecht, 2018). Zhang *et al.*[Error! Reference source not found.] A SOC estimation study was conducted for the lithium-ion battery packs considering balanced currents (Zhang, Cheng, Lu, & Gu, 2018). The KF estimation method leaves a large room for expansion because of its open processing model for the iterative calculations.

A large number of universities and research institutes have conducted continuous research. The parameter detection, modeling of work characteristics and ECM have been explored, obtaining rich research results. A simplified multi-particle model for lithium-ion batteries was conducted (Li et al., 2016). The online SOC estimation was realized by using the particle filter-based data fusion with multi-models (Zhou, Zhang, Ravey, Gao, & Miraoui, 2016). The online dynamic equalization adjustment of high-power lithium-ion battery packs were conducted using the SOB (State Of Balance) estimation (S. L. Wang, Shang, Li, Deng, & Li, 2016). A dynamic battery cell model was proposed together with the SOC estimation (Wijewardana, Vepa, & Shaheed, 2016). The integration issues of lithium-ion battery into EVs were analyzed (Saw, Ye, & Tay, 2016). The voltage detection was performed to evaluate the imbalance degree of the battery cells (Lin, Stefanopoulou, Li, & Anderson, 2015). A novel safety anticipation estimation method was proposed for the aerial lithium-ion battery pack based on the real-time detection and filtering (S. L. Wang, Fernandez, Chen, Wang, & Su, 2018). The SOC and SOH (State Of Health) estimation was realized for lithium batteries using recurrent neural networks (Chaoui & Ibe-Ekeocha, 2017). An integrated online adaptive SOC estimation approach was proposed for high power lithium-ion battery packs (S. L. Wang, Fernandez, Shang, Li, & Yuan, 2018).

The combined methods were also studied for the SOC, SOH and SOF estimation at the same time. A battery dynamic prediction and lag model was constructed (Zhao & de Callafon, 2016). Lithium-ion battery performance and degradation were obtained under different usage scenarios (Samadani, Mastali, Farhad, Fraser, & Fowler, 2016). The joint estimation study of the SOC, SOH, and SOF (State Of Function) were conducted for lithium-ion batteries based on the ECM analysis (Shen, Ouyang, Lu, Li, & Feng, 2018). The error sources of the online SOC estimation of lithium-ion batteries were studied (Zheng, Ouyang, Han, Lu, & Li, 2018). An advanced machine learning approach was proposed for lithium-ion battery state estimation in EVs (X. S. Hu, Li, & Yang, 2016). An ECM was built to achieve the real-time state estimation of lithium-ion batteries (Nejad, Gladwin, & Stone, 2016).

The core parameters were also studied for the real-time monitoring of the power lithium-ion batteries. A prediction of temperature rise was conducted when lithium-ion batteries were exposed to an external short circuit (Z. Y. Chen, Xiong, Lu, & Li, 2018). The effect of temperature non-uniformity was analyzed on the SOC estimation (Osswald et al., 2016). An electrochemical model based charge optimization was proposed for lithium-ion batteries (Pramanik & Anwar, 2016). The electrochemical impedance was tracked for the batteries (Piret, Granjon, Guillet, & Cattin, 2016). The dynamic model study was also initiated for lithium-ion batteries (Mesbahi et al., 2018). Existing studies have achieved remarkable results in the construction of equivalent models of lithium-ion batteries. Because of the high capacity and power requirement, the lithium-ion batteries are usually used as packs, the representative structure as shown in Figure 1.

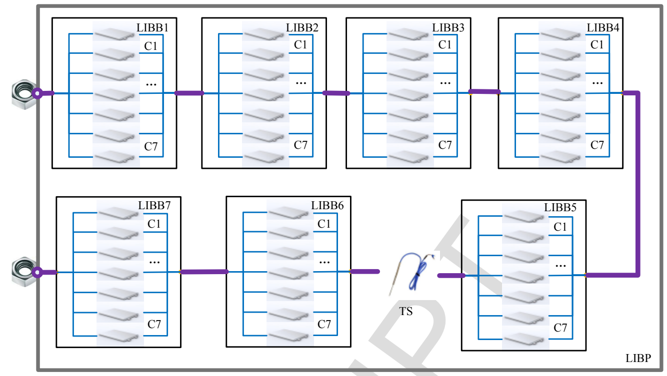

Fig. 1. The representative structure of the lithium-ion battery packs

As a result, modeling of group equivalent circuits under complex operating conditions still needs further development, which will improve the reliability of military aircraft and expanded its application fields with significant social and economic benefits. It is necessary to study the method of group ECM modeling under the complex working conditions through the modular circuit characterization.

This topic focuses on the SOC estimation problem of lithium-ion battery packs, in which the research is conducted on the construction of group ECM modeling, estimation methods, and balance state correction under the influence of complex working conditions. In addition, solving several key problems in the SOC estimation process together with the improved UKF estimation method as well as improving the accuracy of the packing SOC estimation results are also topics which require further investigation.

2. Theoretical analysis

The key factor change law of the aerial lithium-ion battery pack is obtained through the reaction mechanism analysis and the working condition simulation experiments. The circuit equivalent model is used to realize the mathematical expression of the working characteristics for the aerial lithium-ion battery pack. Whereas, the SOC estimation model with self-adaptability is constructed. The impact of the unbalanced inter-cell imbalance on the SOC estimation accuracy is eliminated.

2.1. Working characteristic analysis

The aerial lithium-ion battery pack together with its associated BMS equipment is one of the subsystems find out in the aircraft control system. The operation mode is shown as follows. Firstly, the battery energy supply is cut off in the normal working conditions, in which the engine provides electrical energy by the generator of the whole control system. Secondly, if the voltage abnormal fluctuations in the transformer rectifier are monitored by the associated BMS equipment, the battery energy supply should be conducted and the power supply from the engine should be cut off. Thirdly, when the battery capacity is low which can be monitored by the associated BMS equipment, the engine should be made to furnish power for the entire control system and charge the battery additionally at the same time. The system structure of the energy supplies along with its basic working process can be described in Figure 2.

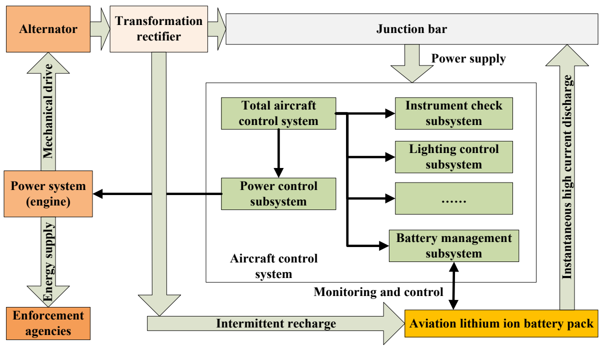

Fig. 2. The energy system structure of the aerial battery pack

The most frequent working states along with intermittent small current charging status in the airborne applications are shelved. However, the sudden power supply requires $1C_5A$ or even higher output current. The phenomenological force and swelling models are constructed and analyzed for the rechargeable lithium-ion battery packs. It is necessary to demonstrate the SOC value clearly for the accurate remaining capacity characterization as the judgment basis of the continuing flight, emergency return or parachuting. Figure 3 describes the working state at different working conditions.

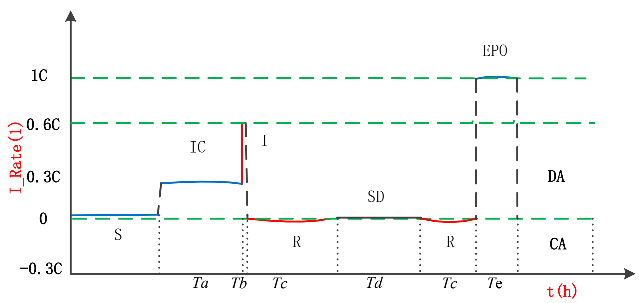

Fig. 3. The working process of aerial battery pack

The symbols in the above Figure: Shelve (S); Instrument Check (IC); Ignition (I); Recharge (R); Self-Discharge (SD); Emergency Power Output (EPO); Discharge Area (DA); Charge Area (CA). According to the change law analysis of the battery voltage under different working conditions, the voltage change trend along with SOC is the same under different working conditions. The voltage at the initial stage of the working condition declines rapidly as well as the end stage. However, due to the difference in the frequency of experimental changes under different operating conditions, the voltage variation curve of the battery pack shows different characteristics as time goes by.

Considering the requirements of the special working conditions, the SOC estimation problems of the aerial lithium-ion battery pack can be concluded as shown below. Firstly, there is current volatility in the equipment inspection and ignition processes. The in-plane non-uniform temperature effects should be studied on the performance of the large-format lithium-ion battery pack. Secondly, the SOC estimation has cumulative error in the frequent use and intermittent small current recharge process due to the current detection error. There is large fluctuation of current emergencies when the output is required to get the accurate SOC value as the emergency treatment. Due to the platform effect characterization in the working process. Thirdly, the imbalance among the connected cells has influence on the SOC estimation accuracy of the lithium-ion battery packs. Fourthly, the Ah integral method used at present ignores the influence of current fluctuation, self-discharge and the equilibrium state among the internal connected battery cells and other factors. As a result, the SOC estimation results are not accurate and rely on the regular ground maintenance correction.

2.2. Equivalent modeling analysis

According to the operating characteristic analysis of the aerial lithium-ion battery pack, an equivalent modeling method combined with the circuit equivalent idea is proposed. The model expression of the characteristics for the battery pack under the dynamic group application working conditions can be applied, constructing the state space equation together with the mathematical description. The key characteristics such as the battery polarization effect are studied, which is based on the analysis results of the battery operating characteristics. Meanwhile, the advantages of Thevenin, PNGV, and RC and various improved equivalent models are analyzed, in which the circuit components are used to achieve the equivalent simulation of battery pack considering the accurate description of the operating characteristics. The simulation and experimental analysis are carried out to evaluate the equivalent simulation effect and the optimization processing performance. Using the modular modeling characterization method, the characteristics of battery packs are explored such as the polarization effects and self-discharge. Through the working characteristic effect analysis of the battery pack and the optimized combination of different description methods, the splice equivalent model design theory based on the circuit simulation is finally constructed and improved.

The influence factor analysis is based on the battery model equivalent design theory. Afterward, the group-based equivalent modeling and improvement methods are explored, in which the operating conditions and the targeted equivalent circuit models are combined. Using the work characteristic circuit simulation, combined with the working condition characterization method and effect analysis, the different component combination modules are constructed and the simulation analysis and structural optimization are performed. A complete battery equivalent model is established by focusing on the characteristics and characterization of each combination of modules, combined with the combination advantage and disadvantage analysis together with the structural changes. The equivalent circuit model structure is modified to achieve the accurate simulation expression of the operating characteristics based on the simulation and experimental analysis. According to a confirmatory experimental study of the equivalent circuit simulation, the difference in the expression of working characteristics caused by the parameter change is analyzed. The equivalent model is improved by modifying the model parameters and the combined structure as shown in Figure 4.

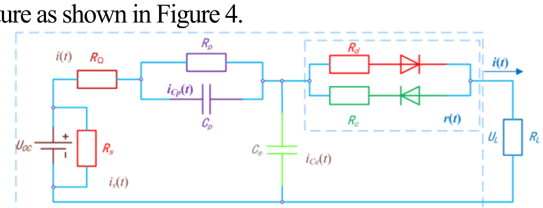

Fig. 4. The splice equivalent circuit model

The meaning of each parameter is as follows. U_{oc} characterizes the OCV value of the aerial lithium-ion battery pack. R_s is a large resistor used to characterize the self-discharge effect of the battery pack. R_o is an ohmic resistance, the divided voltage of which is used to characterize the voltage drop across the positive and negative electrodes of the battery pack during the charge and discharge process. The one-order RC parallel circuit is used to simulate the relaxation effect during the charge and discharge maintenance, in which the transient response of the battery pack is expressed. R_p and C_p are the polarization resistance and capacitance respectively. The parallel circuit of R_p and C_p reflects the generation and elimination of the polarization effect of the battery pack. R_d and R_c are the internal resistances during discharge and charge respectively, characterizing the difference in internal resistance exhibited by the aerial lithium-ion battery pack during the discharge and charging process. U_δ and R_δ are used to characterize the effect of the equilibrium state among the battery cells. $U_L(t)$ is the closed-circuit voltage at both ends of the positive and negative electrodes when the battery pack is connected to an external circuit. $I(t)$ is the current value of its inflow or outflow.

This equivalent model uses an ideal voltage source, U_{oc}, to characterize the OCV value. At the same time, an accurate description of the self-discharge effect is realized by adding a shunt resistor R_s across the ideal voltage source. A resistor parallel circuit is introduced with a series of reverse diodes, combined with the use of resistive devices R_d and R_c, which solves the differential expression problem of internal charging and discharging resistances. The internal resistance R_o that characterizes the ohmic effect is then serially connected to improve the working state characterization accuracy of the lithium-ion battery pack. Taking the consistency difference into account in the packing equivalent process, the equivalent description of the equilibrium state influences on the working state description performance. This phenomenon will result in a change in the composition of the output voltage $U_L(t)$ within a shorter operating voltage range. Therefore, the time-varying voltage source U_δ in series with the open-circuit voltage source U_{oc} is used for the characterization purpose. Meanwhile, this phenomenon will cause the extra accumulation of the ohmic resistance R_o to become larger, so that the heating phenomenon will gradually increase. Therefore, the time-varying resistance parameter R_δ is used to describe this effect.

The dynamic circuit analysis method is used to realize the mathematical description of the equivalent model and the state space representation of the equivalent model is conducted. The combination of the basic experimental analysis with multivariate nonlinear parameter estimation are investigated. In addition, the identification method of model parameters is studied and each state parameter together with its weight coefficient is established. Based on the experimental analysis and improved method exploration, the model parameter verification and error suppression are completed. Combining the state equations and the observation equations, we can construct the state-space equations required for group SOC estimation as shown in Equation 1.

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

In Equation 1, k is the time point at which the SOC value of the lithium-ion battery pack is estimated, and $U_L(k)$ is the closed-circuit voltage value of the battery pack at k time point. R_o is the ohmic resistance of the lithium-ion battery pack and $I(k)$ is the output current of the battery pack. K_s is the amount of change in the SOC per detection cycle under the self-discharge influence of the battery pack. T_s is the detection period of the battery parameter and U_{oc} is an ideal voltage source equivalent parameter that characterizes the OCV of the battery pack. At the same time, the parallel circuit of R_p and C_p is used to reflect the generation and elimination of the polarization process in the battery pack. U_L is the closed-circuit voltage after the battery pack is connected with the external circuit.

2.3. SOC estimation model construction

The robust UKF and its nonlinear expansion methods are studied. Using the methods of lean particle, non-trajectory transformation and function modification, the mathematical description method under different working conditions can be explored, and the SOC estimation model with self-adaptability is constructed as well. Based on the equivalent model of the battery and its state space description, the specificity of the SOC estimation under the power group application conditions is analyzed. The influence law of the key parameters is revealed in the SOC estimation process, and the construction mechanism of the state equation and the observation equation is explored. A correction strategy for the influencing factors of the packing SOC estimation is obtained, in which the theoretical and experimental analysis of the influencing factors has been conducted and the construction mechanism of the estimation model framework has been obtained. Combined with the analysis of the battery pack operating characteristics under the power group application conditions, the construction method of the SOC estimation model framework is explored. The adaptive SOC estimation model framework for the combined conditions is shown in Figure 5.

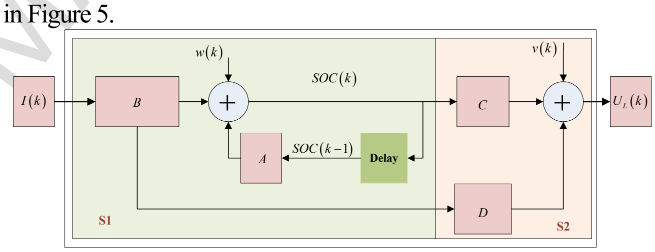

Fig. 5. The SOC estimation model framework

In the above Figure, $I(k)$ represents the current signal input by the system, and $U_L(k)$ is the closed-circuit voltage signal output by the system. $SOC(k)$ is the SOC value at k time point, and $SOC(k\text{-}1)$ is the SOC value at k-1th-time point. The discrete space description of the nonlinear SOC estimation model can be represented by the whole graph. S1 is the state equation and S2 is the observation equation, and then the iterative calculation is realized by combining the discrete processing. By iteratively using the expression $SOC=SOC(k\text{-}1)$ and replacing the effective parameter with the SOC value, an equation that is closely related to time can be obtained and used for the subsequent parameter replacement and characterization. Under the influence of random noise, the estimation process at different time points can be obtained.

S1: By using a series of sampling points, a sequence of Sigma data points is constructed as shown in Equation 2.

$$SOC^{(i)}(k\text{-}1) = \begin{bmatrix} SOC(k\text{-}1) \\ SOC(k\text{-}1) + \sqrt{(n+\lambda)P(k\text{-}1)} \\ SOC(k\text{-}1) - \sqrt{(n+\lambda)P(k\text{-}1)} \end{bmatrix} \tag{2}$$

S2: The first-order prediction of the sinusoidal data point sequence should be calculated with length of 2n+1 as shown in Equation 3.

$$SOC^{(i)}\left(k\mid k\text{-}1\right)=f\left[k,SOC^{(i)}\left(k\text{-}1\right)\right],i=1,2,\cdots,2n+1 \tag{3}$$

S3: One-step prediction of the state space variable for the nonlinear SOC estimation and its variance matrix can be calculated by the following calculation process. The calculation process is mainly obtained by the weighted sum of the Sigma data point sequence, and it is realized by various calculation expressions in the non-transformation process. The algorithm uses the last time point instead of the SOC in the state space function, and only one calculation is needed to obtain the predicted SOC value. This step realizes the prediction process through the set three data points, and calculates the average value by weighting coefficients. The predicted SOC value calculation of the aerial lithium-ion battery pack can be described by Equation 4.

$$SOC\left(k\mid k\text{-}1\right)=\sum_{i=0}^{2n}\omega^{(i)}SOC^{(i)}\left(k\mid k\text{-}1\right) \tag{4}$$

Then, the predicted value of the SOC state variance can be obtained as described by Equation 5.

$$P\left(k\mid k\text{-}1\right)=\sum_{i=0}^{2n}\omega^{(i)}\left[SOC\left(k\mid k\text{-}1\right)-SOC^{(i)}\left(k\mid k\text{-}1\right)\right]\left[SOC\left(k\mid k\text{-}1\right)-SOC^{(i)}\left(k\mid k\text{-}1\right)\right]^{T}+Q \tag{5}$$

S4: The new Sigma data point sequence used in the SOC estimation process of the battery pack can be obtained, by once again applying a non-trace conversion processing procedure to the one-step prediction value as shown in Equation 6.

$$SOC^{(i)}\left(k\mid k-1\right)=\begin{bmatrix} SOC\left(k\mid k-1\right) \\ SOC\left(k\mid k-1\right)+\sqrt{\left(n+\lambda\right)P\left(k\mid k-1\right)} \\ SOC\left(k\mid k-1\right)\text{-}\sqrt{\left(n+\lambda\right)P\left(k\mid k-1\right)} \end{bmatrix} \tag{6}$$

S5: The Sigma data point sequence in the previous step can be substituted into the observation equation of the SOC estimation model for the aerial lithium-ion battery pack, and then the predicted observation variable matrix can be obtained as shown in Equation 7.

$$U_{L}^{(i)}\left(k\mid k-1\right)=h\left[SOC^{(i)}\left(k\mid k-1\right)\right],i=1,2,\cdots,2n+1 \tag{7}$$

S6: The output closed-circuit voltage prediction average value can be calculated together with its autocorrelation matrix and cross-correlation matrix, which is used in the correction step of the SOC estimation for the aerial lithium-ion battery pack. The values can be obtained by weighted sum of the observation and prediction values by using the Sigma data point sequence as shown as follows.

(1) The forecasted mean value is shown by Equation 8.

$$\overline{U}_{L}\left(k\mid k\text{-}1\right)=\sum_{i=0}^{2n}\omega^{(i)}U_{L}^{(i)}\left(k\mid k\text{-}1\right) \tag{8}$$

(2) The autocorrelation matrix is shown in Equation 9.

$$P_{U_L(k)U_L(k)}=\sum_{i=0}^{2n}\omega^{(i)}\left[U_{L}^{(i)}\left(k\mid k\text{-}1\right)-\overline{U}_{L}\left(k\mid k\text{-}1\right)\right]\left[U_{L}^{(i)}\left(k\mid k\text{-}1\right)-\overline{U}_{L}\left(k\mid k\text{-}1\right)\right]^{T}+R \tag{9}$$

(3) The cross-correlation matrix is shown in Equation 10.

$$P_{SOC(k)U_L(k)}=\sum_{i=0}^{2n}\omega^{(i)}\left[U_{L}^{(i)}\left(k\mid k\text{-}1\right)-\overline{U}_{L}\left(k\mid k\text{-}1\right)\right]\left[U_{L}^{(i)}\left(k\mid k\text{-}1\right)-\overline{U}_{L}\left(k\mid k\text{-}1\right)\right]^{T} \tag{10}$$

S7: The Kalman gain matrix for SOC estimation of an aeronautical lithium-ion battery pack can be obtained by the Equation 11.

$$K\left(k\right)=P_{SOC(k)U_L(k)}P_{U_L(k)U_L(k)}^{-1} \tag{11}$$

S8: According to the non-linear characteristics of the SOC estimation for the aerial lithium-ion battery pack, the status update and error covariance update treatment can be achieved through the following two small steps.

(1) The status update is calculated by Equation 12.

$$SOC\left(k\right)=SOC\left(k\mid k\text{-}1\right)+K\left(k\right)\left[U_{L}\left(k\right)-U_{L}\left(k\mid k\text{-}1\right)\right] \tag{12}$$

(2) The update of the error covariance is calculated by Equation 13.

$$P\left(k\right)=P\left(k\mid k\text{-}1\right)-K\left(k\right)P_{U_L(k)U_L(k)}K^{T}\left(k\right) \tag{13}$$

This method implements the estimation process based on the Kalman framework in the estimation process, but does not require the nonlinear equation linearization calculation as the traditional SOC estimation methods. In the one-step prediction calculation process of the SOC estimation model, the nonlinear conversion problem of the estimated mean value and variance is solved by using the reduced UT processing. The posterior probability density in the SOC estimation process is then estimated by using the sample sequence data set to approximate the representation. There is no need to approximate the nonlinear equations and the Jacobian matrix calculations. Since there is no need for the linearized equation processing, the high-order terms ignore treatment is not existent. This statistical feature has the advantage of high computational accuracy and effectively reducing the nonlinear error in the SOC estimation process. On the basis of streamlining the three particles, the weighted Sigma data point selection process is used twice to calculate the mean value of the data sample during the SOC estimation process.

Using the non-trace transform and function fitting approximation, the mathematical description mechanism of the battery pack under different working conditions has been studied to complete the design of the estimated model frame. The mathematical expression is explored for the strong non-linear working characteristics and the mathematical description mechanism is revealed for the battery pack characteristics under different working conditions. The relationship between the working state and the equivalent model parameters is ascertained. And then, the piecewise linearized processing of the nonlinear dynamic system of the battery pack is realized, according to which the mapping relationship between the state space equation and the working state is established. Under the application conditions of different power groups, the accurate mathematical description of the characteristics for the battery pack is provided, and the theoretical basis for constructing an adaptive SOC estimation model is provided. The framework theory of the estimation model is studied. Using the battery equivalent model and the state space equation, a preliminary construction of an adaptive SOC estimation model is realized. Then, the battery equivalent model and its state space representation are transferred to the state equations and observation equations of the SOC estimation model. Through the tracking analysis and the estimation effect optimization, the estimation process has a higher adaptability to the working state of the battery pack. The output response variation of the SOC estimation model under different conditions is studied. The influence of factors such as the current fluctuations and temperature changes on the SOC estimation accuracy is discussed, and the SOC estimation structure is optimized.

2.4. **OCV and SOC functional optimization**

By analyzing the experimental results under complex simulation conditions in the SOC estimation process, it is found that the closed circuit voltage can be corrected very well, but the SOC estimation value has a systematic error, which cannot be effectively corrected at the early stage in the SOC estimation process. This problem cannot be solved by analyzing the influence of various parameters such as α and λ on the SOC estimation effect. The experimental results show that the original OCV-SOC function relationship cannot be corrected effectively when tracking the complex variable current conditions, due to the difference between the nominal capacity and the actual measured value for the aerial lithium-ion battery pack. As a result, its functional relationship is optimized. Considering the working environment of large current rate discharge and small current multiplying charging in the actual working conditions, the 0.20C_5A charging and 1.00C_5A discharging test is chosen as the basis to get the functional relationship, so as to improve the adaptability to the working conditions. In the calculating process, the ampere hour capacity change calculation is conducted in the charge and discharge maintenance experiments by taking the end point as the reference value. On this basis, the average value of closed circuit voltage corresponding to different SOC values the charge and discharge process is calculated and taken as the optimized OCV value as shown in Figure 6.

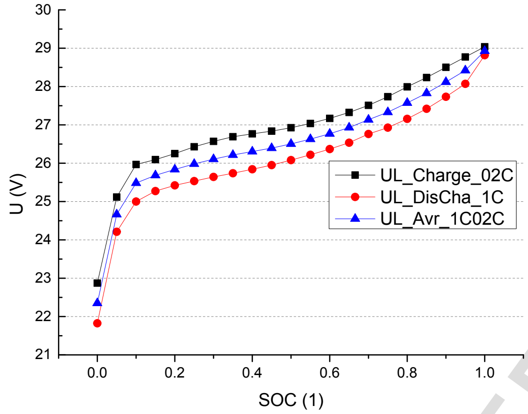

Fig. 6.OCV-SOC relationship Optimization

Then, by comparing the relationship of the original OCV-SOC relationship, the fitting function relation and the functional relation based on 1.00C_5A constant current charge and 1.00C_5A constant current discharge have been calculated. The feasibility of the idea is verified and the experimental results are shown in Figure 7.

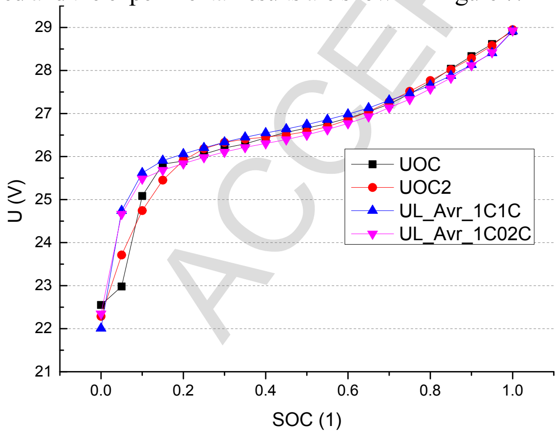

Fig. 7.OCV-SOC relation comparison obtained by different methods

The results with 0.20C_5A charge and 1.00C_5A constant current discharge have more accurate description results, which is more close to the relationship of the original OCV-SOC function. Compared with the original phased discharge and shelving method, it is more close to the change of the battery working characteristics in the case of low SOC. Therefore, the optimization method is reasonable. Then, the curve fitting is used to get the functional relationship between these two optimization methods. By comparing and analyzing the fitting effect of function relation under different orders, 6th-time polynomial is chosen to cooperate and fit the function relationship. By comparing and analyzing the polynomial fitting effects under different degree orders, taking the calculation amount and the fitting accuracy into account, the 6th-order polynomial fitting is finally determined as the mathematical representation equation of the function relation. The related fitting effect is shown in Figure 8.

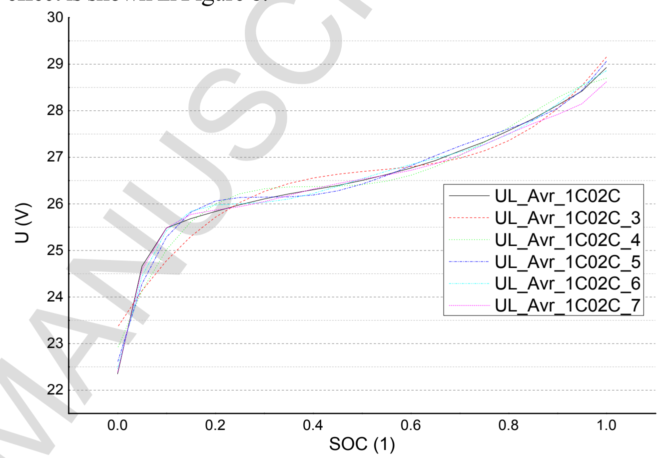

Fig. 8.Multiple degree fitting effect analysis

As can be seen from the figure, the curve fitting result is improved along the degree enlargement when the degree is smaller than 6. When the degree is bigger than 6, the effect is expected to be a lesser extent increased but will bring more complicated calculations. The expression form is calculated by using Equation 14.

$$U_{OC} = f(\varphi) = a_0 + a_1\varphi + a_2\varphi^2 + a_3\varphi^3 + a_4\varphi^4 + a_5\varphi^5 + a_6\varphi^6 \quad (14)$$

In the above expression, the variable φ is used to characterize the SOC value of the aerial lithium-ion battery pack, and the variable U_{OC} is OCV value. The coefficients in the state space equation are obtained by fitting the experimental data curves as shown in Table 1.

Tab.1 Fitting coefficient relation of OCV and SOC

Name	a0	a1	a2	a3	a4	a5	a6
Value	22.46	53.26	-315.08	920.68	-1380.58	1027.01	-298.89

The function relation expression in Equation 14 is applied to calculate the corresponding OCV values under different SOC conditions. The results are compared with the original data to verify the tracking effect of the fitted curve as shown in Figure 9.

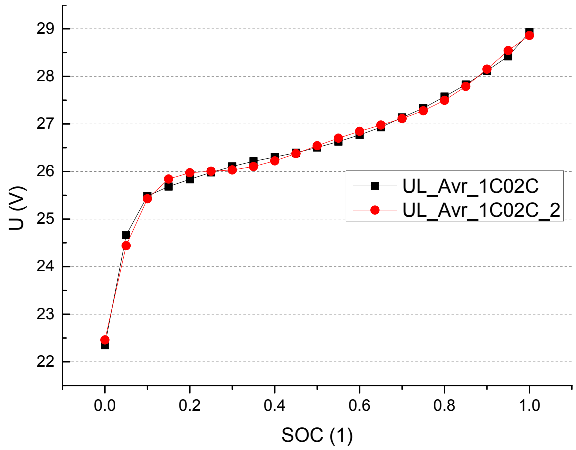

Fig. 9.OCV-SOC curve fitting effect analysis

Aiming for the OCV-SOC fitting effect explanation purpose, a more intuitive explanation is made by supplementing the error as shown in Figure 10.

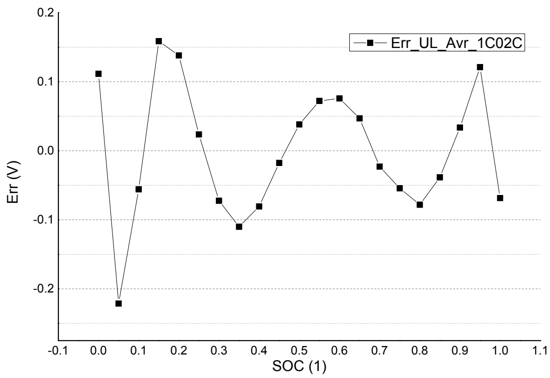

Fig. 10. OCV-SOC curve fitting error results

As shown in the above Figures, the constructed fitting equation has good characterization effect for the working characteristic simulation of the aerial lithium-ion battery pack. In the SOC estimation process under complex simulation conditions, there is still a systematic error between the estimated SOC value and the SOC value obtained by the Ah integral method. The analysis shows that the system error is still caused by the inaccuracy of the OCV, and the OCV value in the middle section is low on the whole OCV-SOC function relationship, which is asymmetrical with the 1C_5A discharge process. The experiment obtained the OCV-SOC function relationship under the condition of 1C_5A charging and 1C_5A discharging treatment is shown in Figure 11.

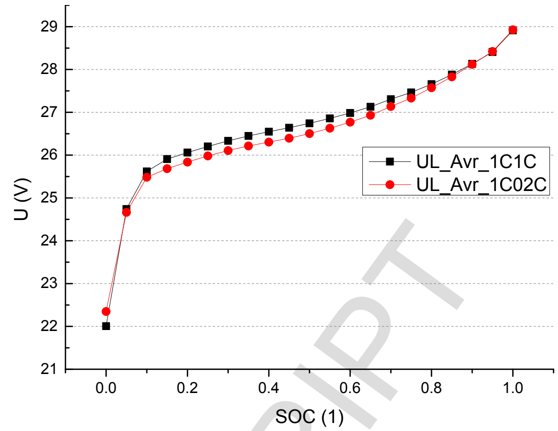

Fig. 11. The OCV-SOC relationship comparison

As can be seen from the above figure, different discharging current rate have significant voltage variation differences under the premise of the same 1C charging treatment. To show this voltage difference more clearly, draw the difference curve as shown in Figure 12.

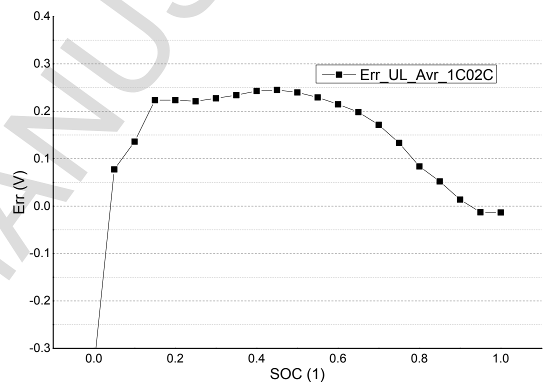

Fig. 12. Voltage variation difference for different discharging currents

Therefore, the function relationship under the condition of 1 C_5A charging and 1 C_5A discharging condition is used as the optimized OCV-SOC relationship. Then, the curve fitting treatment is used to get the functional relationship between these two optimization methods. By comparing and analyzing the fitting effect of function relation under different orders, seven-time polynomial function is chosen to cooperate and fit the function relation. The expression of the calculation form can be realized by using Equation 15.

$$U_{OC} = f(\varphi) = a_0 + a_1\varphi + a_2\varphi^2 + a_3\varphi^3 + a_4\varphi^4 + a_5\varphi^5 + a_6\varphi^6 + a_7\varphi^7 \quad (15)$$

In Equation 15, the SOC value of the aerial lithium-ion battery pack is characterized by the variable φ, and the variable U_{OC} indicates the OCV value of the aerial lithium-ion battery pack. The coefficients in the state space equation are obtained by fitting the experimental data curves in the graph as shown in Table 2.

Tab.2 Fitting coefficient relation of OCV and SOC

name	a0	a1	a2	a3	a4	a5	a6	a7
value	22.05	75.54	-582.03	2336.78	-5172.10	6379.83	-4102.36	1071.23

The function relation expression is applied to calculate the corresponding OCV values under different SOC conditions. Then, comparing them with the original data to verify the tracking effect of the fitting curve as shown in Figure 13.

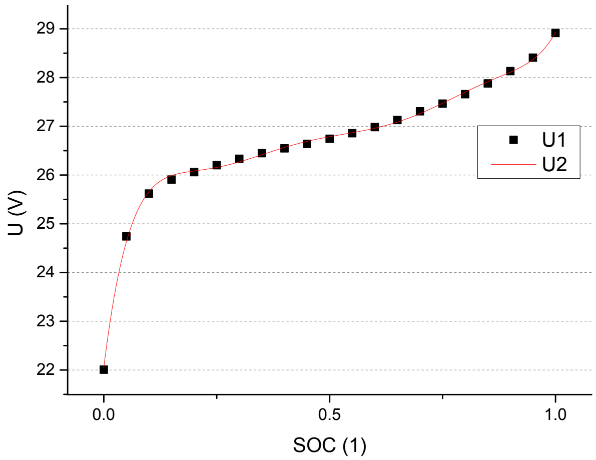

Fig. 13. OCV-SOC curve fitting effect analysis

The curve fitting error of the OCV-SOC relationship can be described as shown in Figure 14.

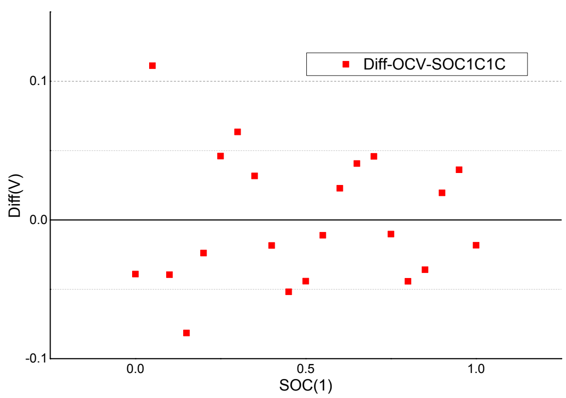

Fig. 14. OCV-SOC curve fitting error results

The constructed fitting equation has good expression effect for the simulation of the working characteristics for the aerial lithium-ion battery pack. The relationship between φ and U_{OC} is used in the subsequent iterative calculation process of the SOC estimation. In view of the safety monitoring requirements of the high pressure section for the aerial lithium-ion battery pack, the SOC estimation can be conducted which corresponds to the feature section description. The correspondence curve between OCV and SOC can be obtained for the aerial lithium-ion battery pack.

3. Experiment and analysis

In order to verify the accuracy and reliability of proposed SOC estimation method for the aerial lithium-ion battery pack, the associated BMS equipment is designed and applied in the energy management of the aerial lithium-ion battery pack, and the BMTS platform is built for the SOC determination to carry out a series of validation experiments. Through the design and construction of the integrated SOC estimation model for the aerial lithium-ion battery pack by using the BMS equipment combined with the BMTS platform, the SOC estimation process is carried out under complex aerial conditions. The experiments are affected by the detection accuracy and the sampling time, which are carried out in the laboratory environment, in which the data detection is realized by the ZKE battery testing module together with the software designed by using the C# programming language. Meanwhile, the deep data analysis is conducted by using MATLAB and the analyzing results are displayed by using the Origin software platform.

3.1. Experimental platform construction

The BMTS (Battery Maintenance and Test System) platform for the aerial lithium-ion battery pack is developed by using the RS485 fieldbus mechanism in order to solve the SOC determination problem of the aerial lithium-ion battery pack. The control strategy is realized by using the IPC (Industrial Personal Computer), in which the HMI (Human Machine Interface) is used as the monitoring interface for the input parameters and the human control strategy. In the BMTS platform the design of the protection circuit unit is conducted to realize the real-time security protection in the discharging and charging process of the aerial lithium-ion battery pack as shown in Figure 15.

Fig. 15. Experimental platform of the aerial LIB pack

There are several components used in the BMTS platform of the aerial lithium-ion battery pack. The high-power digital power supplies are used to simulate the energy output generator of the aerial power system. The low-power digital supplies are used to realize the balancing charge process. The electronic loads are used to simulate the load subsystem of the energy consumption in the power supply process of the aircraft system. The data acquisition and storage subsystem is used to record the voltage values, which can also provide the realization process reference for the associated BMS equipment of the aerial lithium-ion battery pack in the online energy management and SOC estimation process.

The high precision current sensors are applied in the BMTS platform. The control of the sub hardware devices in the BMTS platform can be realized by the C# programming in the IPC. The BMTS platform can conduct the charging, discharging and simulated working conditions of the aerial lithium-ion battery pack. It can put forward to the SOC value determination based on the related object detection and management, which can realize the SOC determination and ensuring that the energy supply process safety of the aerial lithium-ion battery pack is conducted.

The experimental samples of the aerial lithium-ion battery pack are selected for the experimental study, including the heating modules and the monitoring devices. The temperature sensors, the cross connecting plates and the electric connectors are used as well, combined with several composition parts. The basic parameters of the experimental aerial lithium-ion battery pack samples can be described as shown in Table 3.

Tab.3 The parameters of the experimental battery pack samples

Parameter Name	Parameter Value
Maximum size	270.00×255.00×185.00 mm
Maximum weight	19.50 kg
Rated capacity	45.00 Ah
Nominal voltage	25.90 V
Temperature range	-55.00℃ ~ 70.00 ℃
Maximum operating current	300.00 A
Ambient temperature	25.00℃±10.00 ℃
Relative humidity	≤80.00%

According to the emergency power supply working conditions and the power output working hours of the aerial lithium-ion battery pack, the discharging current is usually set as $1C_5A$ in the following experiments. The parameter C_5 represents the capacity obtained by discharging all the battery energy with 5 hours until the terminal discharging voltage. Because the battery discharging capacity has a great relationship with the discharging current conditions, the battery capacity should be used by declaring the discharging current conditions. The parameter C_5 is the discharging conditions and the experimental discharging current is set as 1 × rated capacity values.

3.2. Noise effect on the SOC estimation

The adaptability of the proposed SOC estimation method under the influence of process noise and observation noise is studied to verify the accuracy of the proposed estimation method. Aiming at the source and process noise influence analysis, the SOC estimation under the process noise influence and the observation noise influence are carried out firstly, and then the SOC estimation under the compound noise influence is carried out.

(1) Process noise effect on the estimation accuracy

There are fractional reservation and higher term problems in the iterative computation process, due to the limitation of the processor computing conditions. The estimation effect and adaptability is verified under the influence of different processor precision by adding different process noises. The original process noise setting value is Q=1e-10 and this value means that the process noise is very small under the condition of large computing power such as IPC. In the verification process of the estimation effect under the influence of process noise, Q1=1e-10, Q2=1e-8, Q3=1e-6 and Q4=1e-3, the SOC estimation results of which are shown in Figure 16 and Figure 17.

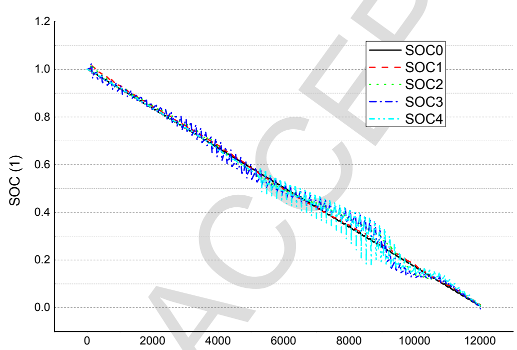

Fig. 16. SOC estimation effect under different working conditions

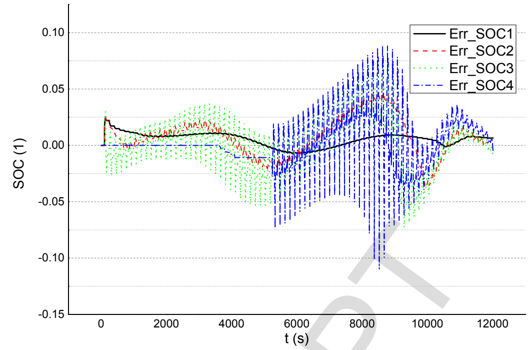

Fig. 17. SOC estimation error under different working conditions

In the above Figures, SOC0 is the SOC value obtained by Ah integral method, SOC1 represents the SOC value that is obtained by the proposed method in the case of Q=1e-10. SOC2 indicates the SOC value obtained by the proposed method in the case of Q=1e-8. SOC3 is the SOC value that is obtained by the proposed method in the case of Q=1e-6. SOC4 is the SOC value obtained by the proposed method in the case of Q=1e-3. The estimation results can still converge to the actual SOC value in the whole simulation process under the influence of process noise and the limit noise. The SOC estimation error is a little larger in the range of 60% to 20%. The reason is that the aerial lithium-ion battery pack is in the platform effect area during this time period, and the influence becomes more and more prominent when the process noise increases.

(2) Observation noise effect on the estimation accuracy

The sampling error and the observation noise cannot be avoided in the iterative computation process. By adding different observation noises, the estimation effect and adaptability of the proposed SOC estimation method can be verified together with the accuracy of different acquisition modules. The set value of the original observation noise is R=0.001 and the observation noise caused by the sampling process is very small. During the estimation effect verification process under the observation noise influence, R1=0.001, R2=0.010, R3=0.100 and R4=1.000 are shown in Figure 18 and Figure 19.

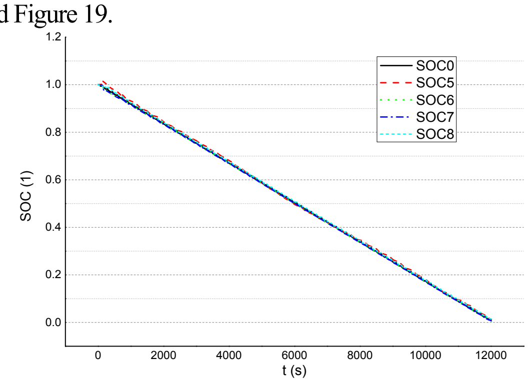

Fig. 18. SOC estimation effect under different working conditions

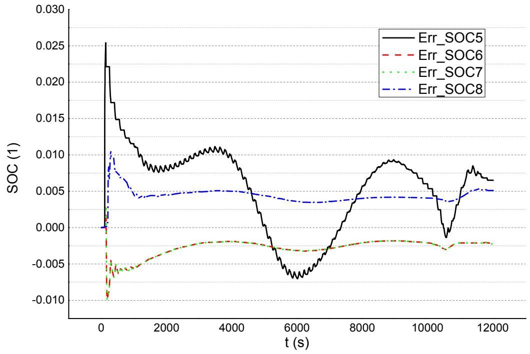

Fig. 19. SOC estimation error under different working conditions

In the above Figures, SOC0 is the SOC value obtained by the Ah method. SOC5 represents the SOC value obtained by the proposed method in the case of R=0.001. SOC6 describes the SOC value obtained by the proposed method in the case of R=0.010. SOC7 is the SOC value that is obtained by the proposed method in the case of R=0.100. SOC8 is the SOC value obtained by the proposed method in the case of R=1.000. The estimation results can still converge to the actual SOC value in the whole simulation process.

(3) Estimation effect under the compound noise influence

Aiming to realize the estimation effect verification under the compound noise influence, the process noise and observation noise are changed synchronously, setting Q1=1e-10, R1=0.001, Q2=1e-8, R2=0.010, Q3=1e-6, R3=0.100, Q4=1e-3 and R4=1.000, the estimation results are shown in Figure 20 to Figure 21.

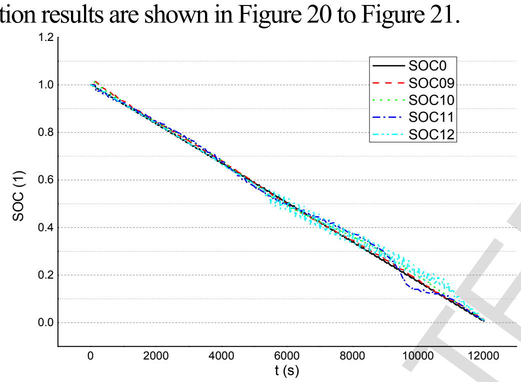

Fig. 20. SOC estimation effect under different working conditions

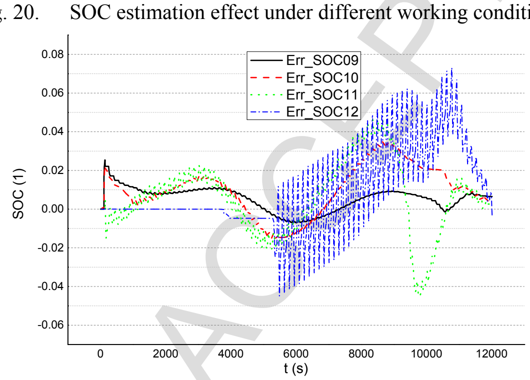

Fig. 21. SOC estimation error under different working conditions

In the above Figures, SOC0 is obtained by Ah method. SOC09 is the SOC value obtained by the proposed method in the case of R=0.001 and Q=1e-10. SOC10 is the SOC value obtained by the proposed method in the case of R=0.010 and Q=1e-8. SOC11 is the SOC value obtained by the proposed method in the case of R=0.100 and Q=1e-6. SOC12 is the SOC value obtained by the proposed method in the case of R=1.000 and Q=1e-3. The estimation results can still converge to the actual SOC value in the whole simulation process under the influence of process noise and the limit noise.

3.3. SOB correction effect analysis

The experimental analysis of the balance state correction effect is carried out through the experimental analysis. One is the estimation effect when the equilibrium state is good and the other is the estimation effect when the equilibrium state is poor. Firstly, each cell in the battery pack is filled with electricity by the balancing charge treatment. Then, the SOC estimation effect is obtained through the estimation effect analysis under the simulated working conditions. The influence description of the balance state and the correction effect can be achieved by the experimental analysis of adding the SOB influence factor and without considering the factors. The SOC estimation results are shown in Figure 22.

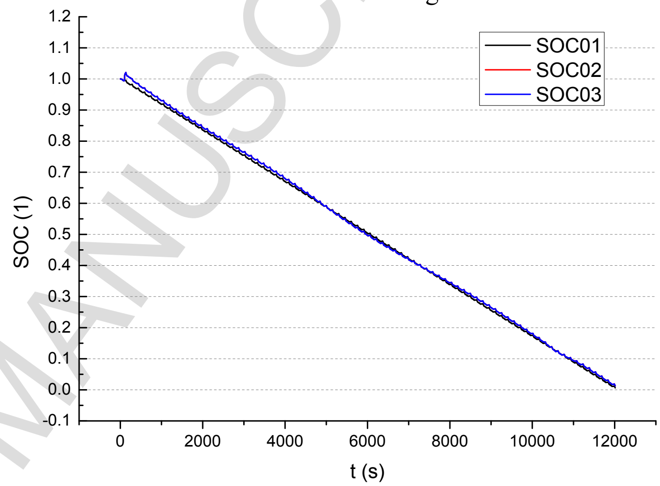

Fig. 22. Equilibrium state correction effect on the SOC estimation

In the above Figure, SOC1 is the SOC value obtained by Ah method. SOC2 indicates the SOC value obtained by the proposed estimation method under the SOB influence. SOC3 represents the SOC value obtained by the proposed method without considering the SOB effect. The experimental results show that the correction factor of SOB is less effective when the equilibrium state is good. Whether the influence of this factor is considered can obtain accurate SOC estimation results for the aerial lithium-ion battery packs. Then, the SOC estimation effect can be obtained by analyzing the estimation effect under the simulated working conditions. In the estimation process, the balance state influence and the correction effect description can be achieved by considering the SOB influence factor and not considering the SOB influence. The SOC estimation results can be obtained as shown in Figure 23.

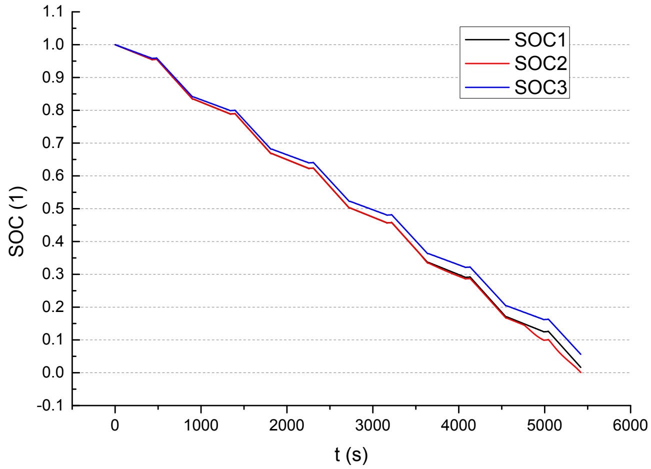

Fig. 23. Equilibrium state correction effect on the SOC estimation

In the above Figure, SOC1 is the SOC value obtained by the Ah method. SOC2 indicates the SOC value obtained by the proposed estimation method under the SOB influence. SOC3 represents the SOC value obtained by the proposed method without considering the effect of SOB. It is shown from the experimental results that the correction effect of the SOB correction factor is obvious in the case of the poor equilibrium state. The SOC estimation results will produce significant estimation deviation when not considering the influence. The continuation of the main discharge conditions along with the influence of SOB is becoming more and more obvious.

3.4. Comparison with other methods

In order to demonstrate the advantages and disadvantages of the proposed algorithm in SOC estimation process of the lithium-ion batteries, the proposed method is compared with the existing related technologies comprehensively based on a large amount of literature review and combined with the research results in recent years for the lithium-ion battery SOC estimation. Based on the above experimental analysis, the comprehensive experimental results of different estimation methods are compared as shown in Table 4.

Tab.4 Effect comparison of the proposed algorithm with others

Model	Algorithm	Simulated Result	Experimental Result
—	OCV-SOC	—	5.00%
Thevenin	OCV+EKF	—	3.00%
PNGV	EKF	1.00%	—
Elec-Chem	AEKF	1.50%	—
2-RC	AKF	—	4.00%
RC	KF+EKF	1.00%	—
Thevenin	UKF	—	4.96%
S-ECM	RP-UKF	0.30%	2.00%

In the experimental results shown in the above table, the left side of the slash is the SOC estimation error result obtained by analog data (variable current, constant current, etc.), and the right side is the SOC estimation error result obtained by the operation condition data (complex current change). As can be seen from the comparative analysis of the experimental results, the SOC estimation method obtained by the proposed algorithm used in this paper demonstrated a good effect. In the case of drastic current change conditions, it can still estimate the state of charge of the battery accurately in real time, which further verifies the advantages of the proposed method in terms of estimation accuracy.

4. Conclusion

This paper presents an effective SOC estimation method for the aerial lithium-ion battery packs by using the battery S-ECM model together with the UKF-based estimation algorithm. The model is based on the RP-UKF estimation constructed for the SOC of the aerial lithium-ion battery pack. Through the charge-discharge process description, the conversion equation and the time-varying parameter change law are obtained, and then the function relationship optimization of key parameters such as temperature, aging, and equilibrium state are combined to realize the accurate SOC estimation and correction. The state space equation of the S-ECM equivalent model is applied, and the initial value of the coefficient is set according to the prior experimental data. According to the influence of different currents and temperatures on the working process, the Coulomb efficiency correction equation is established and the coefficient of the equation is set. By taking the real-time measured operating current and temperature signals as the input parameters of the SOC estimation model, the correction process is incorporated into the influence of the SOC estimation process. Using the recursive calculation based on the unscented Kalman algorithm, combined with the correction processing of the key influencing factors such as the voltage balance state among the battery cells, an accurate estimation of the SOC value is achieved for the aerial lithium-ion battery pack.

Nomenclature

The symbols used in this research can be described as shown in Table 5.

Tab.5 List of symbols

Symbol	Description
Ah	Ampere-hour
BMS	Battery Management System
BMTS	Battery Maintenance and Test System
ECM	Equivalent Circuit Model
EKF	Extended Kalman Filter
EMF	Electro-Motive Force
EVs	Electric Vehicles
HMI	Human Machine Interface
IPC	Industrial Personal Computer
KF	Kalman Filter
OCV	Open Circuit Voltage
RC	Resistance and Capacitance
RMSE	Root Mean Square Error
SOB	State Of Balance
SOC	State Of Charge
SOH	State Of Health
SVM	Support Vector Machine
UKF	Unscented Kalman Filter

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