Journal of Cleaner Production 210 (2019) 43–54

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

A novel endurance prediction method of series connected lithium-ion batteries based on the voltage change rate and iterative calculation

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ARTICLE INFO

Article history:
Received 12 September 2018
Received in revised form
21 October 2018
Accepted 31 October 2018
Available online 2 November 2018

Keywords:
Lithium-ion battery
Endurance prediction
Equivalent model
Voltage change rate
Unmanned aerial vehicles

ABSTRACT

High-power lithium-ion battery packs are widely used in large and medium-sized unmanned aerial vehicles and other fields, but there is a safety hazard problem with the application that needs to be solved. The generation mechanism and prevention measurement research is carried out on the battery management system for the unmanned aerial vehicles and the lithium-ion battery state monitoring. According to the group equivalent modeling demand of the battery packs, a new idea of compound equivalent circuit modeling is proposed and the model constructed to realize the accurate description of the working characteristics. In order to realize the high-precision state prediction, the improved unscented Kalman feedback correction mechanism is introduced, in which the simplified particle transforming is introduced and the voltage change rate is calculated to construct a new endurance prediction model. Considering the influence of the consistency difference between battery cells, a novel equilibrium state evaluation idea is applied, the calculation results of which are embedded in the equivalent modeling and iterative calculation to improve the prediction accuracy. The model parameters are identified by the Hybrid Pulse Power Characteristic test, in which the conclusion is that the mean value of the ohm internal resistance is 20.68 mΩ. The average internal resistance is 1.36 mΩ, and the mean capacitance value is 47747.9F. The state of charge prediction error is less than 2%, which provides a feasible way for the equivalent modeling, battery management system design and practical application of pack working lithium-ion batteries.

1. Introduction

Large and medium-sized Unmanned Aerial Vehicles (UAV) refers to a battery that is fully charged beforehand and supplied to the electric motor. At the same time, the battery is supplemented by an external power source, which has the advantages of low pollution, low noise, high energy efficiency and diversified energy sources. Because they are suitable for the UAV application, lithium-ion batteries are widely used due to low price and excellent cycle performance advantages, as well as having broad prospects of the power supply field.

The Battery-Management-System (BMS) construction method was conducted for the real-time working state monitoring and energy management of the lithium-ion battery packs. Vortex generators were constructed for the active thermal management in lithium-ion battery power supply systems (Mondal et al., 2018). Comparative analysis of lithium-ion battery resistance prediction was realized for the BMS (Mathew et al., 2018). Water cool strategy was studied for the thermal management system of the lithium-ion battery pack (Li et al., 2018). Experimental investigation into the thermal management system was conducted for lithium-ion battery modules with coupling effect by heat sheets and phase change materials (He et al., 2018). Issues and recommendations were analyzed for the energy management system of lithium-ion batteries (Hannan et al., 2018). Impedance-based BMS was designed for the safety monitoring of lithium-ion batteries (Carkhuff et al., 2018). Thermal management system of lithium-ion battery module was realized by using the micro heat pipe array (Ye et al., 2018b). Lifetime management method was investigated for the energy storage system of lithium-ion batteries (Won et al., 2018).

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https://doi.org/10.1016/j.jclepro.2018.10.349

The OCV and SOC relationship functional optimization was conducted for the working state monitoring of the aerial lithium-ion battery pack (Wang et al., 2018e). Performance analysis of the thermal management system was conducted with composite phase change material for lithium-ion battery packs (Wang et al., 2018j). A novel thermal management system was constructed by using the mist cooling method of lithium-ion battery packs (Saw et al., 2018). Afterwards, health management systems were reviewed for lithium-ion batteries (Omariba et al., 2018).

The Equivalent-Circuit-Modeling (ECM) analysis was conducted by mounts of researchers. The State of Charge (SOC) dependent polynomial ECM was investigated for the electrochemical impedance spectroscopy of lithium-ion batteries (Wang et al., 2018a). The parameter identification method study of the Splice-Equivalent-Circuit-Model (S-ECM) was realized for the aerial lithium-ion battery pack (Wang et al., 2018c). A Partnership-for-a-New-Generation-of-Vehicles (PNGV) modeling method together with the State-of-Charge (SOC) prediction algorithm was studied for lithium-ion battery pack adopted in Automated Guided Vehicle (AGV) (Liu et al., 2018b). A mechanism identification model based state-of-health diagnosis of lithium-ion batteries was studied for the energy storage applications (Ma et al., 2018). A comparative study of different ECMs was investigated for the SOC estimation of lithium-ion batteries (Lai et al., 2018). Furthermore, another comparative study of the reduced order ECM was conducted for the on-board state-of-available-power prediction of lithium-ion batteries (Farmann and Sauer, 2018).

The SOC prediction is very necessary for the group working lithium-ion batteries. And the dependent polynomial ECM was realized for the electrochemical impedance spectroscopy of lithium-ion batteries (Wang et al., 2018a). The error sources of the online SOC prediction methods were also investigated (Zheng et al., 2018c). The SOC inconsistency prediction was realized for lithium-ion battery packs by using the mean-difference model and Extended-Kalman-Filter (EKF) algorithm (Zheng et al., 2018b). Incremental capacity analysis and differential voltage analysis based SOC and capacity prediction were conducted for lithium-ion batteries (Zheng et al., 2018a). An online SOC prediction algorithm was proposed for lithium-ion batteries by using an improved adaptive cubature Kalman-Filter (KF) (Zeng et al., 2018). A novel safety anticipation estimation method was proposed for the aerial lithium-ion battery pack based on the real-time detection and filtering (Wang et al., 2018b). The SOC prediction was realized by using a novel reduced order electrochemical model (Yuan et al., 2018). A double-scale and adaptive Particle-Filter (PF) based online parameter identification method was investigated for the lithium-ion batteries (Ye et al., 2018a). Furthermore, the online State-of-Health (SOH) prediction was implied for lithium-ion batteries by the Constant-Voltage (CV) charging current analysis (Yang et al., 2018b). A novel Gaussian processed regression model was investigated for the SOH prediction of lithium-ion battery by using the charging curve (Yang et al., 2018a).

Coupling SOC and SOH prediction effect was analyzed on the mechanical integrity of lithium-ion batteries (Xu et al., 2018). Enhanced Coulomb counting method was conducted by using the Peukert Law and Columbic efficiency (Xie et al., 2018). An energy management system was developed for reusing automotive lithium-ion battery applied in smart-grid balancing (Chiang et al., 2017). Strong tracking effect of H-Infinity Filter was experimentally analyzed to realize the SOC prediction (Xia, Zhang, et al., 2018). Online parameter identification and SOC prediction of lithium-ion batteries were investigated by using the forgetting factor recursive least squares and the nonlinear KF algorithm (Xia, Lao, et al., 2018). The on-line life cycle health assessment was investigated for the lithium-ion battery in EVs (Liu et al., 2018a). Online model identification and SOC estimation were realized for the lithium-ion battery with a recursive total least square based observer method as stated by Wei et al. (Wei et al., 2018). The integration issues of lithium-ion battery into packs were analyzed (Saw et al., 2016). Denoising wavelet treatment was constructed for the SOC prediction of lithium-ion batteries (Wang et al., 2018i) and an Unscented-Kalman-Filter (UKF) observer was also designed for lithium-ion battery SOC prediction (Wang et al., 2018g). An adaptive SOC prediction method was proposed by us for an aeronautical lithium-ion battery pack based on a novel Reduced-Particle-Unscented-Kalman-Filter (RP-UKF) (Wang et al., 2018f). In addition, an integrated online adaptive SOC prediction approach was proposed by us for high-power lithium-ion battery packs (Wang et al., 2018d). The improved SOC dependent polynomial ECM was constructed for electrochemical impedance spectroscopy of lithium-ion batteries (Wang et al., 2018a) together with the influence analysis of battery parametric uncertainties (Shoe et al., 2018).

By analyzing the online safety monitoring methods of lithium-ion battery packs in large and medium-sized UAVs, the high-precision remaining available power prediction is realized, in which the effective State-of-Balance (SOB) evaluation is investigated as well. Then, the safety monitoring equipment is developed for lithium-ion battery packs, laying the foundation for the critical breakthroughs of the reliable power supply. The charge and discharge experiments are designed and the nonlinear parameter identification experiments are also carried out, in which some working characteristics of the lithium-ion battery packs can be obtained. Afterwards, the S-ECM is introduced and the state-space equations are expressed for the endurance prediction to improve its accuracy, which provides an experimental basis for the practical applications, modeling simulation and battery management system design.

2. Mathematical analysis

Through the experimental analysis of lithium-ion battery packs used in the UAVs, the variation law of key factors can be obtained and its rapid detection method is explored. The Voltage-Change-Rate (VCR) and the RP-UKF algorithms are used to realize the online accurate SOC prediction. The variation coefficient calculation method is used to realize the reliable SOB evaluation. In order to meet the reliable energy supply demand, the key technology research such as parameter detection, online fault diagnosis, charging control and safety management, is carried out to realize the safety monitoring equipment development. Technical application and promotion of the system anti-interference, charge and discharge management and safety reliability enhancement are conducted. (1) The integrated chips and digital communication methods are introduced to explore the application of high-precision, fast detection and anti-interference processing technologies for the voltage, current and temperature parameters. (2) By using the application of the VCR and the RP-UKF algorithm, the online high-accuracy SOC prediction is realized while reducing the hardware cost. (3) Applying the variation coefficient calculation idea into the equilibrium state between the lithium-ion batteries of the pack gives an accurate characteristic evaluation. In addition, its stable and reliable operation under complex conditions is successfully achieved. (4) By Combining with the safety control and alarm, charge and discharge control, communication and information storage requirement, a BMS equipment is developed for the UAV lithium-ion battery packs. It provides a basis of the reliable power supply technology breakthrough.

2.1. Parameter detection and anti-interference

Large and medium-sized UAVs have high requirements for the power supply of lithium-ion battery packs, the internal structure of which has large number battery monomers in series and parallel combination characteristics. Aiming at its high-precision and multi-channel signal detection requirements, the anti-jamming technology is researched and a high-reliability detection scheme is designed to realize the multi-channel high-precision detection of key parameters such as voltage, current and temperature for the lithium-ion battery packs. Considering the temperature gradient influence on the detection accuracy, the signal detection and correction methods are studied, which are suitable for different ambient temperatures. By analyzing the noise source of the signal detection process, the photoelectric isolation, transformer isolation, grounding and other technical means are used to solve the anti-interference problem of power supply ripple, electromagnetic interference and violent temperature changes.

During the operation of the lithium-ion battery packs, the detection of the external measurable parameter signal has an inevitable error. At the same time, the noise introduced by the discrete digital sampling and iterative calculation processing is difficult to eliminate, which leads to the cumulative error of the lithium-ion battery state prediction and the intelligent management process. Considering the consistency influence over the monomers, once the equilibrium state information is introduced into the lithium-ion battery ECM constructing process, how these characteristics can be reflected by using the ECM needs to be solved. The expression of key time-varying parameter characteristics, such as voltage, current and temperature, needs to be obtained through the experimental analysis. How to describe the correlation characteristics between time-varying parameters in the battery pack of the perspective ECM requires in-depth studies. The proposed S-ECM method can simulate the internal polarization effect, self-discharge and charge-discharge difference of the battery packs, which is studied to realize the model characteristic expression of the grouped working lithium-ion batteries. Furthermore, the state-space equation is constructed to reveal the variation law of external measurable parameters, which lays a foundation to monitor the reliable energy state of lithium-ion battery packs.

Aiming for the large and medium-sized UAV application scenarios, the lithium-ion battery pack has a large number of serials and parallel combination characteristics. In order to achieve the high-precision, multi-channel signal detection targets, the anti-jamming technology and detection schemes are studied. Meanwhile, the key parameter detection of lithium-ion battery is realized. Based on the high integrated chip and digital communication mechanism, the modular design is conducted to realize the high-accuracy detection, the principle of which is shown in Fig. 1.

In order to solve the multi-channel and high-precision parameter detection problem of lithium-ion battery packs, the influence of different parameters must be considered, such as: temperature gradient change of the detection accuracy, signal detection as well as the correction method suitable for different temperature environments. The anti-interference problem of power supply ripple,

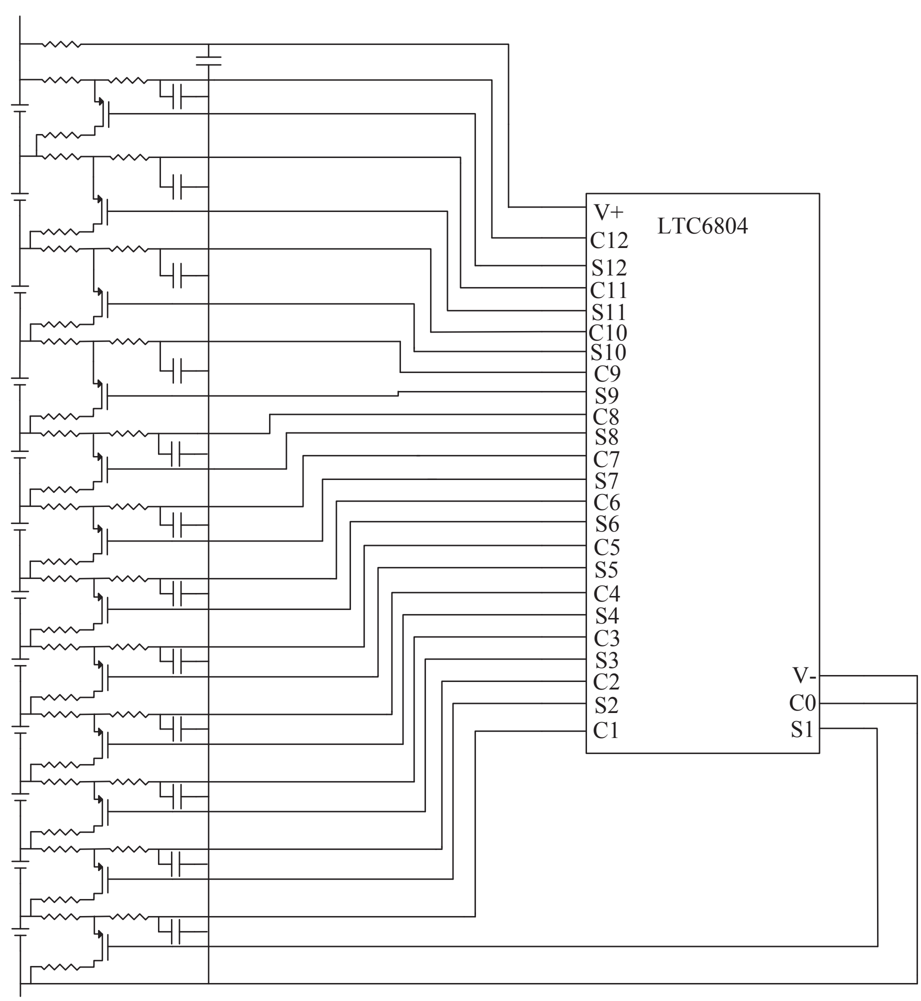

Fig. 1. Key parameter detection sub-module.

electromagnetic interference and other influencing factors should be solved, making it suitable for the complex of UAV application scenarios. The following parameters should be analyzed: the signal detection noise source, anti-interference ability, optical isolation, transformer isolation technologies.

2.2. Residual power prediction and construction

According to the new idea of calculating the SOC value according to the VCR, the SOC prediction model is constructed together with the application of the proposed RP-UKF algorithm. And the recursive operation of the residual available SOC value is realized for the lithium-ion battery packs. Combined with the battery working characteristic analysis of complex working conditions, the improved S-ECM and its state-space equations are implied to improve the calculation efficiency. The linearization process is optimized by streamlining the PF algorithm to eliminate the estimated offset and utilize the equilibrium state. The feedback correction improves the prediction accuracy of the group working batteries, and thus achieves the high-accuracy and online prediction of the remaining available power for the lithium-ion battery packs.

Lithium-ion battery grouping SOC prediction process is affected by the complex monomer structure and aging degree, as well as environmental conditions such as the temperature and humidity. Therefore, the iterative calculation correction of multiple factors needs to be considered in the SOC prediction process. By improving the iterative RP-UKF calculation process, the prediction modeling implementation mechanism is explored, and a real-time optimization model is constructed to provide an overall framework of the SOC prediction. Using high robust KF and its nonlinear extension, combined with the Unscented Transformation (UT) and functional fitting approximation, the mathematical description of working characteristics is explored for different working conditions. Through the modification of model parameters and weighting factors, the influence of inter-monomer imbalance on the SOC prediction is analyzed, and an adaptive SOC prediction model is constructed. Through the experiments, the action law of environmental conditions on the prediction process can be obtained. The typical environmental simulation experiment is used to obtain the change law, and the correction is made to optimize and correct the prediction results, which provides the theoretical basis of the improvement on the SOC prediction adaptability under complex environmental conditions. The relationship between key parameters such as voltage and temperature is obtained, and the influence law is analyzed experimentally. The iterative calculation, correction and functional relationship optimization are used to improve the robustness effect of the SOC prediction model.

Through the reaction mechanism analysis and working condition simulation experiments, the internal reaction process of the lithium-ion battery is clarified, and the variation rules of current, voltage and temperature are studied. The working characteristics of different working conditions are obtained and established, together with the relationship between the Closed Circuit Voltage (CCV), temperature and current. Combined with the working mode analysis under different working conditions, the basic characteristic analyzing experiments are investigated for lithium-ion battery packs. Through the experimental research of different magnification, cyclic charge and discharge, the key factors can be obtained. Based on the simulation experiments at different working conditions, the output response and change trend of lithium-ion battery pack under different working conditions can be obtained and analyzed. The working condition influence is discussed, and the operating characteristic curves and variation laws of different working conditions are obtained. By using the battery ECM and state-space equation expression, the mathematical description methods of different working conditions are explored. Furthermore, using the high robust KF and its nonlinear extension algorithm, combined with the UT and function fitting approximation, the adaptive remaining available power prediction model is constructed.

Based on the simulation and experimental analysis, the relationship between the remaining available electricity and SOB between the monomers can be analyzed during the group working conditions. The model parameters and weighting factors are modified to solve the influence of the imbalance between the monomers on the SOC prediction. On the basis of simulation and experimental analysis, the influence of the equilibrium state is incorporated into the adaptive SOC prediction process by using the mathematical SOB description. As a result, the model parameters and weighting factors are corrected and the prediction model is improved. The remaining available power prediction is verified by the complex working condition experiments, which is realized through the standard current charging, long-term shelving, intermittent replenishment, rapid discharge and other experimental research. Through the normal state, over-charge and over-discharge simulation conditions, the experimental verification of the remaining available power prediction is carried out under complex conditions.

In order to improve the adaptability of the SOC prediction process, the voltage signal is used to detect the combined VCR to achieve the accurate SOC prediction. In the implementation process, the intermediate parameters of U_A, SOB and Rate_U are first calculated by using the mean monomer voltage value, variation coefficient and VCR. Afterwards, the current value I_L under the influence of the complex working condition is obtained by using the functional calculation. The obtained current parameter I_L and the equilibrium stated parameter SOB are used as input parameters, and the proposed S-ECM model is constructed. Then, the corresponding state-space equation *S_E* can be obtained. Finally, the proposed real-time SOC prediction is achieved by the proposed RP-UKF algorithm. In the SOC prediction process of the lithium-ion battery pack, the real-time detected individual cell voltages of U_1, U_2, U_3, … and U_n are used as the main input parameters, combined with the input of the temperature signal *T*. The RP-UKF algorithm is used for iterative calculation to obtain the SOC value. The overall implementation structure block diagram is shown in Fig. 2.

In the above figure, the overall structure of the lithium-ion battery state-space mathematical description is divided into three parts: S1, S2 and S3.

In the S1 section, the inlet parameters are the individual monomer voltages of U_1, U_2, U_3, … and U_n, and finally it is transformed into the state-space equation for the mathematical description. The module Avr is used to calculate the average voltage value U_A. The module Volt_Rate is used to obtain the VCR parameter Rate_U. And the module Var_Coef is used to find the inter-

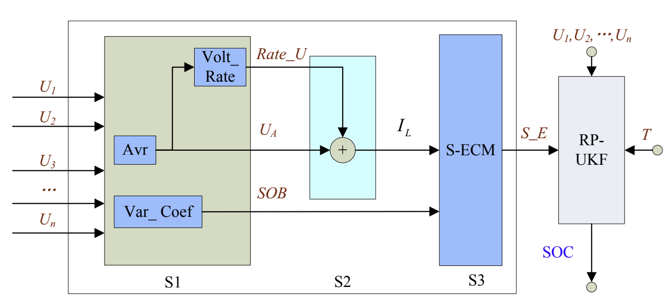

Fig. 2. SOC prediction structure.

monomer balance state SOB as shown below.

$$U_A = \frac{1}{n}(U_1 + U_2 + U_3 + \cdots + U_n) \tag{1}$$

$$Rate\_U = h(U_{A1}, U_{A2}, U_{A3}, \cdots, U_{Am}) \tag{2}$$

$$SOB = \theta^2 = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{U_i - U_A}{U_A}\right)^2 \tag{3}$$

Wherein, n is the number of battery monomers in series, in which the parallel monomers used for expansion are taken as a single battery cell. U_1, U_2, U_3, …, and U_n are the respective monomer voltages. U_{A1}, U_{A2}, U_{A3}, …, and U_{Am} are the U_A values, which are obtained at the first m time moments in front of the present time. $h(*)$ is the functional relationship of the VCR. SOB is an equilibrium state between the internal connected battery monomers, which is obtained by calculating the square value of the variation coefficient θ. U_i is the voltage acquisition value of the i-th battery monomer at the present time.

In the S2 plate, the mean voltage and change rate parameters are used to obtain the estimated operating current value I_L by the following functional relationship, which will replace the measured value to participate in the subsequent iterative calculations.

$$I_L = f(U_A, Rate\_U) \tag{4}$$

In the S3 plate, the inlet parameter is the calculated current value I_L, and the balance state value *SOB*. In the real-time iterative calculation process, the proposed RP-UKF algorithm is adopted. The inlet parameters are the voltage signals of each battery cells and the temperature, and the exit parameter is the SOC value of the group working lithium-ion batteries. The optimized real-time iterative calculation is used to obtain the accurate SOC value. The equivalent model S-ECM can be introduced as shown in Fig. 3.

Through the Kirchhoff law and the SOC iterative calculation of mathematical expression of discrete time conditions, the state-space equation is obtained as shown in the Equation (5).

$$\begin{cases} SOC(k|k-1) = SOC(k-1) - \dfrac{\eta_I \eta_T I(k) T_s}{Q_n} - \dfrac{I_s(k)^* T_s}{Q_n} \\ U_L(k) = (U_{OC} - U_\delta) - (R_o + R_\delta)^* I(k) - I(k) R_p\left(1 - e^{-T_s/R_p C_p}\right) - I(k) R_{cd} \end{cases} \tag{5}$$

Based on the proposed RP-UKF algorithm, the simplified three-particle and double UT treatments are performed to improve the prediction accuracy and reduce the computational complexity. Furthermore, a specific implementation is performed for the real-time SOC prediction, the calculation flow of which is shown in Fig. 4.

The above calculation makes full use of the voltage signal characteristics in the lithium-ion battery pack, and uses the characteristic information covered in the voltage signal obtained by the real-time detection instead of current signal changes to realize the effective real-time working state expression, reducing the hardware cost of the signal detection and the BMS volume. At the same time, the method can adapt to the SOC prediction of lithium-ion battery packs with different capacities by removing the dependence on the current signal detection, which greatly improves the adaptability of the algorithm. The ideal voltage source U_{OC} is used to indicate the OCV characteristics. U_L is the terminal voltage at both ends of the external load. The positive and negative of I_L characters the discharge and charge working conditions. The Ohm internal resistance R_o is determined by the internal structure of the battery and the electrolyte. The polarization internal resistance R_P is the resistance caused by the polarization effect when the positive and negative electrodes of the batteries are chemically reacted, and C_P is the polarization capacitance. The parallel circuit of R_P and C_P describes the polarization process. According to the working characteristics of the capacitor component, the relationship between the current flowing through the battery polarization capacitor and its CCV is shown in Equation (6).

$$Ip(\mathrm{t}) = \mathrm{Cp}\frac{dUCp(t)}{dt} \tag{6}$$

It can describe the dynamic and static performance of lithium-ion batteries, which can simulate the battery behavior accurately under different current and temperature conditions in the charge and discharge process. Its structure is relatively simple and has been widely used in the dynamic modeling of power batteries. When the battery is charged and discharged, the accumulation of current in time causes a SOC change. R_o represents the ohm internal resistance. I_L is its load current, and U_L is the terminal voltage. These parameters need to be obtained by HPPC experiments.

The applied mathematical modeling approach is compared with other approaches that are used in the working state estimation and prediction process of the lithium-ion batteries. The main features and innovations of this method compared with other approaches are as follows: (1) A composite equivalent circuit modeling method is proposed to accurately describe the working characteristics. (2) Based on the improved UKF algorithm, a new model of group working state prediction is constructed. (3) Explanatorily apply key factors such as equilibrium state are introduced to the correction process of SOC prediction. Through the simulation of the dynamic auxiliary power simulation and the prediction effect analysis, the effective characterization of the remaining power of the power lithium battery pack is realized, in which the computational complexity is reduced and the prediction accuracy is improved.

2.3. Reliable equilibrium state evaluation

The equilibrium state is introduced into the ECM modeling analysis process during the SOC prediction process of the group working lithium-ion batteries. Furthermore, these characteristics should to be reflected off the ECM, and applied to the iterative calculation processes of the SOC prediction for the battery packs. Based on the mathematical description of the monomer voltage difference, the equilibrium stated modeling and the correction methods are developed to describe the inconsistent state between the monomers. Furthermore, the model parameters are combined with the weighting factors, which are embedded in the iterative SOC calculation processes. And the iterative calculation process is implemented with modularity to eliminate the monomer difference influence on the SOC prediction accuracy of the group working lithium-ion batteries. Through the modification of model parameters and weighting factors, it can make a reliable numerical evaluation of the equilibrium state between the lithium-ion battery

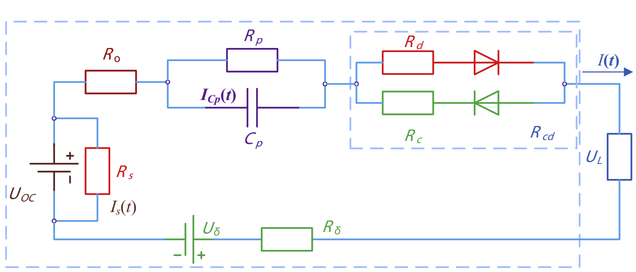

Fig. 3. S-ECM equivalent model.

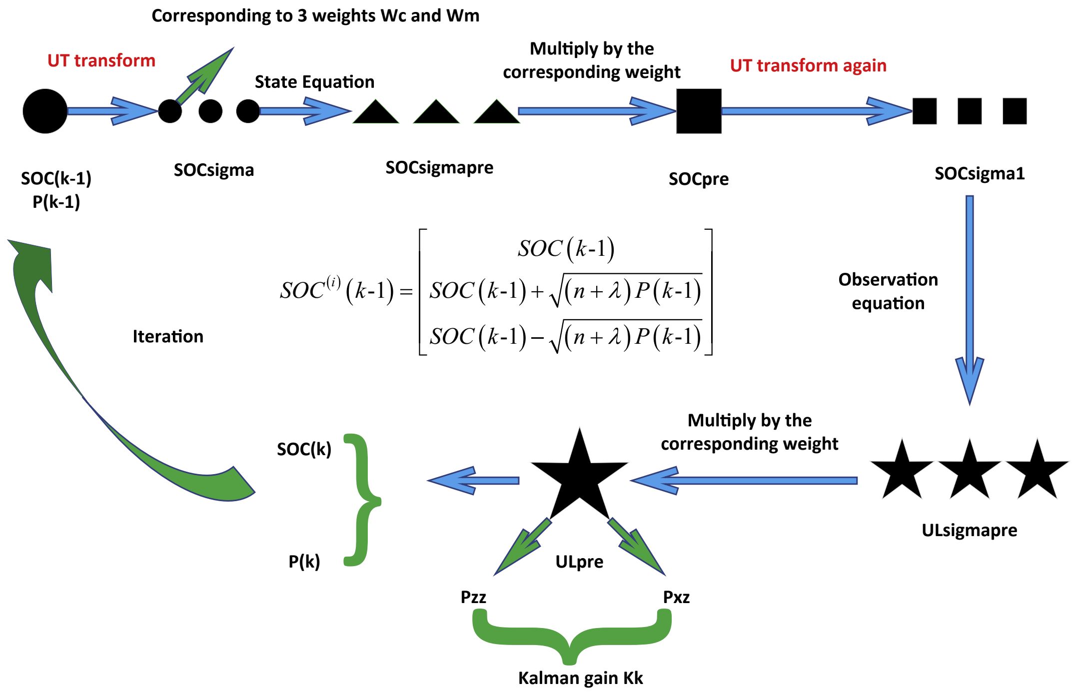

Fig. 4. RP-UKF algorithm based SOC prediction flow.

monomers. Using the monomer voltage to achieve the inter-monomer SOB evaluation, a novel numerical description can be conducted. Combined with the variation coefficient calculation in statistics, the equilibrium stated characteristic between the monomers of the power lithium-ion battery pack is expressed. Finally, the effect of inter-body consistency difference is described in the correction section to eliminate the impact on the inter-monomer inconsistency of the SOC prediction.

The lithium-ion battery packs utilize complex cascade structures to break the limitations of low voltage and small capacity of the battery monomers. Due to the inevitable monomer difference in the manufacturing and application process, the imbalance between the internal monomers of the battery pack occurs, which causes safety hazards in the practical applications and affects the accuracy of the group working SOC prediction. Therefore, it is necessary to study the evaluation method of the equilibrium state and apply it to the correction step of the prediction process. During the application of lithium-ion battery packs, the difference between monomers will increase along with time. Based on the calculation of the variation coefficient, the evaluation and characterization of the equilibrium state are realized. The implementation idea is shown in Fig. 5.

Combined with the influence of environmental conditions, the revised strategy is studied to describe the inconsistent state between monomers and solves the problem of constructing the evaluation model of the equilibrium state between monomers. The influence degree analysis of each input parameter is carried out, and the weight preset of each parameter is realized for the evaluation process, which is then used for the equilibrium state correction in the SOC prediction process. Through the modification of model parameters and weighting factors, a reliable numerical evaluation of the equilibrium state between the monomers is made and applied to the correction process of the state parameters.

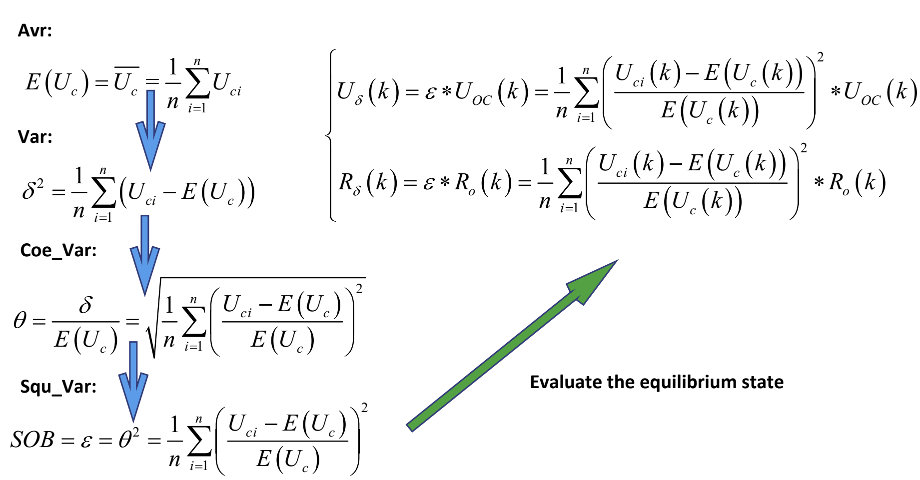

Fig. 5. State of balance evaluation.

2.4. Battery management equipment development

The development of supporting safety monitoring equipment for lithium-ion battery packs embedded in large and medium-sized UAV is mainly realized through the state parameter detection, online fault diagnosis, charging control, safety control and alarm, communication and information storage. Furthermore, the thermal runaway control strategy is studied together with security monitoring and alarm by using the intelligent management strategy and implementation technologies. When the fault is diagnosed, the controller is notified and the processing request is sent to command. When the threshold value is exceeded, the main loop power is cut off to prevent high temperature and over-discharge phenomenon. The system structure of BMS is shown in Fig. 6.

As can be seen from the above Figure, the safety monitoring technologies of lithium-ion battery packs are studied for the large and medium-sized UAVs. In addition, the remaining available power prediction model is embedded in the BMS to realize the online accurate SOC prediction. The key technology research is conducted, such as parameter detection, online fault diagnosis, battery safety control and alarm, charging control. And then, the development of supporting safety monitoring equipment is realized to ensure the safe and reliable operation of lithium-ion battery packs. The power lithium-ion battery pack is maintained at a good operating temperature by using a heater chip and a heat sink. Based on the functional and performance requirements of the power application, a working state detection and analysis subsystem is designed. The operational status detection and analysis includes the SOC prediction of the power lithium battery pack to ensure its safe application for its energy storage and energy supply processes. The data transmission uses the digital signals with strong anti-interference ability, and realizes real-time voltage, current and temperature signal detection during charging and discharging process. Compared with other systems, the improved equivalent model building and endurance prediction methods are introduced in our scientific research, which is put forward considering the characterization accuracy and computational complexity by using the improved equivalent circuit modeling method together with the RP-UKF algorithm investigation. The comprehensive SOB evaluation is conducted real-timely for the internal connected battery cells, which is implied into the iterative calculation process. The corresponding anti-interference processing is carried out and the correction algorithm is employed for the obtained function relation when it is applied to the on-line state prediction process of the safety control system for the lithium-ion battery packs.

3. Experimental analysis

3.1. Charging and discharging process

In order to get the basic working characteristics of the lithium-ion battery packs used in the UAVs, this experiment monitors the electricity variation in real-time. The lithium cobaltate (LiCoO2) battery pack is selected as the experimental sample, which consists of M cells connected in series, heating components, sampling resistors, temperature sensors, sockets and combined cover. Combined with the application of temperature sensors, cross-type connectors and electronic connectors, the organic combination of multiple components is realized. The proposed method is applicable to different types of lithium-ion battery packs, and only needs to modify the coefficient values of the functional relationships, which will be obtained by parameter identification. The voltage and current changes are analyzed for the working state monitoring under different working conditions, and the voltage variation law

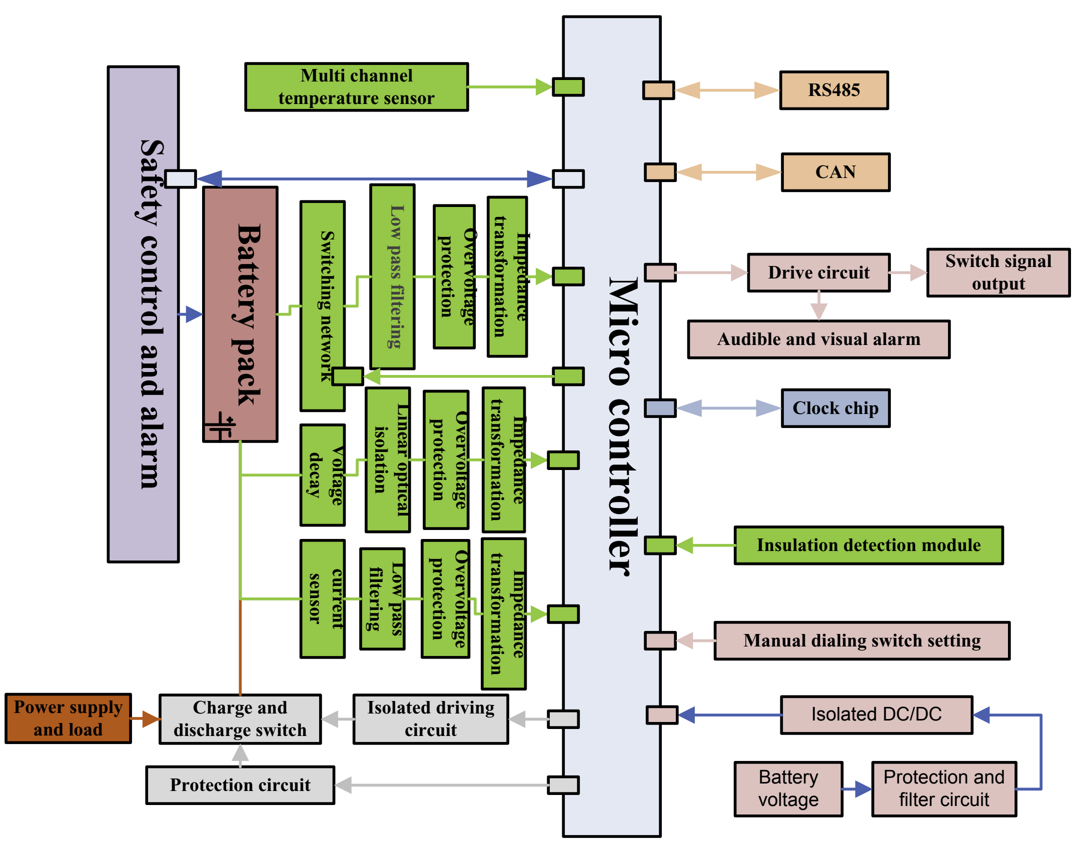

Fig. 6. Supporting safety monitoring equipment structure.

can be obtained towards time. The relationship is shown in Fig. 7.

Firstly, 1C Constant-Current (CC) charging treatment is used for the fast charging process of the charging phase. The voltage has a fast rising phase, a slow rising phase, and a fast rising phase again. When the voltage rises to the rated terminal charging voltage, the current decreases gradually until the current drops to 0.05C when the charging is at the end by using the CC-CV charging treatment. Then, the lithium-ion battery pack is left for 1 h to make the internal reaction returns to the steady state. The discharge test is conducted by 1C CC discharging. When the voltage drops to the end discharge voltage, the discharge process is the end. In the discharge process, the whole figure can be divided into three parts, which are: the voltage of the first part in the CC discharge process is rapidly decreased. The voltage dropped rate of the second part decreases slowly, and the voltage dropped speed of the third part is fast. The discharge is terminated by the drop to the discharge termination voltage. The different charge and discharge curves obtained by controlling the current magnifications of 0.5C, 1C and 1.5C are shown in Fig. 8.

During the discharge process of the lithium-ion battery, most of the time is in the second part, and the length of time occupied by the second part reflects the health state and the battery working performance. The multiple charging characteristics are shown in Fig. 9.

This is the voltage variation curve under different charge and discharge current rate conditions. Its variation law is studied, and a new method is explored for the SOC prediction. At present, the difference seen by the naked eye is quite large and the difference is obvious, but this is seen under the premise of large compression in the time axis. In a short time-frame, the change will be very insignificant. In order to obtain the voltage change rate law, the charge curve is amplified locally. The functional change law is observed and obtained as shown in Fig. 10.

The voltages are the same and the slopes are different. According to the one-to-one correspondence between the different slopes and the discharge current, the discharge current can be obtained. Afterwards, only voltages need to be measured to get the current, which is then used estimate the SOC value.

3.2. OCV-SOC nonlinear parameter identification

At the room temperature of 25 °C, the lithium-ion battery was filled and allowed to stand for 1 h by the CC-CV charging method, and the internal reaction was returned to a stable state. The CC discharge was performed at a discharge rate of 1 C. When the 10% SOC is released, it is set to stand for 30 min. The cyclic operation is performed for 10 times, and the voltage versus time curve is obtained. OCV is the terminal voltage of the battery in the open state,

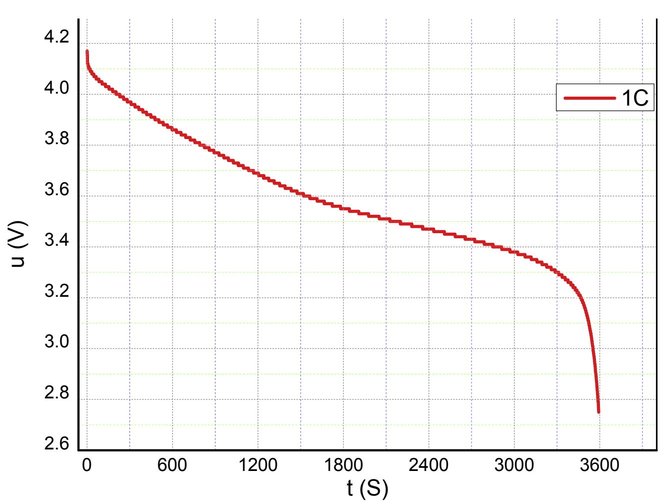

Fig. 7. Charge and discharge characteristics.

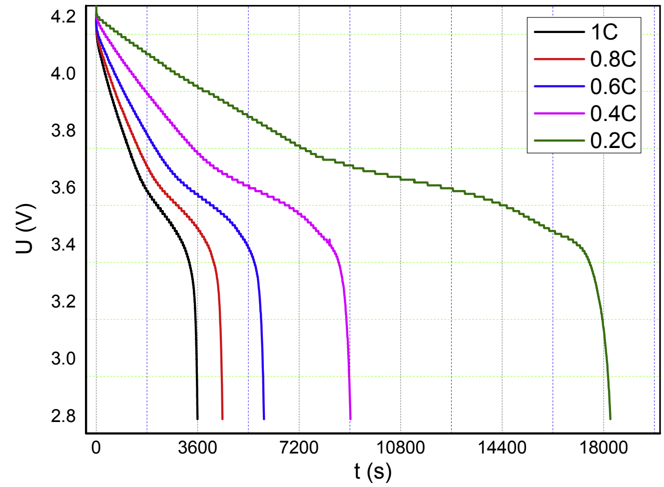

Fig. 8. Discharge at different rates.

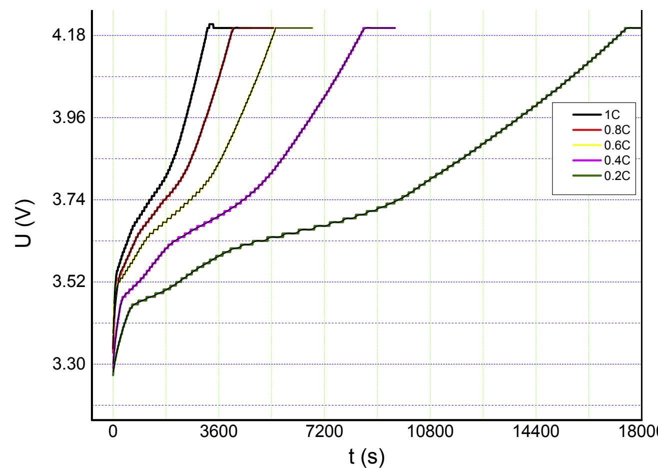

Fig. 9. Charge at different rates.

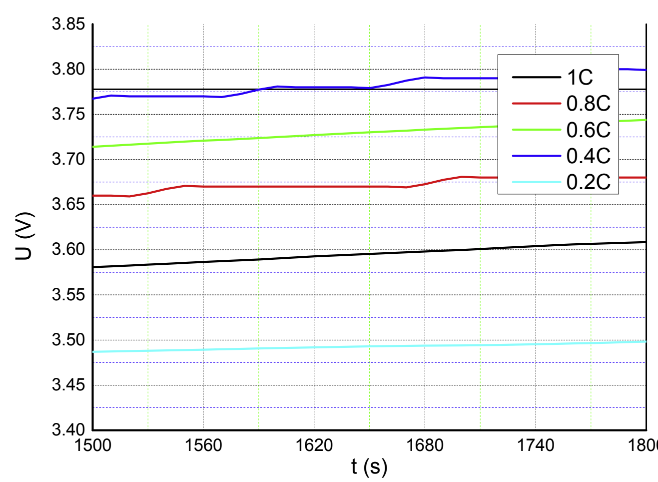

Fig. 10. Local charge at different rates.

which can be recorded after standing for 30 min for every 10% SOC release in the experiment. And the OCV-SOC relationship curve at 1C discharging rate is obtained as shown in Fig. 11.

The curve fitting result of the OCV-SOC relationship is shown in Equation (7).

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

Wherein, $a_0 = 22.3$, $a_1 = 32.9$, $a_2 = -92.4$, $a_3 = 86.6$, $a_4 = 50.9$, $a_5 = -125.3$, $a_6 = 53.9$.

3.3. Pulse power experimental test

The Hybrid Pulse Power Characterization (HPPC) tests are very important, which are used commonly in the parameter identification process. It is currently used by mounts of battery manufacture and UAV companies to evaluate the performance of the battery systems and modules. A single HPPC test is shown in Fig. 12.

In the first step, the lithium-ion battery is subjected to a 1C rate CC pulse discharge 10 s, which will be set aside for 40 s in the second step. In the third step, the lithium-ion battery is charged with a CC pulse of 10C at a rate of 10C. In the cycle test, the lithium-ion battery is fully charged by CC-CV charging, and the SOC value is reduced to 90%, 80%, …, 10% by CC discharging for 40 min. The HPPC test is performed under the SOC value, and the voltage change relationship to time can be obtained.

3.4. Model parameter identification

The test was carried out at a temperature of 25 °C to identify the parameters in the ECM, such as the ohm internal resistance R_o, the polarization internal resistance R_p and the polarization capacitance C_p. Taking the SOC of 0.95 as an example, the single cycle HPPC tested voltage response curve is obtained as shown in Fig. 13.

(1) The parameter identification of ohm internal resistance R_o is conducted by using the following treatment. The current changes at time t_1, and the sudden changes of voltage U_0 to U_1 are caused by the ohm internal resistance R_o, so its value can be obtained by Equation (8).

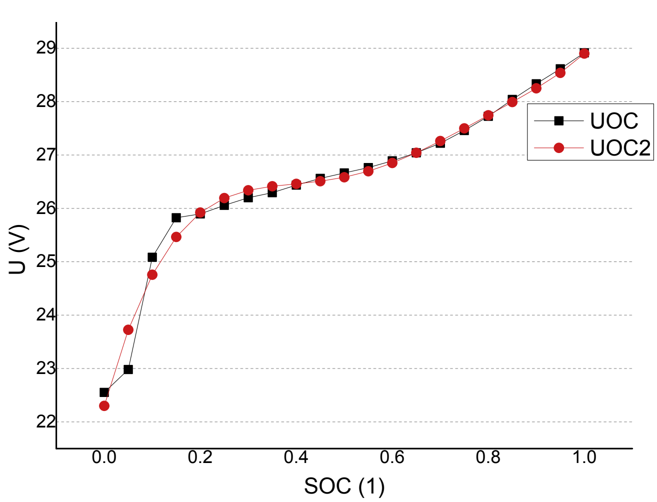

Fig. 11. OCV-SOC curve at 1C discharge rate.

$$R0 = \frac{\Delta U}{I} = \frac{U0 - U1}{I} \tag{8}$$

(2) Parameter identification of polarization internal resistance R_P can be investigated as follows. During the static stage of t_3-t_4, the polarization capacitance C_P is discharged through R_P, and the voltage is slowly increased to U_2 by U_1'. The magnitude of the rise is determined by R_P, so its value can be obtained by using Equation (9). Wherein, I is the discharge current.

$$R_P = \frac{\Delta U'}{I} = \frac{U_2 - U_1'}{I} \tag{9}$$

(3) Parameter identification of time constant can be investigated as follows. The same analysis of the t_3-t_4 static stage, the zero input response to the parallel RC circuit of this stage can be implied to obtain the OCV value by using Equation (10).

$$UOC = U1 - UCP = U1\left(1 - e^{-\frac{t}{\tau}}\right) \tag{10}$$

As can be known from the above Equation, U_1' and U_2 can be obtained as shown in Equations (11) and (12).

$$U_1' = U_0\left(1 - e^{-\frac{t3}{\tau}}\right) \tag{11}$$

$$U_2 = U_0\left(1 - e^{-\frac{t4}{\tau}}\right) \tag{12}$$

Furthermore, the time constant of the simultaneous Equations can be obtained as shown in Equation (13).

$$\tau = -\frac{t4 - t3}{\ln\left(\frac{U_0 - U_2}{U_0 - U_1'}\right)} \tag{13}$$

(4) Parameter identification of the polarization capacitor C_P can be obtained, after obtaining R_P, which is shown in Equation (14).

$$C_P = \frac{\tau}{R_P} \tag{14}$$

According to the HPPC test data, the values of various parameters are calculated, as shown in Table 1.

As can be known from the experimental data analysis, the mean value of ohm internal resistance R_o is 20.68 mΩ. The mean value of the polarization internal resistance R_P is 1.36 mΩ, and the mean value of polarization capacitance C_P is 24421.7F. The ohm internal resistance R_o does not change significantly into the discharge process. As the SOC value decreases, there is a slightly rising process. The polarization internal resistance R_P has little change along with the SOC value, and there is no obvious rising or falling trend. Therefore, the average values are selected as the polarization internal resistance values. The polarization capacitance C_P decreases along with the SOC value, and it increases gradually.

3.5. The SOC prediction effect

The M-ICPXX power lithium-ion battery pack was selected as the experimental sample, which was mainly composed of medium-sized ICPXX lithium-ion battery cells, heating components, sampling resistors, temperature sensors, sockets and composite cover. The combination, combined with the application of temperature sensors, cross-connectors and electrical connectors, enables the

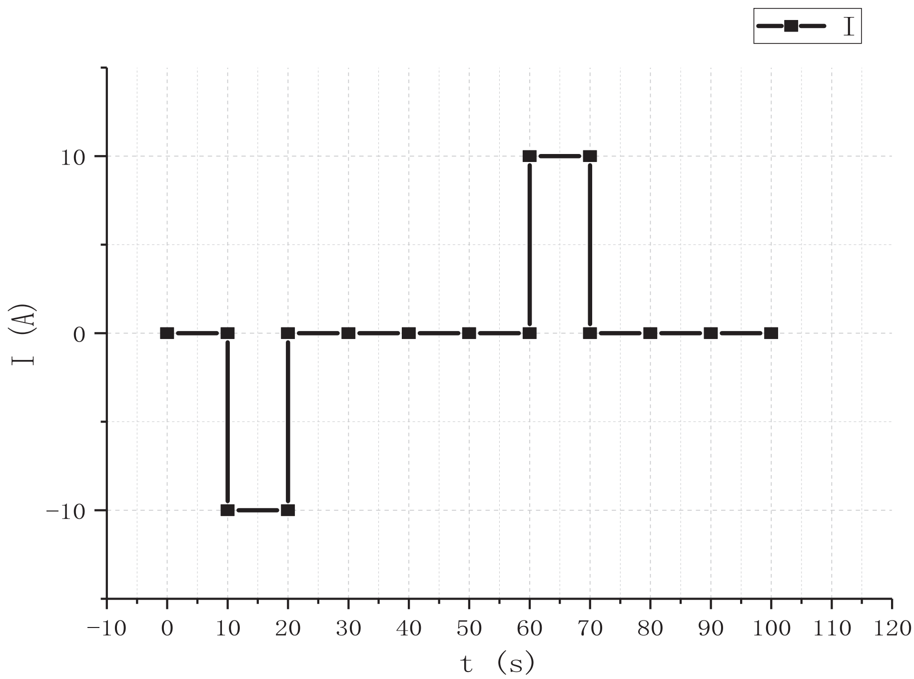

Fig. 12. HPPC test current curve.

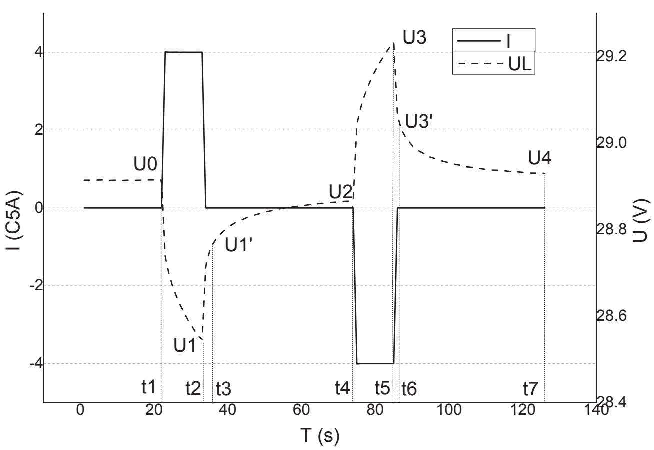

Fig. 13. HPPC single test curve.

Table 1
The parameter value of HPPC test and calculation.

SOC	R_0/mΩ	R_p/mΩ	C_p/F	U_{oc}/V
1	20.7	1.49	93317.1	3.4
0.9	18.6	1.16	49748.1	3.34
0.8	15.7	1.06	54440.5	3.32
0.7	17.9	1.02	56575.4	3.3
0.6	17.1	1.36	42431.6	3.296
0.5	19.55	1.21	47691.7	3.294
0.4	20.3	1.59	36294.2	3.29
0.3	23.4	1.67	34555.5	3.27
0.2	24.9	1.46	39525.8	3.25
0.1	28.6	1.59	22899.1	3.21

organic combination of multiple components. The string XX represents the rated capacity of the lithium-ion battery pack. The single cells are composed of a plurality of batteries connected with parallel and confluent, which is sealed by a battery cell shell and a single cell cover. The heating component includes a polyimide heating film and a heating frame. During the application process of the lithium-ion battery pack, the battery cells formed by the respective parallel battery cells need to be cascaded in series to meet the high voltage and large capacity requirements of the UAV power application. According to the power demand, the number of commonly used series lithium-ion monomers should be 6, 7, and 14. In the experimental analysis process, the lithium-ion battery pack and its internal connected monomers were selected for the experimental analysis. The experimental results are shown in Figs. 14 and 15.

As can be known from the experimental data, the effective CCV tracking and the SOC estimation can be realized under complex working conditions.

After comparison of the results obtained by the Ah-based integral method, the error between the iterative calculated value and the ampere-hour integral value is stable within 2.00%. It can be seen from the experimental data shown in the figure that the tracking error of the CCV in the complex working condition is 1.00%, and the error between the iterative calculation value and the ampere-hour integral value is stable within 2.00%. Experimental data shows that this method can achieve the effective CCV tracking and SOC prediction.

4. Conclusions

The endurance prediction of the power lithium battery pack plays an important role in its energy and safety management, which is an important part of the clean production and the reasonable battery energy management will facilitate its smooth implementation. A new endurance capability predicting method is proposed and realized, which improves the prediction accuracy and reduces the iterative computational complexity. The experimental verification is conducted, combining with the theoretical analysis, model construction, equipment development and experimental verification. In view of the reliable energy management and safety control objectives of lithium-ion battery pack, the battery

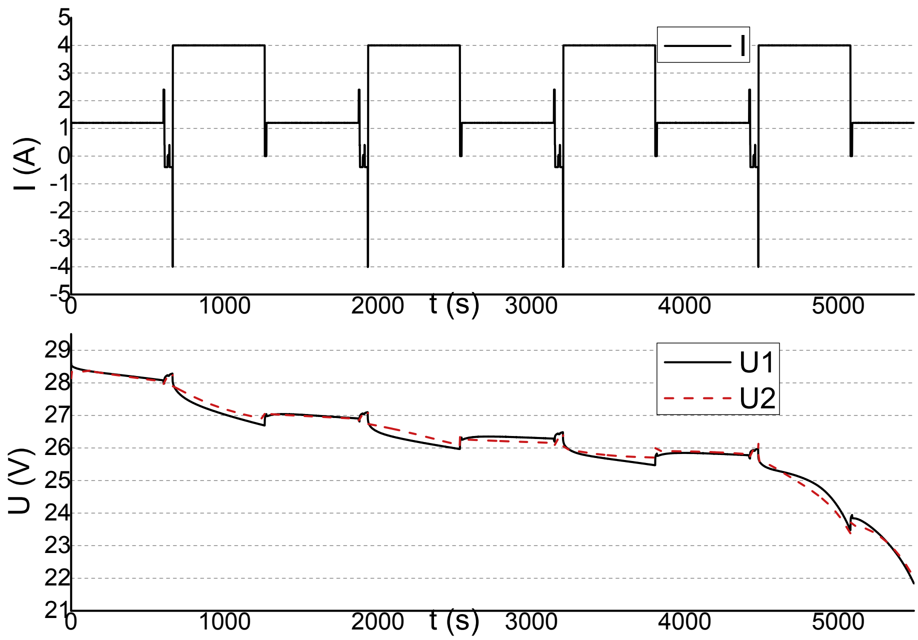

Fig. 14. CCV tracking effect.

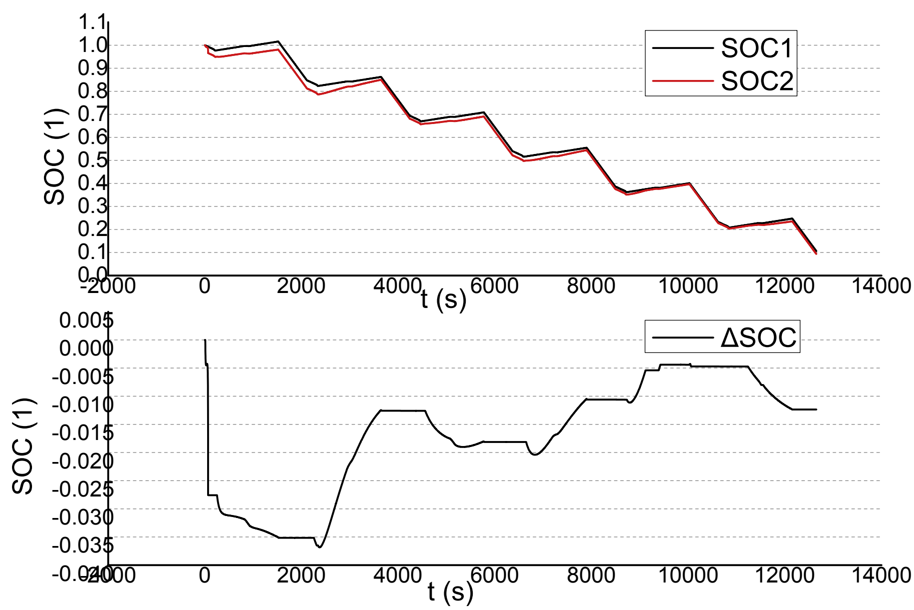

Fig. 15. SOC prediction effect.

equivalent modeling construction method is explored and the adaptive residual available power prediction along with equilibrium state evaluation is realized. In combination with the application scenario analysis of large and medium-sized UAVs, a safety monitoring equipment is developed to conduct the reliable energy management and safety controls. And weighed the complexity and accuracy, the improved ECM has been constructed by using the HPPC test of the parameter identification. The charge and discharge experiments and nonlinear curve identification experiments are carried out to analyze the partial operating characteristics of the lithium-ion batteries, which are also used to verify the prediction effect. It provides experimental basis of the future practical applications, modeling simulation and BMS design. In the future, the following aspects will be further studied: (1) The equivalent modeling methods of group working characteristics by using the electronic components. (2) The calculation improvement on the unscented transformation weights and the Kalman superposition correction factor. (3) The expansion and correction strategy of the influence parameters.

Acknowledgments

This research was supported by National Natural Science Foundation (No. 61801407), Sichuan Province Science and Technology Support Program (No. 2018GZ0390, 2017FZ0013), Scientific Research Fund of Sichuan (No. 17ZB0453), Sichuan Science and

Technology Innovation Miao-Zi Project (No. 2017109), Teaching Research Project (18gjzx11, 18dsts16), Sichuan Science and Technology Innovation Cultivation Project (No. 201710619112), RGU. Thanks to the sponsors.

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